

MODELING OF SHAPE MEMORY ALLOY SPRINGS USING A RECURRENT NEURAL NETWORK

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In this paper, a recurrent neural network structure is proposed for the modeling of the behavior of shape memory alloy springs. Numerous mathematical modeling and experimental evaluations show that the force exerted by SMAs, aside from their length and applied voltages, depends on the loading path. Therefore, in addition to the applied voltage and deformation, a feedback of the voltage applied to, and the force exerted by the SMA spring in the previous time step is included in the inputs to this neural network to represent the loading path. Fed by adequate inputs, the NN estimates the output force of the spring. The results of some thermal loadings of the spring at various fixed lengths and mechanical loadings at various constant voltages are used to train the NN. The performance of the NN model is then evaluated for some constant weight loadings which are not learnt by the NN. Simulation results indicate that compared to other neural network structures, the proposed structure learns the behavior of the SMA spring faster (in less iteration). Moreover, it provides a more general model, i.e. this NN model effectively estimates the output force for almost all possible loadings.

Key words: artificial neural networks, smart materials, shape memory alloy springs

1. Introduction

Shape Memory Alloys have the unique capability of memorizing their shapes in such a way that at low temperatures they can be easily deformed with even small forces. When the temperature is increased above a limit, they recover their memorized shape. If their shape recovering is hindered by an external object, they will apply comparatively large forces on the object which indicates that shape memory alloys can be used as actuators. Possessing advantages like the possibility of being used in small dimensions (a few microns in wire form), a comparatively high force to volume ratio, and smooth and silent operation have made SMAs suitable candidates for actuators especially in tiny systems. Although different types of these actuators are available, they are commonly used in the form of wires and springs. Wire actuators are most suitable for systems in which large forces and small displacements are needed such as microgrippers (Lan *et al.*, 2011). Spring actuators are preferred when large forces and large deflections are required at the same time as in micro-robots (Kim *et al.*, 2006).

Lots of works have been done by researchers to describe the behavior of shape memory alloys. It is known that the shape memory property of SMAs mainly results from a reversible phase transformation from the martensite phase, in low temperatures, to the austenite phase, in high temperatures. Tanaka (1986) derived a constitutive relation for SMAs using thermodynamical principles. He also defined the phase transformation kinetics by introducing an internal variable which describes the portion of each phase in the current crystal structure of the SMA. Further studies revealed that the martensite phase may exist in two separate configurations. When the alloy cools down freely from the austenite phase, the produced martensite phase will have multiple variants and twins will be present in the structure. All the variants are crystallographically equivalent but their orientation is different. This configuration of martensite phase is

commonly called “twinned martensite”. If a load is applied to the specimen and increased over the critical stress, the different variants will begin to reorient in the direction of the applied load. This process is called detwinning and the produced configuration is commonly called “detwinned martensite”. Brinson (1993) and Gao *et al.* (2007) changed Tanaka’s constitutive relation in order to capture the behavior of SMAs when the phase changes from austenite or twinned martensite to detwinned martensite and vice versa. In their model, they also considered the fact that the material properties are different for each phase. There are also many other works done to model the nonlinear behavior of SMAs as in Sun and Hwang (1993) and Zhang *et al.* (1997).

Most of the proposed models for SMAs are one dimensional and describe the relation between axial load and longitudinal displacement which makes them well-suited for SMA wires. From the basic mechanical principals it is known that the prominent stresses and strains in springs are the shear ones. Therefore, one-dimensional models are not directly applicable to SMA springs. By introducing equivalent stresses and strains, Liang and Rogers (1997) developed a multi-dimensional constitutive relation for SMAs and proposed a simple SMA spring model. Aguiar *et al.* (2010) employed Fremond’s one-dimensional model to derive a model to describe the behavior of SMA springs while Hadi *et al.* (2010) used the Brinson model and followed the Liang procedure.

