Research Article

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Hot deformation behavior and microstructure of a 0.5 wt% graphene nanoplatelet reinforced aluminum composite

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Abstract: Through hot compression experiments at temperatures ranging from 603 to 723 K and strain rates ranging from 0.01 to 10 s\(^{-1}\), the hot deformation behavior of a 0.5 wt% graphene nanoplatelet-reinforced aluminum (0.5 wt% GNP/Al) composite prepared by the powder metallurgy method was studied. The constitutive equations obtained by mathematical models and a neural network were evaluated. The deformation property of the composite can be better described by the Johnson–Cook (JC) constitutive model optimized by establishing a relationship between the coefficient and variables obtained in the hot compression test, with a correlation coefficient \((R)\) reaching 99.97% with the average relative error of 0.37% (98.1 and 4.17%, respectively, before optimization). Compared with the JC model, the neural network has perfect calculation accuracy and whole-process effectiveness, providing expanded and more accurate constitutive equations for subsequent simulations and for building the dynamic recrystallization model of the composite. The dynamic recrystallization model, hot processing map, and EBSD results are in agreement with each other and indicate that the optimal strain rate and temperature range of the composite are 0.01–0.1 s\(^{-1}\) and 693–723 K, respectively.

Keywords: 0.5 wt% GNP/Al composite, constitutive model, dynamic recrystallization model, neural networks, hot processing map, EBSD characterization

1 Introduction

In recent years, the fabrication process of graphene-reinforced aluminum composites has become increasingly mature, and perfect mechanical performance has been obtained. Zhao et al. [1] prepared 0.5 wt% graphene-reinforced Al matrix (GNP/Al) composites by high-pressure torsion at room temperature, avoiding the interface reaction between the aluminum matrix and graphene at high temperature. The tensile strength of the composite is 197 MPa, which is 40 MPa higher than that of pure aluminum prepared by the same process. Wu et al. [2] fabricated GNP/Al matrix composites by powder metallurgy (PM) and extrusion, achieving a 73.9% increase in tensile strength compared with that of the matrix. Yan et al. [3] and Li et al. [4] obtained GNP/Al matrix composites by PM and extrusion. Both the tensile and yield strengths were remarkably increased without losing the ductility performance. Askamia et al. [5] prepared 0.5 wt% Al/GO composites using microwave sintering at 600°C, which exhibited significantly increased tensile strength (up to 200%). Bhaduria et al. [6] prepared GNP/Al composites by SPS, and the experiment proved that the mechanical properties were best when the graphene content was 0.5 wt%; fractography indicated a change in the fracture model from ductile to brittle when the GNP content exceeded 0.5 wt%.

In terms of property improvements or the production requirements for finished or semifinished products of GNP/Al composites, hot working processes are necessary and inevitable. Parameters in the hot working process such as temperature and strain rate are very important to the flow of the deformed materials, thus affecting the performance of the products. Studies on the hot deformation behavior of materials, mainly including accurate constitutive equations and effective hot processing maps, which can be obtained by hot expression tests, are the key to determining the processing parameters and predicting
the flow of materials by numerical simulation methods. To date, there have been few studies on the hot deformation behavior of aluminum matrix composites. Chen et al. [7] and Mokdad et al. [8] found that the flow stress behaviors of hybrid composites can be described by the sine-hyperbolic Arrhenius equation, and the deformation activation energy was shown to increase with the addition of reinforcement. Ezatpour et al. [9] found that the higher activation energy \( (Q) \) value of a 7075/Al\(_2\)O\(_3\) nanocomposite was related to the effect of dislocation pinning on the grain boundaries by ceramic nanoparticles. Zhao et al. [10] studied the hot deformation behavior of SiCp/2024Al at temperatures from 623 to 723 K, and the results indicated that the flow stress of the composite decreased with the increasing deformation temperature and the decreasing strain rate, which can be reasonably explained based on the dislocation–particulate interaction model during hot deformation.

