Available online at www.sciencedirect.com
ScienceDirect
Materials and Design 28 (2007) 1678–1684
Materials & Design
www.elsevier.com/locate/matdes

Short communication

Prediction of effect of thermo-mechanical parameters on mechanical properties and anisotropy of aluminum alloy AA3004 using artificial neural network

S. Forouzan, A. Akbarzadeh *

Department of Materials Science and Engineering, Sharif University of Technology, P.O. Box 11365-9466, Azadi Avenue, Tehran, Iran

Received 23 June 2005; accepted 20 March 2006
Available online 5 June 2006

Abstract

An artificial neural network model, using a back-propagation learning algorithm is utilized, to predict the yield stress, elongation, ultimate tension stress, $\bar{R}$ and $|\Delta R|$ during hot rolling, cold rolling and annealing of AA3004 aluminum alloy. Input nodes were chosen as the ratio of initial to final thicknesses, reduction, preheating time and temperature, finish rolling temperature and the final annealing temperature. The maximum error for predicted values was 6.35%, the average of absolute relative error was 0.57% and the RMS was 0.00998. It was found that the mechanical properties and anisotropy of AA3004 alloy sheets can be predicted by this approach.

1. Introduction

AA3004 alloy is widely used in can making. The main reasons for using the AA3004 alloy as can body are its favourble sheet formability and good antigalling properties during ironing, which can be achieved by careful control of the thermo-mechanical processes such as hot rolling, cold rolling and annealing [1–3].

The major problem in production of deep drawn containers is earing, which develop during deep drawing of the metallic sheets. Earing is highly undesirable, since it interferes with the perfect operation of the automated can making process. This phenomenon is attributed to high planar anisotropy ($|\Delta R|$) and can be minimized by a balance of recrystallisation and rolling textures together with a uniform and fine grain microstructure [4].

Neural networks as information processing tools have widely been used in the areas of pattern recognition, signal processing, forecasting, modeling and control. In principle, neural networks perform a nonlinear mapping between input and output vectors. This mapping mechanism has high ability to learn existing patterns between the inputs and outputs [5].

Neural networks provide a fundamentally different approach to material modeling and material processing control techniques in comparison to the statistical or numerical methods. This technique is applicable in many areas of engineering and has produced promising preliminary results in the areas of material modeling and processing. The main advantage of this approach is that there is no need to make a priori assumptions about material behaviour even though in more sophisticated neural network modeling schemes one may take advantage of the knowledge of the process in network design. Although multi-layered neural network models cannot ensure a global minimum solution for any given problem, it is a reasonable assumption that if the network is trained on a comprehensive database with an appropriate representation scheme, the resulting model will approximate all the mechanic laws which the actual material or process obeys [6].

* Corresponding author. Tel.: +98 21 616 5206; fax: +98 21 6005717.
E-mail address: abbasa@sharif.edu (A. Akbarzadeh).

0261-3069/$ - see front matter
doi:10.1016/j.matdes.2006.03.016

2. Back-propagation neural networks

The multi-layered feed-forward back-propagation algorithm is central to much work on modeling and classification by neural networks. This technique, which has evolved from Rosenblatt's simple perceptron model, is currently one of the predominant supervised learning algorithms. Supervised learning implies that a good set of data or pattern associations is needed to train the network. Input–output pairs are presented to the network, and weights are adjusted to minimize the error between the network output and the actual value. The knowledge of neural network is stored in these weights. The back-propagation model, presented in Fig. 1, has three layers of neurons: an input layer, a hidden layer and an output layer. The back-propagation training algorithm is an iterative gradient algorithm, designed to minimize the mean square error between the predicted output and the desired output. It requires continuous differentiable non-linearities. The flow chart of back-propagation is illustrated in Fig. 2. The algorithm of training a back-propagation network is summarized as follows:

1. Initialize weights and threshold values: set all weights and the threshold to small random values.
2. Present input and desired output: present a continuous valued input vector $X_1, X_2, \ldots X_n$ and specify the desired outputs $O_1, O_2, \ldots O_m$. Usually the training sets are normalized to values between -0.9 and 0.9 during processing.
3. Compute the output of each node in the hidden layer:

$$h_j = f\left(\sum_{i=1}^{n} W_{ij} X_j - \theta_j\right) \tag{1}$$

where h_j is the vector of hidden-layer neurons, i is the input-layer neurons, W_{ij} are the weights between the input and hidden layers and u_j is the threshold between the input and hidden layers.

