J MATER RES TECHNOL. 2016;5(1):13–20

ELSEVIER

jmr&t Journal of Materials Research and Technology

www.jmrt.com.br

abm

Original Article

Mechanical properties of Austenitic Stainless Steel 304L and 316L at elevated temperatures

Raghuram Karthik Desu [a,*], *Hansoge Nitin Krishnamurthy* [a], *Aditya Balu* [a], *Amit Kumar Gupta* [a], *Swadesh Kumar Singh* [b]

[a] *Department of Mechanical Engineering, Birla Institute of Technology and Science-Pilani, Hyderabad, India*

[b] *Department of Mechanical Engineering, Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad, India*

ARTICLE INFO

Article history:

Received 23 August 2014

Accepted 2 April 2015

Available online 16 May 2015

Keywords:

Austenitic Stainless Steel

Mechanical properties

Tensile test

Artificial Neural Networks

ABSTRACT

Austenitic Stainless Steel grade 304L and 316L are very important alloys used in various high temperature applications, which make it important to study their mechanical properties at elevated temperatures. In this work, the mechanical properties such as ultimate tensile strength (UTS), yield strength (Y_S), % elongation, strain hardening exponent (n) and strength coefficient (K) are evaluated based on the experimental data obtained from the uniaxial isothermal tensile tests performed at an interval of 50 °C from 50 °C to 650 °C and at three different strain rates (0.0001, 0.001 and 0.01 s^{-1}). Artificial Neural Networks (ANN) are trained to predict these mechanical properties. The trained ANN model gives an excellent correlation coefficient and the error values are also significantly low, which represents a good accuracy of the model. The accuracy of the developed ANN model also conforms to the results of mean paired *t*-test, *F*-test and Levene's test.

1. Introduction

Austenitic Stainless Steel (ASS) 304L is being extensively used in the field of defence and nuclear science due to its excellent corrosion resistance in seawater environment [1]. This property of ASS 304L is due to the presence of molybdenum, which prevents chloride corrosion. It also has a low carbon content due to which the wear and friction properties are improved and a lower susceptibility to intergranular corrosion [2]. ASS 316L also has found applications in the field of nuclear science. It is used as a manufacturing material for nuclear fuel clad tubes and fuel sub assembly wrappers in fast breeder reactors owing to its superior mechanical properties at elevated tempeartures and good compatibility with liquid sodium [3]. Hence, these steels are particularly useful in nuclear reactors. The reactor's temperatures are usually very high. Due to this, it becomes imperative to study the material's behaviour and its properties at elevated temperatures.

* *Corresponding author.*
E-mail: raghuram1991@gmail.com (R.K. Desu).

http://dx.doi.org/10.1016/j.jmrt.2015.04.001

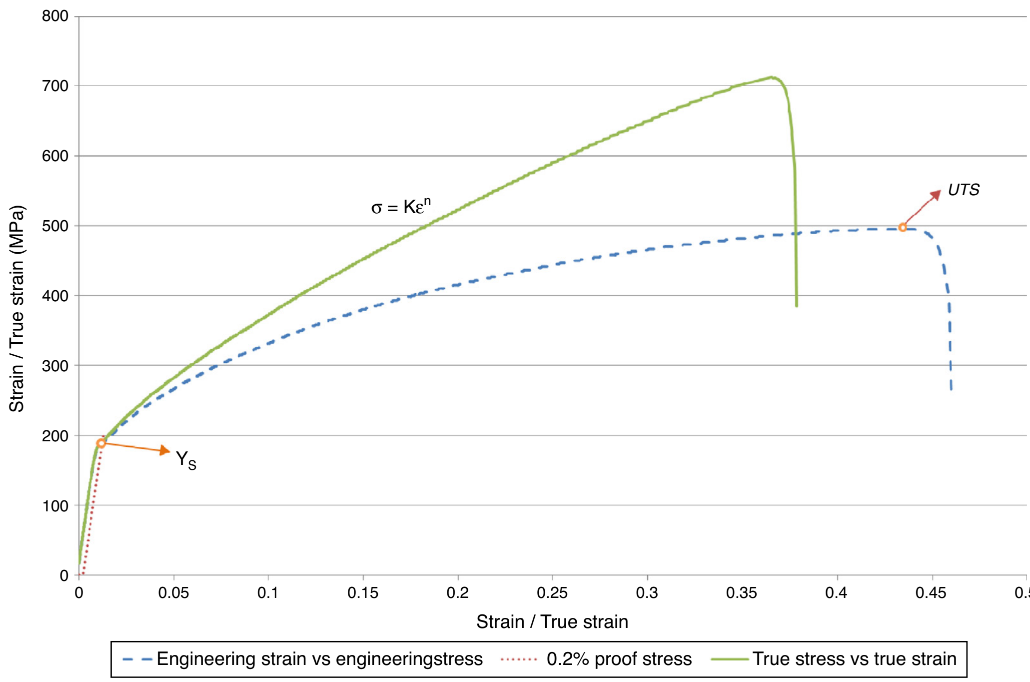

Fig. 1 – Mechanical properties evaluation.

