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Modeling of Hysteresis Effect of SMA using Neuro Fuzzy Inference System

Sriram V .V. N Malladi [1] and Pablo A. Tarazaga [2]
Center for Intelligent Material Syatems and Structures, Department of Mechanical Engineering, Virginia Polytechnic Institute and State University, Blacksburg, Virginia, 24060

Hysteresis is the dependence of a physical property, not only on the present controlled parameters, but also on the path travelled. Although Shape Memory Alloys (SMAs) exhibit a myriad of nonlinearities, SMAs show two major types of nonlinear hysteresis. During cyclic loading of the SMAs, it is observed that one type of hysteretic behavior depends on the rate of heating the SMAs, whilst the variation of maximum temperature of SMA in each cycle results in the other hysteretic behavior. This hysteretic behavior gives rise to major and minor nonlinear loops of SMAs. The present work analyzes the nonlinearities of hysteretic envelopes, given the different maximum temperature reached for each hysteretic cycle on the strain of the SMA. This work then models this behavior using Adaptive Neuro Fuzzy Inference System (ANFIS) and compares it to experimental results. The nonlinear learning and adaptation of ANFIS architecture makes it suitable to model the temperature path hysteresis of SMAs.

I. Introduction

Good thermo-mechanical properties and electrical characteristics make the use of Shape Memory Alloys (SMAs) attractive in a wide range of applications ranging from vibration isolation,[1] to bio-inspired robotics,[2,3]. The major difficulty when using SMAs is their nonlinear hysteric response to any actuating input. SMAs show rich strain characteristics as a result of temperature induced diffusionless transformation of the lattice structure from martensite to austenite. Unless a model captures these nonlinearities accurately, the control of an SMA would result in an error between the desired and actual strain. The hysteresis of SMA is path dependent. Thus, controlling of an SMA in real-time requires a time-series forecasting nonlinear model. An Adaptive Neuro Fuzzy Inference System (or ANFIS),[4] model is proposed to capture and predict the hysteretic strain characteristics of the system.

The unique ability of SMAs to recover strain upon application of heat is highly useful in areas of actuation applications if mechanisms are developed to control required properties of SMAs. The lattice transformation of SMAs results in changes in measurable material properties like resistivity, Seebeck coefficient, conductivity, etc. Sensorless control techniques using resistance of an SMA as a feedback variable,[5-7] has been previously developed in order to detect the state of the lattice structure, and control this transformation of SMAs,. The disadvantage of this method is that the resistance change has a hysteric behavior and resistance measurement is specific to a particular geometry (e.g. length and diameter in the case of SMA wires).

Although, previous research,[8] has shown that the Seebeck coefficient of SMA is affected by the temperature induced phase transformation and has a nonlinear hysteric behavior, thermoelectric properties of SMA have not been used in control applications. Evaluating the Seebeck coefficient of an activated SMA to use as a feedback variable is difficult in practice. Authors have developed a mechanism based on the Seebeck coefficient of SMAs to determine the level of transformation by measuring temperature. A bimaterial junction of SMA and Constantan wires are capable of detecting the junction temperature by measuring the voltage developed across the free ends of the thermocouple. Although the relative Seebeck coefficient of the thermocouple is responsible for this behavior, the Seebeck voltage is measured rather than the Seebeck coefficient.

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[1] Graduate Student, Department of Mechanical Engineering, sriram@vt.edu, and AIAA Student Member.
[2] Assistant Professor, Department of Mechanical Engineering, ptarazag@vt.edu, and AIAA young professional member

In previous work, the authors have studied the Seebeck voltage of SMA – Constantan thermocouples and characterized the relation between the Seebeck voltage and temperature. This work has also led to the development of an ANFIS model,[9, 10] which studies the relationship of environmental temperature and the Seebeck voltage in measuring the change in tip temperature of the developed SMA – Constantan thermocouple. In a step towards the sensorless control of SMA containing Seebeck voltage as feedback, the present work deals with the characterization of hysteric behavior of position characteristics and temperature dependence of SMAs. One of the advantages of using the Seebeck voltage for feedback is its independence of the geometry of the SMA wire. Section II of this work states the overall direction of our research and previous models developed. The experimental and model details of the strain characteristics of SMAs are discussed in the Section III and Section IV. Comparison of ANFIS predicted data with the experimental data is discussed in the last section.

