Original Article

Neural network modeling for anisotropic mechanical properties and work hardening behavior of Inconel 718 alloy at elevated temperatures

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\textbf{A B S T R A C T}

Inconel alloys are gaining a special attention for high temperature applications in service environment of aircraft structures, rocket engines, nuclear reactors, gas turbines and pressure vessels. This makes crucial to understand anisotropic material properties and work hardening behavior of a material. In this study, various mechanical properties such as ultimate strength (\(\sigma_{\text{ut}}\)), yield strength (\(\sigma_{\text{y}}\)), strain hardening exponent (n) and % elongation have been evaluated by using uniaxial tensile tests. The tensile tests have been conducted from room temperature to 600°C at an interval of 100°C with different slow strain rates (0.0001, 0.001, 0.01 \text{s}^{-1}). Additionally, anisotropy of Inconel 718 alloy has been evaluated based on various measurable parameters such as normal anisotropy, planar anisotropy, in-plane anisotropy and anisotropic index. Furthermore, stress-strain response is analyzed by empirical work hardening equation by Hollomon, Swift, Ludwick and Voce. The Artificial Neural Network (ANN) models have been developed to predict various anisotropic mechanical properties and hardening behavior of Inconel 718 alloy. The ANN model is skilled by Levenberg-Marquardt algorithm and signifies a good accuracy of model with an excellent correlation coefficient and significantly low average absolute error. Validation for the accuracy of developed ANN model is confirmed with results from f-test and mean paired t-test.

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1. Introduction

Nonconformity in mechanical properties and work hardening behavior at elevated temperatures attracted continued interest in sight of improving conditions suitable for material processing and confirming safe performance during working. Presently, higher performance requirements and safety concerns have enforced to select high strength and lighter-yet-safer superalloys for aerospace and automotive industries. Moreover, superalloys are being studied to replace conventional metals to improve the performance in many high temperature critical applications. For this concerns, Ni-Fe-Cr based super-alloys, because of their excellent mechanical properties at elevated temperature, were gaining special attention [1]. Since the introduction of Ni-Fe-Cr alloys in the early 1960s, these alloys in a relatively short time became indispensable materials for nuclear reactors, aircraft structures, gas turbines and marine applications [2-4].

Over past decade, neural network analysis has emerged as a real-world technique for recognizing patterns in huge data sets of various variables. Presently, Artificial Neural Network (ANN) is gaining tremendous thrust for prediction purpose in the field of materials because of specific features such as non-linearity, adaptation, generalization, and model independence [4]. In diverse fields of materials science, interest of neural network modeling has been increasing constantly. It has been verified that ANN is capable to model the mechanical properties and work hardening behavior in complex systems with reasonable accuracy [5-8].

Singh et al. [5] predicted the mechanical properties from RT-700 °C of EDD steel in three rolling direction by ANN model by temperature and orientation as input parameter. The experimental results and modeling error for prediction observed within acceptable range. Desu et al. [7] studied the mechanical properties of ASS at elevated temperature by using trained ANN model. Authors observed statistical parameters results, accurate predictions by ANN models and verification of result by hypothesis testing with different test. Wen et al. [6,8] studied work hardening behavior of aged Ni-base super-alloy during hot deformation. From results concluded that the work-hardening behaviors of the tested super-alloy were significantly affected by strain rate, deformation temperature, strain and presence of δ phase. In literature, various mathematical flow relationships have been proposed to describe stress-strain relationship such as Hollomon, Swift, Ludwick, Ludwign and Voce [9-11]. From the previous studies, it is observed that hot deformation behavior of Ni-Fe-Cr superalloys is significantly affected by initial grain texture, morphology of formed secondary phases, followed heat treatments and process parameters like deformation temperature and strain rate [12,13]. Though some constitutive models for Ni-based superalloys have been efficiently proven, further efforts must be made for improving interpolation abilities and prediction accuracy [13].

In present investigation, the various material properties, anisotropic parameters and work hardening behavior of Inconel 718 alloy have been analyzed using hot isothermal tensile test at quasi-static strain rates. Based on tensile test data, ANN models have been developed and verified using various statistical parameters for material properties determination and hardening models.

