A comparative study at the flow behavior description of 2A14 alloy using BP-ANN and strain compensated Arrhenius model

Shi-Shan Li¹, Jie Zhou¹,³, Meng-Meng Zhang¹, Yu-Ting Zhou¹, Fan-Jiao Gong-Ye¹, Shuai Long¹, Xu-Gang Dong¹ and Qiang Liang²

¹ School of Material Science and Engineering, Chongqing University, Chongqing 400044, People’s Republic of China
² School of Mechanical Engineering, Chongqing Technology and Business University, Chongqing, 400060, People’s Republic of China
³ Author to whom any correspondence should be addressed.

E-mail: liss1115@163.com

Keywords: hot compression, BP-ANN model, arrhenius model, flow stress prediction, finite element simulation

Abstract

In this work, a back-propagation artificial neural network (BP-ANN) and Arrhenius constitutive model were used to predict the stress-strain curves of 2A14 aluminum alloy based on the results of isothermal compression tests conducted at the temperature of 648 K–723 K and the strain rate of 0.01 s⁻¹ – 10 s⁻¹. A series of statistical analyses were introduced to compare the accuracy of predictions of the two models. The average absolute relative error (AARE), correlation coefficient (R), relative error (μ) and standard deviation (σ) were 0.4338%, 0.9997, 0.2384, 0.0242 by BP-ANN model and 3.06%, 0.9941, 1.7993, 2.6610 by Arrhenius constitutive model, respectively, which indicates that the trained BP-ANN model is more precise than the Arrhenius constitutive model. Then the finite element simulations were conducted under the same deformation conditions on the basis of the pure experimental results and pure BP-ANN predicted results. As a result, the stroke load curve and the distributions of the effective strain are similar, which further proves that the BP-ANN model have a good capability to predict the flow behavior of 2A14 alloy.

1. Introduction

Due to the advantages of light weight, corrosion resistance, high strength-to-weight ratio and good ductility, aluminum alloys are widely used in automotive, aerospace industries, aviation industries, household appliances [1, 2]. The series of 2xxx and 7xxx aluminum alloys with high strength and good thermos-plasticity are used frequently as structural materials in vehicles and aircrafts for weight saving [3–5]. Particularly, the 2A14 aluminum alloy is one of typical Al-Cu-Mg-Si aluminum alloy, with advantages of high yield strength, good formability, heat resistance, etc [6]. It is commonly used for aerospace applications such as aircraft hub, aircraft tank.

For years, lots of researchers have focused on 2xxx aluminum alloy. Wang et al developed a macroscopic heat transfer and fluid flow model in the laser welding pool of 2024 aluminum alloy and predicted the dendrite growth and solute concentration [7]. Lu et al investigated the microstructures and corrosion behavior of 2219 aluminum alloy under different pre-deformation conditions and found that the tensile strength and corrosion resistance can be improved by reducing the grain size [8]. Moreover, many researches about 2A14 aluminum alloy were reported. For example, Liu et al constructed the thermo-mechanical model of the bobbin tool friction stir welding, and the temperature field of 2014 aluminum alloy work plate of 6mm was simulated. Simulation results show that the temperature field of the cross section presents symmetry approximately about the mid thickness of the work plate, and the max temperature for the retreating side is about 40 °C higher than advancing side [9]. GAN et al have investigated the electrochemical corrosion characteristic of 2A14 aluminum alloy using the polarization curve method, its corrosion mechanism and law in the solution of N₂O₄–HNO₃ were obtained. As a result, the nitric acid with the volume fraction of 30% has the fastest corrode speed and the higher temperature can also increase the corrosion intensity [6]. Wang et al investigated the effects of welding
Table 1. The chemical composition of 2A14 aluminum alloy (wt%).

|   | Cu  | Si   | Mg  | Mn  | Fe  | Zn  | V    | Ti  | Al  |
|---|-----|------|-----|-----|-----|-----|------|-----|-----|
|   | 4.47| 0.63 | 0.58| 0.49| 0.23| 0.021| 0.021| 0.017| Bal |

parameters on microstructures and mechanical properties of the weld joint, and Zheng et al constructed a phase field (PF) model for aluminum alloy 2A14 to investigate the microstructure evolution where close to the fusion line during solidification of the gas tungsten arc welding (GTAW) pool [10–12]. Also, Huang et al acquired the effects of cumulative strain on microstructure and mechanical properties of 2A14 aluminum alloy by multidirectional forging (MDF), they found that the multidirectional forging on 2A14 aluminum alloy at 350 °C can refine grains, and also can make the recrystallized grains stable during deformation [3].

However, most researches of 2A14 aluminum alloy were focused on welding properties, electrochemical properties and forging properties. The investigations of deformation mechanisms of 2A14 aluminum alloy and its constitutive descriptions during hot working are few. Generally, the hot deformation behavior is sensitive to the deformation temperature, strain and strain rate [13], and there is a high degree of nonlinear relationship between them due to the complex hardening, softening mechanisms and their interactions. In order to describe their relationships in detail, many models like Johnson–Cook (JC) model [14], Khan–Huang–Liang (KHL) model [15], Arrhenius equation [16] are introduced. Umbrello et al have described the behavior of AISI 316L steel by Johnson–Cook (JC) model [17]. Khan–Huang–Liang (KHL) model was used to effectively predict the responses observed from experiments of Ti–6Al–4V alloy by Khan et al [18]. It is worth noting that since the flow stress are complicated, the prediction accuracy of regression methods about flow stress curves is low and their application are limited [19]. So, the artificial neural network (ANN) is introduced to solve these problems. Artificial neural network (ANN) is a large class of parallel processing architecture [20], which has a good performance to solve difficult nonlinear problems [21]. As one of the ANN algorithms, back-propagation artificial neural network (BP-ANN) is used most frequently because of its higher precision.

