Using deep neural network model to predict the plastic behaviour of DP780 steel under complex loading

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Abstract. In the forming process of sheet metal, the sheet would be subjected to a complicated loading history. The change of pre-strain and the change of strain path might be concentrated in the sheet metal forming process. Through the tensile-tensile experiment of dual-phase (DP780) sheet steel, the flow stress-strain curve obtained shows the cross effect and permanent hardening behaviour. In order to predict the flow stress of DP780 sheet steel under different pre-strain, strain and strain paths, a deep neural network model is established. The data set is divided into training set, validation set and test set to train, verify and test the deep neural network model. The correlation coefficient between the test set prediction results and the experimental results is 98.88%, and the deep neural network model has great predictive ability. Simultaneously, the deep neural network accurately predicts the cross effect and permanent hardening behaviour of DP780 steel.

1. Introduction

Some scholars have studied the influence of strain path changes on material flow stress-strain, because accurate description of material flow stress-strain behavior is very important for numerical simulation of sheet metal forming process under complex load conditions. For example, predict spring-back [1] and forming limit [2]. The change of strain path will affect the evolution of the microstructure related to dislocations, which will lead to changes in the macroscopic mechanical behavior of the material. Some scholars have established constitutive models to describe the plastic behavior of materials, such as RGBV model [3], MHH model [4] and HAH model [5]. However, the framework of these constitutive models is relatively complex and contains more complex constitutive parameters, so that it is difficult to identify the parameters of the constitutive model.

With the rapid development of artificial intelligence technology, another possibility is provided for simple, convenient and accurate prediction of metal plastic behavior under complex loading conditions. In recent years, researchers have applied artificial intelligence technology to the field of materials science. Peng et al. [6] used a neural network based on back propagation to predict the flow stress of as-cast Ti60 titanium alloy under different strain rates, strains and temperatures. Sun et al. [7] used an artificial neural network based on back propagation to predict the flow stress of Ti40 titanium alloy under different strain rates, strains and temperatures. Guan et al. [8] used an artificial neural network
based on back propagation to predict the flow stress of Ti-6Al-2Zr-1Mo-1V alloy at different strain rates, strains and temperatures. Li et al. [9] used the feedforward backpropagation artificial neural network model to predict the flow stress of Al-Zn-Mg-Sc-Zr alloy under different strain rates, strains and temperatures. Ji et al. [10] used the feedforward backpropagation artificial neural network model to predict the flow stress of Aermet100 steel under different strain rates, strains and temperatures. Li et al. [11] used the feedforward backpropagation artificial neural network model to predict the flow stress of 28CrMnMoV steel under different strain rates, strains and temperatures. Zhao et al. [12] used the feedforward backpropagation artificial neural network model to predict the flow stress of Ti600 titanium alloy under different strain rates, strains and temperatures. Haghdadi et al. [13] used the feedforward backpropagation artificial neural network model to predict the flow stress of A356 aluminum alloy under different strain rates, strains and temperatures. Li et al. [14] used a deep neural network to simulate the thermal deformation behavior of Ti-2Al-9.2Mo-2Fe beta titanium alloy under different strain rates, strains and temperatures. Feng et al. [15] used deep neural networks with small data sets to predict material defects.

Artificial intelligence technology has a wide range of applications in predicting the flow stress of metal materials under different strain rates, strains and temperatures. However, in the past few years, there have been few reports on the application of artificial intelligence technology to predict the plastic behavior of metal materials under different strain paths. Therefore, in this paper, a deep neural network model is used to predict the plastic behavior of dual-phase (DP780) sheet steel under different pre-strain, strain and strain paths within a certain range. The prediction results are in great agreement with the experimental data, indicating that the deep neural network model has great predictive ability.

2. Materials and methods

2.1. DP780 sheet steel and experiment

DP780 is an advanced high-strength steel (AHSS) with a high level of strength and good ductility, which is attributed to the presence of a martensite second phase structure in the ferrite matrix. The influence of the change of pre-strain and strain path on the flow stress-strain behavior is reflected by the tensile-tensile experiment on DP780 sheet steel, as shown in figure 1. Firstly, carry out the first tensile test along the rolling direction (RD) on the long strip of large specimen, where the length of the large sample is parallel to the rolling direction, and the pre-strain of 4% and 10% are generated respectively. Then cut long strip of small specimen from the long strip of large specimen at 0°, 15°, 30°, 45°, 60°, 75° and 90° from the rolling direction. Finally, the second-step tensile experiment is carried out on the long strip of small specimen.

![Figure 1. Schematic illustration for tension–tension test.](image)

2.2. Deep neural network

Traditional shallow neural networks with one or two hidden layers based on backpropagation algorithms have been widely used in the field of materials science. However, deep neural networks have more hidden layers than shallow neural networks. Compared with shallow neural networks, deep neural networks with multiple hidden layers are more effective in modeling complex nonlinear relationships. Because deep neural networks with more hidden layers can perform hierarchical learning through multi-level nonlinearities, complex functions can be modeled with a smaller number of computational units [16]. Due to the complex nonlinear relationship between pre-strain, strain,
strain path and the flow stress of the metal sheet under complex loading conditions, a deep neural network (DNN) is used to establish a prediction model of the flow stress.

