Conceptual modeling of hysteresis in piezo crystals using neural networks

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Abstract: Piezoelectric materials are a subset of a larger class of materials known as ferroelectric materials. Ferroelectricity is the characteristic of certain materials that have a spontaneous electrical polarization that can be reversed by the application of an electric field. Like the magnetic equivalent (ferromagnetic materials), ferroelectric materials exhibit hysteresis loops based on the applied electric field and the history of that applied electric field. Hysteresis compensation is necessary wherever high precision positioning or piezo control of the mechanism is required. For forecasting purposes, of hysteresis, the Bouc-Ven model was most often used, and more recently, hysteresis modeling using neural networks has begun. The paper will show a way of conceptual predicting, and then for hysteresis, using a neural network.

Keywords: ferroelectric materials, hysteresis, neural network

1. INTRODUCTION

The Bouc-Wen model is first proposed by Bouc in 1967 [4], where a function that describes the hysteresis behaviour between the displacement and restoring force was proposed, and it was then generalized by Wen in 1976 [5]. This model consists of a first-order nonlinear state equation and an output equation where the input and state signals appear linearly. Through appropriate choices of parameters in the model, it can represent wide variety of hysteresis behaviours[1].

In the paper [2] is presented the results of the successful application of deep learning based black-box models for characterizing the dynamic behavior of micromanipulators. The excitation signal is a multisine spanning the frequency band of interest and the selected model is validated with semi static individual sinusoidal curves. Various architectures are tested to achieve a reasonable result and we try to summarize the best approach for the fine tuning required for such application. The results indicate the usefulness and predictive power for deep learning based models in the field of system identification and in particular hysteresis modeling and in micromanipulation applications [2].

Paper [3] aims to identify parameters of Bouc-Wen hysteretic model using timedomain measured data. It follows a general inverse identification procedure, that is, identifying model parameters is treated as an optimization problem with the nonlinear least squares objective function. Then, the enhanced response sensitivity approach, which has been shown convergent and proper for such kind of problems, is adopted to solve the optimization problem. Numerical tests are undertaken to verify the proposed identification approach.[3].

From the previous examples and results, it can be seen that the problem of hysteresis is quite old and has been dealt with in many ways. The Bouc-Wen model is the most widespread and is based on an inhomogeneous differential equation with the appropriate definition of parameters. Neural networks have been in use since a recent date and, unlike the Bouc-Wen model, provide greater precision, especially at higher operating frequencies. The use of a neural network described in this paper offers much higher hysteresis prediction accuracy than existing neural network models due to the larger number of input parameters. Those input parameters describe the state of the piezo material itself, from which the sensor or actuator is made. The approach conceived in this way gives us the most approximate form of hysteresis at the output of the neural network for each individual piezo element, and not for a series of piezo elements, as was the case until now.

2. PREDICTION OF HYSTERESIS

This paper describes the method of conceptual predicting hysteresis using neural networks, but with the use of several input parameters that describe the current physical state of the piezo element itself. In this way, a significantly higher accuracy is achieved, which can be seen in chapter 3 on the graphics obtained in MATLAB using the deep network designer tool. . PZT is a Bouc-Wen form of hysteresis that, for the purposes of simulation mentioned in the paper, is modeled using the software package MATLAB Simulink. model, chosen to fit the hysteresis loop is described by the following non-linear differential equation (1):

$$\frac{\mathrm{d}z}{A-|z|^{n}\left[\beta+\gamma\operatorname{sgn}\left(\xi' z\right)\right]}=\mathrm{d}\xi \tag{1}$$

where A, , , β γ n are loop parameters controlling the shape and magnitude of the hysteresis loop z(ξ) . Due to the symmetry of hysteresis curve, only the branches

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AB, BC and CD , corresponding to positive values of the imposed displacement $\xi\ \tau(\ )$, will be considered.

The model parameters are to be determined such as the steady-state solution of equation (1), under symmetric cyclic excitation, to satisfy the matching conditions considered in (2)[6].

$$z(0) = z_0 \text{ at } A,\ z(\xi_m) = z_m,\ z(\xi_0) = 0,\ z(0) = -z_0 \text{ at } D \tag{2}$$

This chapter shows the block diagram of the model for training the neural network and the block diagram of the working model of the neural network for prediction and of hysteresis in piezo elements.