2. Experimental study

The Inconel 718 alloy with chemical composition, as mention in Table 1 and an initial thickness of 1 mm is used for hot isothermal tensile tests. Microstructure of parent alloy is shown in Fig. 1, as received specimen is observed with mostly fine with elongated with substantial carbide stringers in austenitic matrix consisting of fine equiaxed grains. The dimensions of tensile test specimens are prepared as per ASTM E08/E8M-11 sub sized specimen. All the specimens were prepared using wire cut EDM machine for better-quality surface finish and dimensional accuracy. Specimens are prepared along the rolling direction (RD), diagonal to rolling direction (ND), and transverse direction (TD) to rolling direction of sheet. Isothermal tensile test is conducted on computer controlled Universal Testing Machine (UTM) with maximum load capacity 50kN, the heating capacity of 1000 °C ± 5 °C accuracy, as shown in Fig. 2. High temperature contact type extensometer was used for tensile testing. Samples are first heated to their deformation temperature at 20 °C/min, and heat preservation

| Table 1 – Chemical composition of Inconel 718 alloy (wt.%). |
|-----------------|---|---|---|---|---|---|---|---|
| Element         | Ni | Cr | Fe | Nb | Mo | Ti | Al | Mn | Si | Others |
| wt.%            | 51.463 | 18.279 | 20.441 | 5.012 | 2.871 | 1.092 | 0.561 | 0.062 | 0.051 | 0.169 |

Fig. 1 – Microstructure of parent Inconel 718 sheet in rolling direction.
time is 5–6 min in order to ensure a uniform temperature prior to loading. The tensile tests have been conducted from room temperature (RT) to 600 °C at an interval of 100 °C with different slow strain rates (0.0001, 0.001, 0.01 s⁻¹). Three samples were tested in each test setting in order to get more reliable and accurate results.

The stress–strain data from the tensile test machine is used to analyses further for material properties determination and work hardening behavior. The various material properties are calculated namely ultimate strength (σₘₚₓ), yield strength (σ₀₂), strain-hardening coefficient (n) and % elongation. The effect of deformation temperature on tensile strength, strain-hardening coefficient (n) and (% elongation, is shown in Fig. 3a–d. At RT, alloy is ascribed to relatively higher amount of deformation related with the rolling direction. The tensile strength parameters (σ₀₂ and σₘₚₓ) & % elongation values decrease and increase respectively with increase in strain rate. The tensile yield strength (σ₀₂) shows a systematic variation as function of sample orientation regardless of change in strain rate (Fig. 3a). Material properties values are minimum and maximum along diagonal to rolling direction (ND) and rolling direction (RD), respectively. It has been observed from Fig. 3 that material properties are considerably influenced by strain rate, test temperature and orientation of the specimen. Thus it is vital to understand the material behavior for accurate prediction of material properties. ANN is effective modeling technique in this regard. The average material properties of Inconel 718 alloy with different test temperature are mentioned in Table 2.

3. Development of ANN model

ANN is interpretation of biological neuron system, is a highly interconnected system of parallel distribution, neural calculating elements that have capability to grasp and learn to procure knowledge and make available to use. Architecture of neural network consists of a specific of number of layers, number of neurons in each layer, sort of activation function accomplished by each neuron and accessible connections between neurons. There are three basic steps for neural network architecture, namely the data collection, ANN modeling, and application. Data collection is the basic step can be done thorough experimentation. Network architecture is created and configured by weights and biases with training and validating the network. After creating the neural network, it is possible to predict the results by giving concerned input to the proposed model.

In literature, it has been mentioned that controlled learning is designated to train network for performance improvement. Used layered feed-forward ANN’s is accomplished by the back-propagation algorithm, where the artificial neurons are arranged in layers and sending their signals “forward” and then errors are supposed to be promulgated backwards. The back-propagation algorithm practices controlled learning to calculate error i.e. difference between experiment and predicted results. Purpose of back-propagation algorithm is to minimize the error, till network acquires through training data. The training starts with random variables and objective is to arrange such that error have to be minimized [5,6]. The data for testing and training the neutral network is normalized from 0 and 1 using transfer function [7]. For finest combination of layers, experimental data are divided randomly, first 70% training data for training ANN and remaining 30% as test data. The proficient ANN model is executed in MATLAB 2018a and trained by Levenberg–Marquardt algorithm.

3.1. Material properties determination

In this study, the material properties considered are namely σ₀₂, σₘₚₓ, % elongation & n. The input parameter, considered to determine the material properties, is shown in schematic drawing of neural network structure (Fig. 4a). Selection of
Fig. 3 – Effect of deformation temperature on (a) yield strength, (b) ultimate strength, (c) % elongation, and (d) strain-hardening coefficient.


table 2 – Average material properties of Inconel 718 alloy at different test temperatures.