From the literature [1–6], in GNP-reinforced metal matrix composite (MMC) fabrication, 0.5 wt% GNPs is commonly used [11,12] and considered to be better for obtaining perfect GNP dispersion [13] in these MMCs. In this article, by studying the flow stress of a 0.5 wt% graphene nanoplatelet-reinforced aluminum (0.5 wt% GNP/Al) composite at different deformation temperatures and strain rates, a constitutive model and hot processing maps are established to study the hot forming behavior of the composite. The hot forming parameters of this kind of composite were formulated and optimized, providing a theoretical basis for the subsequent hot extrusion tests and numerical simulation. Two common constitutive models are used to express the hot deformation behavior of the composite. The JC constitutive model has good accuracy for aluminum (0.5 wt% GNP/Al) composites; this model is optimized by considering the relationship between some of the material coefficients and the temperature or strain rate. In addition, a BP-trained neural network is directly called to improve the accuracy of the constitutive model and to calculate the segment of the stress–strain curve with the strain value ranging from 0 to 0.1, which cannot be calculated for the traditional constitutive model. The constitutive curve can also be expanded to obtain the volume fraction of the dynamic recrystallization of the deformed composite by a BP-trained neural network. Therefore, the optimized constitutive model obtained in this article has incomparable calculation accuracy and whole-process adaptability, providing more accurate constitutive equations for subsequent simulations of the 0.5 wt% GNP/Al composite. Moreover, the calculation method of the constitutive model and dynamic recrystallization model can be a reference for some other Al-based composites.

2 Experimental

2.1 Material

Pure aluminum powder with a particle size of approximately 30 μm was used. Three to five layers of graphene nanoplatelets (GNPs) with a specific surface area of approximately 400 m\(^2\)/g and a particle size of 0.1–5.0 μm were used as reinforcement.

The 0.5 wt% GNP/Al composite billet was prepared by ultrasonic (90 min) + ball milling (300 rpm for 6 h) + hot pressing sintering (at 600°C and 30 MPa), as shown in Figure 1. The detailed fabrication process and microstructural

Figure 1: Schematic diagram of the composite preparation process.
characteristics of the composite such as Raman spectra and XRD patterns can be found in our previous work [14]. The GNP dispersion is perfect, and no obvious metallurgical defects are observed (as shown in Figure 2(c)), which will be beneficial to improving the mechanical properties of the composite [15,16], whose tensile strength reaches 121.6 MPa, as shown in Figure 3.

2.2 Hot pressing test

The hot pressing test was carried out on a thermal simulated test machine (Gleeble-3500), and the size of the sample was φ8 mm × 12 mm. A stainless heat-resistant alloy was used as the base support for temperature constancy. To minimize the effect of friction, lubricating oil was used on both sides of the sample, and graphite paper was placed between the chunk and the sample.

The samples were heated to deformation temperatures (603, 633, 663, 693, 723 K) at a rate of 10°C/s; then, additional hot compression experiments at different strain rates (0.01, 0.1, 1, and 10 s⁻¹) were performed. The samples were subjected to 50% compression (the real strain is 0.7).

3 Results and discussion

3.1 True stress–strain curve

Figure 4 shows the true stress–strain curves of the composite at different strain rates and temperatures. At the same strain rate, the softening mechanism (dynamic recovery and dynamic recrystallization) is weaker, and the material’s ability to resist deformation is stronger at low temperatures. At the same temperature, the ability to resist deformation increases with the increasing strain rate because there is not sufficient time to start the softening process. The true stress–strain curves can be roughly divided into four stages: at stage I, the stress increases linearly with the strain (the elastic stage); at stage II, initially, the composite begins to yield, and work hardening also starts at this time, so the stress increases with the strain. Then, the composite begins to undergo dynamic recovery, which has a softening effect on the material, and the increase in stress slows until the peak when the dynamic recovery and work hardening reach an equilibrium. Next, at stage III, when the effect of dynamic recovery exceeds that of work hardening, the curves begin to decline as the strain increases. Moreover, dynamic recrystallization, which can soften the materials more effectively, is likely to start, the degree of which depends on the cumulative energy. Therefore, in Figure 4(a) and (b), when the strain rate is low, the curve is climbing because the recrystallization level is low and work hardening prevails, while in Figure 4(c) and (d), when the strain rate is high, the curve is plateaued (Figure 4(c)) or even declining (Figure 4(d)) because the recrystallization level is high and the softening process prevails. The higher the temperature is, the easier recrystallization dominates.