2.1 A working model of a neural network

The principle of hysteresis compensation using the neural network shown in Figure 1 is as follows:

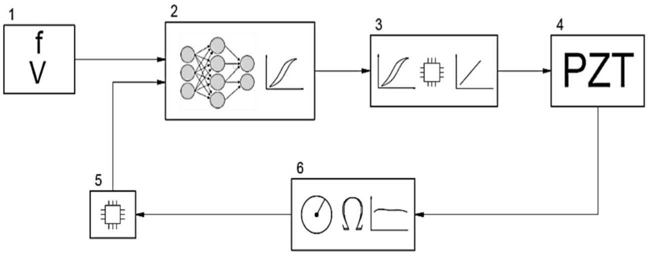

Fig 1.Working principle of predicting hysteresis using a neural network while taking into account the electro-mechanical parameters of the piezo element

the signal generator (1), together with the signal supplied from the microcontroller (5) represents the input parameters to the neural network. Based on those parameters, and after the training process carried out according to the scheme from the previous picture, the neural network (2) itself knows in advance what form of hysteresis, for a certain generated signal from the signal generator (1), is generated by the specific piezo element (4) that is used at that moment. The output from the neural network (2) describes the shape and magnitude of the hysteresis based on the signal that will drive the piezo element (4), generated by the signal generator (1) and the signal coming from the microcontroller (5).That output is then sent to the microcontroller (3), which will, if necessary, correct the control voltage of the piezo element (4), in order to achieve linearity and exact and required position of the piezo element (4) at every moment.

The improvement compared to the current state of science is reflected in the fact that the previous solutions hysteresis using neural networks described in the paper, only takes into account the behavior of a large number of pieces of piezo elements. In this way, an approximate form of hysteresis is obtained for a specific type and type of piezo element.

The assumption thus obtained does not take into account the degradation of the piezo element during exploitation and does not take into account the imperfections of the piezo element during the production itself. The principle shown in the picture also takes those parameters into account. Piezo crystal current measurement device (6) measures electrical resistance at each voltage used to drive a particular piezo element. Also, the device for measuring the current state of the piezo element (6), measures the electrical resistance of the piezo element housing itself and measures the electrical capacitance of the piezo element. The obtained parameters are then forwarded to the microcontroller (5), which adjusts the obtained values and converts them into a format suitable for input to the neural network (2).

Hysteresis usually has a smooth function, but during exploitation or due to the inhomogeneity of the material, it may cause noise or a sharp change in the hysteresis function in some area. In the described way, with all the mentioned measurements, we can predict where noise or a sudden change in the hysteresis function will occur. Such prediction is more accurate than existing solutions and therefore the piezo element itself can be used in places where even greater precision and even greater control of the piezo element itself or the mechanism driven by the piezo element is necessary.

2.2 Neural network training method

Training of the neural network for hysteresis prediction shown in Figure 2: the signal generator (1) generates a signal of the required amplitude and frequency to drive the piezo element (4), also the same signal is fed to the input of the neural network (3). The mechanical elongation of the piezo element (4) is measured by a digital comparator (6) which is connected to the microcontroller (5). The device for measuring the state of the piezo element (7) measures the electrical resistance at all voltages in the range required for the operation of the piezo element (4), measures the electrical resistance of the housing of the piezo element (4), and measures the electrical capacitance of the piezo element (4).

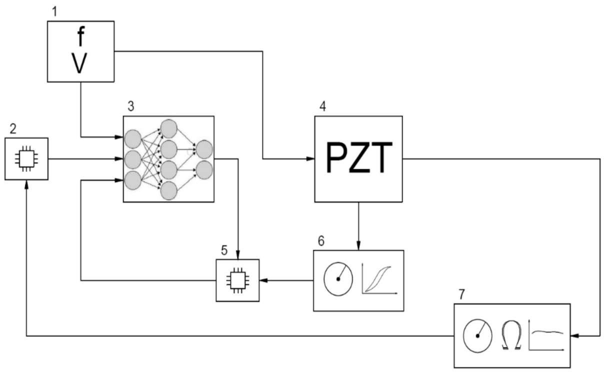

Fig 2.Method of training the neural network for prediction of hysteresis, taking into account the electromechanical state of the piezo element

The obtained measurements are forwarded to the microcontroller (2). The microcontroller (2) adjusts the signals so that they are suitable for input to the neural network (3). The microcontroller (5), based on the comparison of the generated signal of the desired position of the piezo element (4) and the actual value measured by the digital comparator (6), corrects the parameters of the neural network (3) in order to obtaining a match between the desired value and the measured value. When the values approach an acceptable level, the signal generator (1) changes the frequency and amplitude parameters.

The training continues until the desired and measured values are close to an acceptable level. The training then continues with all the desired parameters in terms of frequency and amplitude. In this way, the neural network (3) will be trained for the specific piezo element (4) that is being used at the given moment. Training should be carried out with as many different piezo elements as possible in order to obtain the highest possible accuracy of hysteresis prediction. An improvement over existing solutions is that this training model takes into account both electrical parameters that can tell us in what physical and mechanical state the piezo element is at a given moment.