<table>
<thead>
<tr>
<th>Temperature (°C)</th>
<th>σy (MPa)</th>
<th>σuts (MPa)</th>
<th>% elongation</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>RT</td>
<td>505.64 ± 6%</td>
<td>931.92 ± 10%</td>
<td>41.97 ± 0.6</td>
<td>0.59 ± 0.02</td>
</tr>
<tr>
<td>100 °C</td>
<td>486.30 ± 5%</td>
<td>873.52 ± 6%</td>
<td>44.20 ± 0.6</td>
<td>0.58 ± 0.04</td>
</tr>
<tr>
<td>200 °C</td>
<td>443.91 ± 3%</td>
<td>863.58 ± 5%</td>
<td>47.75 ± 0.5</td>
<td>0.57 ± 0.06</td>
</tr>
<tr>
<td>300 °C</td>
<td>424.20 ± 5%</td>
<td>844.40 ± 4%</td>
<td>48.16 ± 0.5</td>
<td>0.57 ± 0.08</td>
</tr>
<tr>
<td>400 °C</td>
<td>394.66 ± 4%</td>
<td>819.73 ± 6%</td>
<td>49.22 ± 0.7</td>
<td>0.55 ± 0.09</td>
</tr>
<tr>
<td>500 °C</td>
<td>370.83 ± 6%</td>
<td>781.33 ± 8%</td>
<td>51.91 ± 0.4</td>
<td>0.53 ± 0.07</td>
</tr>
<tr>
<td>600 °C</td>
<td>358.57 ± 4%</td>
<td>753.22 ± 6%</td>
<td>53.62 ± 0.4</td>
<td>0.52 ± 0.06</td>
</tr>
</tbody>
</table>

optimum hidden layer for neutral network is by novel technique as mentioned by Desu et al. [7]. Based on the trial and error method, different number of hidden layers are varied, in order to get least mean square error. Fig. 4b shows representative plot of mean square error and number of hidden layers for Inconel 718 alloy material properties determination. It has been seen from Fig. 4b that least mean square error achieved for 22 hidden layers. Thus, chosen ANN model has a single layer with 2 inputs (strain & temperature) and 4 outputs (σy, σuts, % elongation and n) as shown in Fig. 4a. The ANN architecture of Inconel 718 has [2–22–4] layers, indicates 22 neurons in the middle-hidden layers with (2) inputs and (4) outputs.

The directionality of the material properties is defined as anisotropy (R) and related to the variance of atomic spacing within crystallographic orientations. Typical anisotropic behavior is explained by Lankford coefficient (R), normal anisotropy (R), planar anisotropy (∆R), in-plane anisotropy (AIP) and anisotropic index δ [14-17], are listed below:

Lankford coefficient [15]

\[ R = \frac{\varepsilon_{\omega}}{\varepsilon_{t}} \]  (1)

Normal anisotropy (R) [15]

\[ \bar{R} = \frac{R^0 + 2R^{45} + R^{90}}{4} \]  (2)
Planer anisotropy ($\Delta R$) [15]

$$\Delta R = \frac{R^0 - 2R^{45} + R^{90}}{2}$$  \hspace{1cm} (3)

In-plane anisotropy ($A_{ip}$) [16]

$$A_{ip} = \frac{2 \times \sigma_{ys}^0 - \sigma_{ys}^{90} - \sigma_{ys}^{45}}{2 \times \sigma_{ys}^0}$$  \hspace{1cm} (4)

Anisotropic index ($\delta$) [17]

$$\delta = \frac{(%\%Ei)^0 - (%\%Ei)^{90}}{(%\%Ei)^0 + (%\%Ei)^{90}}$$  \hspace{1cm} (5)

where, $\varepsilon_{w}$ & $\varepsilon_{t}$ are width plastic strain & thickness plastic strain, R$^0$, R$^{45}$ & R$^{90}$ are ratio of plastic strains along 0°, 45° & 90° orientation to RD, $\sigma_{ys}^0$, $\sigma_{ys}^{45}$ & $\sigma_{ys}^{90}$ are tensile yield strengths at 0° orientation, 45° orientation & 90° orientation to RD and (%\%Ei)$^0$ & (%\%Ei)$^{90}$ are % elongation in 0° & 90° to RD respectively.

