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MODELLING OF HYSTERESIS BEHAVIOUR OF NICKEL-TITANIUM SHAPE MEMORY ALLOY USING ARTIFICIAL NEURAL NETWORK

Shape memory alloys (SMAs) are a class of materials that have the ability to return to their previous shape when exposed to temperature or mechanical stress. The main functional properties of these alloys, the shape memory effect (SME) and superelasticity (SE), make them indispensable in various industries. The SMA superelasticity is the ability of a material to return to its original shape after loading and unloading due to transformations between austenite and martensite. These phase transitions are accompanied by hysteresis, which can be observed in the stress-strain diagram. In this study, the hysteresis behavior of SMA, particularly nickel-titanium alloy (NiTi or Nitinol), was modeled using artificial neural networks. The use of neural networks in the study made it possible to obtain accurate material strain predictions and reduce the number of actual experiments. The results showed the high accuracy of the prediction model, which indicates the prospects of using artificial neural networks in the study of SMA characteristics.
Keywords: SMA, machine learning, Nitinol, neural network, hysteresis.

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МОДЕЛЮВАННЯ ГІСТЕРЕЗИСНОЇ ПОВЕДІНКИ НІКЕЛЬ-ТИТАНОВОГО СПЛАВУ З ПАМ'ЯТТЮ ФОРМИ З ВИКОРИСТАННЯМ ШТУЧНОЇ НЕЙРОННОЇ МЕРЕЖІ

Сплави з пам'яттю форми (СПФ) є класом матеріалів, які мають здатність повертатися до своєї попередньої форми під впливом температури або механічного навантаження. Основні функціональні властивості цих сплавів, ефект пам'яті форми та надпружність, роблять їх незамінними в різних галузях. Надпружність СПФ полягає у здатності матеріалу повертатися до початкової форми після навантаження та розвантаження завдяки перетворенням між аустенітом і мартенситом. Ці фазові переходи супроводжуються широким гістерезисом, який можна спостерігати на діаграмі напруження-деформація. У даному дослідженні методом штучних нейронних мереж спрогнозовано гістерезисну поведінку СПФ, зокрема нікель-титанових сплавів (NiTi або Nitinol). Застосування нейронних мереж у дослідженні дозволило отримати точні прогнози деформації матеріалу і зменшити кількість фактичних експериментів. Результати показали високу точність моделі для прогнозування, що свідчить про перспективність застосування штучних нейронних мереж у вивченні характеристик SMA.
Ключові слова: SMA, машинне навчання, Nitinol, нейронна мережа, гістерезис.

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Introduction

Shape memory alloys (SMAs) are a class of materials that have the unique property of returning to their previous shape or structure. This property is based on phase transformations that occur in the alloy when the temperature or load of the material changes. The Shape Memory Effect (SME) and Superelastic behavior (SE) determine the functional properties of SMA [1].

Due to their unique properties, namely the SME and SE effects, SMAs are widely used in aviation [2], medicine [3] [4], robotics [5], automotive and construction [6].

The superelasticity of a material is its ability to return to its original shape after being loaded and unloaded. This effect is due to the transformation of austenite into martensite, which occurs under loading. During unloading, the transformation back to austenite occurs. Phase transitions in such alloys are characterized by wide hysteresis. The hysteresis can be observed in the stress-strain diagram during the loading and unloading of SMA specimens.

Nickel-titanium alloy NiTi, known as Nitinol, is one of the most widely employed SMAs. The purpose of this study is to predict Nitinol hysteresis loops using a supervised machine learning method, namely a neural network.

In modern research, artificial neural networks play an essential role in modeling complex physical processes [7] [8] [9] [10]. Hysteresis curves are complex nonlinear relationships between stress and strain that are difficult to describe using traditional mathematical models. This study used a neural network to predict the material strain in SMAs depending on the applied stress. Also, the dissipated energy during the loading-unloading cycle was calculated

based on the hysteresis loops predicted by the neural network and compared with the energy obtained from experimental hysteresis loops. The use of neural networks in such studies allows us to obtain more accurate and flexible models for analyzing and predicting the behavior of SMAs, which is essential for developing new technologies and applications of these materials.

Main part

The experimental data from [11] were used to train, validate, and test the neural network. In [11], there was studied a wire with a diameter of 1.5 mm made of $Ni_{55,8}Ti_{44,2}$, manufactured by Wuxi Xin Xin Glai Steel Trade Co., LTD. The length of the specimen was 210 mm, the elastic modulus in the austenitic phase (E_A) was 52.7 GPa, and the stress σ_{AM} at the beginning of the transformation was 338 MPa. The experiment was performed at room temperature on a servo-hydraulic testing machine STM-100.