The mechanical properties evaluated in this work are ultimate tensile strength (*UTS*), yield strength (Y_S), % elongation, strain hardening exponent (n) and strength coefficient (K). The value of yield strength is taken at 0.2% engineering strain. Knowledge of these properties is important for the control of many material production techniques such as forging, rolling, or drawing. % elongation is calculated using the following formula [4],

$$\%\,\text{elongation} = \frac{\text{Final guage length} - \text{Initial guage length}}{\text{Initial guage length}} \times 100 \tag{1}$$

The strength coefficient and strain hardening exponent gives a measure of increase in hardness due to plastic deformation. This gives an idea about how much the material can be formed. A material with a high strain hardening exponent value has a greater capacity for being formed [5]. These values are obtained from the true stress – true strain graph using the following equation,

$$\sigma = K\varepsilon^n \tag{2}$$

Fig. 1 shows how to calculate the mechanical properties from the stress–strain graphs. *UTS* and Y_S are calculated from the engineering stress–strain graph, whereas n and K are obtained from the true stress–strain graph. % elongation is calculated based on the final gauge length as measured using a vernier calliper after the sample is broken. In other words, it is the true plastic strain at fracture in percentage.

2. Experimental study

In this work, two grades of Austenitic Stainless Steel are investigated, namely ASS 304L and ASS 316L. Their composition is given in Table 1. To extract the experimental data and to predict the mechanical properties, the tensile tests are conducted at three different strain rates (0.0001, 0.001 and 0.01 s^{-1}) and temperatures ranging from 50 °C to 650 °C at an interval of 50 °C. Hence, a total of 39 experiments for both materials are conducted at 13 different temperatures and 3 different strain rates. Wire-cutting electro-discharge machining process is used to machine out the tensile test samples. The dimensions of the specimens are as per the sub-sized ASTM E8/E8M-11 standards. The details of the experimental setup are as mentioned by Gupta et al. [1].

Figs. 2 and 3(a–e) shows the variation of these mechanical properties with temperature at various strain rates. It can be seen from these graphs that the value of the properties decreases with increase in temperature, but in the

Table 1 – Chemical composition of Austenitic Stainless Steel 304L and 316L (wt.%).

	Element	Fe	C	Mn	Si	Mo	Co	Cr	Cu	Ni	Others
Composition	ASS304L	70.780	0.025	1.140	0.410	0.360	0.210	18.40	0.180	8.190	0.305
(% by weight)	ASS316L	67.69	0.018	1.28	0.38	2.42	0.21	16.63	0.21	10.85	0.312