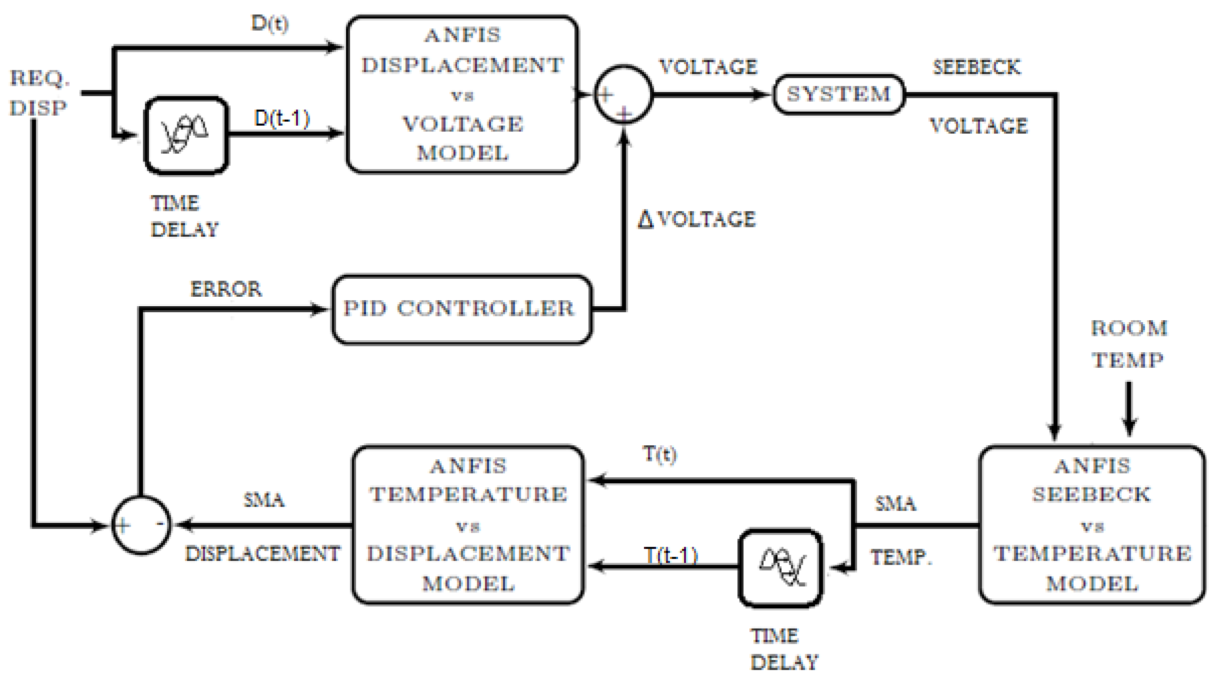

Figure 1 Block diagram for feedback strain control of SMA wires

II. ANFIS Models in Control Loop

The SMA – Constantan thermocouple allows the use of thermoelectric voltage in feeding back the temperature change of SMA, wires results in strain properties of the system. In this section the application of different models developed in this paper towards sensorless control of strain of SMA wires with application of voltage is presented. Several models have been proposed using soft computing methodologies to capture and model the hysteretic behaviors,[11]. Here ANFIS is used to model the nonlinear displacement characteristics of SMAs based on the data collected experimentally. The fusion of fuzzy decision making capacity with the learning abilities of neural networks makes ANFIS architecture an attractive approach to model the nonlinear hysteretic behavior of SMAs. As shown in the block diagram in Figure 1, several models are developed in order to describe the closed-loop system response and study the applicability of such modeling methodology. The system present in this figure is a structure based on an assembly of SMA wires. In order to govern the dynamics of this system the displacement of parts actuated by SMAs in this arrangement has to be established.