In this study, the stress–strain curves of as-cast 2A14 aluminum alloy were obtained by isothermal compression tests with different temperatures and strain rates on a Gleeble-3500 isothermal simulator. An improved Arrhenius constitutive model was constructed to predict the flow stress of 2A14 aluminum alloy, and the parameters ($\alpha$, $n$, $A$ and $Q$) of the constitutive model were calculated by linear fitting. Then, a trained BP-ANN model was established to predict the strong nonlinear relationship between the stress and strain. Subsequently, statistical parameters including the relative error ($\delta$), average absolute relative error (AARE), mean value ($\mu$), standard deviation ($\omega$) and correlation coefficient ($R$) were used to evaluate the accuracy of the two models. Finally, the finite element simulation software DEFORM was used to simulate the hot compression process under the real experimental condition, the forming load and the effective strain distributions of different methods are compared to prove the prediction ability of the BP-ANN model. The main novelties of this article were listed as following:

1. A developed Arrhenius constitutive model and a trained BP-ANN model were constructed to predict the flow behavior of 2A14 aluminum alloy.
2. A series of statistical analyses were used to compare the prediction precision of two model.
3. The experimental conditions were simulated by FEM software, and proved that the BP-ANN model have a good capability to predict the flow behavior of 2A14 alloy.

2. Experimental

2.1. Acquisition of experimental flow curves

The as-received 2A14 aluminum alloy is an as-cast bar with a diameter of 360 mm and a height of 110 mm afforded by South West Aluminum Industry Group Company of China. Its chemical composition is listed in table 1 and the initial microstructure is shown in figure 1. In figure 1, the cast voids and coarse grains can be observed. For the hot compression tests, 16 specimens were prepared and each of them was machined into a cylinder with a height of 12 mm and a diameter of 8 mm. The hot compression tests were conducted on a Gleeble-3500 isothermal simulator at the strain rate of 0.01−10 s$^{-1}$ and the temperatures of 648–723 K with an interval of 25 K. To assure the temperature distribution uniform, all specimens were heated by 5 K·s$^{-1}$ to the testing temperatures and held for 3 min before compression. The both ends of each specimen were coated with graphite lubricant to minimize the effect of friction. The specimens then were compressed with height
reductions of 60% and water quenched immediately after deformation. The true stress strain data were obtained and recorded automatically by the equipment.

2.2. Construction of ANN model

Artificial neural network (ANN) is an efficient method which can learn and mimic the relationship especially the non-linear relationship between variables. To achieve higher accuracy, the error back-propagation algorithm was introduced to train the artificial neural network, which constructed the back-propagation artificial neural network, namely BP-ANN. This method has been used to compute the constitutive relationships of alloys including AZ31 alloy [22, 23], Amermet 100 steel [24], super alloy nimonic 80A [25], Al−6.2Zn−0.70Mg−0.30Mn−0.17Zr alloy [26] and Ti–5Al–2Sn–2Zr–4Cr–4Mo alloy [27]. The typical structure of BP-ANN in computing the constitutive relationships is shown in figure 2. The strains, temperatures and strain rates were set as inputs. After a series of training and mimicking in hidden layers, the stresses were obtained by output layer. Before calculation, the inputs and outputs were normalized in the range of −1 to 1 by the following equation:

\[
X' = \frac{2 \times (X - X_{\min})}{X_{\max} - X_{\min}} - 1
\]  

(1)

Where \(X\) is original data, \(X'\) is the normalized data of \(X\), \(X_{\min}\) and \(X_{\max}\) are the minimum and maximum values of \(X\) respectively.

The accuracy of the BP-ANN model depends on the number of hidden layer and neural nodes. In the researches of Lin et al[19] and Toros et al[28], one single hidden layer can reach relative high accuracy in
training and prediction. While Quan et al [23] made a comparison of accuracy between the BP-ANN structure with one single hidden layer and two hidden layers, the result showed that the latter one was better. Thus, in this work, BP-ANN structure with two hidden layers was chosen for computing. Besides, a trial-and-error procedure was conducted to find the appropriate number of neural nodes. In this procedure, the sum square error (SSE) expressed as in equation (2) between experimental and predicted results was introduced as an evaluator to assess the accuracy of the trained BP-ANN model [29]. The lower SSE-value means that higher accuracy the trained model could achieve. Figure 3 shows the results of the trial-and-error procedure. In figure 3, it is obvious that the SSE value in log scale reaches the lowest value when the number of neural nodes in each hidden layer is 22. Thus, two hidden layers and 22 neural nodes were believed to be most appropriate.

\[
SSE = \sum_{i=1}^{N} (E_i - P_i)^2
\]  

where \(E_i\) is the sample of experimental value, \(P_i\) is the sample of predicted value by BP-ANN model, and \(N\) is the number of true stress-strain samples.

