Latin American Journal of Solids and Structures
www.lajss.org

Applicability of Artificial Neural Network and Nonlinear Regression to Predict Mechanical Properties of Equal Channel Angular Rolled Al5083 Sheets

Abstract

Equal channel angular rolling (ECAR) is a severe plastic deformation (SPD) process in order to achieve ultrafine-grained (UFG) structure. In this paper, the mechanical properties of ECAR process using artificial neural network (ANN) and nonlinear regression have been illustrated. For this purpose, a multilayer perceptron (MLP) based feed-forward ANN has been used to predict the mechanical properties of ECARed Al5083 sheets. Channel oblique angle, number of passes and the route of feeding are considered as ANN inputs and tensile strength, elongation and hardness are considered as the outputs of ANN. In addition, the relationship between input parameters and mechanical properties were extracted separately using nonlinear regression method. Comparing the outputs of models and experimental results shows that models used in this study can predict and estimate mechanical properties appropriately. Where, the performance of ANN model is better than the correlations to predict mechanical properties. Finally, the developed outputs of neural network model are used to analyze the effects of input parameters on tensile strength, elongation and hardness of ECARed Al5083 sheets.

Keywords

ECAR, Mechanical properties, Ultrafine-grained, Artificial neural network, Nonlinear regression

Masoud Mahmoodi [a] *
Ali Naderi [b]

[a] School of Mechanical Engineering, Semnan University, Semnan, Iran.
mahmoodi@profs.semnan.ac.ir
[b] School of Mechanical Engineering , Semnan University, Semnan, Iran.
alinaderi@students.semnan.ac.ir

* Corresponding author

http://dx.doi.org/10.1590/1679-78252154

Received 21.05.2015
In revised form 23.02.2016
Accepted 23.03.2016
Available online 12.04.2016

NOMENCLATURE

O output value
I input value

NOMENCLATURE (continuation)

m experimental data
p predicted data
W weight function
ξ activation function
b bias value
R correlation coefficient
ρ performance ratio
φ channel oblique angle
N number of passes

1 INTRODUCTION

In the last decade, SPD was introduced as an effective method in the production of metals with nano structure. Recently UFG materials produced by SPD processes have been considered by many researchers. ECAR process is a SPD method that leads to UFG structure and improved mechanical properties of material. This process is presented for continuous forming of sheets and strips and like ECAP can apply large strain to the material with no change in cross-section of piece (Sedighi et al., 2013).

In this decade, many researchers have investigated the ECAR process and micro-structure of its samples. Kavackaj et al (2012). The effect of the temperature on the accelerated grain refining during the continuous ECAP operation was discussed by Lee et al (2002). Chen et al. (2007) illustrated the effect of ECAR pass on microstructure and properties of magnesium alloy sheets.

Chung et al. (2006, 2007) analyzed the accumulated deformation and the control of thickness uniformity of Al 6063 alloy in the ECAR process. Cheng et al. (2007, 2008) illustrated ECARed AZ31 magnesium alloy sheet drawability and its improvement at room temperature. The effect of ECAR process on AZ31 magnesium alloy has been studied by Hasani et al. (2011) to achieve a nano-structure. Habibi et al. (2011, 2012) illustrated the effect of ECAR process on strength and electrical conductivity of pure copper. They also applied ECAR and post-annealing to enhance the properties of nano-grained pure copper. Mahmoodi et al. (2012) studied the residual stress distribution through the thickness of ECARed aluminum alloy.

Since experiments require fairly high cost and time, ANN has been attended considerably by researchers in various fields because of its ability in modeling variables with a few experiments. In fact, ANN is a new method for predicting the nonlinear behavior of material properties (Anaraki et al., 2008). The main advantage of ANN compared to conventional methods is its high speed in solving the complicated relationships (Zhangtt et al., 1995). ANN has capability of modeling and predicting the behavior of complex processes based on specified data (Derogar et al., 2011).

Recently, a tendency toward modeling using neural network in different fields of metal forming has increased (Toros et al., 2011; Forcellese et al., 2011; Ambrogio et al., 2010). Djavanroodi et al. (2013) and Esmailzadeh et al. (2012) applied ANN to model ECAP process based on experimental and three-dimensional finite element method. They indicated a good agreement between experimental results and ANN outputs.