The different ANFIS models involved in monitoring the present position of the system and then realizing the voltage required to track a predefined path are listed and described below:

- *ANFIS Seebeck Voltage vs. Temperature:* In order to actuate the system, SMA wires present in the system are heated by the application of voltage across the terminals of SMA wires. To control the rate and amount of actuation, SMA – Constantan thermocouple senses the temperature of the actuated SMA wires. The temperature of the excited SMA is recorded by measuring the Seebeck voltage developed due to the temperature gradient across the SMA-Constantan thermocouple. This model converts this observed Seebeck voltage into the temperature of the bimaterial junction. The relationship between the Seebeck voltage and tip temperature is also dependent on the ambient temperature of the thermocouple. This can be seen in Figure 2. Thus, with the Seebeck voltage of the SMA-Constantan thermocouple and the room temperature as inputs this model predicts the tip temperature of the thermocouple. Room temperature can be obtained by using another thermocouple or thermistor. The dependence of Seebeck voltage on room temperature and model parameters are discussed in detail in the authors' previous work,[7, 12].

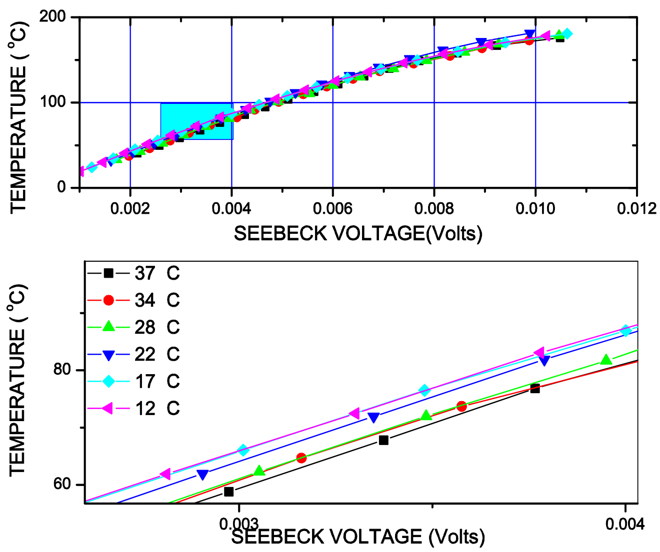

Figure 2 Dependence of room temperature on Seebeck Voltage – tip temperature relation

- *ANFIS Temperature vs. Displacement:* The next step is to determine the change in position of the system. This model predicts the position of the system of SMA wires from the feedback temperature of the activated SMA obtained from the previous model. As the strain of the SMA wires is a path dependent hysteric behavior, the input should also include a time in the form of a delayed variable. This model represents the non-linear map of SMA temperature at times t and $t-1$ with the strain of the SMA wires.

- *ANFIS Desired Displacement vs. Output Voltage:* Depending on the required position of the system, this model predicts the required voltage to be applied across the terminals of the SMA. Similar to the other models, the desired displacement - output voltage relationship of this model is a nonlinear hysteresis. A time delay input is required to predict the path dependent output-voltage of the model. Displacements at times t and $t+1$ are considered as the inputs to this model.