3. Results and discussion

3.1. Flow curve characteristics

The flow curves of 2A14 aluminum alloy at different deformation conditions are shown in figure 4. It is obvious that the stress level increases with rising strain rate and decreasing temperature. Besides, the stress increases dramatically at the initial stage, which is commonly believed that working hardening (WH) predominates. Then, the stress decreases stably with increasing strain after reaching a peak value, which indicates the occurrence of dynamic softening including dynamic recovery (DRV) and dynamic recrystallization (DRX) [30–35]. In figure 4, it can be seen that the flow curves at the strain rate higher than 0.1 s\(^{-1}\) show relative violent drop tendencies comparing with other curves, which reveals that the softening effect is stronger and DRX may predominate. While the flow curves are relative flat at the strain rate of 0.01 s\(^{-1}\), which indicates that DRV predominates [36].

3.2. Arrhenius constitutive model

The Arrhenius constitutive model is widely used to describe the effect of strain rate (\(\dot{\varepsilon}\)) and temperature (T) on flow stress (\(\sigma\)), and it is expressed as equation (3) [19,37–40]

\[
\dot{\varepsilon} = F(\sigma) \exp \left(-\frac{Q}{RT}\right)
\]

where

\[
F(\sigma) = \begin{cases} 
A\sigma^n & \alpha\sigma < 0.8 \\
A \exp(\beta\sigma) & \alpha\sigma > 1.2 \\
A[\sinh(\alpha\sigma)]^n & \text{for all } \sigma
\end{cases}
\]

Where \(\dot{\varepsilon}\) is the strain rate (s\(^{-1}\)), \(\sigma\) is the flow stress (MPa), \(Q\) is the activation energy of hot deformation (kJ · mol\(^{-1}\)), \(R\) is the universal gas constant (8.31 J · mol\(^{-1}\) · K\(^{-1}\)), \(T\) is the absolute temperature (K), \(\alpha\), \(\beta\), \(A\), \(n\) and \(n'\) are the material constants, \(\alpha = \beta/n'\).
The equations (4) and (5) can be obtained by taking the natural logarithms on both sides of equation (3). Generally, the equation (4) is suitable for low stress level ($\alpha \sigma < 0.8$) and the equation (5) is suitable for high stress level ($\alpha \sigma > 1.2$).

\begin{align*}
\ln \dot{\varepsilon} &= \ln A + n' \ln \sigma - Q/RT \quad (4) \\
\ln \dot{\varepsilon} &= \ln A + \beta \sigma - Q/RT \quad (5)
\end{align*}

Based on equations (4) and (5), the linear relationships of $\ln \dot{\varepsilon} - \ln \sigma$ and $\ln \dot{\varepsilon} - \sigma$ can be found. Figure 5 shows the fitted lines of $\ln \sigma - \ln \dot{\varepsilon}$ and $\sigma - \ln \dot{\varepsilon}$ at the strain of 0.5. The reasonable adjusted correlation coefficient (adj. R2) is used to evaluate the accuracy of fitting curves. Material constants $n'$ and $\beta$ can be obtained from the reciprocal of the slopes of the lines in figure 5. The values of $n'$ and $\beta$ are 9.576 and 0.153 MPa$^{-1}$ respectively and the value of $\alpha$ is determined to be 0.016 MPa$^{-1}$.
For all the stress level (including low and high-stress levels), equation (3) can be rewritten as the following:

\[ \dot{\varepsilon} = A [\sinh(\alpha\sigma)]^n \exp(-Q/RT) \]  

(6)

Taking natural logarithms at both sides of the equation (6):

\[ \ln \dot{\varepsilon} = [\ln A + n[\ln \sinh(\alpha\sigma)]] - Q/RT \]  

(7)

Thus, the exponent \( n \) can be obtained by the following equation when the temperature \( T \) is determined:

\[ n = \frac{\partial \ln \dot{\varepsilon}}{\partial \ln(\sinh(\alpha\sigma))} \bigg|_T \]  

(8)

Also, the activation energy \( Q \) can be calculated at a certain strain rate \( \dot{\varepsilon} \) by the following equation:

\[ Q = nR \left( \frac{\partial \ln(\sinh(\alpha\sigma))}{\partial (1/T)} \right) |_{\dot{\varepsilon}} \]  

(9)

Based on the equations (8) and (9), the linear relationships of \( \ln(\sinh(\alpha\sigma)) - \ln \dot{\varepsilon} \) and \( \ln(\sinh(\alpha\sigma)) - 1/T \) are shown in figure 6. Consequently, the values of parameter \( n, A \) and activation energy \( Q \) calculated are 7.219, \( 3.476 \times 10^{14} \text{s}^{-1} \) and 195.15 kJ·mol\(^{-1} \) respectively.