Chan et al. (2008) developed a comprehensive methodology based on finite element method and ANN to estimate the design parameters and determine the optimal network structure. Qin et al. (2010) used ANN model to evaluate and predict the deformation behavior of ZK60 magnesium alloy during hot compression. ANN modeling to predict the hot deformation behavior of A356 aluminum alloy was performed by Haghdadi et al. (2013). Sheikh et al. (2008) estimated the flow stress behavior of AA5083 using ANN with regard to the dynamic strain aging effect.

The tensile strength, elongation and hardness have traditionally been the most widely quoted and applied determinants of mechanical behavior. In this paper, mechanical properties of ECARed Al5083 alloy sheet have been estimated by using artificial neural network. Likewise, nonlinear regression has been employed to propose equations for mechanical properties in terms of channel oblique angle and number of passes.

2 ECAR PROCESS

Figure 1 shows a schematic of ECAR process equipment. In this process, the sample passes through the die channel with no change in cross section under a continuous severe shear deformation. According to Figure 1, ECAR process takes place in routes A and C. In route A, the strip moves along rolling direction with no rotation, while in route C, the strip is rotated 180 degrees in rolling direction before the process.

Input and output channel thickness is 2 mm and the thickness of strip after rolling reduction is 1.95 mm. The Al 5083 samples with the dimension of 400 * 40 * 2 mm were annealed for one hour at 350 ċ. The experiments were accomplished in channel oblique angles of 110, 120 and 130 degrees for 1 to 3 passes at room temperature (Mahmoodi et al., 2011).

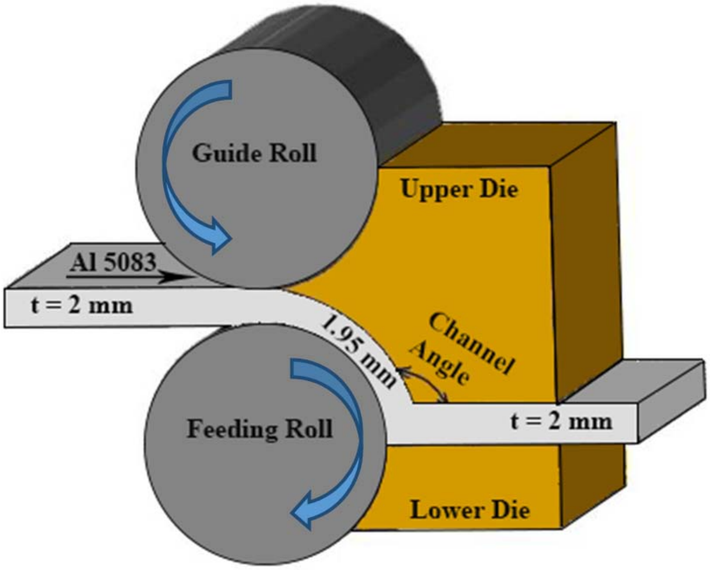

Figure 1: schematic of ECAR process.

3 DESIGN AND TRAINING ARTIFICIAL NEURAL NETWORK

Artificial neural network is a general tool for modeling nonlinear functions, so that it can approximate any complex behavior with any desired level of accuracy. ANN flexibility to estimate nonlinear functions has made it a valuable tool in data processing. ANN modeling process is given in Figure 2.

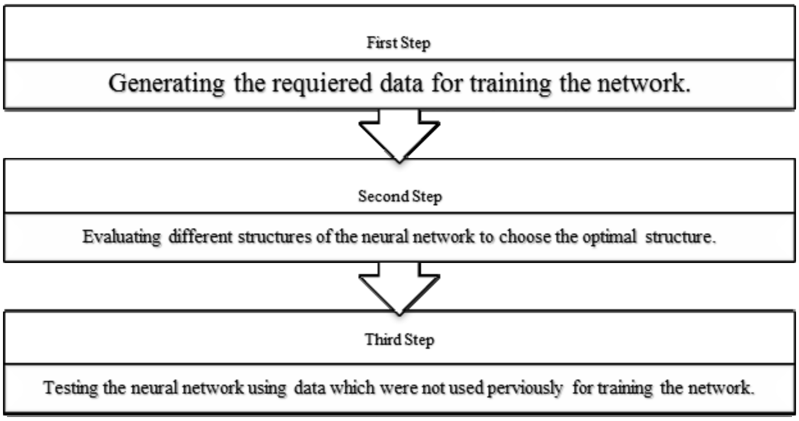

Figure 2: ANN modeling process.