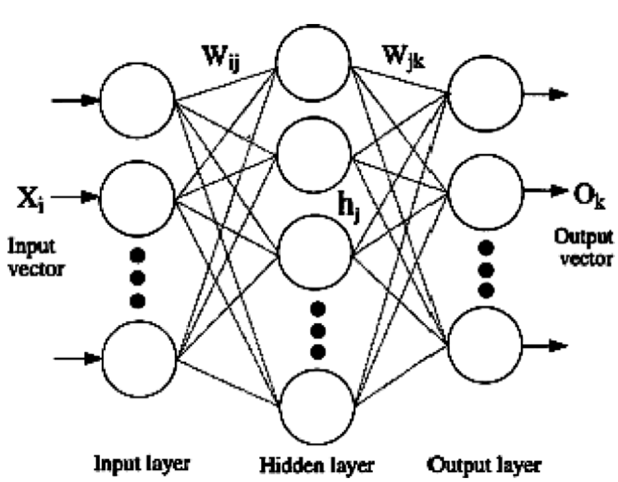

Fig. 1. A three-layer feed-forward neural network.

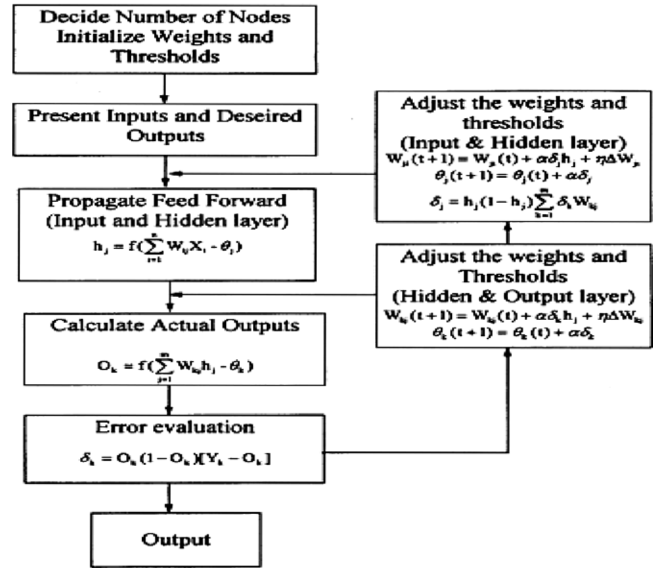

Fig. 2. Flow chart of the back-propagation learning algorithm.

4. Compute the output of each node in the output layer:

$$O_k = f\left(\sum_{j=1}^{m} W_{kj} X_j - \theta_k\right) \tag{2}$$

where O_k represents the output layer, W_{kj}, are the weights connecting the hidden and output layers, θ_k is the threshold connecting the hidden and output layers, and $f(x)$ is a logistic sigmoid activation function:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

5. Compute the output layer error between the target and the observed output:

$$\delta_k = O_k(1 - O_k)(Y - O_k) \tag{4}$$

where δ_k is the vector of errors for each output neuron and Y_k is the target activation of output layer.

6. Compute the hidden layer error:

$$\delta_i = h_j(1 - h_j)\sum \delta_k W_k \tag{5}$$

where δ_j is the vector of errors for each hidden layer neuron.

7. Adjust the weights and thresholds in the output layer:

$$W_{kj}(t+1) = W_{kj}(t) + \alpha\delta_k h_j + \eta(W_{kj}(t) - W_{kj}(t-1)) \tag{6}$$

$$\theta_k(t+1) = \theta_k(t) + a\delta_k \tag{7}$$

Where α is the learning rate and h is the momentum factor used to allow the previous weight change to influence the weight change in this time period, t.