Figure 2. Schematic illustration of the DNN architecture.
Figure 3. Experimental flow stress-strain data under pre-strain change and strain path change.

The deep neural network model of this study consists of an input layer, multiple hidden layers and an output layer. The input layer has three input neurons, which respectively correspond to pre-strain, strain and strain path. The output layer has an output neuron, which corresponds to the flow stress. The schematic illustration of this DNN model is shown in figure 2. The deep neural network model of this research uses the back-propagation algorithm with tanh transfer function as the activation function. The formula of the tanh transfer function is as follows:

$$\tanh(x) = \left( e^x - e^{-x} \right) \left( e^x + e^{-x} \right)^{-1}$$  \hspace{1cm} (1)

The loss function used in this model is mean squared error (MSE), and the optimizer used is Nesterov-accelerated Adaptive Moment Estimation (Nadam) [17]. Just like Adam is essentially a combination of RMSProp and momentum, Nadam is a Nesterov momentum version of the Adam optimizer. The experimental data of this study adopts literature [18]. Collect 14 groups of 434 data sets (2 pre-strain×31 strain×7 strain path) from the experimental data, including input (pre-strain, strain, strain path) and output (flow strain), as shown in figure 3. The data set is divided into training set, validation set and test set according to 10:2:2. The data set is preprocessed by Z-score normalization to facilitate training the model. Spearman’s correlation coefficient ($R$) is used to quantify the predictive ability of the deep neural network model, and its expression is as follows:
\[ R = \left( \sum_{i=1}^{N} (E_i - \bar{E})(P_i - \bar{P}) \right) \left( \sum_{i=1}^{N} (E_i - \bar{E})^2 \right)^{1/2} \]  

Where \( E \) is the experimental value and \( P \) is the predicted value obtained from the model. \( \bar{E} \) and \( \bar{P} \) are the average values of \( E \) and \( P \), respectively. \( N \) is the total number of data used.

3. Results and discussion

The parameters of the optimizer Nadam include learning rate, exponential decay rate for the 1st moment estimates and exponential decay rate for the exponentially weighted infinity norm. In the case of Nadam's parameters using default values, number of samples per gradient update is 31 and number of epochs to train the model is 1000. Through parameter tuning, it is found that a fully connected deep neural network with four hidden layers and 32 hidden neurons in each layer has the best performance. The degree of correlation between the predicted value of the flow stress of the trained DNN and the experimental value is shown in figure 4. In the figure, the best line inclined 45 degrees from the horizontal is drawn. In order to make a perfect prediction, all circles should lie on this straight line. In figure 4(a), the correlation coefficient is 0.9986 and most of the circles are on a straight line, which indicates that the training set has obtained a good correlation between experimental and predicted flow stress. In figure 4(b), the correlation coefficient is 0.9980 and most of the circles are on a straight line, which indicates that the verification set has obtained a good correlation between the experimental and predicted flow stress. In figure 4(c), the correlation coefficient is 0.9888 and most of the circles are on or close to a straight line, which indicates that the test set has obtained a good correlation between the experimental and predicted flow stress. Therefore, the trained DNN has great predictive ability.
Figure 5. Experimental flow stress-strain curve and DNN prediction flow stress under pre-strain change and strain path change.

The change of pre-strain, the change of strain and the change of strain path cause the flow stress to show anisotropic characteristics. When changing the strain path and reloading, the hardening rate increases sharply, resulting in an instant increase in stress. When the reload is cross loading, the cross effect occurs, resulting in a yield stress higher or lower than the monotonic loading stress, that is, cross hardening or cross softening. It shows that the stress-strain curve after the change of the strain path is higher or lower than the stress-strain curve of monotonic loading. In the subsequent continuous loading process, permanent softening occurs, which is manifested as the stress-strain curve after strain path change has been lower than the stress-strain curve of monotonic loading. The above phenomenon is shown in figure 3. In figure 5, the flow stress data predicted by DNN under different pre-strains, strains and strain paths are in good agreement with the experimental flow stress data, indicating that DNN accurately predict the cross-hardening, cross-softening and permanent softening behaviors of DP780 within a certain range.

4. Conclusions
In this study, a deep neural network is used to establish the plastic behavior prediction model of DP780 steel plate under different pre-strain, strain and strain paths. The plastic behavior of DP780 showed cross hardening, cross softening and permanent softening. The trained DNN can accurately predict the flow stress of DP780 sheet steel. The flow stress predicted by the DNN model has a good correlation with the experimental data, indicating that the DNN model can accurately predict the flow stress of the DP780 sheet steel with the pre-strain, strain, and strain path changes. Moreover, the DNN model can be well used to predict the cross-hardening, cross-softening and permanent softening behavior of DP780 sheet steel. Therefore, DNN can be successfully applied to predict the plastic behavior of DP780 sheet steel under different pre-strain, strain and strain paths. Without using the traditional constitutive model with a large number of complex parameters, DNN can also be used as a choice for predicting the complex constitutive relationship of DP780 sheet steel.

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