Uniaxial tensile tests were performed under sinusoidal cyclic loading in the controlled stress mode. During the test, the displacement (displacement) and elongation of the wires were recorded. Elongation was measured using a BISS model Bi-06-308 extensometer with a maximum error of 0.1%, and displacement was measured using an inductive sensor model Bi-02-313, with an error of no more than 0.1%. Stresses and strains were determined from the registered force-elongation relationships obtained from the Test Builder program [11].

The input data for the neural network consisted of stress and cycle number, and the output parameter was the material strain. The cycle number is an index indicating the number of the loading-unloading cycle. For training and testing the neural network, 100-120 cycles of loading and unloading of SMA material were used. The train_test_split function split the sample into training and testing. The training and testing samples contained 70 and 30 percent of the total data set, respectively.

To customize the architecture and training process of the neural network, there were optimized the hyperparameters. The following hyperparameters were set in the model creation function: the number of neurons in two hidden layers (units_1, units_2), and the probability of neuronal dropout (dropout_1, dropout_2). The present study employed the RandomSearch from the keras_tuner library to automatically find the best values for the hyperparameters. Hyperparameters such as the number of neurons, the probability of neuronal dropout, and others were randomly selected for each sample. After the hyperparameter search was completed, the best model was automatically selected based on the selected evaluation metric. To select the best model, we used the evaluation metric val_mean_squared_error. This metric measures the average of the squared differences between the predicted and actual values on the validation dataset. The lower the value of this metric, the higher the accuracy of the model on the validation data. In the search process, each model was evaluated by this metric, and the one with the lowest val_mean_squared_error was considered the best. Accordingly, this model also had the most optimal values of hyperparameters.

Figures 1 and 2 graphically show the search for the best hyperparameters for predicting the SMA loading and unloading stage.

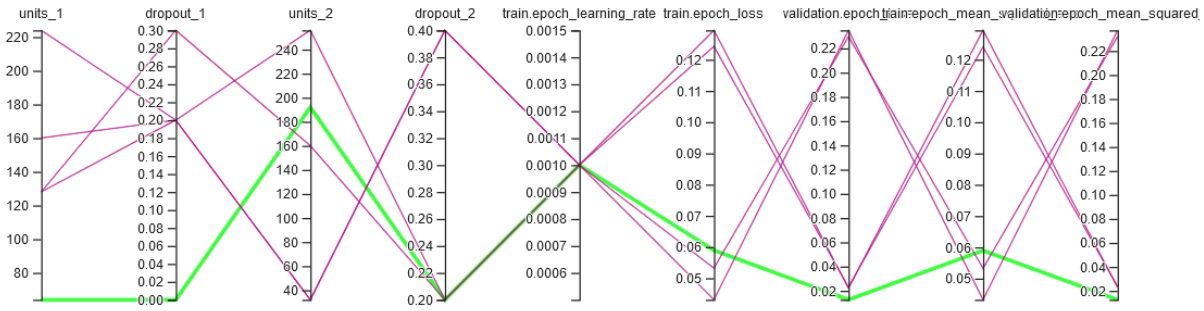

Fig. 1 Finding the best hyperparameters of the neural network for predicting the loading stage

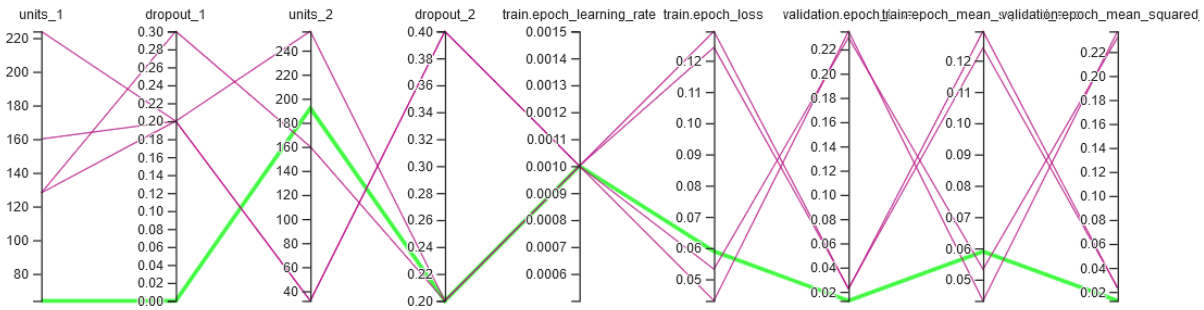

Fig. 2 Finding the best hyperparameters of the neural network for predicting the unloading stage

Figures 1 and 2 show the best model in green, which is automatically selected based on the evaluation metric to predict 125 and 130 cycles of loading and unloading of SMA materials.