ANN is specified by important features such as network architecture, activation function and training algorithm. The network complexity depends on the number of hidden layers and the number of neurons in each layer. The small number of hidden layer neurons may cause under fitting. Conversely, a large number of hidden layer neurons may result in over fitting. In most cases, the optimal number of hidden layer neurons can be achieved through trial and error.

Selecting the appropriate input parameters has an important role in ANN method and can affect the quality of prediction. In this research, channel oblique angle, routes of feeding and number of passes are considered as the input variables and tensile strength, elongation and hardness of ECARed Al5083 are considered as the output variables.

A neuron is the basic processing element in ANN modeling. In a neuron, each input is multiplied by the weights, and the results are added to each other and bias. The activation function of neurons in each layer is determined and is used to produce output neurons by calculating sum of input weights and bias (Equation1).

$$O = \xi(WI + b) \tag{1}$$

Where O, I, b, W and ξ are output value, input value, bias value, weight function and activation function, respectively.

In this study, TANSIG function is used as activation function of neurons in hidden layer and PURELIN linear function is used as activation function of neurons in output layer. The data are normalized in the range of -1 to 1 before the network training to ensure that ANN is trained effectively and without any deviation.

ANN is trained using data obtained from experiments to estimate the mechanical properties of ECARed Al5083 sample. The aim of training process in ANN is to achieve near zero errors with the proper adjustment of the training parameters, including updating the weights to achieve the desired error. In the present study, Levenberg-Marquardt back-propagation algorithm is used for modeling the mechanical properties of ECARed Al5083 sample. For this purpose, the experimental data set is used in which 70% of data set is used for training, and the remaining data set is used to test and validate the network. The mechanical properties of ECARed Al5083 sheets are predicted using a multilayer perceptron (MLP) feed forward network (Fig. 3). The network has a good ability to estimate nonlinear relations and is one of the most common models of ANN in engineering applications. Haghdadi (2013).

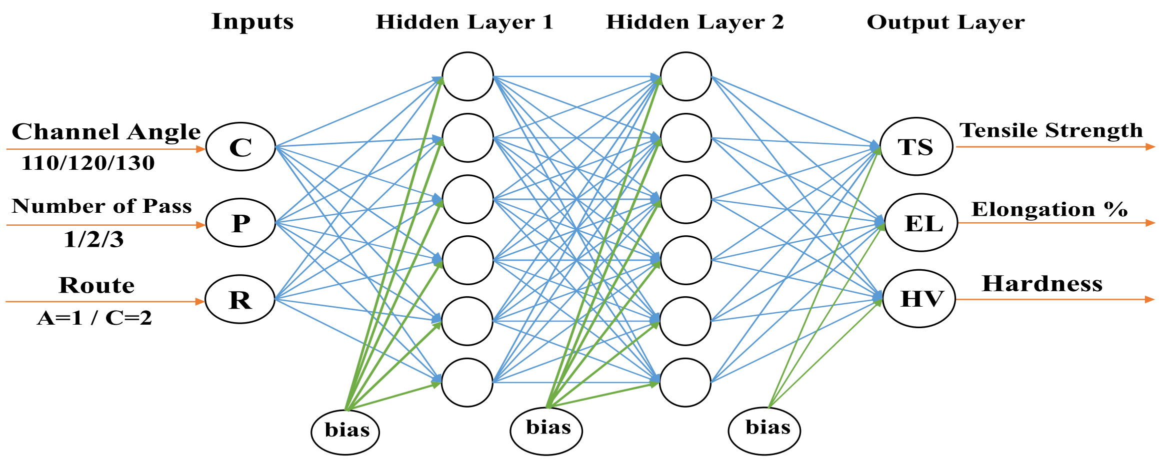

Figure 3: MLP feed forward neural network.

One of the most commonly used performance functions in a MLP feed forward network is mean square error (MSE). MSE and correlation coefficient (R) are used to evaluate the performance of ANN. MSE and R-values are obtained from the following equations.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} \left[p_i - m_i \right]^2 \tag{2}$$

$$R = \frac{\sum_{i=1}^{n}(m_i - \overline{m})(p_i - \overline{p})}{\sqrt{\sum_{i=1}^{n}(m_i - \overline{m})^2 \sum_{i=1}^{n}(p_i - \overline{p})^2}} \tag{3}$$

Where m_i represents experimental data values, p_i represents predicted values, and n is the number of samples. $\overline{m}$ and $\overline{p}$ are mean values of m and p, respectively.

