A BP Neural Network Modeling Method Based on Global Error for the Hysteresis of Piezoelectric Actuator

IOP Conf. Series: Materials Science and Engineering **585** (2019) 012070 doi:10.1088/1757-899X/585/1/012070

A BP Neural Network Modeling Method Based on Global Error for the Hysteresis of Piezoelectric Actuator

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Abstract. Piezoelectric actuator (PZT) is used widely in nano positioning, nano measurement and nano mechanics. However, its hysteresis, creep and nonlinearity affect the positioning accuracy seriously, especially the hysteresis. The paper proposes a BP neural network modeling method based on global error to model the hysteresis of the PZT. The network contains input, hidden and output layers. Its training goal is based on global errors. And the network could adjust the connection weight of the network dynamically according to different inputs till the global errors reduce to the threshold. Experiments prove that the method could fit the hysteresis curves of the PZT well. And the training errors could be controlled under 0.05.

1. Introduction

The piezoelectric driver is a commonly nano positioner due to its high precision and accuracy [1, 2]. However, it has three main characteristics: hysteresis, creep and nonlinearity, leading to errors during positioning [3]. Especially, its hysteresis affects the positioning accuracy seriously. As reported in some papers, the positioning errors could achieve to several tens of nanometers. And the errors will increase apparently as the driving range raises.

To reduce the positioning errors induced by the hysteresis, many research groups proposed many methods to model the hysteresis characteristic of the PZT, such as Preisach [4] model, Prandtl-Ishlinskii model [5-7], Bouc-Wen model [8-10] and Duhem model [11]. Preisach model is an earliest proposed method. Its principle is to describe the hysteresis by relay operator. Many researchers proposed methods to improve the Preisach model. However, the model needs many parameters, resulting to complex computing. Habineza D proposed the Bouc-Wen model. The precision of the model is limited. Prandtl-Ishlinskii model is a commonly used modeling method. It is simple. Its parameters and computation are less than others. However, its errors are larger. Some researcher proposed polynomial fitting method [12]. Its precision is limited when the inputs are dynamic. Some researchers proposed modeling methods based on neural networks [13, 14]. The methods have good precision and accuracy. Therefore, the methods exist local extreme and false saturation.

In view of the high precision and accuracy of BP neural networks, the paper proposes a modeling method based on BP neural networks. And the method is based on global errors, avoiding the local extreme and false saturation. The network contains inputs, conceal and outputs. It could adjust the connection weight of the network dynamically according to different inputs till the global errors could reduce to the preset value.

2. BP Neural Network Based on Global Errors

The structure of a BP neural network is shown in figure 1. We use the following equations to describe the network.

$$\mathrm{y(k)} = f(x_1, x_2, x_3, \dots, x_n) \tag{1}$$

$$f(\mathrm{x}) = \frac{1}{1+e^{-x}} \tag{2}$$

According to the two equations, we can get the output of the input layers:

$$O_i^{(1)} = X_i(k), i = 1,2,3 \dots, n \tag{3}$$

Then the input and output of the hidden layer are as follows:

$$\mathrm{net}_j^{(2)} = \sum_{i=1}^{n} w_{ji}^{(1)}(k-1)O_i^{(1)}(k) \tag{4}$$

$$O_j^{(2)}(k) = f\left(net_j^{(2)}(k)\right), j = 1,2, \dots, m \tag{5}$$

The output of the output layer is:

$$y_m(k) = \sum_{j=1}^{m} w_j^{(2)}(k-1)O_j^{(2)}(k) \tag{6}$$

The global error of the neural network is:

$$E_g = \frac{1}{2}\sum_{k=1}^{L}[y(k) - y_m(k)]^2 \tag{7}$$

The neurons have learning and working states. In working state, the neural networks calculate the output according equation (6). In learning state, the neural network will calculate outputs according equations (1) and (2). The weight values are tuned according to equations (4)-(6). If the global errors (equation 7) are adjusted to the threshold 0.05, the learning state is over.

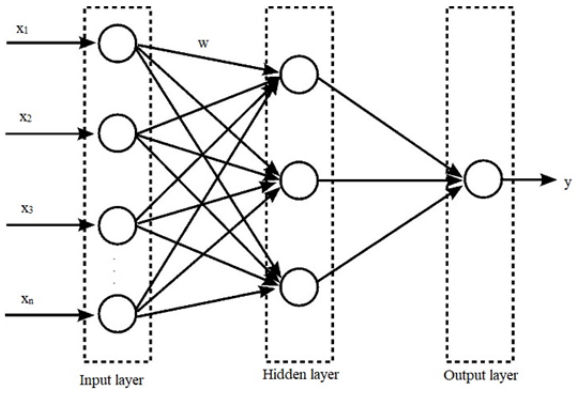

Figure 1. The structure of the BP neural network

3. Experiments and Results

Experiments are carried out to achieve the hysteresis curve of the PZT at different frequencies. The PZT is a nano-positioning stage (NP100XY25Z) from nPoint corporation (USA). The data acquisition system from National Instruments (USA) is applied to achieve the input and output signals.