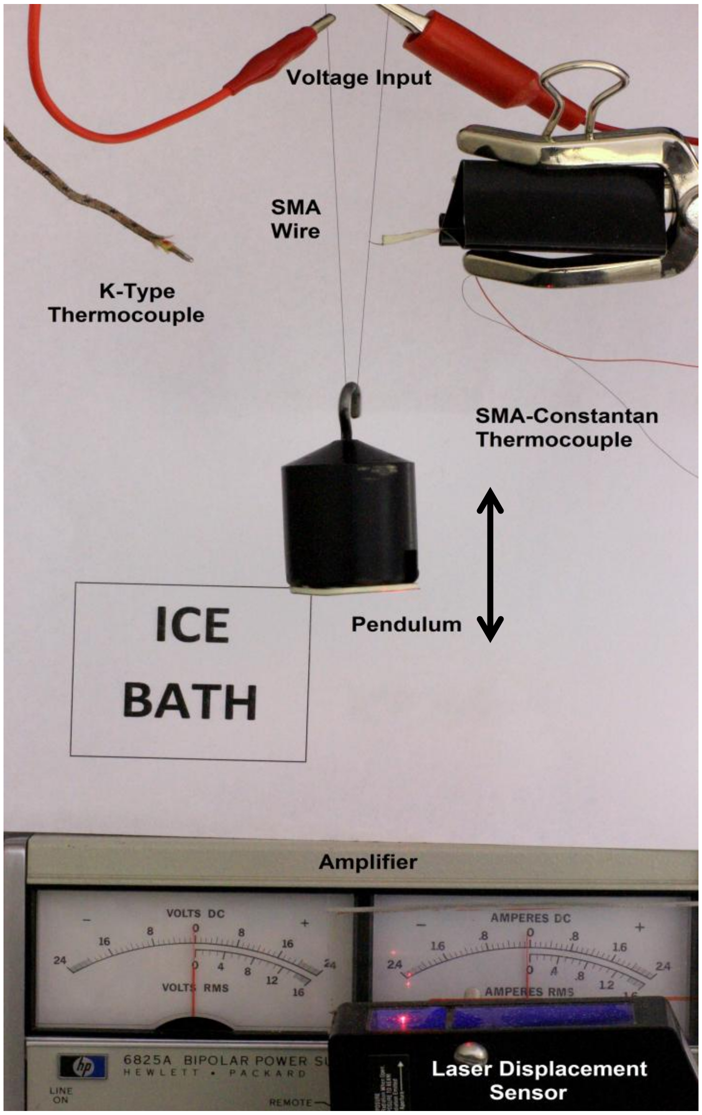

Figure 3 Experimental Setup

III. Experimental Setup

In order to validate the proposed modeling approach an experimental setup is developed (as shown in Figure 3) to record the strain characteristics of a single SMA wire at constant stress. A Flexinol® SMA wire of diameter 0.005 inches and length 14 inches is considered in this experiment. The stress of the SMA wire is maintained by suspending a weight of 200 grams on a SMA wire secured at both ends to a nonconductive frame.

In order to capture the strain variation of the SMA with temperature, the terminals of the SMA wire are subjected to a periodic sinusoidal voltage. NI DAQ system is used to vary the amplitude and frequency of the sinusoidal voltage generated. This voltage signal is amplified by a HP 6825A bipolar amplifier before applying it to the SMA wire. This input indirectly heats and cools the SMA wire periodically allowing the SMA to transform from Martensitic state to Austenite state and vice versa.

The alternate rise and fall in temperature of SMA results in the contraction and expansion of the SMA wire, which causes a periodic displacement of the weight. The contraction of the SMA wire is obtained by measuring the displacement of the suspended weight with the help of a laser displacement sensor.

The change in temperature of this SMA wire is captured through the Seebeck voltage of an SMA-Constantan thermocouple. SMA and constantan wires of diameter 0.005 inches are selected and a bimaterial junction is formed by a capacitive discharge-welding machine. As the Seebeck voltage of a thermocouple is generated due to temperature gradient across the terminals of thermocouple, the free ends of this sensor are placed in an ice bath. This gives rise to the Seebeck voltage generated due to the actual temperature of the bimaterial junction. A K-type thermocouple is employed to measure room temperature.

During actuation by a sine wave, the characteristic response of SMA wire depends on the variation of both amplitude and frequency of excitation. Present work studies the effect of change in amplitude of the sinusoidal input to the system. Although experiments were conducted by varying the input voltage from 6 to 10 volts in steps of 0.1 volts, only data from nine experiments was used to train the ANFIS models. The system is run at an input voltage frequency of 0.05 HZ. At every input voltage the experiment was conducted for 30 cycles and two cycles were selected as data to the ANFIS models.