The Zener-Hollomon parameter expressed as following equation (10) [16] is commonly used to describe the comprehensive relationship between temperature (T) and strain rate (\( \dot{\varepsilon} \)):

\[ Z = \dot{\varepsilon} \exp(Q/RT) \]  

(10)

According to equations (6) and (10), the relationship between stress (\( \sigma \)) and parameter \( Z \) can be rewritten as equation of Zener-Hollomon parameter:

\[ \sigma = \frac{1}{\alpha} \ln \left\{ \left( \frac{Z}{A} \right)^{\frac{1}{2}} + \left[ \left( \frac{Z}{A} \right)^{\frac{1}{2}} + 1 \right]^{\frac{1}{2}} \right\} \]  

(11)

Based on the equations (6)–(9), the material parameters \( \alpha, A, n \) and \( Q \) can be calculated by fitting curves under different strains range from 0.05 to 0.9 with the interval of 0.05. The six-order polynomials as equation (12) were used to fit the plots in figure 7 and acquire the relationship between material constants (\( \alpha, A, n \) and \( Q \)) and strain. Then, the coefficients in polynomial function can be obtained in table 2.

\[
\begin{align*}
\alpha &= B_0 + B_1 \varepsilon + B_2 \varepsilon^2 + B_3 \varepsilon^3 + B_4 \varepsilon^4 + B_5 \varepsilon^5 + B_6 \varepsilon^6 \\
\ln A &= C_0 + C_1 \varepsilon + C_2 \varepsilon^2 + C_3 \varepsilon^3 + C_4 \varepsilon^4 + C_5 \varepsilon^5 + C_6 \varepsilon^6 \\
n &= D_0 + D_1 \varepsilon + D_2 \varepsilon^2 + D_3 \varepsilon^3 + D_4 \varepsilon^4 + D_5 \varepsilon^5 + D_6 \varepsilon^6 \\
Q &= E_0 + E_1 \varepsilon + E_2 \varepsilon^2 + E_3 \varepsilon^3 + E_4 \varepsilon^4 + E_5 \varepsilon^5 + E_6 \varepsilon^6
\end{align*}
\]  

(12)
Thus, the improved Arrhenius constitutive model can be expressed as the equation (13):

$$
\sigma = \frac{1}{f(\varepsilon)} \ln \left\{ \left( \frac{\dot{\varepsilon} \exp \left[ g(\varepsilon) / 8.314 T \right]}{h(\varepsilon)} \right)^{\frac{1}{n}} + \left( \frac{\dot{\varepsilon} \exp \left[ g(\varepsilon) / 8.314 T \right]}{h(\varepsilon)} \right)^{\frac{1}{n}} + 1 \right\}^{\frac{1}{2}}
$$

(13)

Where $f(\varepsilon)$, $g(\varepsilon)$, $h(\varepsilon)$ and $i(\varepsilon)$ are polynomial functions of strain for $\sigma$, $n$, $A$ and $Q$.

Therefore, the true stress values of the developed constitutive equation can be calculated by equation (13) at the different experimental conditions and the results are compared with the experimental data in figure 8. Evidently, the improved constitutive equation can accurately predict the flow stress of 2014 aluminum alloy to some extent.

### 3.3. Extrapolation ability of BP-ANN model and Arrhenius constitutive model

Both BP-ANN model and the improved Arrhenius constitutive model were used to predict the flow stress at aforementioned work in this study. The predicted data of the two models are compared with experimental results as shown in figure 9. It can be seen that the predicted data of the two models are very close to the experimental data, which indicates that both of them can predict the true stress of material well. Obviously, the

---

**Table 2.** The values of $\alpha$, $A$, $n$ and $Q$ of 2014 aluminum alloy by polynomial fitting.

| $\alpha$ | $\ln A$ | $n$ | $Q$     |
|----------|---------|----|---------|
| $B_0$    | 0.01562 | 32.43249 | 8.77509 | 198.18014 |
| $B_1$    | -0.02176 | -59.49679 | -29.48067 | -364.86712 |
| $B_2$    | 0.16931 | 151.99372 | 181.36203 | 3139.74905 |
| $B_3$    | -0.52590 | -1742.73902 | -538.06894 | -10849.53134 |
| $B_4$    | 0.83407 | 2878.50732 | 837.23413 | 17600.23935 |
| $B_5$    | -0.66317 | -2342.29300 | -652.51251 | -14285.16932 |
| $B_6$    | 0.20907 | 271.10367 | 201.04695 | 4562.12755 |

---

**Figure 7.** Relationships between material coefficient and strain $\sigma$: (a) $\alpha$; (b) $\ln A$; (c) $n$; (d) $Q$ under polynomial fit.
predicted result of BP-ANN model has a higher prediction accuracy, especially at the temperature of 698 K and 723 K.

In order to compare the prediction accuracy of the two methods intuitively, the statistical parameter relative error ($\delta$) is introduced and it is expressed as equation (14).

$$\delta(\%) = \frac{P_i - E_i}{E_i} \times 100\%$$

Where $\delta$ is the relative error, $P_i$ and $E_i$ represent the predictions experimental data respectively.

The relative error $\delta$ of predictions at the deformation conditions of 673 K & 1 s$^{-1}$ and 698 K & 0.1 s$^{-1}$ by BP-ANN model and Arrhenius constitutive model were calculated by equation (14), and they were listed in table 3.

It can be seen from table 3 that the $\delta$-values of BP-ANN model and Arrhenius constitutive model are range from $-1.11625\%$ to $3.95755\%$ and $-2.04907\%$ to $5.97564\%$, respectively. It means that both the two methods can give a good prediction for the rheological behavior of the material, and the data fit better in the BP-ANN model than in the Arrhenius constitutive model. In order to observe the distribution of relative error more intuitively, a series of statistical analyses of $\delta$ were carried out, and a type of normal distribution expressed as equation (15) can be found clearly when fitting the curve of relative errors of the BP-ANN model and the Arrhenius constitutive model. Therefore, the mean value ($\mu$) and standard deviation ($\omega$) of normal distribution were calculated by equations (16) and (17) to express the central tendency and dispersion degree of the relative error. Generally, the smaller the values of $\mu$ and $\omega$ are corresponding to smaller error between predicted and experimental result. As shown in Figure 10, the mean value ($\mu$) and the standard deviation ($\omega$) are 0.2384 and 0.0242 for the predictions of BP-ANN model, and they are 1.7993 and 2.6610 respectively for the Arrhenius constitutive model. It is clear that the distribution of the relative error from the BP-ANN model is more centralized than that from the Arrhenius constitutive model, which indicates that the BP-ANN model has a better predictive ability.
Where $y$ is probability density of $\delta$ respectively, $\delta_i$ is the value of relative error, $\mu$ is the mean value and $\omega$ is standard deviation, $N$ is number of relative error.