The aforementioned models use some mathematical relations to describe the behavior of SMA springs. Due to intense hysteresis and nonlinearities in SMA response, it is so difficult to find a mathematical model which can exactly predict the SMA behavior in general. On the other hand, these models often need some parameters which are very hard to be determined practically (Lee and Lee, 2000). These roadblocks have motivated researchers to seek for new modeling methods such as artificial neural networks.

The NN’s great ability to learn nonlinear relations has made it one of the first choices in modeling complicated systems where analytical expressions cannot be found or could take a long time to be simulated. NN modeling can be classified under black box modeling methods since regardless of the system type it only needs the inputs to the system and the corresponding outputs to provide a model of the system. When responses of a system are presented to an appropriately adjusted neural network, the NN extracts the relation between the data and stores it as the network weights. However, the training data need to be chosen suitably, i.e. contain sufficient information about the system for the NN model to be as close to the true system as possible.

The input-output set of the NN should be chosen carefully according to the type of the system. In a simple system like a single-input function, the suitable input and output for the network can be easily recognized. However, for more complicated systems like an SMA-actuated system, finding an appropriate set is not a trivial task and different neural networks with diverse input-output sets and various structures are to be designed.

Lee and Lee (2000) used neural networks to evaluate the characteristics of an SMA spring actuator for an active catheter. They employed a multilayer perceptron with an error back-propagation algorithm consisting of two input neurons, two hidden layers with four neurons in each layer, and one output neuron. The proposed network takes the initial deflection of the spring and its current temperature as the inputs and predicts the shape recovery force in the output. Using some experimental data, they evaluated the network in fixed-length thermal loadings and showed that the NN works very well in prediction of the constrained shape recovery force, even better than Liang’s model. Regarding the input-output set of this NN, it seems obvious that the application of this model is limited to fixed-length tests because it takes in the initial deflection and not the current length of the spring. Moreover, measuring the temperature of the spring (as an input to the network) is not easy in practice.

Song *et al.* (2003) trained a neural network with a representative inverse hysteresis loop and obtained an inverse model of an SMA wire. Then they used the network in combination with a

sliding-mode based robust compensator for precision tracking control of the length of an SMA wire. In addition to the deflection of the SMA wire, a tag input is also provided for the network to determine which branch of the hysteresis loop the training data belongs to. The adopted network has two hidden layers with four neurons in the first layer and five neurons in the second one.

Asua *et al.* (2008) employed NN to learn an inverse model of the hysteresis in an SMA wire. Then they controlled the length of the wire combining the NN compensator with a PI controller. The hysteresis in an SMA wire depends on the amplitude, speed and frequency of the deflection. So the length of the wire at the current time and the two previous signal samples y_i , y_{i-1} and y_{i-2} are taken as the inputs to the network, while the electrical current through the wire is the output. The proposed input-output set obviates the requirement for a tag input since the hysteresis branch can be recognized by comparing the successive inputs. In addition to the input and the output layer, the network includes one hidden layer with 80 neurons and uses Levenberg-Marquardt algorithm to learn offline the dynamics of the SMA wire. As they have stated, this network yields good results in obtaining an inverse model of the hysteresis in some constant weight tests. Nevertheless, as previously mentioned, the general behavior of the SMAs cannot be predicted by measuring a single quantity. Thus, it seems this network will not be able to perform well under various circumstances.

In this paper, a new neural network is presented for the modeling of an SMA spring. The input-output set is chosen in such a way that the obtained global model is capable of appropriately predicting the behavior of the SMA spring in almost all conditions. The results of several experiments in the case of constant length as well as constant voltage are utilized to train the network. Then the network capability is evaluated in some unlearned fixed-stress tests.

Section 2 describes the structure of the proposed neural network. The setup which is utilized to carry out the experimental tests is described in Section 3. The results of training and evaluation of the neural network are provided in Section 4. Finally, Section 5 concludes the paper and lists up future works.