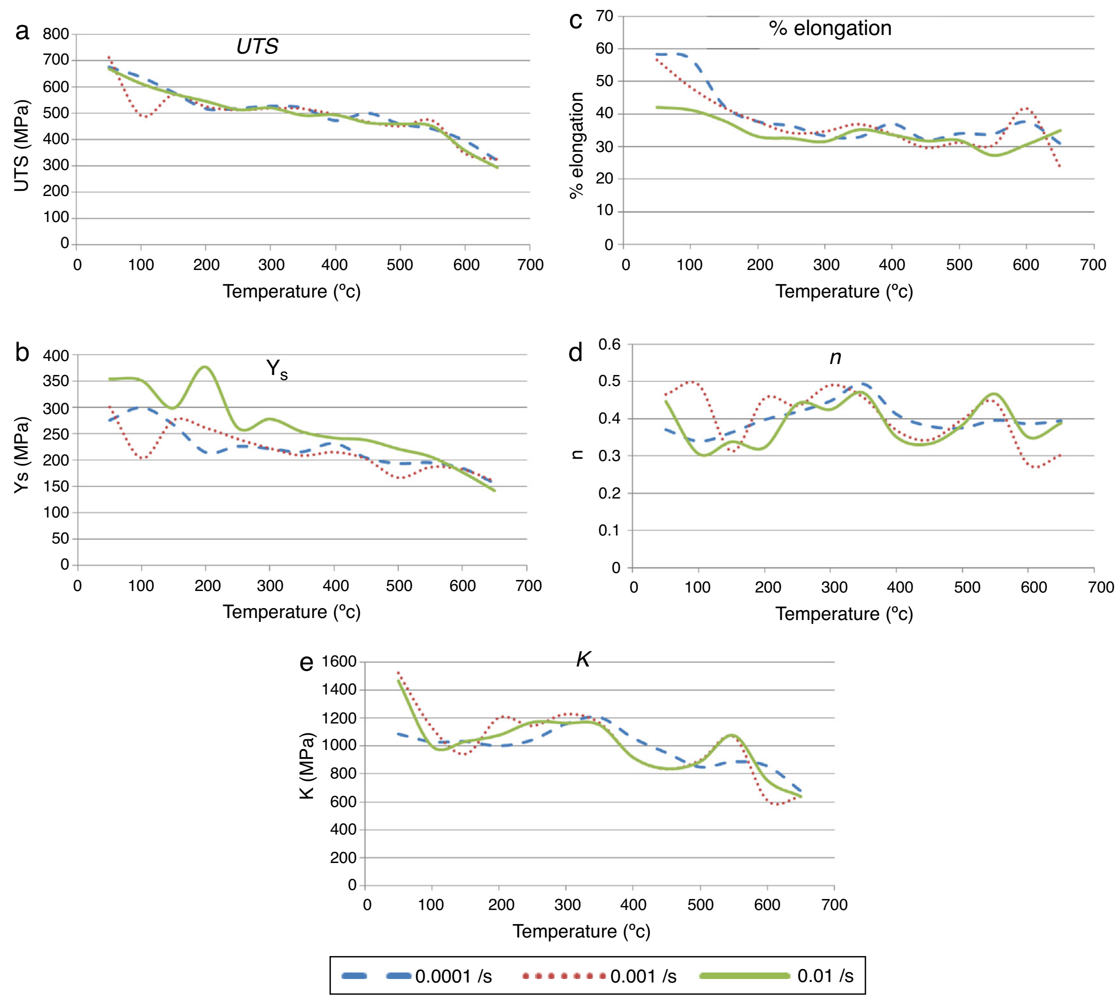

Fig. 2 – Variation of (a) *UTS*, (b) Y_S, (c) % elongation, (d) *n*, (e) *K* of ASS 304L with respect to temperature for different strain rates.

temperature range of 300–550 °C, this trend is not followed. The *UTS* is seen to decrease till the temperature of 300 °C and further seen to become approximately constant till 550 °C. The Y_S and % elongation are also found to decrease drastically and become constant and again decrease. K and n values were found to decrease and then increase in the above mentioned region and then decrease after 600 °C. This irregular variation in the properties is due to the effect Dynamic Strain Ageing (DSA phenomenon, which may be associated with the Portevin–Le Chatelier effect) [6,7].

These mechanical properties do not follow any particular trend, which makes it difficult to predict with any kind of equations. Artificial Neural Network (ANN) technique is ideally suited for this purpose. ANN is an artificial intelligence technique, which has been applied to describe many processes wherein the understanding of the physical mechanisms is quite tough [8,9]. The behaviour of biological neural systems is imitated by ANN in a digital software or hardware. This approach does not require a well-defined process for algorithmically converting an input to an output. One of the greatest advantages of ANNs is that they use an arbitrary function approximation mechanism, which 'learns' from a set of representative data. Then ANN adapts itself and reproduces the desired output when the training sample is given as input. For this model, neither explicit mathematical understanding nor physical knowledge of variation of properties is required. In the predictive modelling application of the ANN, it acts as a sum of weighted inputs combining to give the output or the predicted value. In comparison with modelling by mathematical equations, the estimation of mechanical properties becomes a lot easier by using ANN technique [5].

3. Development of ANN model

Neural network architecture consists of a specification of the number of layers, the number of neurons in each layer, the type of activation function performed by each neuron, and the available connections between the neurons. Values for the weight, w, is assigned to the connections in the network A, the weighted input (x) sum is mapped to $y1(x, w, A)$, the predicted value of the output. These parameters change the effective