Table 3 represents the anisotropic properties of Inconel 718 alloy at different test temperature. (R) is main influencing parameter of the maximum drawability of sheet. During a deep drawing operation, metal with high (R) experience less thinning than metal with small (R) with same metal flow characteristics [15]. Smaller value of ($\Delta R$) indicates lesser possibility of formation of earing. This will reduce the defect of wrinkling and tearing in deep drawing. Increase in the values of ($A_{ip}$), indicates increase in extent of anisotropic nature. Presence of low values of anisotropic index $\delta$ indicates very less elongation anisotropy with rise in deformation temperature.

The input parameters considered to determine the anisotropic properties is similar to neural network structure (Fig. 4a) with input (thickness, orientation, temperature and yield strength) and 5 outputs. The minimum mean square error (MSE) observed when number of hidden layers is 19. Selected ANN architecture of Inconel 718 alloy has [4–19–5] layers.

3.2. Work hardening behavior

Work hardening behavior of alloy defines increase in stress, need to continue deformation at any phase of plastic strain. The nature of curves in plastic deformation stage in stress–strain curve, explains interfering with the dislocation movement, grain boundaries. Various mathematical flow relationships proposed to describe stress–strain relationships. In present study, some popularly known models, such as Hollomon, Swift, Ludwick, and Voce [10,11] are discussed and listed below:

Hollomon equation

$$\sigma = k H \varepsilon^{n_H}$$  \hspace{1cm} (6)

Ludwick equation

$$\sigma = \sigma_f + k_L \varepsilon^{n_L}$$  \hspace{1cm} (7)

Swift equation

$$\varepsilon = (e + k_S (e_0)^{n_S})$$  \hspace{1cm} (8)

Voce equation

$$\sigma = \sigma_S - (\sigma_S - \sigma_1) \left[ 1 - \exp \left(-\frac{e}{\varepsilon_c}\right) \right]$$  \hspace{1cm} (9)

where, $\sigma$ is true stress, $\varepsilon$ is true plastic strain, $k_H$, $k_L$, $k_S$ are strength coefficient, and $n_H$, $n_L$, $n_S$ are strainhardening exponent, $\sigma_S$ is saturation stress (saturation stress at high strains where instantaneous work hardening is negligible), $\sigma_1$ is initial true stress onset of plastic deformation, $\varepsilon_c$ is a constant & $n_S = -1/\varepsilon_c$, rate at which flow stress reach steady value, usually occurs high strains.

The input parameters considered to determine the work hardening behavior is similar to neural network structure (Fig. 4a) with input (strain, strain rate, true strength and temperature) and 4 outputs. As shown in Fig. 5, minimum mean
Table 3 – Anisotropic properties of Inconel 718 alloy at different test temperatures.

<table>
<thead>
<tr>
<th>Temperature (°C)</th>
<th>R</th>
<th>R</th>
<th>ΔR</th>
<th>AIp</th>
<th>δ</th>
</tr>
</thead>
<tbody>
<tr>
<td>RT</td>
<td>0.8515</td>
<td>1.0665</td>
<td>0.0979</td>
<td>0.0332</td>
<td>0.0482</td>
</tr>
<tr>
<td>100 °C</td>
<td>0.7737</td>
<td>1.0877</td>
<td>-0.0297</td>
<td>0.0287</td>
<td>0.0461</td>
</tr>
<tr>
<td>200 °C</td>
<td>0.9169</td>
<td>1.0121</td>
<td>-0.1194</td>
<td>0.0240</td>
<td>0.0441</td>
</tr>
<tr>
<td>300 °C</td>
<td>0.7177</td>
<td>0.9580</td>
<td>-0.1062</td>
<td>0.0207</td>
<td>0.0405</td>
</tr>
<tr>
<td>400 °C</td>
<td>0.7798</td>
<td>0.9231</td>
<td>-0.0209</td>
<td>0.0225</td>
<td>0.0382</td>
</tr>
<tr>
<td>500 °C</td>
<td>0.6808</td>
<td>0.7196</td>
<td>-0.4283</td>
<td>0.0216</td>
<td>0.0379</td>
</tr>
<tr>
<td>600 °C</td>
<td>0.5972</td>
<td>0.7086</td>
<td>-0.2603</td>
<td>0.0228</td>
<td>0.0361</td>
</tr>
</tbody>
</table>

Fig. 5 – Plot of mean square error vs. number of hidden layers for hardening models.

