Mechanical properties prediction of high-strength aluminium alloy components formed under the PHF process

Huijuan Ma[1,2,3,*], *Peiliao* Wang[1,2,3], *Zhili* Hu[1,2,3], and *Lin* Hua[1,2,3]

[1] Hubei Key Laboratory of Advanced Technology for Automotive Components, Wuhan University of Technology, Wuhan 430070, China
[2] Hubei Collaborative Innovation Center for Automotive Components Technology, Wuhan 430070, China
[3] Hubei Research Center for New Energy & Intelligent Connected Vehicle, Wuhan 430070, China

Abstract. Pre-strengthening hot/warm forming (PHF) technology can effectively shorten the microstructure evolution process of aluminium alloy deformation and heat treatment, and has a broad application prospect. In this paper, the process parameters in PHF are abstracted into sequence data, which is used as the input of long short-term memory neural network (LSTM) model to predict mechanical properties of aluminium alloy components after PHF process. Besides, the prediction models based on Random Forest (RF), Support Vector Regression (SVR) and Back Propagation Neural Network (BPNN) are established and compared with LSTM model. In addition, a Few-Shot Learning method based on the constitutive model is proposed to predict the properties of aluminium alloys.

1 Introduction

7000 series aluminium alloy material has been widely used in aerospace and automobile fields due to high specific strength, outstanding corrosion resistance and toughness. However, this kind of high-strength aluminium alloy is difficult to form into components with complex shape and high forming precision by traditional cold stamping. Academician Jianguo Lin of Imperial College London early proposed hot forming and cold-die quenching technology (HFQ)[1], which greatly improves the formability of aluminium alloy materials and reduces the springback of materials. Even for complex components, it is possible to achieve one-step forming through HFQ, but the additional aging treatment in the process will lead to low forming efficiency and increased cost. In recent years, the team of Professor Hua Lin of Wuhan University of Technology proposed the pre-strengthened hot/warm forming technology (PHF)[2], which can effectively reduce the production cycle of parts, and the pre-strengthened sheet can retain good formability, while the formed parts have high mechanical properties, so the process has broad application prospects.
For high-strength aluminium alloy materials, the traditional preparation logic is mainly trial and error, the process parameter matching efficiency is low, and the component properties

* Corresponding author: mahuijuan21@whut.edu.cn

are difficult to optimize. As a newly proposed warm/hot forming technology, the past experience provides limited guidance for determining the process parameters of PHF process. When exploring the application of PHF warm forming process on various types of aluminium alloys, a large number of experiments need to be carried out, which consumes a lot of time and funds. Therefore, it is necessary to explore new methods for matching process parameters, aiming to shorten the process window determination process for PHF technology. In this paper, the relationship model between PHF process parameters and mechanical properties of formed components is established by machine learning method, which can provide guidance for the design of PHF process parameters.

2 Experiment

2.1 Material and specimen design

The applied material is 7075 aluminium alloy rolled sheet from Alnan Aluminium Co., Ltd., with the thickness of 1.5 mm. The chemical composition is shown in Table 1.

Table 1. The chemical composition of 7075 Aluminium alloy.

Composition	Al	Cu	Mg	Zn	Cr	Si	Fe
Content(wt%)	Bal.	1.76	2.81	6.63	0.29	0.15	0.31

The geometric shape and dimensions of the tensile specimens are shown in Figure 1. The specimens are cut using wire cutting method, with the cutting direction aligned along the rolling direction of the sheet.

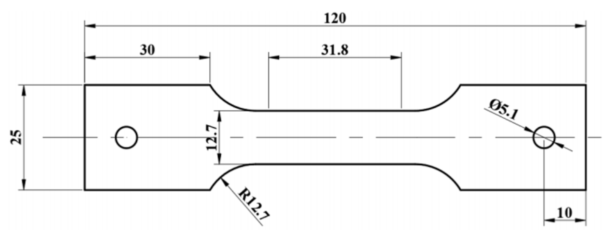

Fig. 1. Specimen design for tensile tests

2.2 Mechanical test

The sample was first held at 475℃ for 30min for solid solution treatment(SHT), then water quenched and pre-strengthened immediately. Finally, the warm forming simulation experiment was carried out on the MMS200 thermal simulation machine to study the effects of pre-strengthening temperature, pre-strengthening time, forming temperature, strain rate and soaking time on the mechanical properties of aluminium alloy formed components. The temperature curve of the warm forming simulation experiment is shown in Figure 2. Finally, tensile test at room temperature was carried out on the MTS electronic universal test machine to measure the mechanical properties of the deformed specimens.