The best model for predicting the load period contains two hidden layers with 64 and 192 neurons, respectively. The probability of randomly disconnecting neurons during training is 0.2, which means that 20% of the neurons will be randomly disconnected at each training iteration for each hidden layer.

The best model for predicting the unloading period contains two hidden layers with 96 and 224 neurons, respectively. The probability of accidental disconnection of neurons during training is 0% for the first hidden layer and 30% for the second.

Both models have a ReLU activation function in all hidden layers, with a single neuron in the output layer and a linear activation function. Both models also use the Adam optimization algorithm, which automatically adjusts the learning rate for each model parameter. The models calculated the mean_squared_error (MSE) and mean_absolute_error (MAE) metrics. The metrics are used to evaluate model performance and do not affect the optimization process during training. They provide additional information about the model's accuracy.

The EarlyStopping function was used to stop model training automatically. This function allows to stop the model training if no improvement in the loss metric on the validation dataset is observed for a certain number of epochs. After setting up EarlyStopping, the function is passed as a callback to the model fit method. Figures 3 and 4 show the graph of the neural network loss function for the training and validation datasets for the loading (Up Direction) and unloading (Down Direction) stages of the sample using Early Stopping.

Fig. 3 Graph of the neural network loss function for predicting the loading stage of an SMA sample

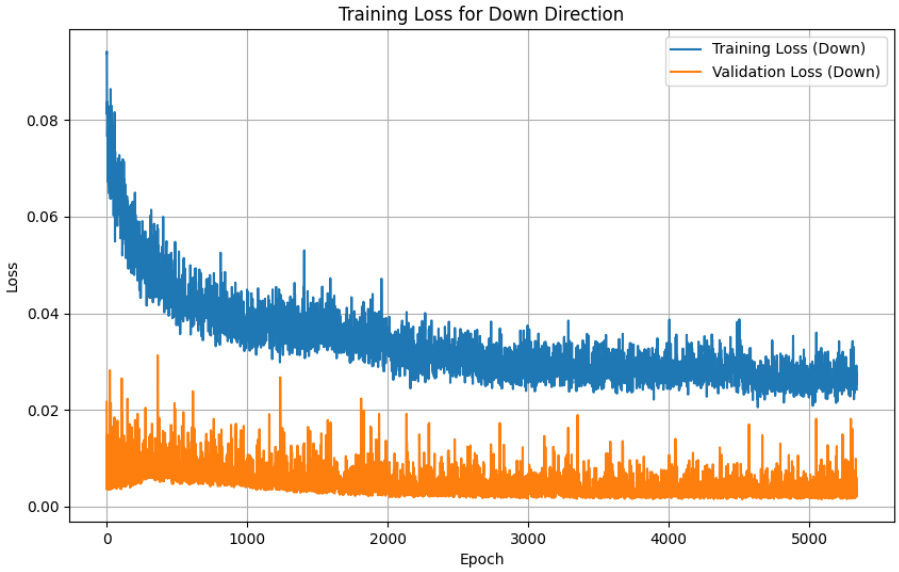

Fig. 4 Graph of the neural network loss function for predicting the unloading stage of an SMA sample

The graph shows no signs of overfitting. Both curves (train and validation loss) remain consistently low and do not diverge over time. The model demonstrates good generalisability.

Figures 5 and 6 show the hysteresis loop for the 125th and 130th cycle of the SMA loading and unloading stage, constructed using a neural network and the corresponding experimental data. The prediction results are very close to the experimental data. When predicting the 125th cycle, the MAE metric was 0.03, when predicting the 130th cycle, the MAE was 0.04.

As expected, the prediction of the 130th cycle of loading and unloading SMA is less accurate than that of the 125th cycle. However, despite this, the prediction accuracy is relatively high, making it possible to reduce the number of actual experiments significantly.