3.2 Constitutive model

Constitutive models are used to state the mathematical relation between the stress and the strain. The models commonly used in metal deformation include the Arrhenius constitutive relationship model and JC constitutive model.
3.2.1 Arrhenius constitutive

According to the Arrhenius thermal deformation behavior model \( \dot{e} = f(\sigma) \exp(-Q/RT) \), the Arrhenius constitutive model of 0.5 wt% GNP/Al obtained by using the hyperbolic sine function \( \dot{e} = A_0 \sinh(a \sigma) \exp(-Q/RT) \) is shown in formula (1):

\[
\ln A = 35.78746 - 30.55018 \epsilon + 161.81799 \epsilon^2 \\
- 185.04867 \epsilon^3 + 82.71795 \epsilon^4 \\
\alpha = 0.0219 - 6.53781 \times 10^{-4} \epsilon - 0.0398 \epsilon^2 + 0.1437 \epsilon^3 \\
- 0.1381 \epsilon^4 - 0.072 \epsilon^5 + 0.1274 \epsilon^6 \\
n = 16.98768 - 47.85249 \epsilon + 194.67654 \epsilon^2 \\
- 310.82562 \epsilon^3 + 191.34284 \epsilon^4 \\
Q = 222.56931 - 199.72575 \epsilon + 1113.76718 \epsilon^2 \\
- 1666.68151 \epsilon^3 + 1021.4363 \epsilon^4 \\
\dot{e} = A(\epsilon) \sinh(a(\epsilon) \cdot \sigma) \exp(-Q(\epsilon)/RT),
\]

where \( Q \) is activation energy, \( R \) is gas constant and \( R = 8.31 \text{kJ/(mol K)} \).

3.2.2 JC constitutive model

Formula (2) is the equation of the JC constitutive mode, which is the relationship of the stress \( \sigma \) with the strain \( \epsilon \) strain rate \( \dot{\epsilon} \), and the temperature \( T \).

\[
\sigma = (B_0 + B_1 \epsilon + B_2 \epsilon^2)(1 + C_0 \ln \epsilon') \exp[(\lambda_1 \\
+ \lambda_2 \ln \epsilon') T^*],
\]

where \( T^* = T - T_r \), \( T_r \) is the reference temperature and set as 603 K, and \( \epsilon' = \dot{\epsilon}/\dot{\epsilon}_0 \) is the reference strain rate and set as 1 s\(^{-1}\).

The stress, strain, strain rate, and temperature of the composite are obtained through hot compression tests.

Figure 4: The true stress–strain curves of the composite. (a) 0.01 s\(^{-1}\), (b) 0.1 s\(^{-1}\), (c) 1 s\(^{-1}\), and (d) 10 s\(^{-1}\).
The value of the strain rate is 0.01, 0.1, 1, and 10, the strain value ranges from 0.1 to 0.6, and the corresponding temperature ranges from 603 to 723 K, by which the coefficients $B_0$, $B_1$, $B_2$, $C_0$, $\lambda_1$, and $\lambda_2$ are calculated.

(1) Calculation of the constants $B_0$, $B_1$, and $B_2$

When $T = 603$ K, $\dot{\varepsilon} = 1$ s$^{-1}$, formula (2) is expressed as follows:

$$\sigma = (B_0 + B_1 \dot{\varepsilon} + B_2 \dot{\varepsilon}^2).$$  \hspace{1cm} (3)

As shown in Figure 5(a), the quadratic fitting of one variable is performed on the experimental values of $\sigma$ and $\varepsilon$. It can be calculated that $B_0 = 57.88516$, $B_1 = 42.72762$, and $B_2 = -42.40932$.

(2) Material constants $C_0$

Only when $T = 603$ K, the following equation can be established:

$$\sigma/[(B_0 + B_1 \dot{\varepsilon} + B_2 \dot{\varepsilon}^2)] = 1 + C_0 \ln \varepsilon'. \hspace{1cm} (4)$$

The relationship between $\sigma/[(B_0 + B_1 \dot{\varepsilon} + B_2 \dot{\varepsilon}^2)]$ and $\ln \varepsilon'$ under different strains is plotted, as shown in Figure 5(b), and the average value of all the fitting line slopes is the value of $C_0$; $C_0 = 0.051$.