Modified performance function is one of the methods which improve ANN generalization. By applying this performance function makes network have smaller biases and weights and forces the network reaction to be smoother and less probably to over fit. The typical performance function

MSE has been modified by adding a term, including the mean square network weights (MSW). The modified performance function is:

$$MSEreg = \rho \times MSE + (1 - \rho)MSW \tag{4}$$

Where $MSEreg$ is the modified performance function and ρ is the performance ratio.

4 RESULTS AND DISCUSSION

In this section, the mechanical properties of ECARed Al5083 samples have been investigated by using nonlinear regression and ANN. The performance of these models has been measured and compared to each other. For this purpose, MSE and Correlation coefficient have been used. Finally, the mechanical properties of ECAR process have been analyzed based on adequate model.

4.1 Proposed Empirical Correlation

The mechanical properties of samples were modeled using nonlinear regression equation as well as ANN. For this purpose, experimental data set was used as the pattern. The resulting equations are extracted as a function of channel oblique angle and number of passes. For accurate evaluating model output to get the best correlation, mean square error and correlation coefficient are calculated and compared (Equations 2 and 3). Finally, equations of 5, 6 and 7 were selected as correlations with less error for tensile strength, elongation and hardness, respectively.

$$\begin{aligned}\text{Tensile Strength} = {} & 323 + 231.9N + 1.59 \times 10^{-6}\varphi + 16.2N^3 + 0.709\varphi N^2 - 1.41\varphi N \\ & - 110N^2 - 0.106\varphi N^3\end{aligned} \tag{5}$$

$$\begin{aligned}\text{Elongation\%} = {} & 16.5 + 131 \times 10^{-6}\varphi + 0.123\varphi N + 16.5N^2 + 0.0122\varphi N^3 - 30.9N \\ & - 2.84N^3 - 0.0683\varphi N^2\end{aligned} \tag{6}$$

$$\begin{aligned}\text{Hardness} = {} & 89 + 44.6N + 3.25 \times 10^{-7}\varphi + 9.72N^3 + 0.294\varphi N^2 + 7.92N\sin(1.8 + 0.8N^2 - 2.4N) \\ & - 0.335\varphi N - 36.7N^2 - 0.081\varphi N^3 - 11.9\sin(1.8 + 0.8N^2 - 2.4N)\end{aligned} \tag{7}$$

Where φ is the channel oblique angle and N is the number of passes. Mean square error values of equations of tensile strength, elongation and hardness are 2.1, 0.1283 and 0.37 and their correlation coefficients are 0.9983, 0.9986, and 0.9979, respectively. The results show that the equations can estimate the mechanical properties favorably.

4.2 Results of Ann Modeling

Table 1 shows the trial-and-error process to find the best structure of MLP feed forward neural network among different architectures of ANN to predict the mechanical properties of ECARed Al5083 sheet.

Number of hidden layer	Number of neuron in each hidden layers	MSE	R_1	R_2	R_3	R
1	2	4.4186	0.9925	0.99133	0.99048	0.99196
1	3	1.3995	0.99793	0.99831	0.9972	0.99756
1	4	0.7716	0.99829	0.99927	0.99804	0.9984
1	5	0.2538	0.99929	0.99962	0.99915	0.99924
1	6	0.3666	0.99914	0.99944	0.99988	0.99932
1	7	0.6219	0.99831	0.99758	0.99808	0.99813
1	8	0.4514	0.9988	0.9991	0.99906	0.99889
1	9	0.4278	0.99916	0.99956	0.9999	0.99926
2	2	2.8301	0.99446	0.99682	0.99372	0.99483
2	3	0.4068	0.9986	0.99866	0.99877	0.99847
2	4	0.5667	0.99834	0.99879	0.99854	0.99833
2	5	0.4765	0.99934	0.99882	0.9994	0.99886
2	6	0.0972	0.99954	0.99977	0.99938	0.99952
2	7	0.3407	0.99936	0.9992	0.99954	0.99936
2	8	0.6221	0.99829	0.9997	0.99906	0.99858
2	9	0.5048	0.99715	0.99783	0.9994	0.99743

Table 1: Error and trial procedure for finding optimal number of hidden layers and neurons.