During exploitation, these parameters change, and in this way we will be able to predict the hysteresis after the degradation of the piezo element, which gives us the possibility of more precise management of the piezo element. Also in this way, inhomogeneities in the piezo element itself, which arise during the production of the piezo element itself, will be shown. The inhomogeneity of the material will also be detected by the neural network (3), after training it will predict, and then the microcontroller in operation will compensate for it.

3. SIMULATION AND RESULTS

For simulation purposes, the MATLAB 2021 a software package was used. Within that package, the Deep Network Design tool was used. Within that tool, the process of creating and training a neural network is maximally simplified in order to quickly create a simulation and process the results.

The NARX Feedback Neural Network was used for the above method of hysteresis prediction. It was used because it gives the best results, both for the existing methods and for the new method described in the paper. Figure 3 shows the shape of the hysteresis in the time domain in the upper graph, and the deviation from the exact solution in the lower one. We can see that the deviation is small, and the largest in the places of sudden changes (maximum value).

Figure 4 shows the hysteresis in the time domain in the upper plot and the deviation from the exact solution in the lower plot, but unlike Figure 3, Figure 4 shows the plots of the case where more input parameters to the neural network were used. All input parameters are explained in section 2.2 and Figure 2 shows the block diagram of the neural network training model with multiple input parameters.

Figure 4 shows the hysteresis in the time domain in the upper plot and the deviation from the exact solution in the lower plot, but unlike Figure 3, Figure 4 shows the plots of the case where more input parameters to the neural network were used. All input parameters are explained in section 2.2 and Figure 2 shows the block diagram of the neural network training model with multiple input parameters.

4. CONCLUSION

In both cases, the NARX Feedback Neural Network with 100 neurons in the hidden layer was used. The algorithm used for training is Bayesian Regularization. Finally, comparing the graphics from Figure 3 and Figure 4, we can conclude that the improvement is significant with the use of more input parameters that describe the physical state of the piezo element itself and as mentioned at the very beginning of the paper, in this way we can predict the hysteresis for each piezo element individually at every moment of its working life (each percentage of degradation can be immediately predicted based on the input parameters described in this paper), while with the existing solutions, hysteresis prediction was only possible for the entire series of piezo elements based on a large number of samples from the same series.

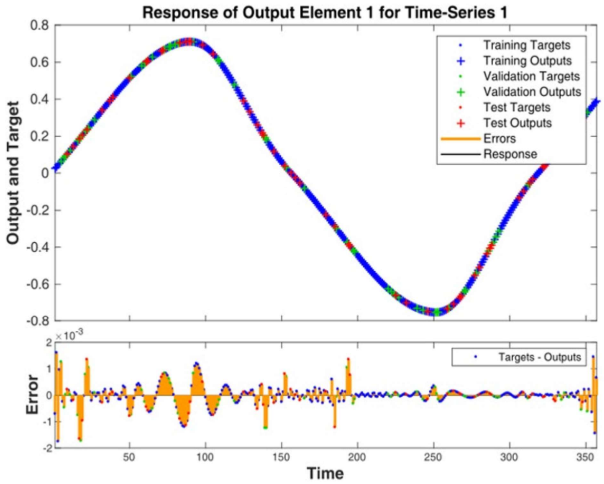

Fig 3.Hysteresis in the time domain in the upper graph and the deviation from the exact solution in the lower graph.

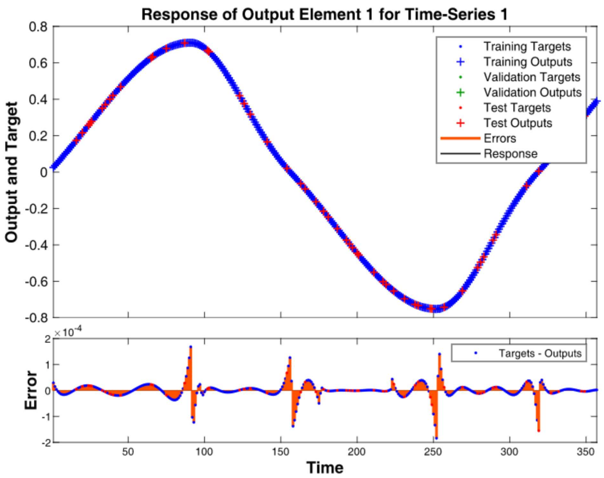

Fig 4. Hysteresis in the time domain in the upper plot and the deviation from the exact solution in the lower plot.

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