2. Neural network model

In this paper, a new neural network model of SMA springs will be introduced. The model should be able to predict the force exerted by the SMA spring. Since the responses of a SMA spring largely depend on the loading history, to obtain a global NN model, it is necessary to provide the network with some information about the loading path. Therefore, the applied voltage and the force exerted by the SMA spring at a previous time step are included in the input set as well as the current voltage and deflection. It is noteworthy that here the voltage is taken as a representative of the temperature in order to get rid of the difficulties related to practical measurement of the temperature.

The SMA behavior is also rate dependent, so the deflection of the spring at the previous time step is added to the input set. Comparing the two successive inputs, the network will be able to recognize the rate of change of the applied voltage and the spring length. When two successive signals of a quantity, say S_{i-1} and S_i , received by the NN, the signal speed can be approximated by $(S_i - S_{i-1})/\Delta t$, where Δt is the sampling time. As Asua *et al.* (2008) mentioned, the sampling time should be suitably chosen so that the NN receives accurate information. If the sampling time is too short the signal will be noisy, while a slow sampling rate may lead to information loss.

Considering the input-output set, it can be seen that a feedback of the SMA force is included in the NN input which leads to a recursive structure for the network. An illustration of the NN model is provided in Fig. 1.

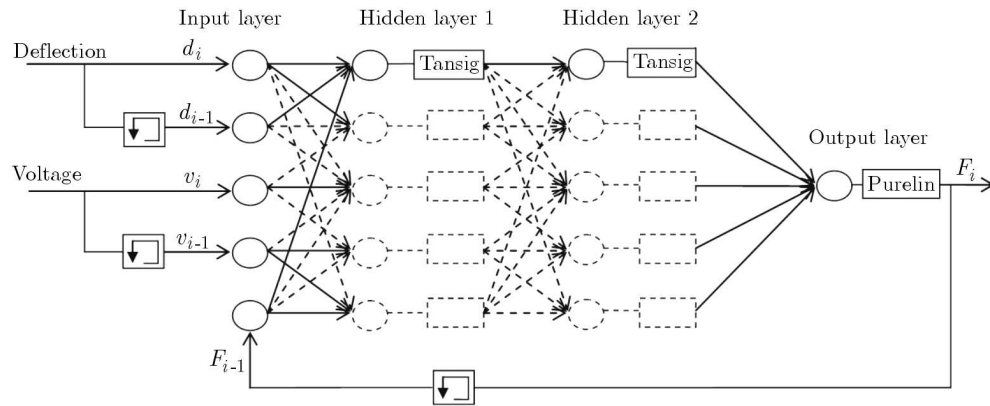


Fig. 1. Structure of the proposed neural network model

3. Experimental setup

As illustrated in Figs. 2 and 3, an experimental test bed is prepared to obtain the required data for training and evaluating the NN model. The setup is designed in a way that can afford different fixed-stress, fixed-strain, fixed-voltage and some arbitrary tests.

A NiTi spring with 6 mm inside diameter, 0.65 mm wire diameter, and 20 mm undeformed length is used to perform tests. A low rpm DC motor is employed to pull the SMA spring at different speeds. The deflection of the spring is measured by a rotational potentiometer and a load cell is used to measure the force exerted by the spring. The measured data are transferred to a PC via a data acquisition board. The voltage is applied to the spring through the DAQ board and a current amplifier.

In fixed-voltage tests, in order to unify the initial condition of the SMA spring, after each test the spring is freely heated to return to its original shape and then cooled down. Therefore, at the beginning of all the fixed-voltage tests, the spring is at its original length. After applying a constant voltage V_c to the spring, it is stretched up to a definite length with a constant speed while the load cell measures the spring force. Finally, by reversing the motor rotation, the length of the SMA spring is decreased with a constant speed until no force is exerted on the load cell.