In Table 1, R1, R2 and R3 are the correlation coefficients between the model output and training data, model output and validation data and finally model output and test data, respectively.

Likewise, R is the correlation coefficient between the model output and the whole experimental data. MSE and R-values have been calculated and compared in Table 1 for different ANN architectures.

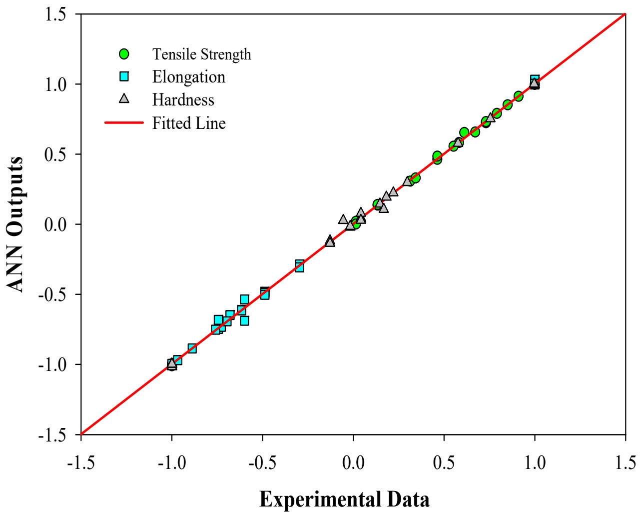

Figure 4: Regression plot for ANN modeling by use of normalized data.

As it can be observed in Table 1, a network with three hidden layers and eight neurons at either of them shows the best performance. MSE value is 0.0972 for selected network architecture that is a suitable value on scale of output parameters. Figure 4 shows the network regression graph after training. Obviously, R-value is close to one, which confirms the proper performance of the selected network.

4.3 Comparing the Outputs of Models with Experimental Results

As it has been illustrated, artificial neural network and nonlinear regression models can estimate the mechanical properties accurately. Figure 5 shows the comparison between experimental results and models outputs. According to this figure, the experimental results and the models outputs for all three properties are in a very good agreement.