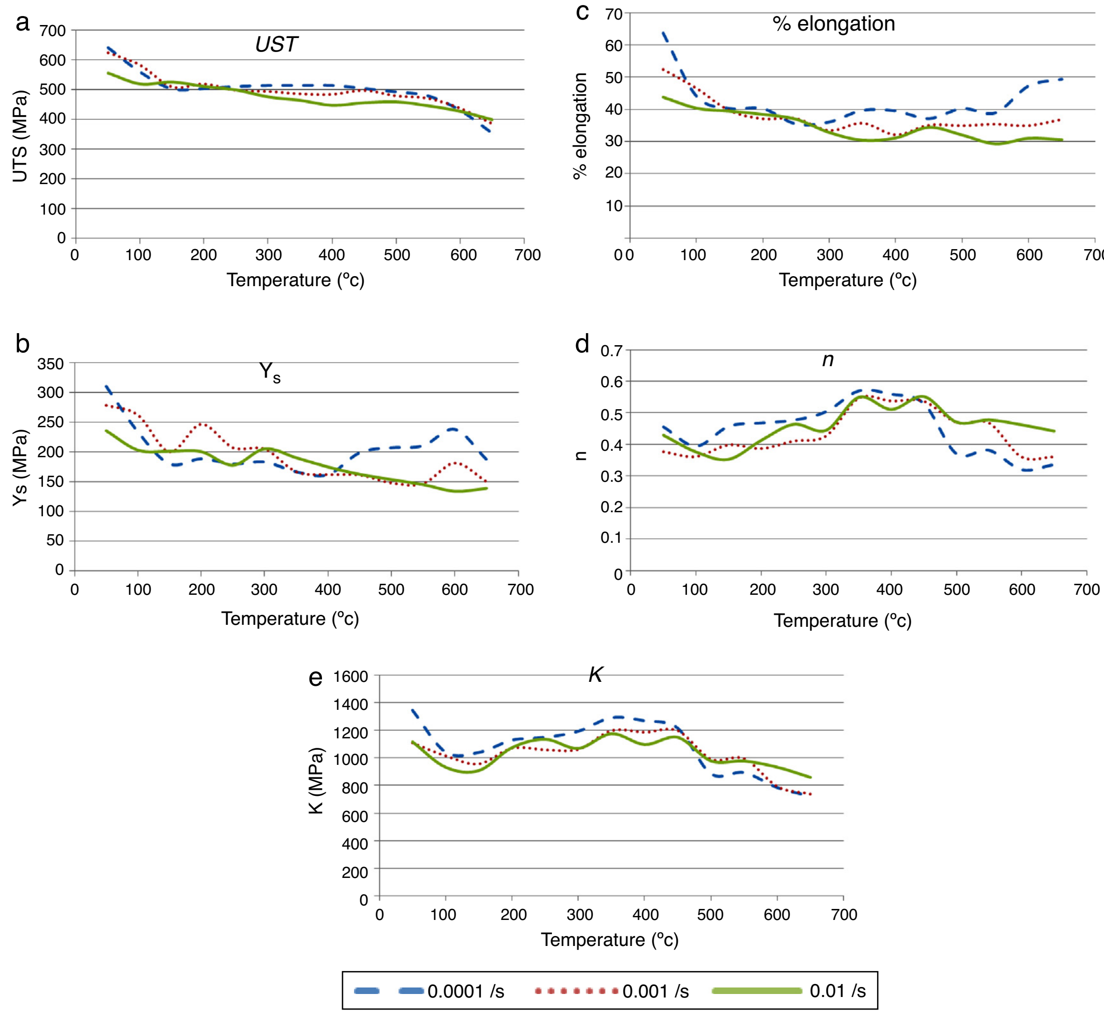

Fig. 3 – Variation of (a) UTS, (b) Y_S, (c) % elongation, (d) n, (e) K of ASS 316L with respect to temperature for different strain rates.

learning model, for example, number of hidden neurons, and weight decay terms etc.

In literature, it has been found that feed forward back propagation neural networks are being used to train the network which is very reliable [8,9]. The back propagation learning algorithm uses a gradient search technique to minimize the mean square error of the output of the network.

The parameters mentioned above of the back propagation networks are generally set by trial and error and the use of reserved test data to assess the generalization ability (or more sophisticated cross-validation). However, there is another novel technique for finding the best architecture of the Neural Network. The method is to first find the number of layers for which the neural network has the minimum mean square error (MSE) [9]. This layer is the optimum layer for the neural network, which can train the training set. However, in some cases the testing data might not be satisfying the network due to loss of generalization capability. Hence, using the techniques of machine learning of regularization, i.e., reducing the number of layer and reducing epochs of the network, the optimum layers were found to be 6 for ASS 304L and 17 for ASS 316L. As shown in Fig. 4(a), the minimum MSE occurs when the number of layers is 16, but the testing data is not satisfied by the network and hence using the techniques of machine learning of regularization, 6 layers are chosen. Fig. 4(b) shows the plot of MSE vs. number of layers for ASS 316L.