IV. Results and Discussion

The goal of the present work is the development of "*ANFIS Temperature vs. Displacement"* and "*ANFIS Desired Displacement vs. Output Voltage"* from experimentally obtained data. The implementation of the closed loop control algorithm will be considered in future work.

A. ANFIS Desired Displacement vs. Output Voltage Model

A nonlinear mapping that reflects the relationship between inputs and outputs is constructed based on the experimental data. As the nonlinearities present in strain characteristics of SMAs are path dependent, the voltage required to track a specific path of the pendulum using SMA wires at time *t* is assumed to depend on the direction of change in displacement of pendulum. This model assumes the displacements of the pendulum at time *t* and time *t+1* as the inputs required for predicting voltage at time *t*. Experimental data points used as input vectors to train the ANFIS model are shown in Figure 4 Initial membership functions are obtained by feeding input-output data pairs into a subtractive clustering algorithm. The radius of the cluster is tuned to obtain a minimum error. For 4845 sets of data points a cluster radius of *0.07* computes *113* gauss membership functions using *genfis2* function in MATLAB.

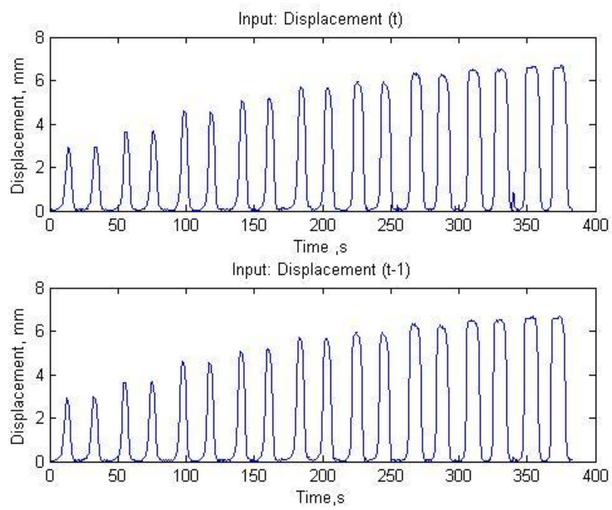

Figure 4 Input to ANFIS Displacement vs. Voltage

The parameters of this set of membership functions are updated using the gradient descent back propagation algorithm. Figure 5 displays the transition in root mean squared error (RMSE) with epochs. As expected, the RMSE initially reduces with epochs and finally reaches a plateau to 0.294. The comparison of the output voltage predicted by the ANFIS model with the experimental data is shown in Figure 6. This plot shows that the ANFIS model is able to predict the different trends of output with reasonable accuracy.