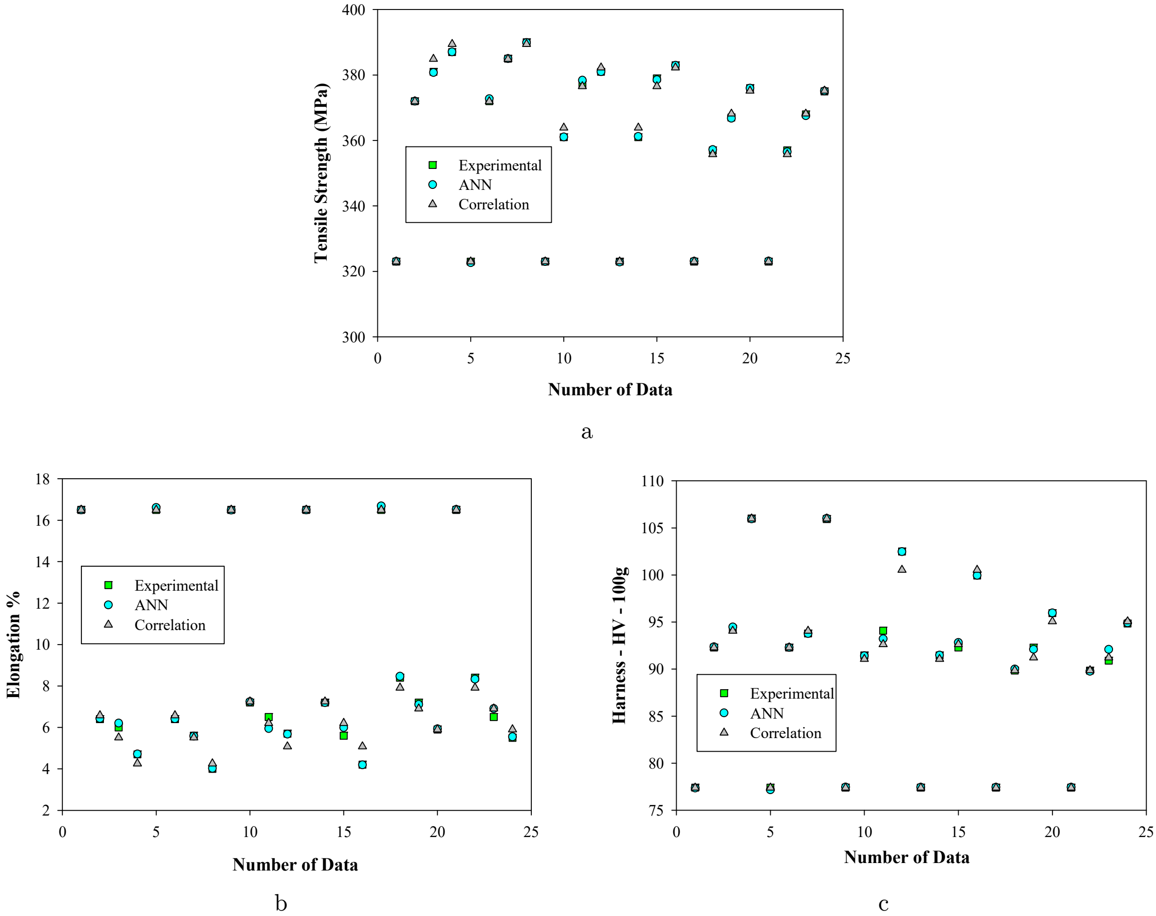

Figure 5: Comparison between experimental results and models outputs, a. Tensile strength b. elongation c. hardness

However, ANN estimates mechanical properties at higher precision. The maximum errors of ANN model for estimating tensile strength, elongation and hardness are 0.30, 0.18 and 0.23, respectively. Although, the maximum error values for nonlinear regression model to estimate the tensile strength, elongation and hardness are 3.93, 0.63 and 1.97, respectively.

4.4 The Mechanical Properties Analyzed Using Ann Model

The ANN model has been used for developing the mechanical properties of ECARed Al5083 samples after selecting the best model with proper performance. The tensile strength, elongation and hardness at different channel oblique angles of 110 to 130 ° for annealed and one to three passes samples have been shown separately in Figure 6.

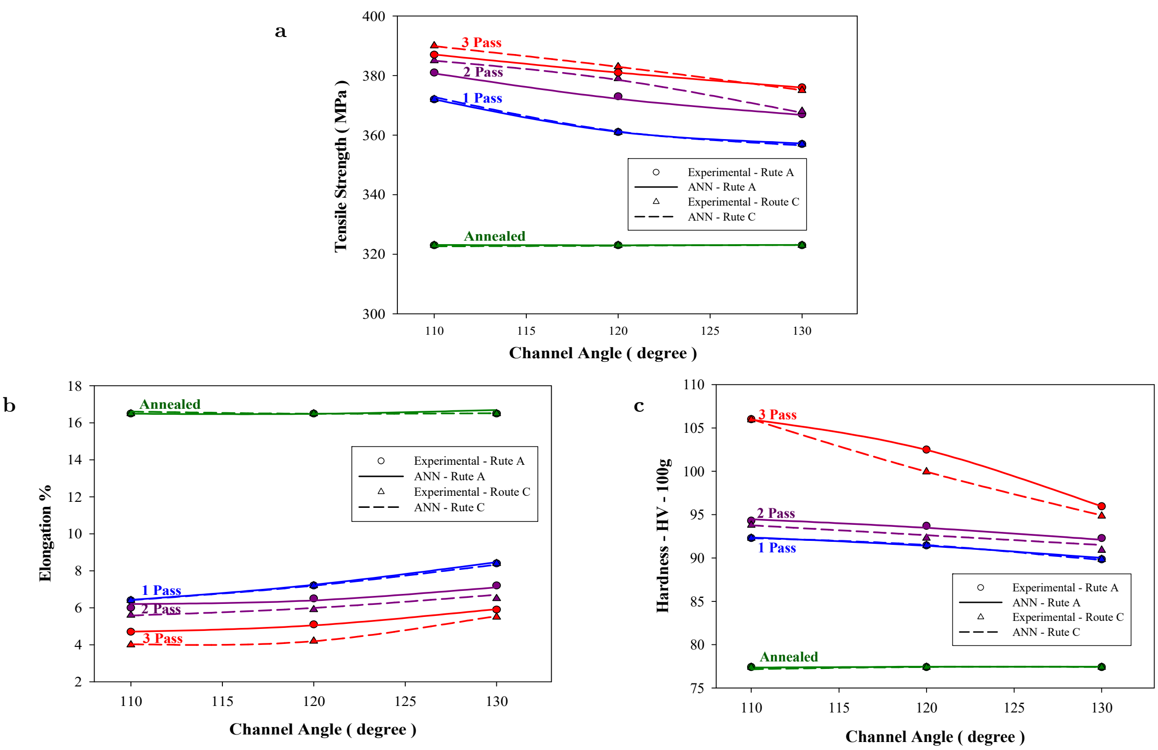

Figure 6: The developed data using trained ANN based on experimental data,
a. Tensile strength b. elongation c. hardness