The input parameters in ANN model are temperature and strain rate, and output parameters are *UTS*, Y_S, % elongation, n and K. The input is first normalized from 0.05 to 0.95 using the following equation for transfer function to activate efficiently.

$$x_n = 0.05 + 0.9 * \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3}$$

where x_{min} and x_{max} are the minimum and maximum values of input x and x_n is the normalized data of the corresponding x. Once the best trained network is found, all the transformed data returns to their original value using the following equation,

$$x = x_{min} + (x_n - 0.05) * (x_{max} - x_{min})/0.9 \tag{4}$$

The experimental data is randomly divided into two parts. 85% of the data points are selected as training data for training

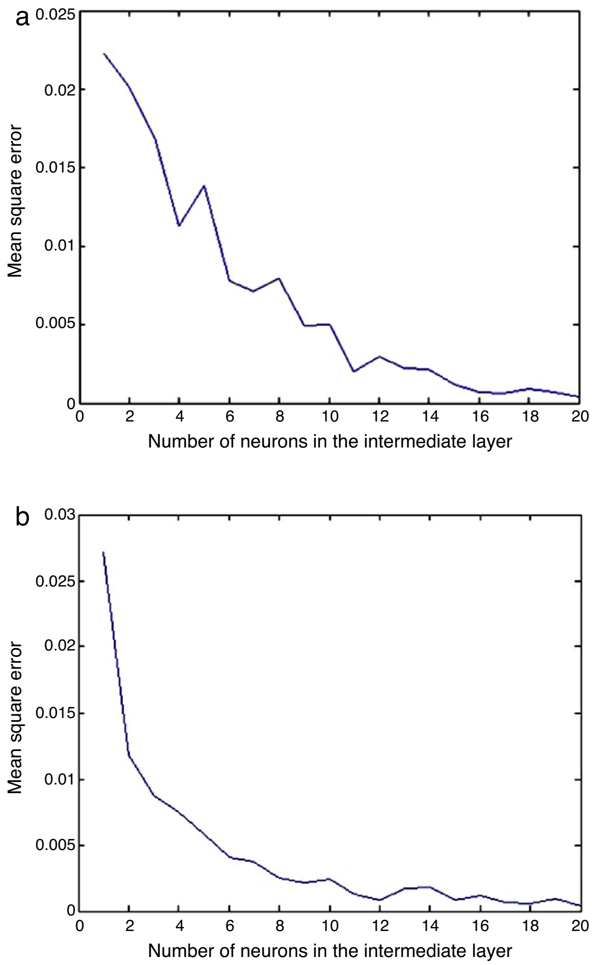

Fig. 4 – ANN architecture for (a) ASS 304L and (b) ASS 316L.

ANN and the remaining 15% are used as test data in order to get best combination of layers in the single layer ANN. This training-testing-validating procedure is adopted from Hastie et al. [10]. This network is implemented in MATLAB 2012a version. The training function used to get the back propagation neural network (BPNN) is *Levenberg–Marquardt* training function (*trainlm*).

A good neural network will have a good correlation in both training and testing dataset. However, selection of the best architecture of the network is difficult. The training sets have a good correlation but when it comes to some unseen data, most of the networks either over fit or under fit the data. The best neural network is one that has maximum correlation on the testing data and a reasonably high correlation for the training data. This is further validated by calculating the correlation of the total data set with the predicted value. The selection of the architecture of the neural network is done using the above mentioned criteria. Hence the best network was found to be [2-6-5] for ASS 304L and [2-17-5] for ASS 316L. The architecture has been found out for a single middle layer with 2 inputs and 5 outputs. The architecture of ASS 304L as mentioned [2-6-5] implies there are 6 neurons in the middle layers and the numbers 2 and 5 are fixed as per the inputs (2) and outputs (5).

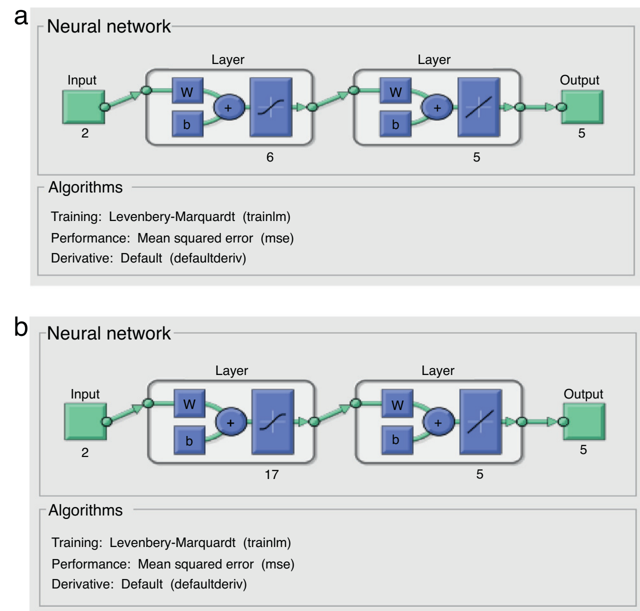

Fig. 5 – Plot of mean square error vs. number of layers for (a) ASS 304L and (b) ASS 316L.

The architecture of ASS 316L implies it has 17 neurons in the middle layer. This architecture is shown in Fig. 5(a) and (b) for ASS 304L and ASS 316L respectively.