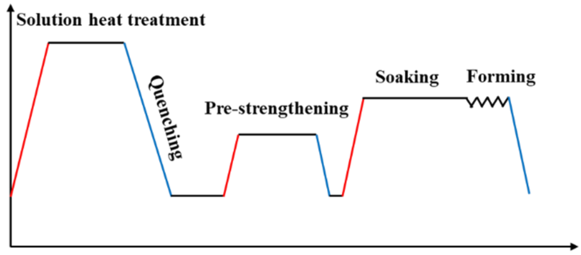

Fig. 2. The temperature curve of the warm forming simulation experiment.

3 PHF process parameter-mechanical property prediction model

3.1 Dataset preparation

In this paper, the results of 83 experiments are used as dataset, where the defined input parameters including pre-strengthening temperature, pre-strengthening time, forming temperature, strain rate and soaking time, and the outputs including the yield strength, tensile strength and elongation. The dataset is randomly separated into three groups, the training dataset (70%), the validation dataset (15%) and the testing dataset (15%).

To improve both the prediction accuracy and convergence speed of the model, the Equation (1) is employed to realize linear normalization[3]:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x_{max} and x_{min} represent the maximum and minimum values of each feature in the original data samples, respectively; x_{norm} denotes the normalized values of each feature, ranging from 0 to 1.

3.2 Long Short-Term Memory network

Recurrent Neural Network takes sequential data as input, preserving the sequence information and allowing continuous information flow within the network through chained connections of all nodes, can effectively process sequential data. Hochreiter et al. introduced Long Short-Term Memory network (LSTM), which add a cell to the original RNN structure to retain long-term information, thereby mitigating issues such as gradient disappearance and gradient explosion[4]. While in the PHF forming process, the blanks are treated by solid solution treatment, pre-strengthening, soaking, and stamping sequentially. Hence, the PHF forming process can be abstracted as sequential data and used as input for LSTM models to predict the mechanical properties of aluminium alloy formed parts.

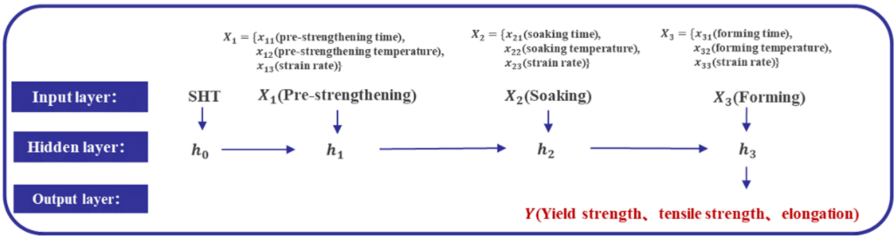

Fig. 3. Schematic diagram of the LSTM prediction model for the mechanical properties of aluminium alloy components under the PHF process.

The optimal parameter combination determined in this paper includes a hidden layer count of 3, 512 neurons in each hidden layer, 217 iterations, a dropout rate of 0.22, and a learning rate of 0.0001. The Adam and Relu are used as optimizer and activation function. The prediction results of the test dataset samples are shown in Figure 4. With the change of process parameters, the prediction results of the LSTM model and the test results share a similar trend, which indicates that the LSTM model can effectively predict the mechanical properties of materials.

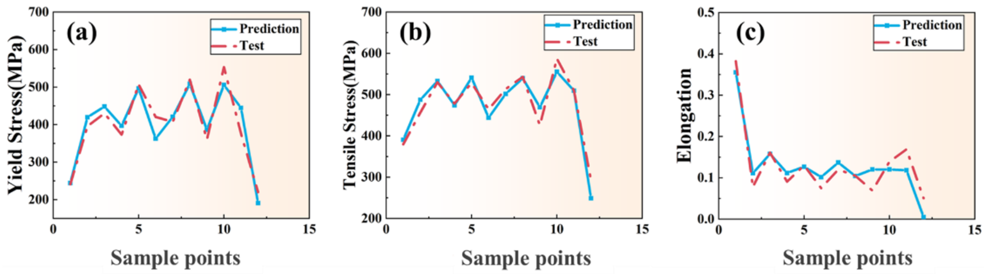

Fig. 4. The predicted results of LSTM model.

3.3 Comparison of different machine learning models

In order to evaluate the accuracy of the prediction model, correlation coefficient (R^2), mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE) were selected as statistical evaluation standards. And the prediction model based on Random Forest (RF), Support Vector Regression (SVR) and Back Propagation Neural Network (BPNN) were established and compared with LSTM model. The results depicted in Figure 5(c) indicate that the RF, BPNN, and LSTM models perform well in predicting elongation, with correlation coefficients all exceeding 0.9, and the values of error indexes of the three model, such as MSE, RMSE, and MAE, are at similar levels. Besides, as shown in Figures 5(a) and 5(b), the LSTM model exhibits lower prediction errors for yield strength and tensile strength compared to other models, and shows the highest coefficient of determination. Therefore, it can be concluded that the LSTM model demonstrates significant superiority in predicting the mechanical properties of 7075 aluminium alloy under PHF process.