(3) Material constants $\lambda_1$ and $\lambda_2$

A new material coefficient $\lambda$ is introduced into formula (2), which is expressed as follows:

$$\lambda = \lambda_1 + \lambda_2 \ln \varepsilon'. \hspace{1cm} (5)$$

By substituting formula (5) into formula (2), formula (6) can be obtained.

$$\ln[\sigma/[(B_0 + B_1 \dot{\varepsilon} + B_2 \dot{\varepsilon}^2)(1 + C_0 \ln \varepsilon')] = \lambda T'. \hspace{1cm} (6)$$

Then, the material coefficients $B_0$, $B_1$, $B_2$, and $C_0$, which were obtained earlier, are substituted into formula (6) to fit $T'$ and $\ln[\sigma/[(B_0 + B_1 \dot{\varepsilon} + B_2 \dot{\varepsilon}^2)(1 + C_0 \ln \varepsilon')]$, as shown in Figure 6, and the average value of the fitting line slopes is the value of $\lambda$ under different strain rates. As shown in Figure 5(c), according to formula (6), the relationships of $\lambda$ and $\ln \varepsilon'$ are fitted by a straight line, so the value of $\lambda_1$ is the intercept of the line, $\lambda_1 = -0.00354$ , and the value of $\lambda_2$ is the slope of the line, $\lambda_2 = -1.4006 \times 10^{-4}$.

The JC model can be expressed as follows:

$$\sigma = (57.88516 + 42.72762 \dot{\varepsilon} - 42.40932 \dot{\varepsilon}^2)(1 + 0.051 \ln \varepsilon') \times \exp[-0.00354 - 1.4006 \times 10^{-4} \ln \varepsilon'T']. \hspace{1cm} (7)$$

Figure 5: Fitting curve of the material coefficients. (a) $C_0$; (b) $B_0$, $B_1$, and $B_2$; (c) $\lambda_1$ and $\lambda_2$. 

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During the calculation of the JC model, although the material coefficients $\lambda_1$ and $\lambda_2$ calculated earlier are accurate, there are certain errors in the calculations of $B_0$, $B_1$, $B_2$, and $C_0$ because the reference values $T^*$ and $\varepsilon'$ are selected in advance. Therefore, further optimization can be carried out to further improve the accuracy of the JC model.

### 3.2.3 Optimization of JC model

The four material coefficients $B_0$, $B_1$, $B_2$, and $C_0$ were recalculated by numerical calculation, constructing a three-dimensional matrix to redetermine these coefficients. The three-dimensional graphs of $B_0$, $B_1$, and $B_2$ versus strain rate and temperature and of $C_0$ versus strain and temperature are obtained, as shown in Figure 7; the specific data of the four material coefficients can be found in Tables 1–4, respectively.

The values that are not included in Table 4 can be obtained by interpolation. After recalculation, the average relative error (ARE) of the optimized JC model is 0.37%, which is much lower than that of the Arrhenius model (4.14%, as shown in Figure 8(a)) and JC model before optimization (4.17%, shown in Figure 8(b)). In addition, the correlation coefficient of the optimized JC model reaches 99.97%, as shown in Figure 8(c), higher than that of the Arrhenius model (97.20%) and JC model before optimization (98.1%).

### 3.2.4 Constitutive model by neural network

Although the JC constitutive model has a good correlation coefficient, it is difficult to calculate accurately at strains ranging from 0 to 0.1, where a large gap between the JC-determined value and true value exists. Therefore, a neural network could be used to train the stress and

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**Figure 6**: Fitting curves under different strain rates. (a) $0.01 \text{s}^{-1}$, (b) $0.1 \text{s}^{-1}$, (c) $1 \text{s}^{-1}$, and (d) $10 \text{s}^{-1}$.
Figure 7: Three-dimensional graphs of $B_0$, $B_1$, $B_2$, and $C_0$. (a) $B_0$, (b) $B_1$, (c) $B_2$, and (d) $C_0$.

Table 1: Material constant $B_0$

| Strain rate ($s^{-1}$) | 603 K       | 633 K       | 663 K       | 693 K       | 723 K       |
|------------------------|-------------|-------------|-------------|-------------|-------------|
| 0.01                   | 62.89233    | 52.37136    | 53.65291    | 63.11981    | 60.03526    |
| 0.1                    | 58.52042    | 54.81370    | 59.76904    | 60.53152    | 61.50093    |
| 1                      | 57.88516    | 60.05095    | 60.47013    | 60.35033    | 61.06003    |
| 10                     | 61.30403    | 59.07351    | 59.89493    | 65.27877    | 63.67389    |