According to Figure 6.a, the results of ANN show that the tensile strength increases in route C compared to route A. In agreement with conducted research, volume fraction and the velocity of formation of coaxial grains for route C are more than route A. (Dobatkin et al., 2007).

As shown in Figure 6.b, the material strength increases by decreasing the channel oblique angle of 130° to 110°, but the elongation decreases. An increase in strength and decrease in elongation at the first pass may be due to dislocation multiplication in the structure during deformation in the ECAR process. The dislocations can be formed within the grains and grain boundaries. The higher dislocation density in the material, the higher resistance to movement of dislocations and consequently the higher forces required for plastic deformation. This matter explains the increase in strength during plastic deformation.

After the first pass, the tensile strength increases with a much lower rate and elongation reduces to a very small extent. It can be due to the sharp decline of work hardening in subsequent passes. The fine grains produced by high angle boundaries obstruct dislocation movement. Other deformation mechanisms are begun by increasing passes, such as grain boundary sliding and rotating grains (Meyers et al., 2006).

The reduction in elongation will not continue with increasing the number of passes. Increasing the cumulative plastic strain and generation of fine grains can be as a result of the dynamic equilibrium between the generation and the annihilation of dislocations (Lee et al., 2003)

As Figure 6.c shows, a sever increase in hardness of samples occurs in the first pass. The reason is because of the work hardening of sample caused by the sub-grain boundaries formation.

5 CONCLUSIONS

In this paper, two methods of ANN and nonlinear regression modeling were used to estimate the mechanical properties of ECARed Al5083 sample. For this purpose, MLP feed forward network was employed. Furthermore, the relationship between the channel oblique angles and the number of passes as the input parameters and tensile strength, elongation and hardness as the output parameters was presented separately using the nonlinear regression model. Performance of ANN and nonlinear regression model shows that both models estimate the mechanical properties of ECARed Al5083 samples accurately. However, the ANN model estimates the output parameters with high accuracy. Mean square error and correlation coefficient are 0.0972 and 0.99952 for ANN, respectively.

The results of mechanical properties obtained by trained ANN show that tensile strength values increases in route C more than corresponding values at route A. By decreasing the channel oblique angle especially at the first pass, the strength increases and the elongation decreases. The greater number of passes leads to increase in tensile strength, hardness and reduction in elongation.

References

Ambrogio G., Filice L., Guerriero F., Guido R., Umbrello D., (2010). Prediction of incremental sheet forming process performance by using a neural network approach. Int. J. Adv. Manuf. Technol., 54:921–930.

Anaraki M. T., Sanjari M., Akbarzadeh A., (2008). Modeling of high temperature rheological behavior of AZ61 Mg-alloy using inverse method and ANN. Mater. Des., 29:1701–1706.

Chan W. L., Fu M. W. Ã., and Lu J., (2008). An integrated FEM and ANN methodology for metal-formed product design. Engineering Applications of Artificial Intelligence, 21:1170–1181.

Chen Z., Cheng Y., Xia W., (2007). Effect of Equal-Channel Angular Rolling Pass on Microstructure and Properties of Magnesium Alloy Sheets. Material and Manufacturing Processes, 22:51–56.

Cheng Y. Q., Chen Z. H., Xia W. J., (2007). Drawability of AZ31 magnesium alloy sheet produced by equal channel angular rolling at room temperature. Mater. Charact., 58:617–622.

Cheng Y. Q., Chen Z. H., Xia W. J., Zhou T., (2008). Improvement of Drawability at Room Temperature in AZ31 Magnesium Alloy Sheets Processed by Equal Channel Angular Rolling.Journal of Material Engineering and Performance, 17:15–19.

Chung Y. H., Park J., Lee K. H., (2006). An Analysis of Accumulated Deformation in the Equal Channel Angular Rolling (ECAR) Process. Metal and Material International, 12:289-292.