In addition, the correlation coefficient ($R$) and the average absolute relative error (AARE) are introduced to validate their predictive capability, and they are expressed as shown in equations (18) and (19) respectively. The correlation coefficient expresses the degree of linear correlation between the two variables, whose value is range from $-1$ to $1$, and value of $R$ close to $1$, $0$ and $-1$ represent a positive correlation, no relationship and negative correlation between the predicted value and the experimental value, respectively. On the other hand, the average absolute relative error shows the degree of deviations from the experimental value and the predicted value, and lower absolute value of it indicates that the error between the predicted value and the experimental value is closer to $0$.

$$y = \frac{1}{\sqrt{2\pi}\omega} e^{-\frac{\delta_i - \mu^2}{2\omega^2}}$$

$$\mu = \frac{1}{N} \sum_{i=1}^{N} \delta_i$$

$$\omega = \sqrt{\frac{1}{N - 1} \sum_{i=1}^{N} (\delta_i - \mu)^2}$$

$$R = \frac{\sum_{i=1}^{N} (E_i - \bar{E})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{N} (E_i - \bar{E})^2 \sum_{i=1}^{N} (P_i - \bar{P})}}$$

$$AARE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{E_i - P_i}{E_i} \right| \times 100\%$$
Table 3. The Relative error $\delta$ of predictions by BP-ANN model and Arrhenius constitutive model to experimental under the condition of 673 K & 1 s$^{-1}$ and 698 K & 0.1 s$^{-1}$.

| Temperature (K) | Strain rate (s$^{-1}$) | True strain | True stress (MPa) | Relative error (%) |
|-----------------|------------------------|-------------|-------------------|--------------------|
|                 |                        |             | Experimental | BP Equation | BP Equation |
| 673             | 1                      | 0.05        | 76.01         | 76.31        | 77.86       | 0.38 | 2.42 |
|                 |                        | 0.10        | 77.35         | 76.71        | 80.42       | −0.84 | 3.96 |
|                 |                        | 0.15        | 77.07         | 77.10        | 79.96       | 0.05 | 3.76 |
|                 |                        | 0.20        | 76.58         | 76.77        | 78.98       | 0.25 | 3.14 |
|                 |                        | 0.25        | 75.95         | 76.22        | 77.74       | 0.35 | 2.35 |
|                 |                        | 0.30        | 75.15         | 75.46        | 76.34       | 0.41 | 1.58 |
|                 |                        | 0.35        | 74.14         | 74.49        | 75.02       | 0.47 | 1.175 |
|                 |                        | 0.40        | 73.32         | 73.54        | 73.77       | 0.30 | 0.61 |
|                 |                        | 0.45        | 72.59         | 72.72        | 72.53       | 0.19 | −0.09 |
|                 |                        | 0.50        | 71.83         | 71.94        | 71.42       | 0.15 | −0.57 |
|                 |                        | 0.55        | 70.92         | 71.12        | 70.40       | 0.28 | −0.47 |
|                 |                        | 0.60        | 70.25         | 70.32        | 69.33       | 0.09 | −1.03 |
|                 |                        | 0.65        | 69.61         | 69.62        | 68.83       | 0.03 | −1.12 |
|                 |                        | 0.70        | 69.01         | 68.96        | 68.28       | −0.06 | −1.05 |
|                 |                        | 0.75        | 68.23         | 68.14        | 67.77       | −0.13 | −0.66 |
|                 |                        | 0.80        | 67.71         | 67.22        | 67.38       | −0.73 | −0.48 |
|                 |                        | 0.85        | 67.25         | 66.94        | 66.99       | −0.45 | −0.37 |
|                 |                        | 0.90        | 66.87         | 67.57        | 66.71       | 1.05 | −0.23 |
| 698             | 0.1                    | 0.05        | 55.80         | 55.72        | 54.98       | −0.14 | −1.46 |
|                 |                        | 0.10        | 56.42         | 56.18        | 55.31       | −0.43 | −1.97 |
|                 |                        | 0.15        | 55.78         | 55.56        | 54.64       | −0.40 | −2.05 |
|                 |                        | 0.20        | 54.19         | 54.32        | 53.75       | 0.23 | −0.82 |
|                 |                        | 0.25        | 52.86         | 52.99        | 52.81       | 0.27 | −0.08 |
|                 |                        | 0.30        | 51.25         | 51.58        | 51.86       | 0.65 | 1.183 |
|                 |                        | 0.35        | 50.01         | 50.13        | 51.00       | 0.25 | 1.99 |
|                 |                        | 0.40        | 48.85         | 48.83        | 50.19       | −0.03 | 2.75 |
|                 |                        | 0.45        | 47.51         | 47.74        | 49.38       | 0.50 | 3.92 |
|                 |                        | 0.50        | 46.60         | 46.77        | 48.70       | 0.36 | 4.50 |
|                 |                        | 0.55        | 45.80         | 45.86        | 48.12       | 0.12 | 5.06 |
|                 |                        | 0.60        | 45.18         | 45.14        | 47.66       | −0.09 | 5.50 |
|                 |                        | 0.65        | 44.66         | 44.73        | 47.31       | 0.20 | 5.93 |
|                 |                        | 0.70        | 44.48         | 44.65        | 47.14       | 0.36 | 5.98 |
|                 |                        | 0.75        | 44.48         | 44.60        | 47.01       | 0.26 | 5.68 |
|                 |                        | 0.80        | 44.48         | 44.58        | 46.92       | 0.22 | 5.48 |
|                 |                        | 0.85        | 44.48         | 45.07        | 46.85       | 1.31 | 5.32 |
|                 |                        | 0.90        | 44.48         | 45.89        | 46.80       | 3.16 | 5.20 |