Table 2: Material constant $B_1$

| Strain rate ($s^{-1}$) | 603 K       | 633 K       | 663 K       | 693 K       | 723 K       |
|------------------------|-------------|-------------|-------------|-------------|-------------|
| 0.01                   | 35.545955   | 38.22825    | 38.574426   | 33.428620   | 29.728649   |
| 0.1                    | 30.482168   | 27.640630   | 16.062949   | 18.136123   | 14.568123   |
| 1                      | 42.727618   | 28.617052   | 24.490535   | 24.938196   | 21.441601   |
| 10                     | 35.368520   | 33.720244   | 25.088743   | 10.017623   | 13.050572   |

Table 3: Material constant $B_2$

| Strain rate ($s^{-1}$) | 603 K       | 633 K       | 663 K       | 693 K       | 723 K       |
|------------------------|-------------|-------------|-------------|-------------|-------------|
| 0.01                   | -50.604106  | -46.417891  | -42.410436  | -51.239655  | -50.004562  |
| 0.1                    | -30.733920  | -26.045960  | -17.242388  | -21.57068   | -17.370224  |
| 1                      | -42.409324  | -28.666414  | -20.771795  | -19.415388  | -19.013765  |
| 10                     | -45.984878  | -40.897952  | -28.605227  | -11.068608  | -16.565618  |
strain of the material to simulate the whole stress–strain curve.

In this neural network, strain, strain rate, and temperature are used as the input layer, and stress is used as the output layer. The tansig function is the transfer function of the hidden layer, and the purelin function is the transfer function of the output layer. The neural network is created with two hidden layers that include 100 and 50 neurons, separately, as shown in Figure 9.

The stress–strain curve obtained by the neural network, true value, and JC constitutive model is shown in Figure 10. It can be seen that the data calculated by the neural network are closer to the true value than those

| Strain | 603 K | 633 K | 663 K | 693 K | 723 K |
|--------|-------|-------|-------|-------|-------|
| ε = 0.1 | 0.0526 | 0.0532 | 0.0529 | 0.0542 | 0.0521 |
| ε = 0.15 | 0.0568 | 0.0558 | 0.0550 | 0.0546 | 0.0563 |
| ε = 0.2 | 0.0566 | 0.0570 | 0.0585 | 0.0573 | 0.0578 |
| ε = 0.25 | 0.0568 | 0.0571 | 0.0574 | 0.0561 | 0.0568 |
| ε = 0.3 | 0.0562 | 0.0557 | 0.0552 | 0.0558 | 0.0567 |
| ε = 0.35 | 0.0542 | 0.0542 | 0.0545 | 0.0546 | 0.0544 |
| ε = 0.4 | 0.0527 | 0.0538 | 0.0527 | 0.0538 | 0.0536 |
| ε = 0.45 | 0.0510 | 0.0507 | 0.0507 | 0.0505 | 0.0494 |
| ε = 0.5 | 0.0489 | 0.0480 | 0.0482 | 0.0489 | 0.0477 |
| ε = 0.55 | 0.0460 | 0.0458 | 0.0464 | 0.0465 | 0.0457 |
| ε = 0.6 | 0.0415 | 0.0420 | 0.0417 | 0.0409 | 0.0428 |

Figure 8: Correlation coefficient diagram of constitutive model. (a) Arrheni model, (b) JC Model, and (c) optimized JC model herein.

Figure 9: Neural network structure diagram.
Figure 10: The stress–strain curve by the neural network, true value, and JC constitutive mode. (a) and (b) $0.01 \text{s}^{-1}$, (c) and (d) $0.1 \text{s}^{-1}$, (e) and (f) $1 \text{s}^{-1}$, and (g) and (h) $10 \text{s}^{-1}$. 
obtained by the JC constitutive model during the entire strain process. Furthermore, the accuracy of conventional constitutive models, such as the JC or Arrhenius constitutive model, requires abundant experimental data, which is time consuming and labor intensive. Moreover, when the strain is small, the conventional constitutive model will have large errors. The trained neural network can effectively calculate the change in flow stress during the entire strain process. Its general confidence level $R^2$ reaches 0.96209, even when the data are out of the trained samples, as shown in Figures 10 and 11.