Chung Y. H., Park J. W. Lee K. H., (2007). Controlling the Thickness Uniformity in Equal Channel Angular Rolling (ECAR). Mater. Sci. Forum, 539–543: 2872–2877.

Derogar A., Djavanroodi F., (2011). Artificial Neural Network Modeling of Forming Limit Diagram. Mater. Manuf. Process., 26:1415–1422.

Djavanroodi F., Omranpour B., Sedighi M., (2013). Artificial Neural Network Modeling of ECAP Process. Mater. Manuf. Process., 28:276–281.

Dobatkin S. V., Szpunar J. a., Zhilyaev A. P., Cho J.-Y., Kuznetsov A. A., (2007). Effect of the route and strain of equal-channel angular pressing on structure and properties of oxygen-free copper. Mater. Sci. Eng. A, 462:132–138.

Esmailzadeh M., Aghaie-Khafri M., (2012). Finite element and artificial neural network analysis of ECAP. Comput. Mater. Sci., 63:127–133.

Forcellese A., Gabrielli F., Simoncini M., (2011). Prediction of flow curves and forming limit curves of Mg alloy thin sheets using ANN-based models. Comput. Mater. Sci., 50:3184–3197.

Habibi A., Ketabchi M., Eskandarzadeh M., (2011). Nano-grained pure copper with high-strength and high-conductivity produced by equal channel angular rolling process. J. Mater. Process. Technol., 211:1085–1090.

Habibi A., Ketabchi M., (2012). Enhanced properties of nano-grained pure copper by equal channel angular rolling and post-annealing. Mater. Des., 34:483–487.

Haghdadi N., Khalesian A. R., Abedi H. R., (2013). Materials and Design Artificial neural network modeling to predict the hot deformation behavior of an A356 aluminum alloy. Mater. Des., 49:386–391.

Hassani F. Z., Ketabchi M., (2011). Nano grained AZ31 alloy achieved by equal channel angular rolling process. Mater. Sci. Eng. A, 528:6426–6431.

Kvačkaj T., Kováčová A., Kvačkaj M., Kočiško R., Lityńska-Dobrzyńska L., Stoyka V., Miháliková M., (2012). TEM studies of structure in OFHC copper processed by equal channel angular rolling. Micron,43:720-724.

Lee J. C., Seok H. K., Suh J.Y., (2002). Microstructural evolutions of the Al strip prepared by cold rolling and continuous equal channel angular pressing. Acta Mater, 50:4005-4019.

Lee J., Suh J., Ahn J., (2003). Work-Softening Behavior of the Ultrafine-Grained Al Alloy Processed by High-Strain-Rate , Dissimilar-Channel Angular Pressing. Metallurgical and Materials Transactions A, 34:625–632.

Mahmoodi. M., (2011). The effect of ECAR parameters on residual stresses and mechanical-microstructural properties of Al sheets. Ph.D. thesis, (in Persian), Iran University of Science and Technology.

Mahmoodi M., Sedighi M., and Tanner D. A., (2012). Investigation of through thickness residual stress distribution in equal channel angular rolled Al 5083 alloy by layer removal technique and X-ray diffraction. J. Mater., 40:516–520.

Meyers M.A., Mishra A., Benson D.J., (2006). Mechanical properties of nanocrystalline materials. Prog. Mater. Sci., 51:427–556.

Qin Y. J., Pan Q. L., He Y. B., Li W. B., Liu X. Y., Fan X., (2010). Artificial Neural Network Modeling to Evaluate and Predict the Deformation Behavior of ZK60 Magnesium Alloy During Hot Compression. Mater. Manuf. Process., 25,:539–545.

Sedighi M., Mahmoodi M., (2013). Residual Stresses Evaluation in Equal Channel Angular Rolled Al 5083 by IHD Technique: Investigation of Two Calculation Methods. Materials and Manufacturing Processes, 28:85–90.

Sheikh H., Serajzadeh S., (2008). Estimation of flow stress behavior of AA5083 using artificial neural networks with regard to dynamic strain ageing effect. J. Mater. Process. Technol., 196:115–119.

Toros S., Ozturk F., (2011). Flow curve prediction of Al–Mg alloys under warm forming conditions at various strain rates by ANN. Appl. Soft Comput,11:1891–1898.

Zhangtt H., Huangt S. H., (1995). Applications of neural networks in manufacturing : a state-of-the-art survey. Int. J. Prod. Res., 33:705–728.