Figure 10. The distribution of relative error on the true stress predicted by (a)BP-ANN model and (b)Arrhenius constitutive model.
Where $E_n$, $P_i$ are the experimental and the predicted value of the sample, respectively; $\bar{E}$ and $\bar{P}$ are the average value of experimental and the predicted value of the sample; $N$ is the number of sample.

The relationship between the experimental value and the predicted value is shown in figure 11. It can be seen that both of the slopes of the straight line after fitting are close to 1, which shows that the predicted true stress values are in a good agreement with the corresponding experimental values. Moreover, The $R$-values were calculated to be 0.9997 and 0.9941 for the BP-ANN model and the Arrhenius constitutive model respectively, which shows that the predicted results of BP-ANN model have a stronger correlation with the experimental results than the predicted results of Arrhenius constitutive model. The AARE relative to the experimental true stress is 0.4338% for the BP-ANN model, but 3.06% for the Arrhenius constitutive model. It indicated that the BP-ANN model has smaller error than the Arrhenius model in the prediction capability. The value of $R$ and AARE both prove that the BP-ANN model has a better accuracy in the prediction of the true stress.

On the basis of comparison above, it can be concluded that the BP-ANN model has a better performance in the prediction of flow stress than the Arrhenius constitutive model. Interestingly, the curves of 673 K & 1 s$^{-1}$ and 698 K & 0.1 s$^{-1}$ were not added to the training process of the BP-ANN model, but the model also shows a good accuracy in the prediction. Therefore, it is sufficiently proved that the BP-ANN model has a higher prediction accuracy than the Arrhenius constitutive model in the flow stress prediction of 2A14 aluminum alloy.

4. Application of BP-ANN model in FEM simulation

In order to verify the accuracy of BP-ANN model, the finite element software DEFORM was used to simulate the isothermal compression by importing experimental results (under the temperatures of 648 K, 673 K,698 K and 723 K, and strain rates of 0.01 s$^{-1}$, 0.1 s$^{-1}$, 1 s$^{-1}$ and 10 s$^{-1}$).named scheme-a in the following text) and the extended flow stress by BP-ANN model (at the temperatures of 648 K, 673 K,698 K and 723 K and the strain rates of 0.05 s$^{-1}$,0.5 s$^{-1}$,and 5 s$^{-1}$) (named scheme-b in the following text), respectively. To make the simulation results reliable, the deformation parameter (693 K and 1 s$^{-1}$) which is outside both imported data and need to be interpolated was set as the simulation condition to ensure the same interpolation condition in the DEFORM. Also, all the other simulation conditions including thermal radiation, friction coefficient, the method of mesh generation were set as the same for the both schemes. Figure 12 shows the effective strain distributions of upsetting simulation for the two schemes. It can be seen that both the shape of the blank after deformation and the distributions of the effective strain are similar. the values of average strain are 0.895 (scheme-a) and 0.902 (scheme-b), the maximum values are 4.75 (scheme-a) and 5.92 (scheme-b). Also, the stroke-load of different stress-strain curves is shown at figure 13, it is worthy pointing out that the load curves for two schemes are very close, and the maximum load are 0.6140 t and 0.6030 t for scheme-a and scheme-b respectively. Based on the results above, it can be concluded that the stress-strain curves predicted by BP-ANN model has better agreement with the experimental results.
5. Conclusions

In this study, the BP-ANN model and Arrhenius constitutive model were used to predict the deformation behaviors of 2A14 aluminum alloy based on the experimental data of isothermal compression in the temperature range from 648 K to 723 K and the strain rate between 0.01 s\(^{-1}\) to 10 s\(^{-1}\). The statistical analysis is used to compare their prediction accuracy. The main conclusions can be obtained as following:

(1) A trained BP-ANN model and a developed Arrhenius constitutive model were used to predict the deformation behavior of 2A14 aluminum alloy, the parameters of Arrhenius constitutive model \((Q, \alpha, n, A)\) were calculated by derivation and linear fitting. Both models show a high accuracy in predicting rheological stress of 2A14 aluminum alloy.