4. Results and discussion

Validation of neural network is compared through standard deviation, correlation coefficient and average absolute error. Correlation coefficient is statistical tool provides relation between predicted and experimental variables. Closeness of predicted value with experimental value is calculated with average absolute error. Equations used to calculate correlation coefficient and average absolute error are,

\[
R = \frac{\sum_{i=1}^{N} (y_{\text{exp}}^i - \bar{y}_{\text{exp}}) (y_{\text{p}}^i - \bar{y}_{\text{p}})}{\sqrt{\sum_{i=1}^{N} (y_{\text{exp}}^i - \bar{y}_{\text{exp}})^2} \sum_{i=1}^{N} (y_{\text{p}}^i - \bar{y}_{\text{p}})^2}
\]

\[
\Delta = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_{\text{exp}}^i - y_{\text{p}}^i}{y_{\text{exp}}^i} \right| \times 100
\]

where, \( y_{\text{exp}} \) & \( y_{\text{p}} \) are experimental and predicted values, \( y_{\text{exp}}^i \) & \( y_{\text{p}}^i \) are average values of \( y_{\text{exp}} \) & \( y_{\text{p}} \) respectively, and \( N \) is complete number of data points considered [7].
Fig. 6 – Correlation coefficient between the experimental & predicted values for testing data of (a) yield strength, (b) ultimate strength, (c) % elongation, (d) strain hardening coefficient, (e) normal anisotropy, (f) planer anisotropy, (g) in-plane anisotropy, (h) anisotropy index.
4.1. Material properties and work hardening behavior

Table 4 represents the correlation coefficient, standard deviation and average absolute error for the Inconel 718 alloy. The training data for Inconel 718 alloy shows excellent correlation as R value for all properties is greater than 0.97 and average percentage error less than 2.5%, indicates true prediction of the ANN model. Higher R values of $\sigma_{ys}$ and $\sigma_{uts}$, indicate that the Inconel 718 alloy follows the power law or Hollomon equation (Eq. (6)). It is observed that even through R value of $\sigma_{ys}$ & $\dot{R}$ is high, with high average percentage error, compared to other material properties. Hence, standard deviation with error values, has to be taken in account while validation of model. The plots for correlation coefficient for testing data of material properties determined, are shown in Fig. 6.

The experimental strain hardening behavior of Inconel 718 alloy is analyzed using well-known empirical relations mentioned in Eqs. (6)–(9). Fig. 7 shows various analysis used to explain the hardening behavior of Inconel 718 alloy at different test temperature namely Hollomon Analysis, Crussard-Jaoul (C-J) analysis for Swift Equation & Ludwik Equation, and Kocks–Mecking (K–M) analysis for Voce equation. From plot, strain hardening in two stages is identified with high sensitivity of strain hardening exponent to temperature change. For Hollomon analysis (Fig. 7a), the log-log plots of true stress–strain at various temperature are linear at high strains, signifying applicability of Hollomon equation only at high strains. For Crussard-Jaoul (C-J) analysis for Swift equation & Ludwik equation (Fig. 7b and c), the three distinct regions are observed in all test conditions (higher, transition and lower strain region). Significant variation in lower strain region i.e. linear decreases in work hardening rate with increase in plastic stress or strain.

The Kocks–Mecking (K-M) phenomenological model gives the physical significance of Voce equation (Fig. 7d). In K-M approach, evaluation of dislocation movement is responsible for the plastic deformation, which increases with strain at constant strain rate. During plastic deformation, work hardening rate is usually organized by dislocation movement or rearrangement of dislocations in crystal structure. Observed strain hardening stages in the Inconel 718 alloy are stage III with parabolic hardening, followed by linear strain hardening stages IV and V. The curve is shifting to lower stresses with increase in temperature. Stage IV is observed for large net flow stress i.e. at large plastic strain. Strain hardening rate has decreased with increase in test temperature. Further, a steady reduction in region IV length has been noticed with increase in test temperatures. Finally the strain hardening stops at stage

![Fig. 7](image-url)  
Fig. 7 – Various analyses used to explain the hardening behavior of Inconel 718 alloy at different test temperature: (a) Hollomon analysis, Crussard-Jaoul (C-J) analysis for (b) Swift equation, (c) Ludwik equation, (d) Kocks–Mecking (K–M) analysis for Voce equation.
Table 4 – Statistical parameters for training data for Inconel 718 alloy.