Selecting three triangular voltage signals at 10Hz, 50Hz and 100Hz as input signals, the PZT scanners would output displacement signals. The data acquisition system records the inputs and outputs of ascending and descending sections. The hysteresis curves describing the inputs and outputs are shown in figure 2. The curves indicate that the hysteresis becomes more apparent at higher frequency. So the frequency of the input is one main factor affecting the hysteresis. In our BP neural network, the frequency is used as one training input.

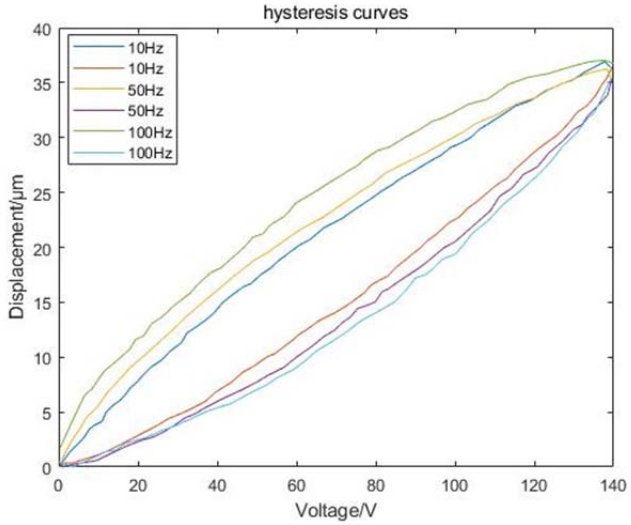

Figure 2. The hysteresis curves of the PZT at 10Hz, 50Hz and 100Hz

Half of the above experimental data are used as the training data of the neural network. The rest are used as the testing data. The neural network has 21 input layers (containing the frequency), 10 hidden layers and one output layers. The training steps are as follows:

(1)Set the initial value of the system. The original weight value of the neural network is set to be random value. The hidden layers are set to be 10. The global errors are set to be 0.05.

(2)The current outputs of the neural network can be achieved using training data according to equations (1)(2) .

(3)The weight increment can be achieved according to equation (3).

(4)The weight value could be calculated using equations (4) (5).

(5)Calculate the global error and determine whether it meets the requirements. If it does, the training is ending. If not, step (2)-(5) are repeated.

While training, the neural network would adjust the weight value dynamically until the global errors are down to the setting value (0.05). After training, the neural network is used to fit the hysteresis curve at 10Hz, 50Hz and 100Hz. The neural network based on the global errors yields good results from figures 3-5.