8. Adjust the weights and thresholds in the hidden layer:

$$W_{ji}(t+1) = W_{ji}(t) + \alpha\delta_j h_j + \eta(W_{ji}(t) - W_{ji}(t-1)) \tag{8}$$

$$\theta_j(t+1) = \theta_j(t) + \alpha\delta_j \tag{9}$$

9. Repeat steps 1–8 on the all pattern pairs until the output layer error is within the specified tolerance for each pattern and for each neuron [5].The root mean square functional error was used as a measure of performance as given by

$$\mathrm{RMS} = \sqrt{\frac{\sum(\sigma - \sigma^*)^2}{n\sigma^2}} \tag{10}$$

where σ is the experimental value, σ^* is the predicted value and n is the total number of patterns.

3. Experimental procedure and data

Alloying was done in graphite crucible and ingot casting was performed in metallic mold. The casting specimens were in the shape of small blocks of $300 \times 250 \times 20$ mm^3. Chemical composition of the prepared 3004 alloy is presented in Table 1.

At this stage the samples were homogenized with two conditions of temperature and time in an electrical furnace according to the chart in Fig. 2. Hot rolling was performed with 70% and 76% reductions by four and five passes, respectively. The specimens were annealed at temperatures 350 °C, 375 °C, 400 °C and for 1 h. Specimens had a 90% cold reduction before final annealing were did for all of specimens at 350 °C and for 1 h. The experimental conditions are shown in the flowchart of Fig. 3.

Yield strength, ultimate tensile strength and total elongations were determined by tension tests performed along rolling and transverse directions as well as 45° to the rolling direction of the sheets. The ratio of R is a measure of the normal anisotropy of sheet. The variation of R through the sheet is called the planar anisotropy (ΔR) and is usually taken as:

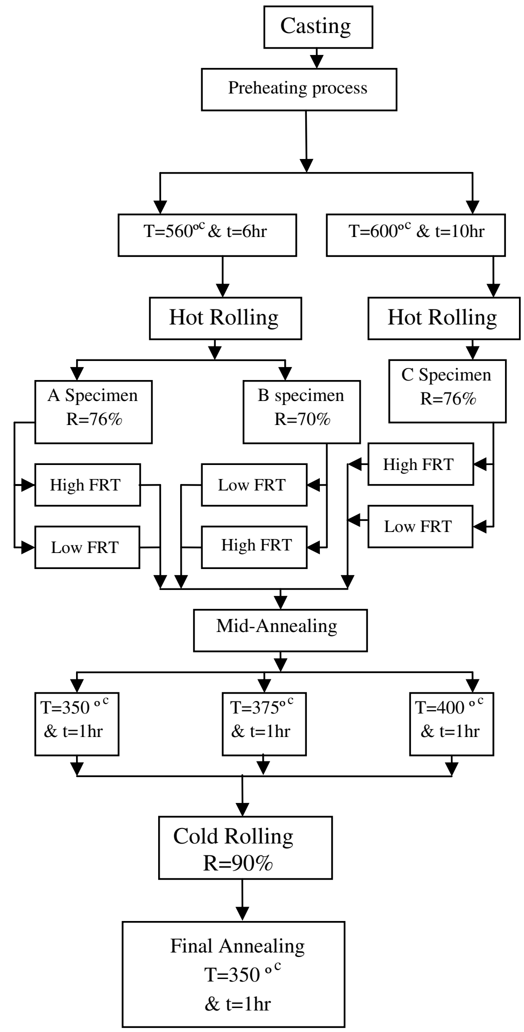

Fig. 3. Flowchart of experiments.