4. Results and discussion

To validate the predictions of the ANN model, three statistical parameters are compared, i.e., correlation coefficient, average absolute error and standard deviation. Correlation coefficient (R) is a statistical tool that provides information on the strength of linear relationship between the experimental and predicted values. The average absolute error (Δ) is a quantity used to measure how close the prediction values are to the experimental ones. These are calculated using the following equations,

$$R = \frac{\sum_{i=1}^{i=N}(y^i_{exp} - \bar{y}_{exp})(y^i_p - \bar{y}_p)}{\sqrt{\sum_{i=1}^{i=N}(y^i_{exp} - \bar{y}_{exp})^2 \sum_{i=1}^{i=N}(y^i_p - \bar{y}_p)^2}} \quad (5)$$

$$\Delta = \frac{1}{N}\sum_{i=1}^{i=N}\left|\frac{y^i_{exp} - y^i_p}{y^i_{exp}}\right| \times 100 \quad (6)$$

where y_{exp} is the experimental value, y_p is the predicted value, $\bar{y}_{exp}$ and $\bar{y}_p$ are the average values of y_{exp} and y_p, respectively, and N is the total number of data points being considered. Standard deviation (s) gives the deviance of the values from the mean. The correlation coefficient alone is not sufficient to validate the predictions. The predictions of the model may be biased towards higher or lower values. Hence, average absolute error (Δ_{avg}) between the predicted and the experimental values and its standard deviation are also calculated.

J MATER RES TECHNOL. 2016;5(1):13–20

Table 2 – Statistical parameters for the training data (85% of the data).

Training	ASS 304L			ASS 316L		
	R	Δ_{avg} (%)	Std. deviation (%)	R	Δ_{avg} (%)	Std. deviation (%)
UTS	0.9839	2.87	2.37	0.9947	0.89	0.66
Y_S	0.9518	5.62	5.45	0.9887	1.86	2.04
% elongation	0.9014	6.60	6.29	0.9830	2.12	1.94
n	0.8625	5.80	5.30	0.9918	1.15	1.46
K	0.9401	5.91	4.84	0.9941	1.02	0.96

Table 3 – Statistical parameters for testing data (15% of the data).

Testing	ASS 304L			ASS 316L		
	R	Δ_{avg} (%)	Std. deviation (%)	R	Δ_{avg} (%)	Std. deviation (%)
UTS	0.9899	1.72	1.34	0.9706	3.57	3.78
Y_S	0.9734	7.95	3.95	0.9655	5.27	4.45
% elongation	0.9667	7.76	8.58	0.9456	7.54	6.50
n	0.7103	7.49	1.53	0.8175	14.23	15.77
K	0.9847	7.44	3.92	0.9219	10.36	10.55

Table 2 shows the statistical parameters, viz., correlation coefficient, average absolute error and standard deviation for the training data set for both the materials. As it can be seen from the table, the R value for % elongation of ASS 304L is 0.9014 and for n is 0.8625, but the value of average absolute error is 6.6% and 5.8%, respectively. This clearly shows that even though the R value is higher for % elongation, the error value is also higher as compared to n. This indicates that the model is biased towards the higher value of % elongation, which means that even the error value and its standard deviation has to be considered while validating the model predictions. The training for ASS 316L is excellent as R values for all properties are above 0.98 and the average absolute error and standard deviation value less than 3%. In case of ASS 304L, the correlation coefficients are above 0.9, except for n (0.8625) and error values are less than 6.6%. This indicates that the DSA phenomenon is more prominent in ASS 304L than ASS 316L.

Having a total of 39 data points, 15% of the data, i.e., 5 data points are selected randomly as testing set. Table 3 shows the statistical parameters for the testing set. The R values for n of both ASS 304L and ASS316L are 0.7103 and 0.8175 respectively. This may be due to the fact that the flow curves of these materials do not follow the power law, i.e., $\sigma = K\varepsilon^n$. The R values of other properties of ASS 304L are above 0.96 and of ASS 316L are above 0.92, which depicts the accurate prediction of the ANN model. The graphs of correlation coefficient between the experimental and predicted values are shown in Fig. 6 for ASS 304L and Fig. 7 for ASS 316L.

The overall validation of the model for the complete data set gave value of correlation coefficient above 0.94, except for n

Table 4 – Statistical parameters for the complete data.

Validation	ASS 304L			ASS 316L		
	R	Δ_{avg} (%)	Std. deviation (%)	R	Δ_{avg} (%)	Std. deviation (%)
UTS	0.9797	3.67	2.94	0.9875	1.24	1.64
Y_S	0.9429	7.58	9.23	0.9822	2.29	2.65
% elongation	0.9250	6.23	7.40	0.9568	2.82	3.33
n	0.8353	6.75	5.95	0.9185	2.82	6.90
K	0.9471	5.54	5.39	0.9529	2.22	4.75

Table 5 – Hypothesis testing to validate the ANN training.