(2) A series of statistical analyses were calculated to compare the accuracy of prediction, including the relative error \((\delta)\), average absolute relative error \((\text{AARE})\), mean value \((\mu)\), standard deviation \((\omega)\) and correlation coefficient \((R)\). The relative error \((\delta)\) for BP-ANN model is between 1.11625% to 3.95755% and it varies from −2.04907% to 5.97564% for the Arrhenius constitutive model. Besides, the values of AARE, \(\mu\), \(\omega\) and \(R\) were 0.4338%, 0.2384, 0.0242 and 0.9997 by BP-ANN model respectively, while the corresponding values are 3.06%, 1.7993, 2.6610 and 0.9941 by Arrhenius constitutive model. All the circumstances show a fact that the BP-ANN model have better performance in flow stress prediction than the Arrhenius constitutive model.

(3) Two finite element simulations were conducted under the same deformation conditions on the basis of the pure experimental results and pure BP-ANN predicted results. As a result, the stroke-load curve and the distributions of the effective strain are similar, which further proves that the BP-ANN model have a good capability to predict the flow behavior of 2A14 alloy.

Figure 12. The distributions of effective strain predicted by (a) Scheme-a and (b) Scheme-b at numerical simulation at 693 K and 1 s\(^{-1}\).

Figure 13. The stroke-load curves of different stress-strain curves.
Acknowledgments

This work was supported by National Natural Science Foundation of China (No.51775068), graduate research and innovation foundation of Chongqing, China (Grant No.CYB19005), Chongqing special fund for basic science and frontier technology research (cstc2017jcyjAX0175), Open Research Fund Program of Manufacturing Equipment Mechanism Design and Control Chongqing Key Laboratory of Chongqing (CTBU-KFJJ2019078).

ORCID iDs

Shi-Shan Li @ https://orcid.org/0000-0003-4223-7404

References

[1] Wang M, Zhou J, Yin Y, Nan H, Xue P and Tu Z 2017 Hot deformation behavior of the Ti6Al4V alloy prepared by powder hot isostatic pressing J. Alloys Compd. 721 320–32
[2] Chong Y, Bhattacharjee T, Yi J, Shibata A and Tsuji N 2017 Mechanical properties of fully martensite microstructure in Ti-6Al-4V alloy transformed from refined beta grains obtained by rapid heat treatment (RHT) Scr. Mater. 138 66–70
[3] Wang M, Huang L P, Liu W S, Ma Y Z and Huang B Y 2016 Influence of cumulative strain on microstructure and mechanical properties of multi-directional forged 2A14 aluminum alloy (in English) Materials Science and Engineering a-Structural Materials Properties Microstructure and Processing 674 40–51
[4] Nakai M and Eto T 2000 New aspects of development of high strength aluminum alloys for aerospace applications (in English) Materials Science and Engineering a-Structural Materials Properties Microstructure and Processing 285 62–8
[5] Williams J C and Starke E A 2003 Progress in structural materials for aerospace systems11 The Golden Jubilee Issue—Selected topics in Materials Science and Engineering: Past, Present and Future Acta Mater. 51 5755–99
[6] Tian G, Jin G F, Zhang W, Huang Z Y and Yang Z W 2017 Investigation on Electrochemical Corrosion Characteristic of 2a14 Aluminum Alloy in Nitric Acid (in English) Surf. Rev. Lett. 24
[7] Wang L et al 2017 Simulation of dendrite growth in the laser welding pool of aluminum alloy 2024 under transient conditions (in English)J. Mater. Process. Technol. 246 22–9
[8] Lu Y, Wang J, Li X, Li W, Li R and Zhou D 2018 Effects of pre-deformation on the microstructures and corrosion behavior of 2219 aluminum alloys Materials Science and Engineering: A 723 204–11
[9] Liu X M, Yao J S, Cai Y, Meng H and Zou Z D 2013 Simulation on the temperature field of bobbin tool friction stir welding of AA 2014 aluminum alloy ed K Galkowski and Y H Kim Advances in Mechatronics and Control Engineering (in Chinese) Proc 1–3 Applied Mechanics and Materials (Durrten-Zurich: Trans Tech Publications Ltd) 433–435 p2091–4
[10] He J, Chen F, Wang B and Zhu L B 2018 A modified Johnson–Cook model for 10%Cr steel at elevated temperatures and a wide range of strain rates Materials Science and Engineering: A 715 1–9
[11] Zheng W J, Dong Z B, Wei Y H, Song K J, Guo J L and Wang Y 2014 Phase field investigation of dendrite growth in the welding pool of aluminum alloy 2A14 under transient conditions (in English) Comput. Mater. Sci. Article 82 525–30
[12] Chen M S et al 2019 Precipitation and dissolution behaviors of delta phase inside a deformed nickel-based superalloy during annealing treatment Applied Physics a-Materials Science & Processing 125
[13] Nan Y, Ning Y, Liang H, Guo H, Yao Z and Fu M W 2015 Work-hardening effect and strain-rate sensitivity behavior during hot deformation of Ti–5Al–5Mo–5V–3Cr–1Fe alloy Mater. Des. 82 84–90
[14] Johnson G R and Cook W H 1983 in: Proceedings of the Seventh International Symposium on Ballistics, International Ballistics Committee 541–547 A constitutive model and data for metals subjected to large strains, high strain rates and high temperatures
[15] Khan A S and Huang S 1992 Experimental and theoretical treatment of the deformation of Ti–5Al–5Mo–5V–3Cr–1Fe alloy Mater. Des. 32 1733–59
[16] Zener C and Hollomon J H 2004 Effect of Strain Rate Upon Plastic Flow of Steel J. Appl. Phys. 15 22–32
[17] Umbrello D, M’Saoubi R and Outeiro J C 2007 The influence of Johnson–Cook material constants on finite element simulation of machining of AISI 316L steel International Journal of Machine Tools & Manufacture 47 462–70
[18] Khan A S, Kazmi R, Farrokh B and Zupan M 2007 Effect of oxygen content and microstructure on the thermo-mechanical response of three Ti–6Al–4V alloys: experiments and modeling over a wide range of strain-rates and temperatures Int. J. Plast. 23 1105–25
[19] Lin Y C and Chen X M 2011 A critical review of experimental results and constitutive descriptions for metals and alloys in hot working Mater. Des. 32 1733–59
[20] Sheikh H and 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. 196 115–9
[21] Rao K P and Prasad Y K D V 1995 Neural network approach to flow stress evaluation in hot deformation J. Mater. Process. Technol. 53 552–66
[22] Forcellino A, Gabrielli F and Simoncini M 2011 Prediction of flow curves and forming limit curves of Mg alloy thin sheets using ANN-based models Comput. Mater. Sci. 50 3184–97
[23] Quan G-Z, Zhang Z-H, Pan J and Xia Y-F 2015 Modelling the Hot Flow Behaviors of AZ80 Alloy by BP-ANN and the Applications in Accuracy Improvement of Computations Mater. Res. 18 1331–45
[24] Ji G, Li F, Li Q, Li H and Li Z 2010 Prediction of the hot deformation behavior for Aermet100 steel using an artificial neural network Comput. Mater. Sci. 48 626–32
[25] Quan G-Z, Pan J and Wang X 2016 Prediction of the hot compressive deformation behavior for superalloy nimonic 80A by BP-ANN Model Applied Sciences 6 66
[26] Yan J, Pan Q-L, Li A-D and Song W-B 2017 Flow behavior of Al–6.2Zn–0.70Mg–0.30Mn–0.17Zr alloy during hot compressive deformation based on Arhenius and ANN models Transactions of Nonferrous Metals Society of China 27 638–47
[27] Li M, Liu X, Wu S and Zhang X 2013 Approach to constitutive relationships of a Ti–5Al–5Mo–3Cr–1Fe–4Mo alloy by artificial neural networks Mater. Sci. Technol. 14 136–8
[28] Toros S and Ozturk F 2011 Flow curve prediction of Al–Mg alloys under warm forming conditions at various strain rates by ANN Appl. Soft Comput. 11 1891–8