3.3 Hot processing map

In the dynamic model of materials, the energy input $P$ is mainly composed of the power dissipation $G$ and power dissipation coquantity $J$, and its distribution is shown in formula (8).

$$P = \sigma \cdot \dot{\varepsilon} = G + J = \int_0^\dot{\varepsilon} \sigma d\dot{\varepsilon} + \int_0^\sigma \dot{\varepsilon} d\sigma. \quad (8)$$

From formula (8), the relationship between $J$ and $G$ can be obtained:

$$\frac{dJ}{dG} = \dot{\varepsilon}\sigma/\sigma d\dot{\varepsilon} = d\ln \sigma/d\ln \dot{\varepsilon} = m. \quad (9)$$

From formulas (8) and (9), formula (10) can be obtained:

$$J = \sigma \cdot \dot{\varepsilon} - \int_0^{\dot{\varepsilon}} \dot{\varepsilon}^m d\dot{\varepsilon} = \left( \frac{m}{m + 1} \right) \sigma \cdot \dot{\varepsilon}. \quad (10)$$

During the hot working process, the power dissipation coquantity $J$ will cause a change in the deformation process, whose maximum value is $J_{\max} = 1/2\sigma \cdot \dot{\varepsilon}$, but $J$ cannot reach the maximum in actual production, so the dissipation efficiency $\eta = J/J_{\max}$ is introduced.

$$\eta = \frac{2m}{m + 1}. \quad (11)$$

The contour line of $\eta$ is shown in Figure 12(a), (c), and (e).

According to Prasad criterion, the dynamic model satisfies the following relationship:

$$\ln J = \ln (m/m + 1) + \ln \sigma + \ln \dot{\varepsilon}. \quad (12)$$

According to Prasad criterion $dD/d\dot{\varepsilon} < D/d\dot{\varepsilon}$, the derivatives of the two sides of formula (12) are taken and are simplified, and the instability factor $\xi$ is obtained:

$$\xi(\dot{\varepsilon}) = \left[ \frac{\partial \ln (m/m + 1)}{\partial \ln \dot{\varepsilon}} \right] + m < 0. \quad (13)$$

The contour map of $\xi$, that is, the instability diagram of the material, is obtained, as shown in Figure 12(b), (d), and (f). The contour line of $\eta$ and the instability map are superimposed to obtain the hot processing map of the composite, as shown in Figure 12(a), (c), and (e).

As presented in Figure 12(a), (c), and (e), when the value of $\varepsilon$ increases, the instability zone of the composite gradually tends to be located in areas of low temperature and a low strain rate. When the temperature exceeds 723 K, the composite tends to lose stability. The instability tends to increase as the value of $\varepsilon$ increases (as the deformation processes increase).

3.4 Dynamic recrystallization model

The dynamic recrystallization (DRX) model is very important for studying the dynamic recrystallization behavior of materials during thermal deformation. The DRX model [17] referred to in this study, as shown in formula (14), describes the DRX characteristics of the 0.5 wt% GNP/Al composites.

$$X_{\text{DRX}} = 1 - \exp \left\{-\beta \left( \frac{\varepsilon - \varepsilon_c}{\varepsilon_c} \right)^m \right\}, \quad (14)$$

where $X_{\text{DRX}}$ is the dynamic recrystallization volume fraction, $\beta$ and $m$ are material constants, $\varepsilon_c$ is the strain value.
Figure 12: Hot processing diagram of the composite. Hot processing diagram (a) $\varepsilon = 0.3$, (c) $\varepsilon = 0.4$, (e) $\varepsilon = 0.5$; instability diagram: (b) $\varepsilon = 0.3$, (d) $\varepsilon = 0.4$, and (f) $\varepsilon = 0.5$. 
at the beginning of dynamic recrystallization, and $\varepsilon_s$ is the strain value at the end of dynamic recrystallization.

If the strain rate is too large, the temperature will increase substantially, and the deformation will be uneven, resulting in poor stability of the stress–strain curve. Therefore, the stress–strain curve with strain rates of 0.01, 0.1, and 1 s$^{-1}$ is selected to build a dynamic recrystallization model.

The dynamic recrystallization volume fraction is shown in formula (15)

$$X_{\text{DRX}} = \frac{\Delta \sigma}{\sigma_a - \sigma_s} = \frac{\sigma_a - \sigma}{\sigma_a - \sigma_s},$$  \quad (15)

where $\sigma_a$ is the stress when there is only dynamic recovery and $\sigma_s$ is the stress when the dynamic recrystallization flow stress is stable.