Table 1
Chemical composition of alloy AA3004

%AL	%Mn	%Mg	%Fe	%Si
Other	1.12	1.22	0.24	0.12

Table 2
The experiment data used in input layer of neural network

No.	$t1/t2$	Percentage of reduction	Temperature of preheat (°C)	Time of preheat (h)	Final temperature of hot rolling (°C)					Temperature of final annealing (°C)
1	4.17	76	560	6	491	447	381	300	242	350
2[a]	4.17	76	560	6	491	447	381	300	242	375
3	4.17	76	560	6	491	447	381	300	242	400
4	4.17	76	560	6	506	464	410	361	315	350
5	4.17	76	560	6	506	464	410	361	315	375
6	4.17	76	560	6	506	464	410	361	315	400
7	3.42	70	560	6	453	395	313	253	–	350
8[a]	3.42	70	560	6	453	395	313	253	–	375
9	3.42	70	560	6	453	395	313	253	–	400
10	3.42	70	560	6	501	452	394	317	–	350
11[a]	3.42	70	560	6	501	452	394	317	–	375
12	3.42	70	560	6	501	452	394	317	–	400
13	4.17	76	600	10	521	474	400	328	250	350
14	4.17	76	600	10	521	474	400	328	250	375
15[a]	4.17	76	600	10	521	474	400	328	250	400
16	4.17	76	600	10	538	497	452	390	312	350
17	4.17	76	600	10	538	497	452	390	312	375
18	4.17	76	600	10	538	497	452	390	312	400

[a] Unseen data.

Table 3
Experiment, predicted data and absolute error that were given from network

No.	Y.S			U.T.S			El (%)			$\overline{R}$			$\lvert\Delta R\rvert$		
	Experiment	Predicted	Absolute relative error (%)	Experiment	Predicted	Absolute relative error (%)	Experiment	Predicted	Absolute relative error (%)	Experiment	Predicted	Absolute relative error (%)	Experiment	Predicted	Absolute relative error (%)
1	73	73.03	0.038	185	184.97	0.017	19.3	19.30	0.008	0.525	0.52	0.050	0.75	0.75	0.055
2	67	68.65	2.469	178	179.82	1.021	21	20.08	4.399	0.535	0.53	0.224	0.81	0.77	4.369
3	65	64.99	0.008	175	175.01	0.006	21.3	21.30	0.009	0.44	0.44	0.020	0.68	0.68	0.026
4	63	63.03	0.050	169	168.95	0.029	23.3	23.31	0.025	0.37	0.37	0.019	0.52	0.52	0.023
5	60	59.63	0.623	163	164.35	0.828	24.6	24.39	0.838	0.465	0.47	0.049	0.63	0.63	0.054
6	58	57.97	0.058	161	161.04	0.023	25.4	25.39	0.023	0.355	0.35	0.031	0.49	0.49	0.039
7	60	60.00	0.007	164	163.99	0.006	24.2	24.20	0.012	0.435	0.44	0.018	0.63	0.63	0.017
8	55	55.02	0.030	157	156.99	0.009	25.7	25.70	0.017	0.495	0.51	2.103	0.71	0.72	1.521
9	54	53.99	0.014	154	154.01	0.004	25.9	25.90	0.006	0.385	0.39	0.010	0.56	0.56	0.013
10	52	51.98	0.034	156	156.04	0.028	28.1	28.10	0.014	0.31	0.31	0.013	0.44	0.44	0.014
11	51	50.41	1.149	152	152.44	0.293	28.7	28.98	0.969	0.35	0.37	5.723	0.48	0.51	5.590
12	50	50.00	0.001	150	149.98	0.017	29.1	29.10	0.013	0.295	0.29	0.014	0.41	0.41	0.017
13	66	65.83	0.253	171	171.22	0.127	22.1	22.05	0.242	0.33	0.33	0.182	0.46	0.46	0.226
14	60	60.06	0.099	165	164.92	0.046	22.4	22.43	0.120	0.365	0.36	0.219	0.49	0.49	0.269
15	56	56.33	0.591	164	160.44	2.169	23.9	22.38	6.352	0.265	0.27	0.328	0.39	0.38	1.715
16	59	59.36	0.608	167	166.52	0.288	25.1	25.20	0.406	0.255	0.25	0.192	0.35	0.35	0.271
17	56	55.41	1.058	162	162.68	0.418	26.5	26.35	0.554	0.305	0.31	0.203	0.41	0.41	0.278
18	53	53.33	0.614	160	159.67	0.203	26.8	26.86	0.231	0.17	0.17	0.035	0.28	0.28	0.032