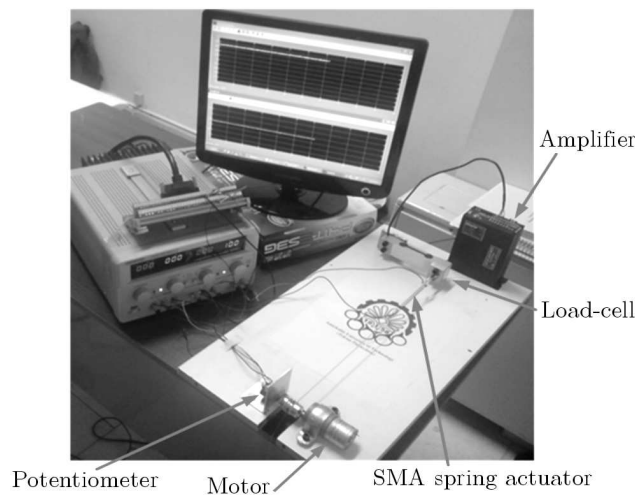


Fig. 2. SMA spring test bed

During fixed-length tests, the SMA spring is hold at some definite lengths L_c . The applied voltage to the spring is increased up to a specific value (2V) and then decreased to zero with a constant slope while the force of the spring is measured by the load cell.

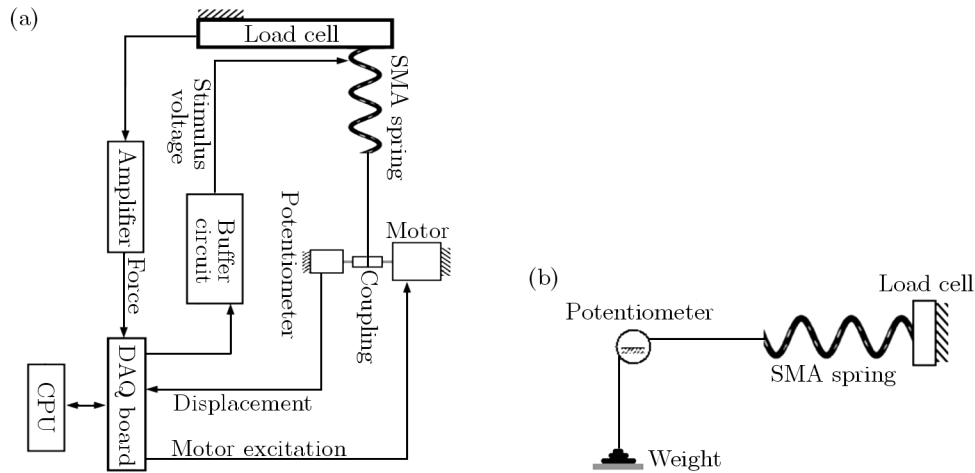


Fig. 3. Schematic overview of the setup; (a) top view with electronic circuit (fixed-voltage and fixed-length tests), (b) side view (fixed-stress tests)

In fixed-stress tests, the DC motor is excluded from the test bed and some specific weights, W_c , are hung from the spring. The applied voltage to the SMA spring is increased up to a definite value (2V) and then decreased to zero while the deflection of the spring is measured by the potentiometer. It is noteworthy that despite the term “fixed-stress”, during these tests the spring does not apply a constant force because of accelerated motion of the hanging weight.

4. Results and discussion

Some samples of experimental fixed-voltage and fixed-length tests are depicted in Fig. 4 and Fig. 5a, respectively. These results are used in the training of the neural network model. Figure 5b illustrates some instances of fixed-stress tests which are utilized to evaluate the performance of the NN model.