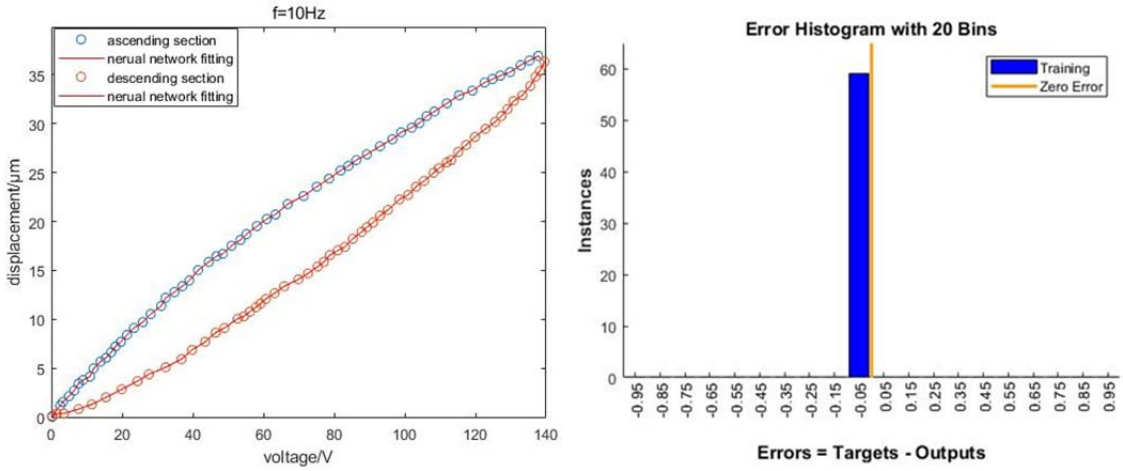

Figure 3. The fitting result using the new neural network for the PZT at 10Hz

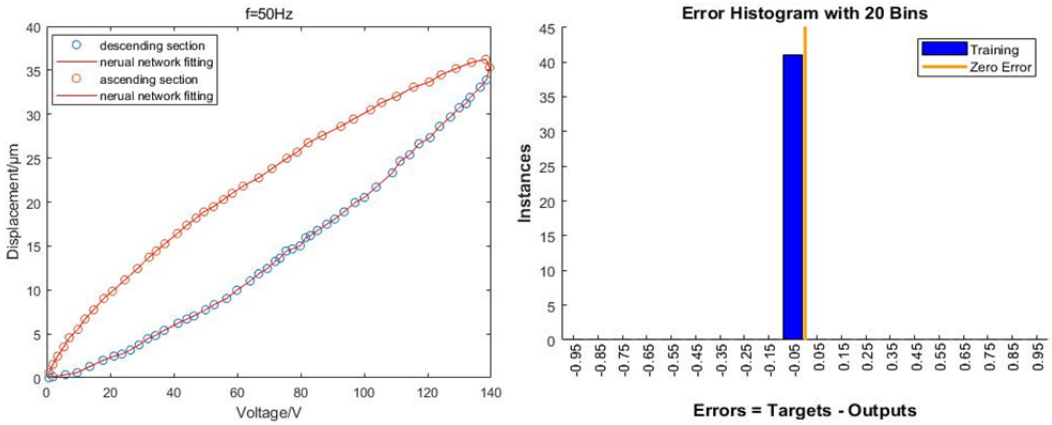

Figure 4. The fitting result using the new neural network for the PZT at 50Hz

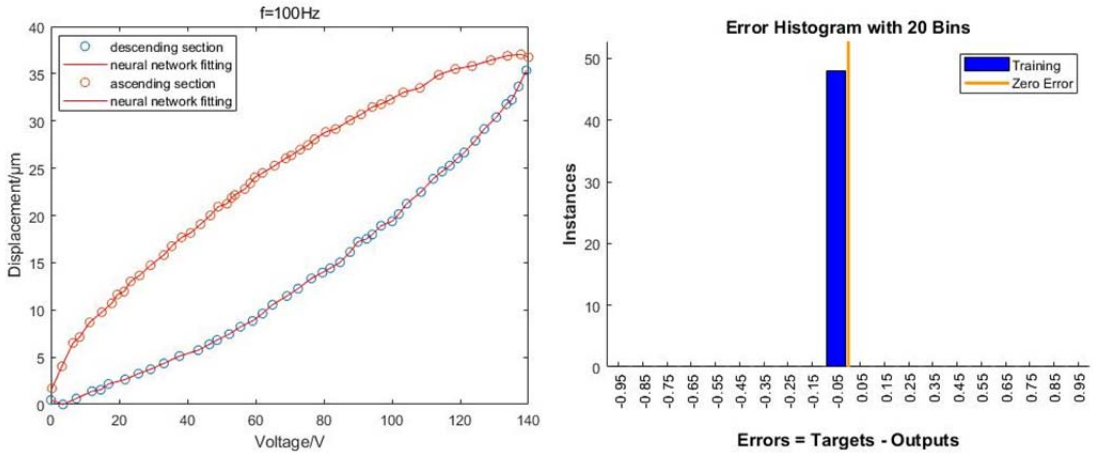

Figure 5. The fitting result using the new neural network for the PZT at 100Hz

4. Conclusions

The paper proposes a new BP neural network based on global errors to model the hysteresis of PZT. Since the hysteresis become more apparent with the increment of the input frequency, the new neural network set the frequency as one input. The new method could adjust the connection weight of the network dynamically according to different inputs until the global errors reduce to the threshold. Experiments prove that the method could model the hysteresis curve very well. Our future work will focus on how to achieve the inverse model of the new BP neural network. Then the feedforward controller based on the inverse model could be applied to PZT and improve its positioning precision and accuracy.

5. Acknowledgments

This work was supported by Tianjin Natural Science Foundation [grant number 18JCQNJC05600], the science and technology project of Tianjin Education Committee [grant numbers JWK1612] and Tianjin Science and Technology Project [grant number 17KPXMSF00120].

6. References

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