	ASS 304L p-values			ASS 316L p-values		
	t-Test	F-Test	Levene's test	t-Test	F-Test	Levene's test
UTS	0.840	0.917	0.983	0.713	0.855	0.952
Y_S	0.724	0.949	0.670	0.836	0.867	0.953
% elongation	0.573	0.255	0.358	0.854	0.390	0.840
n	0.941	0.397	0.304	0.904	0.455	0.568
K	0.602	0.612	0.503	0.926	0.446	0.751

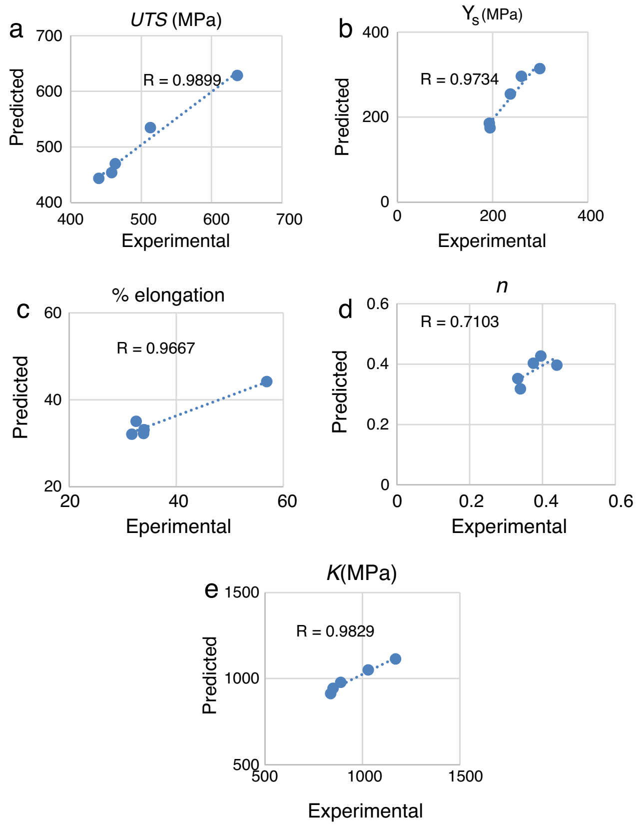

Fig. 6 – Correlation coefficient between the experimental and predicted values for the testing data of (a) *UTS*, (b) Y_S, (c) % elongation, (d) *n*, (e) *K* for ASS 304L.

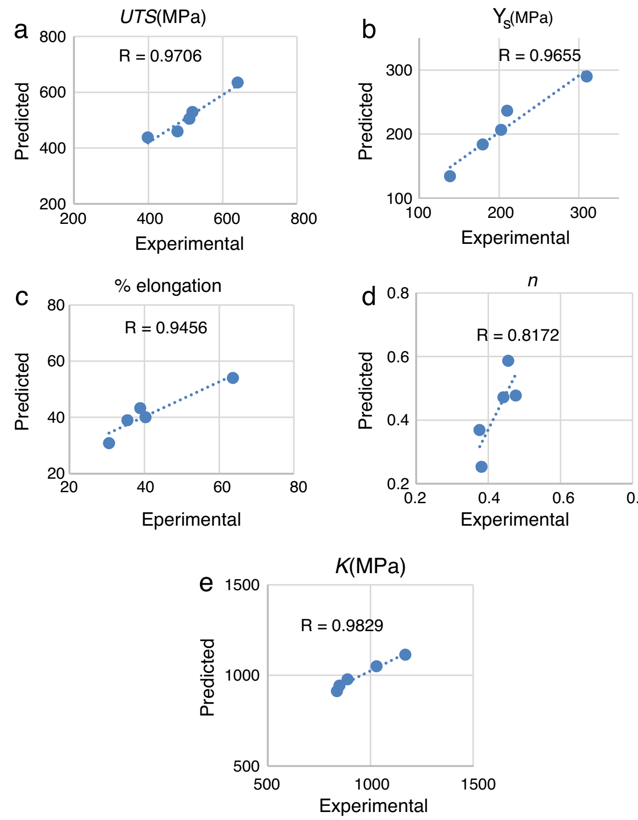

Fig. 7 – Correlation coefficient between the experimental and predicted values for the testing data of (a) *UTS*, (b) Y_S, (c) % elongation, (d) *n*, (e) *K* for ASS 316L.