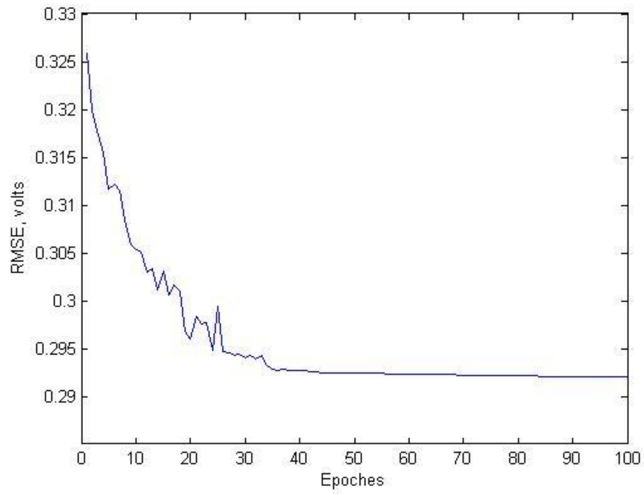

Figure 5 Variation of RMSE with epoches for ANFIS Displacement vs. Voltage

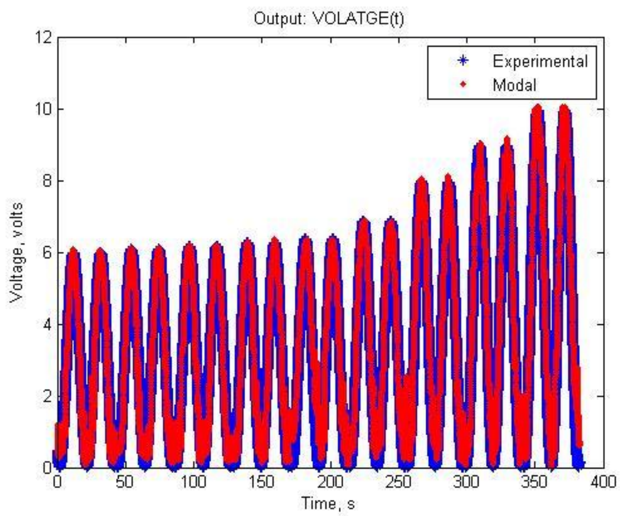

Figure 6 Experimental and ANFIS predicted Voltage

Figure 7 shows the hysteretic behavior of the displacement with voltage applied across the length of SMA wire. It can be noted that for each cycle the model is able to learn the nonlinearity of the output. Although the model works for training data it is the ability of the model to generalize the fuzzy rules and interpolate this behavior to other data that is important. The interpolation capabilities of this black box system are validated by testing the model with a data set corresponding to an output voltage of 6.5 volts. This data set has not been used in building and training the parameters of the model. The experimental results are plotted along with the ANFIS predicted points in Figure 8 for this data set. The predictions from the model quite track the experimental results. This ability of the model to predict and generalize the fuzzy rules for any data validates the learning capabilities of the model.

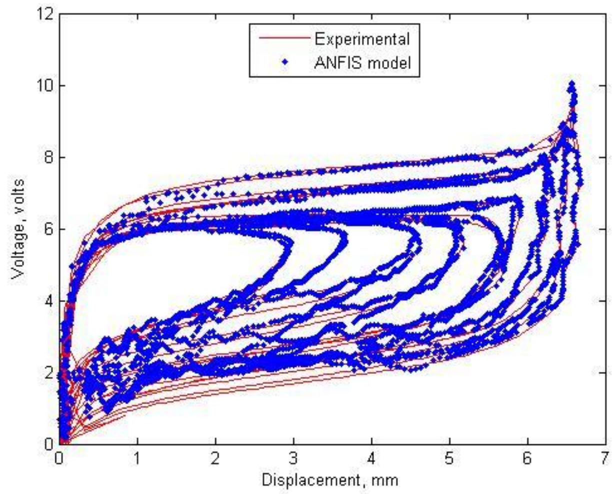

Figure 7 Displacement vs. Output voltage Hysteresis

B. ANFIS Feedback Temperature vs. Displacement Model

In this model the displacement of the pendulum due to the excitation of the SMA wire is predicted from the feedback temperature obtained from the SMA-Constantan thermocouple. The path dependence of strain characteristics is considered to be nonlinearly dependent on temperature and time. In real time situations, while the system is running and SMA wires are actuated, only the previously collected data is available. Thus in order to predict the position of the pendulum at time *t* it is assumed that the temperatures history of SMA is sufficient. Based on this assumption this black box model has the temperatures at time *t* and *t-1* as inputs and voltage at time t as output. As the distribution of data points is crucial in determining initial fuzzy membership function, a nonlinear sampling is employed in feeding inputs into the model and is shown in Figure 9. An initial model of 140 rules is developed using subtractive clustering algorithm in MATLAB. These rules are tuned into an ANFIS model by training with 4232 data points. The change in error with epochs is plotted in Figure 10. The RMSE error at the end of 200 epochs is 0.056 mm.