Table 4
Maximum of error and mean of error of output data

Property	Y.S	U.T.S	%El	$\overline{R}$	$\|\Delta R\|$
Max error (%)	2.469	2.169	6.351	5.722	5.589
Mean error (%)	0.428	0.307	0.79	0.524	0.807

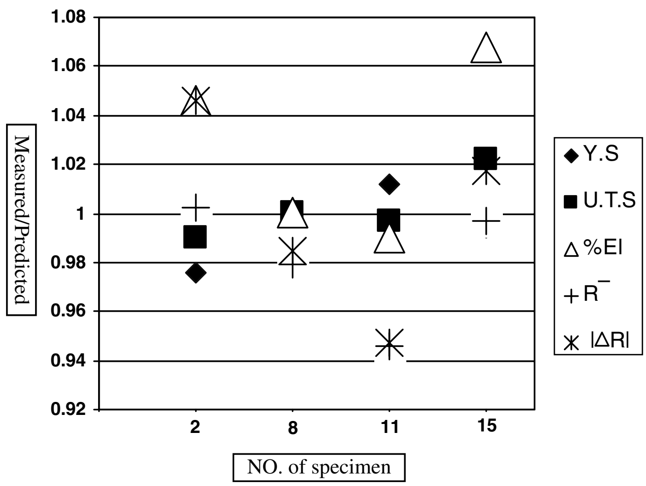

Fig. 4. Relative errors of predicted values for unseen data.

$$|\Delta R| = (R_0 + R_{90} - 2R_{45})/2 \tag{11}$$

Where the subscripts give the angle to the rolling direction at which the value of R was measured. The average of R ($\overline{R}$) is obtained by this equation:

$$\overline{R} = \frac{R_0 + 2R_{45} + R_{90}}{4} \tag{12}$$

4. Modeling by back-propagation neural network

First step in developing a neural network model is to arrive at a set of parameters to predict the mechanical properties and their anisotropy in the alloy. This set is clearly not unique and depends on the expected accuracy of the model. Table 2 shows all data that are considered as input layer for training and testing. Ten variables or nodes were considered for input layer and 5 nodes were for output layers. As for some samples 4 passes for others 5 passes of rolling were performed. For the samples with 4 passes the input data for the fifth passes was set at zero. Outputs include the yield strength, elongation, ultimate tension strength, $\overline{R}$ and $|\Delta R|$. Note that for converging of the model and increasing of accuracy reduction and relation between final and initial thickness simultaneously was used. As the used function for modeling was sigmoid, before training all the data must be normalized by this formula:

$$X_{\text{Normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{13}$$

Many models were trained and tested. A network with three hidden layers which are of 20 nodes each showed the best. Learning rate (α) in this network was 0.01 and momentum (η) was 0.8. After 50,000 iterations the network converged to a solution and further iterations had no insignificant effect on error reduction.

5. Results and discussion

For all cases of this study, a fully connected feed forward back-propagation network was designed, trained and tested. Table 3 shows the results which were obtained by neural networking and the error of each predicted data. Maximum of relative error and the average of absolute relative error are shown Table 4. Maximum of relative error in this model was found to be 6.35%, the average of error was 0.57% and the value of RMS was 0.00998. This level of error is satisfactory and smaller than the errors than normally arise due to experimental variations and accuracy of instrumentation. Fig. 3 is presented for better study of ability of prediction of model. In this figure the network prediction for unseen data is shown (Fig. 4).