[29] Quan G-Z, Lv W-Q, Mao Y-P, Zhang Y-W and Zhou J 2013 Prediction of flow stress in a wide temperature range involving phase transformation for as-cast Ti–6Al–2Zr–1Mo–1V alloy by artificial neural network Mater. Des. 50 51–61

[30] Xia Y.-f., Long S, Zhou Y.-t., Zhao J, Wang T.-y. and Zhou J 2016 Identification for the Optimal Working Parameters of Ti–6Al–4V–0.1Ru Alloy in a Wide Deformation Condition Range by Processing Maps Based on DMM Mater. Res. 19 1449–60

[31] Lin Y C, Wen D X, Deng J, Liu G and Chen J 2014 Constitutive models for high-temperature flow behaviors of a Ni-based superalloy (in English) Mater. Des. 59 115–23

[32] Lin Y C, Liang Y J, Chen M S and Chen X M 2017 A comparative study on phenomenon and deep belief network models for hot deformation behavior of an Al–Zn–Mg–Cu alloy (in English) Applied Physics a-Materials Science & Processing Article 123 11

[33] Yao C G, Wang B, Yi D Q, Wang B and Ding X F 2013 Artificial neural network modelling to predict hot deformation behaviour of as HIPed FGH4169 superalloy Mater. Sci. Technol. 30 1170–6

[34] Lin Y C, Zhang J and Zhong J 2008 Application of neural networks to predict the elevated temperature flow behavior of a low alloy steel Comput. Mater. Sci. 43 752–8

[35] Li H, Fan L, Chen L and Jia L 2019 Effect of cooling mode on the microstructure and mechanical properties of medium carbon steel after warm rolling Iron making and Steel making (https://doi.org/10.1080/03019233.2019.1663908)

[36] Long S, Zhou J, Qiu Z-L, Zhou Y-T and Li S-S 2019 A GA-optimized Johnson–Cook model of flow behavior for Ti-6554 alloy in cross-phase temperature range Mater. Res. Express 6

[37] Sellars C M and McTegart W J 1966 On the mechanism of hot deformation Acta Metall. 14 1136–8

[38] Lin Y C, Chen M S and Zhong J 2008 Constitutive modeling for elevated temperature flow behavior of 42CrMo steel (in English) Comput. Mater. Sci. Article 42 470–7

[39] Long S et al 2019 Hot deformation behavior and microstructure evolution of Ti–6Cr–5Mo–5V–4Al alloy during hot compression Vacuum 160 171–80

[40] Long S et al 2019 Constitutive modelling, dynamic globularization behavior and processing map for Ti–6Cr–5Mo–5V–4Al alloy during hot deformation J. Alloys Compd. 796 65–76

[41] Haghdfadi N, Zarei-Hanzaki A, Khalebian A R and Abedi H R 2013 Artificial neural network modeling to predict the hot deformation behavior of an A356 aluminum alloy (in English) Mater. Des. 49 386–91