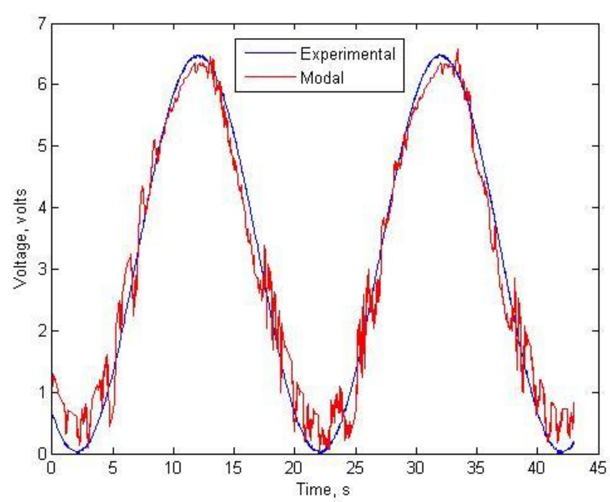

Figure 8 Experimental vs. Model test data - 6.5 volts

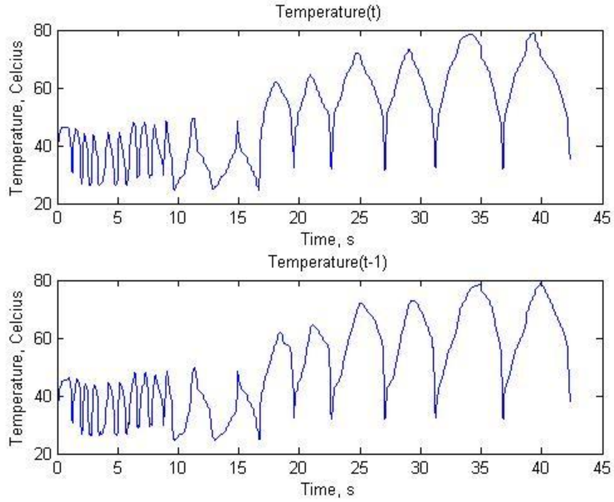

Figure 9 Inputs of ANFIS Temperature vs. Displacement

The ANFIS model predicted experimental data is compared with the experimental data in Figure 11. It can be seen from this plot that the correlation between the model and experimental data is near the line of slope one. The model predicts and tracked the experimentally obtained displacement with reasonable accuracy. The previously made assumption of displacement having a time history dependence on temperature is proven to be correct. The nonlinear behavior of displacement with temperature can be seen in Figure 12. As before the generalization and interpolation characteristics of this nonlinear model is tested by feeding the experimentally obtained temperature path data in ANFIS model. From the results shown in Figure 13 it can be inferred that the model can track the path followed by the pendulum by having temperature history of any new data with good accuracy.