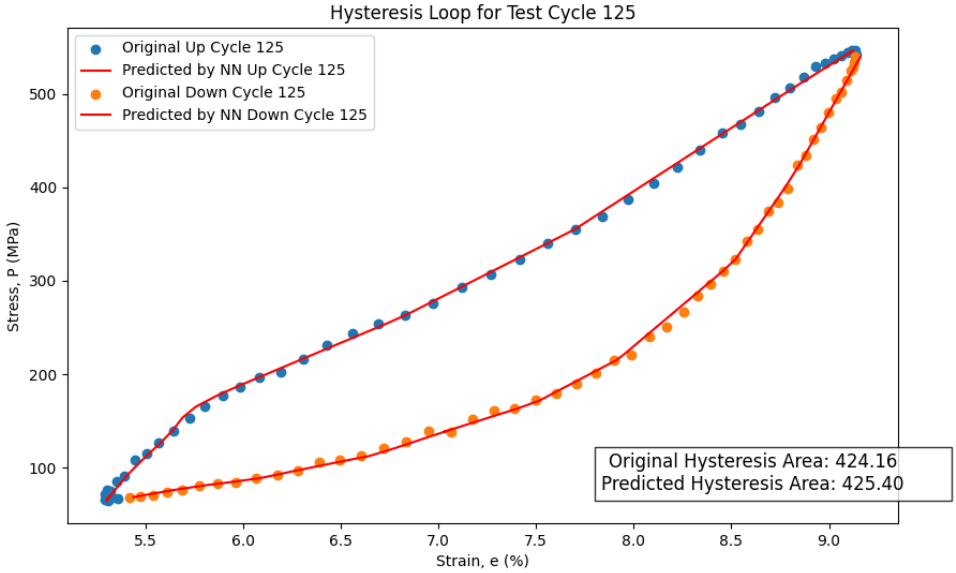

Fig. 5 Predicted and experimental (original) hysteresis loop for 125 cycles and its area

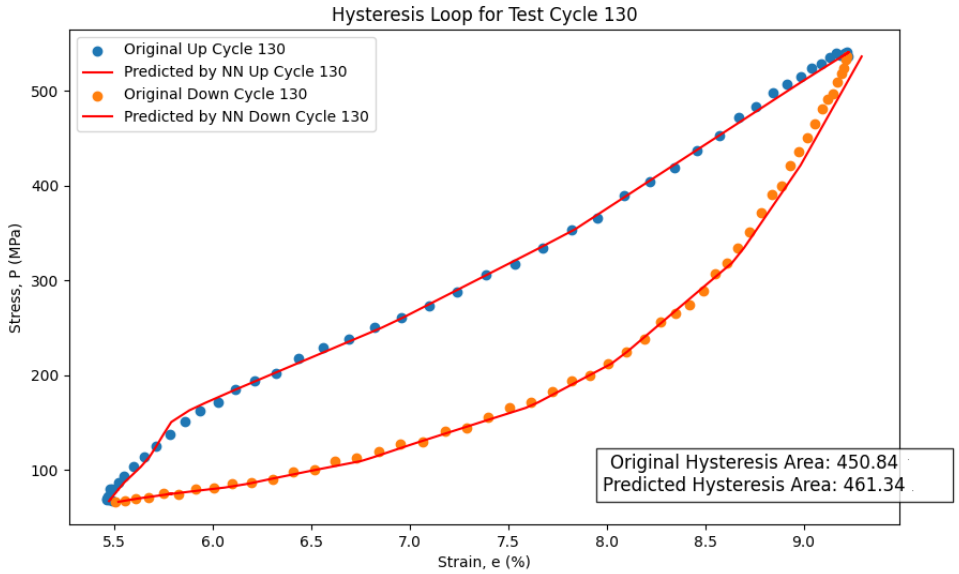

Fig. 6 Predicted and experimental (original) hysteresis loop for 130 cycles and its area

To calculate the areas of the hysteresis loops, we used a software implementation of the trapezoid method. The areas of the hysteresis loops are numerically equal to the dissipated energy Wdis. The values of Wdis for the experimental and predicted by the neural network hysteresis loop curve are 4.2416 MJ/m^3 and 4.2540 MJ/m^3 for the 125th cycle and 4.5084 MJ/m^3 and 4.6134 MJ/m^3 for the 130th cycle, respectively.

Conclusions

This study demonstrated that the optimized artificial neural network could reliably reproduce the nonlinear hysteresis behavior of a NiTi-based shape memory alloy. The automated search for hyperparameters ensured the

construction of accurate models for the loading (64 and 192 neurons) and unloading (96 and 224 neurons) stages. The obtained values of the MAE metric were 0.03 for the 125th cycle and 0.04 for the 130th cycle, which indicates high prediction accuracy. The predicted hysteresis loops closely matched the experimental data, and the deviations in the calculated energy dissipated in the cycle did not exceed 0.3 % for the 125th and 2.3 % for the 130th cycles. Further development of the study involves the use of recurrent neural networks (RNNs), in particular LSTM and GRU architectures, to more accurately account for the history of cycles and improve the extrapolation ability of the model.

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