Chen and coworkers [18] proposed the flow stress formula during dynamic recovery:

$$\sigma = \left[ \sigma_a^2 - (\sigma_a^2 - \sigma_s^2) \exp(-\varepsilon) \right]^{1/2}. \quad (16)$$

A work hardening exponent is introduced here, $\theta = \frac{d\sigma}{d\varepsilon}$, and it is substituted into formula (16):

$$\sigma = \sigma_a - 0.5\rho_a \sigma_a^2 - 0.5\rho_s \sigma_s^2. \quad (17)$$

Figure 13 shows the relationship between the values of $\sigma_a$ and $\sigma_s$ at $T = 723$ K and $\dot{\varepsilon} = 0.01$ s$^{-1}$. According to the fitting results, $\sigma_a$ is 31.30 MPa, and the peak stress $\sigma_p$ is 31.39 MPa, so the value of $\sigma_a$ can be approximately replaced by $\sigma_p$ [19].

It is impossible to obtain the values of $\sigma_s$ and $\varepsilon_s$ because dynamic recrystallization has not yet fully occurred during the hot compression test of the aluminum-based material. Therefore, the stress–strain curve expanded by the trained BP neural network could be applied to obtain the values of $\sigma_s$ and $\varepsilon_s$.

For the 0.5 wt% GNP/Al composite, $\sigma_p$ and $\varepsilon_p$ can be regarded as a function of $Z$. Therefore, the relationship between $\ln(\sigma_p)$ – $\ln(Z/A)$ and $\ln(\varepsilon_p)$ – $\ln(Z/A)$ can be obtained as shown in Figure 14(a) and (b), according to which formulas (18) and (19) can be obtained:

$$\ln(\sigma_p) = A - a \ln(Z/A),$$  \quad (18)

$$\ln(\varepsilon_p) = B - b \ln(Z/A),$$  \quad (19)

Table 5: $\varepsilon_s$ and $\varepsilon_p$ at difference temperature and strain rate

| Strain rate (s$^{-1}$) | Temperature (K) | 603 | 633 | 663 | 693 | 723 |
|------------------------|-----------------|-----|-----|-----|-----|-----|
| $\varepsilon_p$        | 0.01            | 0.12| 0.08| 0.07| 0.0482| 0.06 |
|                        | 0.1             | 0.33| 0.2623| 0.2056| 0.1237| 0.1025|
|                        | 1               | 0.42| 0.3665| 0.3338| 0.2661| 0.1783|
| $\varepsilon_s$        | 0.01            | 49.81| 44.91| 37.1208| 38.9| 28.3 |
|                        | 0.1             | 58.1| 55.0391| 47.153| 45.2424| 38.1709|
|                        | 1               | 68.03| 63.1147| 54.6074| 49.2625| 45.677|

Figure 13: Relationship between the value of $\theta \sigma$ and $\sigma^2$ at temperature of 723 K and strain rate of 0.01 s$^{-1}$.

Figure 14: Dynamic recrystallization model. (a) $\ln(\varepsilon_p)$ – $\ln(Z/A)$, (b) $\ln(\varepsilon_s)$ – $\ln(Z/A)$, and (c) $X_{\text{DRX}}$ in different temperature at 0.01 s$^{-1}$. 

Table 5: $\varepsilon_s$ and $\varepsilon_p$ at difference temperature and strain rate.
Figure 15: Grain size and misorientation angle of the (a) 603 K, 10 s$^{-1}$, (c) 693 K, 0.1 s$^{-1}$, (e) 723 K, 10 s$^{-1}$, (b) 663 K, 0.01 s$^{-1}$, (d) 693 K, 0.01 s$^{-1}$, and (f) 723 K, 0.01 s$^{-1}$. 
Figure 16: IPF mapping and misorientation map of the composite (EBSD). IPF: (a) 603 K, 10 s$^{-1}$, (c) 663 K, 0.01 s$^{-1}$, (e) 693 K, 0.01 s$^{-1}$, (g) 723 K, 0.01 s$^{-1}$, misorientation angle: (b) 603 K, 10 s$^{-1}$, (d) 663 K, 0.01 s$^{-1}$, (f) 693 K, 0.01 s$^{-1}$, and (h) 723 K, 0.01 s$^{-1}$. 