5.1. *Sensivity analysis*

For examination of the effect of thermomechanical parameters on mechanical and anisotropy properties,

Table 5
Applied variations on specimens 3 and 9

No.	$t2/t1$	Reduction	Temperature of preheat	Time of preheat	Output temperature of hot rolling					Temperature of final annealing
3	4.167	76	560	6	491	447	381	300	242	400
3(a)	4.167	76	560	8	491	447	381	300	242	400
3(b)	4.167	76	600	6	491	447	381	300	242	400
3(c)	4.167	76	560	6	491	447	381	300	266	400
3(d)	4.167	76	560	6	491	447	381	350	242	400
3(e)	4.167	76	560	6	491	447	381	350	300	400
9	3.417	70	560	6	453	395	313	253	0	400
9(a)	3.417	70	560	8	453	395	313	253	0	400
9(b)	3.417	70	560	10	453	395	313	253	0	400
9(c)	4.167	76	560	6	453	395	313	253	242	400

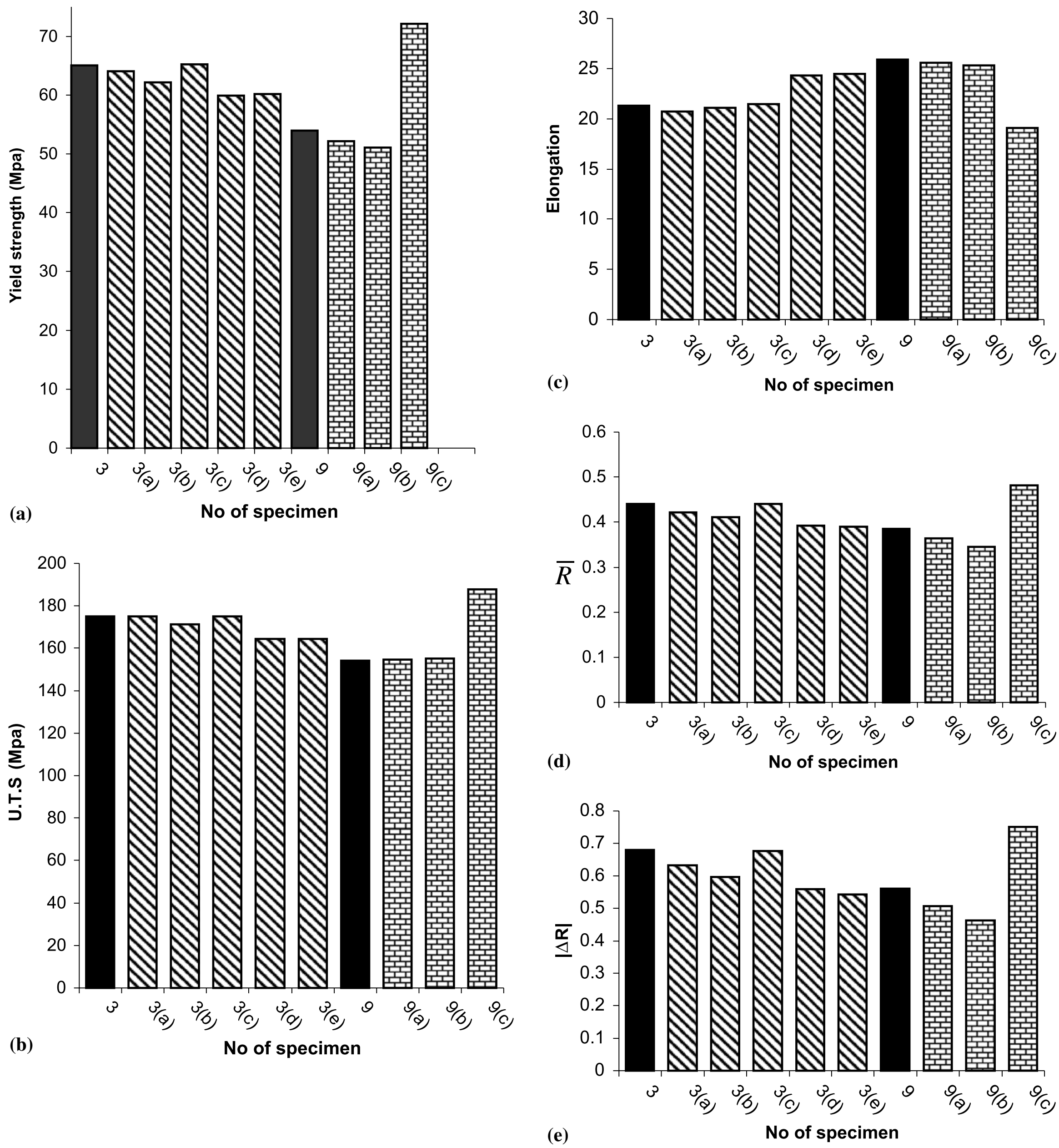

Fig. 5. Comparison between mechanical and anisotropy of main specimens and modified specimens: (a) yield strength; (b) U.T.S; (c) elongation; (d) $\overline{R}$; (e) $|\Delta R|$.

two specimens (Nos. 3 and 9) were selected and some parameters (input nodes) were varied. Table 5 shows the variations of these parameters. The data were fed to the model, Fig. 5 shows this data. By increasing the time and temperature of preheating and final temperature of rolling (specimens Nos. 3(a), 3(b), 9(a) and 9(b)) the $\overline{R}$ and ΔR decreased. Although there is no significant effect on mechanical properties. It is observed that the temperature increase at 4th pass (3d) is more effective on mechanical and anisotropy properties than the final pass of rolling (3c). Also this can be realized by comparison between 3d and 3e. By enhancing the amount of reduction and rolling temperature as well as number of passes were effectively increased mechanical properties and anisotropies. Such results are similar to the results of references [1,2].

6. Conclusion

In the present study, the back-propagation learning algorithm is used to predict properties of AA3004. This method is applicable in many areas of behavioral science and has produced promising preliminary results in the areas of materials modeling and processing.