(0.8353) for ASS 304L and it is above 0.95, except for *n* (0.9185) for ASS 316L, which shows that ANN model can accurately predict the mechanical properties. The values of average absolute error and standard deviation for ASS 304L are less than 7.5% and 9.23% respectively and for ASS 316L they are less than 2.82% and 6.90% respectively (Table 4), which illustrate the accuracy of the model.

To compare the goodness of fit of the ANN model, some representative hypotheses tests are conducted for the model construction process. These tests are *t*-test to test the means, f-test for variance and Levene's test. A paired *t*-test is used to compare means of two sample population in which observations in one sample can be paired with observations in the other sample. A *F*-test is used to test if the variances of two populations are equal [11]. Levene's test is an inferential statistic used to assess the equality of variances in different samples [12]. After performing these tests, *p*-values are obtained. If the *p*-values are greater than 0.05, then the null hypothesis cannot be rejected [13]. These statistical tests are performed using the Minitab v16 software. The *p*-values for the mean paired *t*-test conducted between the experimental and the predicted data are above 0.05 as it can be seen from Table 5, which shows that the mean of the predicted data is very close to the mean of experimental data. Also, it can be clearly seen from Table 5, that none of the *p*-values are less than 0.05 and therefore, the ANN prediction model has statistically satisfactory goodness of fit from the modelling point of view.

5. Conclusion

In this work, the mechanical properties, viz., *UTS*, Y_S, % elongation, *n* and *K* for ASS 304L and ASS 316L are evaluated based on the experimental data obtained from uniaxial isothermal tensile tests. To predict these properties at any unknown temperature and strain rate, feed forward back propagation ANN models have been developed. 85% of the data is used to train the ANN model and 15% data is used for testing it. Based on the machine learning techniques, the best ANN architecture is found to be [2-6-5] for ASS 304L and [2-17-5] for ASS 316L. The ANN model accuracy is validated based on the statistical parameters such as correlation coefficient, average absolute error and its standard deviation. The results of these statistical parameters indicate the highly accurate predictions of ANN models. The goodness of fit of these models is also verified by conducting the hypothesis testing using mean paired *t*-test, *F*-test and Levene's test.

Finite element (FE) analysis in simulating the various processes, like drawing requires the mechanical properties at various temperatures. The current practice in FE simulations is to feed the values of these mechanical properties manually at different temperatures. The future work is envisaged to incorporate the ANN model in the FE code to obtain accurate simulation results.

Conflicts of interest

The authors declare no conflicts of interest.

REFERENCES

[1] Gupta AK, Krishnamurthy HN, Singh Y, Prasad KM, Singh SK. Development of constitutive models for dynamic strain aging regime in Austenitic stainless steel 304. Mater Des 2013;45:616–27.
[2] Wang XY, Li DY. Mechanical, electrochemical and tribological properties of nano-crystalline surface of 304 stainless steel. Wear 2003;255:836–45.
[3] Karthik V, Murugan S, Parameswaran P, Venkiteswaran CN, Gopal KA, Muralidharan NG, et al. Austenitic stainless steels for fast reactors – irradiation experiments, property evaluation and microstructural studies. Energy Procedia 2011;7:257–63.
[4] Dieter GE, Bacon D. Mechanical metallurgy, Vol. 3. New York: McGraw-Hill; 1986.
[5] Singh S, Mahesh K, Gupta A. Prediction of mechanical properties of extra deep drawn steel in blue brittle region using artificial neural network. Mater Des 2010;31: 2288–95.
[6] Armas AF, Bettin OR, Alvarez-Armas I, Rubiolo GH. Strain aging effects on the cyclic behavior of austenitic stainless steels. J Nucl Mater 1988;155:644–9.
[7] Peng K, Qian K, Chen W. Effect of dynamic strain aging on high temperature properties of austenitic stainless steel. Mater Sci Eng A 2004;379:372–7.
[8] Anirudh VK, Amrutha G, Gupta AK, Singh SK. Flow stress prediction in austenitic stainless steel 316 at elevated temperatures. n.d.;500078:1–6.
[9] Gupta AK, Singh SK, Reddy S, Hariharan G. Prediction of flow stress in dynamic strain aging regime of austenitic stainless steel 316 using artificial neural network. Mater Des 2012;35:589–95.
[10] Hastie T, Tibshirani R, Friedman J, Franklin J. The elements of statistical learning: data mining, inference and prediction. Math Intell 2005;27:83–5.
[11] Snedecor GW, Cochran WG. Statistical methods. 8th ed. Iowa State Univ Press; 1989.
[12] Brown M, Forsythe A. Robust tests for the equality of variances. J Am Stat Assoc 1974:278–92.
[13] Gupta AK. Predictive modelling of turning operations using response surface methodology, artificial neural networks and support vector regression. Int J Prod Res 2010;48: 763–78.