<table>
<thead>
<tr>
<th>Testing</th>
<th>70% of the data</th>
<th>30% of the data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R</td>
<td>Δavg (%)</td>
</tr>
<tr>
<td>Material properties</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_{0.2}$</td>
<td>0.99994</td>
<td>2.49346</td>
</tr>
<tr>
<td>$\sigma_{0.2}$</td>
<td>0.99994</td>
<td>1.72241</td>
</tr>
<tr>
<td>% elongation</td>
<td>0.99686</td>
<td>1.06172</td>
</tr>
<tr>
<td>$n$</td>
<td>0.99344</td>
<td>1.22887</td>
</tr>
<tr>
<td>Anisotropic properties</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R$</td>
<td>0.99941</td>
<td>2.00247</td>
</tr>
<tr>
<td>$\Delta R$</td>
<td>0.97435</td>
<td>1.09865</td>
</tr>
<tr>
<td>$A_{IP}$</td>
<td>0.99948</td>
<td>1.89824</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.99978</td>
<td>1.77483</td>
</tr>
<tr>
<td>Work hardening behavior</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hollomon Eq.</td>
<td>0.99799</td>
<td>0.62322</td>
</tr>
<tr>
<td>Ludwik Eq.</td>
<td>0.99888</td>
<td>0.87502</td>
</tr>
<tr>
<td>Swift Eq.</td>
<td>0.99699</td>
<td>0.74652</td>
</tr>
<tr>
<td>Voce Eq.</td>
<td>0.99869</td>
<td>0.50217</td>
</tr>
</tbody>
</table>

Fig. 8 – Correlation coefficient between the experimental & predicted values for testing data of hardening models.

V. A transition stage occurs nearly parabolic in nature for test temperature for Inconel 718 alloy.

Hardening models (namely Hollomon, Ludwik, Swift & Voce) are developed with application of ANN with regression methods (namely multiple regression and logistic regression methods). Significant variables were constituted to predict the strain hardening behavior of Inconel 718 alloy. Fig. 8 gives the correlation coefficient between for testing data of hardening models and results shows good correlation (>97%).

For comparing the exactness in fit of ANN model, some hypotheses tests namely t-test (for test the means) and f-test (for variance), are done for model construction process. Two sample t-test compare location parameter of two independent sample population i.e. paring of the samples from one to another. Two sample f-test is related to the test statistic (ratio of two sample variances) [18]. In paired t-test, two sample population (observations in one sample & observations in the other sample) can be paired. f-test can be used only for equal variances of two populations [18]. The p-values are obtained after performing test. Rejection of null hypothesis will not be done, if p-value lies above 0.05. These statistical tests are performed using MATLAB 2018a. The paired t-test
piloted between experimental data and predicted data. Table 5 shows p-values for mean paired t-test and f-test directed between two data (experimental and predicted) are above 0.05. For all material properties and hardening model, p-values are observed greater than 0.05. Therefore, statistically ANN prediction has satisfied goodness of fit for modeling.

## 5. Conclusion

The present study is mainly focus of experimental determination and ANN prediction of mechanical properties, anisotropic parameters and work hardening behavior of Inconel 718 alloy using hot tensile tests. The important conclusions from the study are:

i. ANN model is used to predict the mechanical properties like $\sigma_y$, $\sigma_{uts}$, % elongation, n, R, A$P$ and $\delta$ at elevated temperature for Inconel 718 alloy (with input variables strain & temperature for $\sigma_y$, $\sigma_{uts}$, % elongation, n and thickness, orientation, temperature & yield strength for R, $\Delta R$, A$P$ and $\delta$). ANN shows a consistency and better agreement with experimental data.

ii. The stress–strain behavior is defined by Hollomon empirical relation represented by two stage hardening with different n value. Differential C-J analysis method for Ludwik and Swift empirical relation revealed, the decrease in n with rise in temperature. The two-stage work hardening behavior of Inconel 718 during hot deformation is well defined by Hollomon and Voce relationship with the correlation coefficient (>99%).

iii. Hardening models (namely Hollomon, Ludwik, Swift & Voce) are developed with application of ANN with regression methods. Significant variables were constituted to predict the strain hardening behavior of Inconel 718 alloy and results shows good correlation (>97%). Accuracy of developed ANN model validated by hypothesis testing with mean paired t-test and f-test results, shows goodness of fit these models. Hence, it can be conclude that well-trained ANN models offer accurate, fast and consistent results.

Future work involves implementation of ANN model for Inconel 718 alloy in finite element studies to enhance the accuracy of simulation results.

## Conflicts of interest

The authors declare no conflicts of interest.

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## References


[12] Wen DX, Lin YC, Li HB, Chen XM, Deng J, Li LT. Hot deformation behavior and processing map of a typical