In this work a new set of parameters was considered to estimate yield strength (Y.S), ultimate tensile strength (U.T.S), elongation (El), average of anisotropy ($\overline{R}$) and planar anisotropy ($|\Delta R|$). Thermo-mechanical parameters were included in the model.

The feasibility of the approach was evaluated by utilizing a neural network to find the correlation between the new set of input parameters for estimating mechanical properties and anisotropy.

The neural network based model clearly indicates that it is able to learn the training data set and accurately predict the output of unseen test data. Well-trained neural network models provide fast, accurate and consistent results, making them superior to all other techniques.

Many networks were tested, among which a network of 3 hidden layers and each layer 20 nodes, was the best. Maximum of error was 6.35% and mean error was 0.57%. RMS in this network was 0.00998. Thus good predictive ability was observed.

The sensivity analysis of the model indicates that the $\overline{R}$ and $|\Delta R|$ can be controlled by the preheating conditions and the final rolling temperature.

References

[1] Hutchinson WB, Oscarsson A, Karlsson A. Control of microstructure and earing behavior in aluminum alloy AA3004 hot bands. Mater Sci Technol 1989;5:1118–27.

[2] Liu YL, Liu Y, Liao G, Morris JG. The effect of preheat treatment on microstructure, recrystallization and texture f strip cast AA3004 alloy. Aluminum Trans 2000;2:97–106.

[3] Ding Sx, Ren B, Morris Jg. Influence of initial structure *n* hot rolling and recrystallization texture in AA3004 aluminum alloy. In: Jonas JJ, Beiler TR, Bowman KJ, editors. Advance in hot deformation texture and microstructure. TMS; 1993. p. 281–311.

[4] Zhou Y, Jonas JJ, Savoie J, Makinde A, MacEwen SR. Effect of texture on earing in FCC metals: FEM simulation. Int J Plasticity 1998;14:117–38.

[5] Fotovati A, Goswami T. Prediction of elevated temperature fatigue crack growth rates in Ti–6Al–4V alloy – neural network approach. Mater Des 2004;25:547–54.

[6] Chun MS, Biglou J, Lenard JG, Kim JG. Using neural network to predict parameters in hot working of aluminum alloys. J Mater Proc Technol 1999;86:245–51.