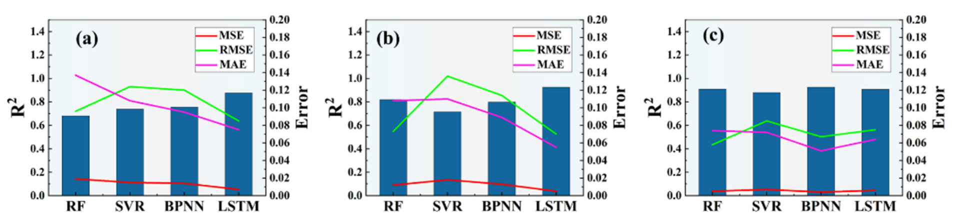

Fig. 5. Evaluation for the predicted results of each model: (a) Evaluation for yield strength prediction results; (b) Evaluation for tensile strength prediction results; (c) Evaluation for elongation prediction results.

3.4 A Few-Shot Learning method based on the constitutive model

In this paper, a Few-Shot Learning method of aluminium alloy based on the constitutive model is proposed as Figure 6, which helps to improve the efficiency and reliability of machine learning model training for PHF process. As shown in Figure 6, the forward and reverse LSTM models are utilized to generate the "hard sample" dataset firstly, and then finite element simulations based on the established constitutive model are carried out. According to the results of finite element simulation, a constitutive model-based pre-training dataset was established to conduct pre-training of the LSTM model. The pre-trained model is finally fine-tuned by experimental dataset.

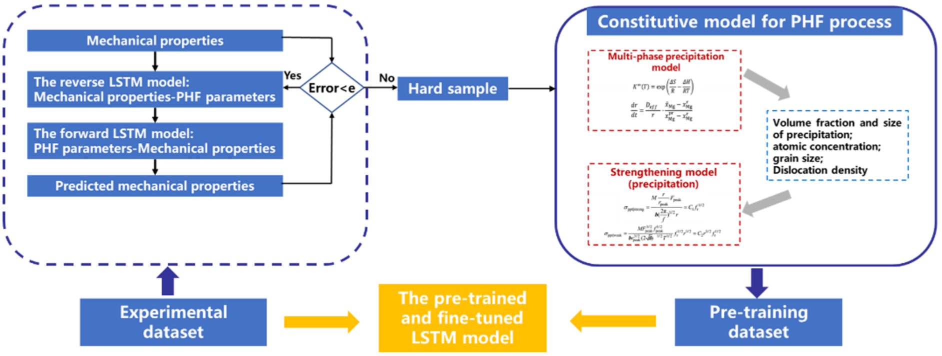

Fig. 6. The flow chart of the Few-Shot Learning method of aluminium alloy based on the constitutive model.

The final comparison results between the LSTM model pre-trained by the dataset based on constitutive model and fine-tuned by the experimental dataset and the LSTM model directly trained by the experimental data are shown in Table 2. The results show that the values of error index MSE of LSTM model with pre-training are reduced by 16%-29% than that of LSTM model directly trained by experimental data.

Table 2. Comparison of LSTM model with and without pre-training

	LSTM model without pre-training				LSTM model with pre-training			
Standards	MSE	RMSE	MAE	R^2	MSE	RMSE	MAE	R^2
Yield strength	0.007	0.085	0.075	0.877	0.005	0.07	0.063	0.913
Tensile strength	0.005	0.070	0.055	0.925	0.004	0.068	0.053	0.927
Elongation	0.006	0.075	0.064	0.906	0.005	0.062	0.058	0.908

4 Conclusions

In this paper, PHF process parameters are abstracted as sequence data and used as the input of LSTM model to predict the mechanical properties of aluminium alloy components after PHF process. The results show that LSTM model can effectively predict the mechanical properties of aluminium alloy components formed under PHF process, and exhibits higher prediction accuracy than other machine learning models such as RF, SVR and BPNN. In addition, a Few-Shot Learning method based on the constitutive model for aluminium alloy performance prediction is also proposed. The accuracy of the LSTM model pre-trained by the dataset based on constitutive model and fine-tuned by the experimental dataset can reduce the prediction error by 16%-29%.

References

1. K. Zheng, Y. Dong, J. Zheng, A. Foster, J. Lin, H. Dong, T. A. Dean, Mater. Sci. Eng. A. **761**, 138017(2019)
2. L. Hua, W. Zhang, H. Ma, Z. Hu, Int. J. Mach. Tools Manuf. **169**, 103799(2021)
3. Y. Chen, L. Wen, S. Wang, Z. Zhang, C. Yin, N. Zhou, K. Zheng, Crystals **4**, 432(2021)
4. T. G. Fischer, C. Krauss. Eur. J. Oper. Res. **270**, 654-669(2017)