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\[ \varepsilon_p = 0.0886(Z/A)^{0.166}, \quad (18) \]
\[ \varepsilon_s = 29.994(Z/A)^{0.097}. \quad (19) \]

Usually, \( \varepsilon_c \) and \( \varepsilon_p \) are positively correlated, with a proportional coefficient between 0.6 and 0.8 [20]. According to the characteristics of the stress–strain curve, \( \varepsilon_c = 0.6\varepsilon_p \) here. By nonlinear fitting of the relationship between \( X_{DRX} \) and \( (\varepsilon - \varepsilon_c)/\varepsilon_p \), the value of \( m \) is determined to be 2.304, and the value of \( \beta \) is determined to be 2.304.

The values of \( m \) and \( \beta \) are substituted into formula (14), and the recrystallization model of the composite is established. For example, when the strain rate is 0.01 s\(^{-1}\), the dynamic recrystallization volume fraction can be expressed as formula (20).

\[ X_{DRX} = 1 - \exp\left\{-0.724\left(\frac{(\varepsilon - \varepsilon_c)}{\varepsilon_s}\right)^{2.304}\right\}. \quad (20) \]

Figure 14(c) shows that a higher temperature and lower strain rate contribute to recrystallization of the composite. The higher the temperature is, the lower the strain rate, and the smaller the stress required for complete dynamic recrystallization of the material.

### 3.5 Microstructure

Figures 15 and 16 show the grain size, misorientation angle, and IPF map of the composite by EBSD. According to Figure 15(b), (d), and (f), combined with Figure 16(c), (e), and (g), as the temperature increases, an increasing number of small equiaxed grains appear. However, when \( \dot{\varepsilon} = 0.1 \) s\(^{-1}\), more subgrains appear in the deformed grain, increasing the proportion of small misorientation angles and decreasing the proportion of large misorientation angles. In Figure 16(g), a vast number of equiaxed grains appear, and the proportion of large misorientation angles increases, indicating that the prevailing softening mechanism has been continuous dynamic recrystallization. The higher the temperature is, the higher the degree of dynamic recrystallization. As shown in Figure 15(c) and (d), when the strain rate increases, the average grain size is reduced from 4.36 to 4.14, and the large misorientation angle fraction increases from 78 to 82%, indicating that the dynamic recrystallization nucleation rate is higher. However, when the strain rate reaches 10 s\(^{-1}\) (Figure 15(e)) or the temperature is too high (exceeding 723 K), there is not enough time for sufficient dynamic recrystallization, so the accumulated energy will be in the state of power dissipation \( G \), and the material will be unstable (Figure 12(a), (c), and (e)), which is consistent with the hot working map in Figure 12. Therefore, an appropriate strain rate ranging from 0.01 to 0.1 s\(^{-1}\) and temperature ranging from 693 to 723 K during processing are conducive to the grain refinement, hot working properties, and mechanical properties of the deformed composite.

### 4 Conclusion

1. The optimized JC constitutive model of the 0.5 wt% GNP/Al composite is obtained as follows:

\[ \sigma = (B_0 + B_1\dot{\varepsilon} + B_2\dot{\varepsilon}^2)(1 + C_0 \ln \varepsilon') \exp\left[-0.00354 \times 10^{-6} \ln \varepsilon'\right]. \]

2. The specific values of \( B_0, B_1, B_2, \) and \( C_0 \) can be obtained directly or by interpolations corresponding to the tables. The ARE is 0.37%, and the correlation coefficient \( R \) is 99.97%.

3. The trained two-layer BP neural network can be used to improve the accuracy (with general confidence \( R^2 \) reaching 0.96209) and whole-process adaptivity of the constitutive model and to obtain the volume fraction of the dynamic recrystallization of the deformed composite.

4. The dynamic recrystallization model of the 0.5 wt% GNP/Al composite at a strain rate of 0.01 s\(^{-1}\) is as follows:

\[ X_{DRX} = 1 - \exp\left\{-0.724\left(\frac{(\varepsilon - \varepsilon_c)}{\varepsilon_s}\right)^{2.304}\right\}. \]

5. From the combined analysis of the hot processing map and the microstructures of the composite, it can be concluded that a large strain rate and high temperature can result in instability of the material, so the optimal hot processing parameter windows for the composite were a strain rate ranging from 0.01 to 0.1 s\(^{-1}\) and temperature ranging from 693 to 723 K.

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