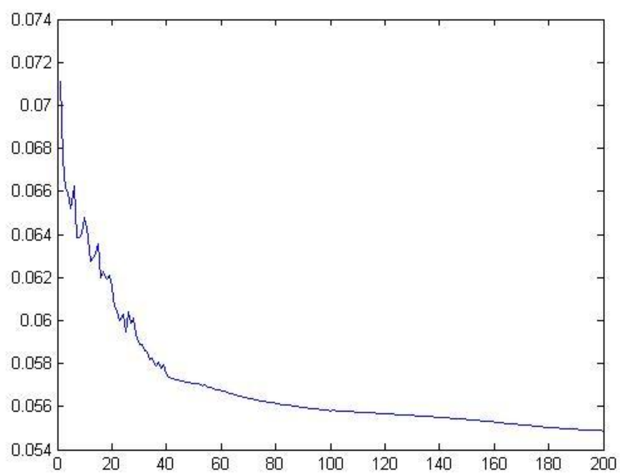

Figure 10 Variation of Epoches for Temperature vs. Displacement model

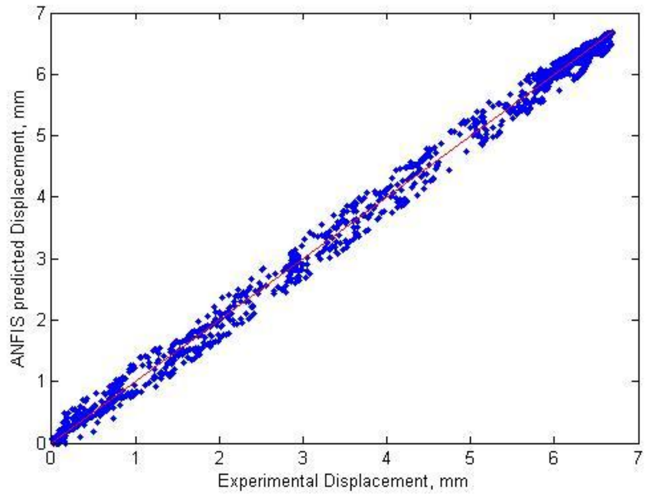

Figure 11 Experimental Displacement vs. ANFIS predicted Displacement

V. Conclusion

In this present work the authors have tried to characterize the nonlinear hysteretic behavior of strain characteristics of SMAs. The nonlinear learning capabilities of Adaptive Neuro Fuzzy Inference System are able to simulate and predict the voltage required to excite SMA wires in a pendulum system in order to track a specific path. The ANFIS model is able to capture the relationship between the temperature history data and nonlinear strain characteristics of SMA wires. The interpolative features of this black-box model have been validated by comparing experimental data with the ANFIS predicted output of a data set that has not been used for building the ANFIS model.

In the work presented, the variation of amplitude of sinusoidal inputs on the strain characteristics of SMA is studied. In the future the effect of frequency of exciting voltage on the hysteresis of SMA wires will be studied. In this work it was assumed that data with a time history of one second is sufficient to predict the nonlinear trends. The relationship of time delay on the accuracy of prediction will be considered in future work. Present work lays a basis for utilizing the concept of SMA- Constantan thermocouple in feeding back the level of transformation of SMA in real-time control situations.

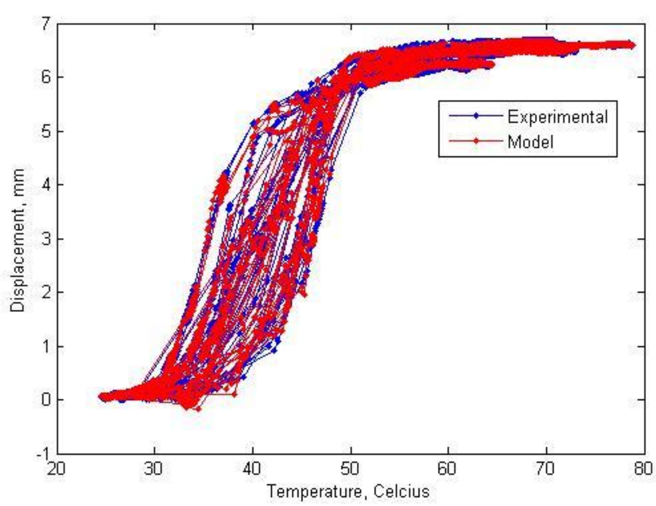

Figure 12 Temperature vs. Displacement Hysteresis

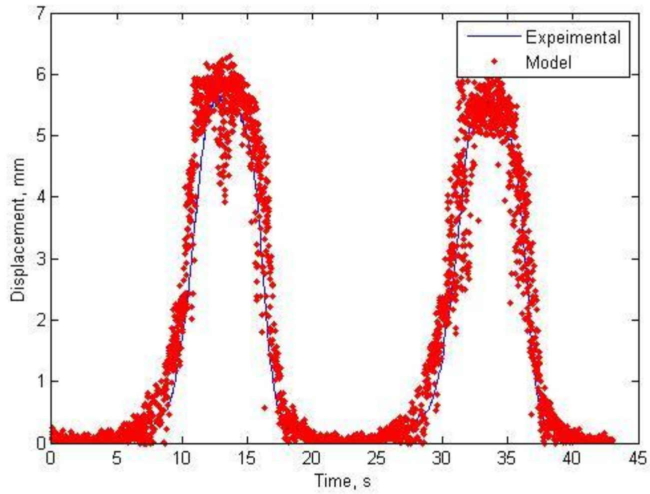

Figure 13 Experimental and Model Test data- 6.5 Volts

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