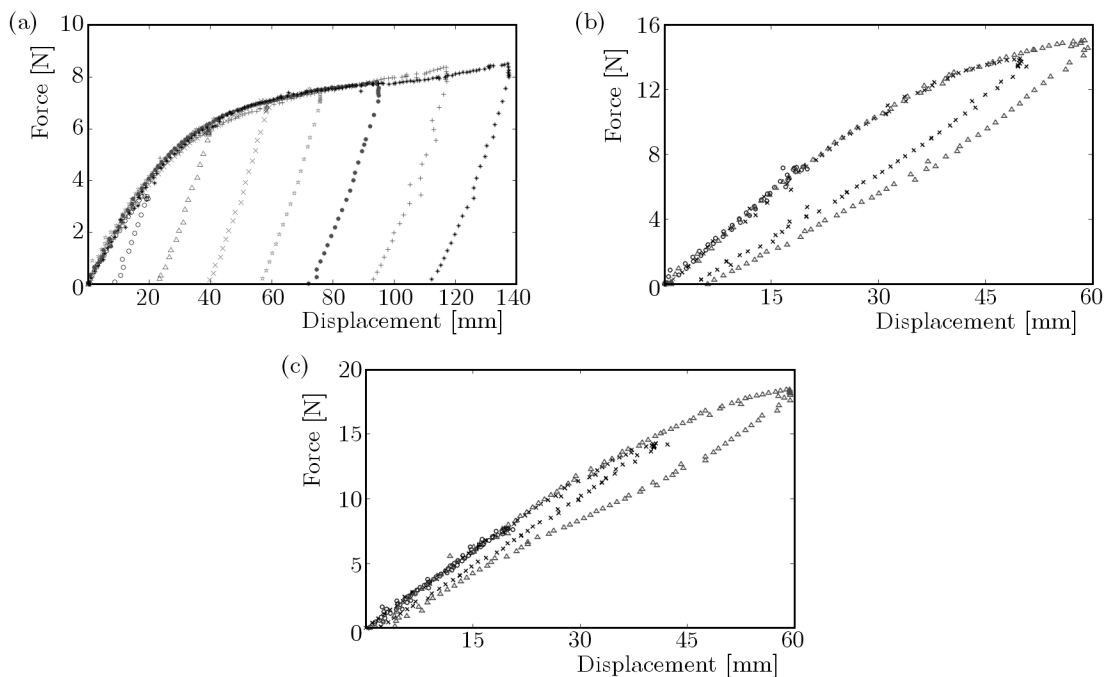


Fig. 4. Some samples of fixed-voltage tests results; (a) $V_c = 0.3\text{ V}$, (b) $V_c = 0.9\text{ V}$, (c) $V_c = 1.2\text{ V}$

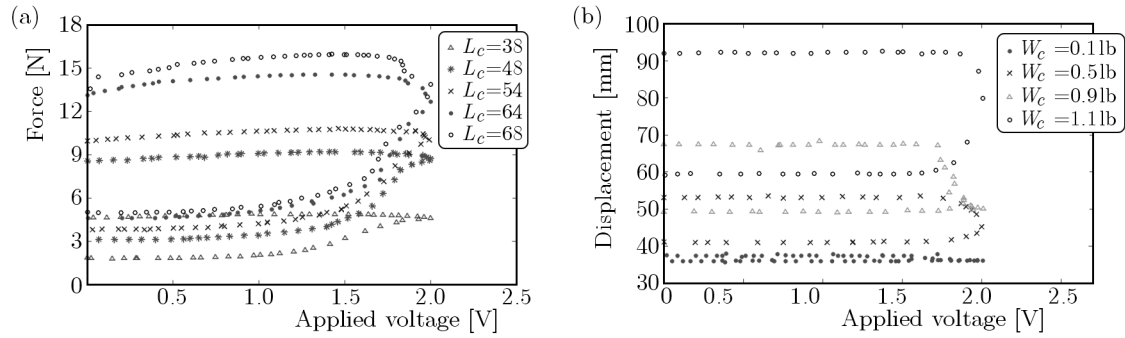


Fig. 5. Some samples of fixed-length and fixed-stress tests results; (a) fixed-length, (b) fixed-stress

As previously mentioned, the SMA response is a function of the loading path. So, in order to preserve the loading information, the training points belonging to each individual test curve are presented to the NN in the order they are obtained. On the other hand, the tests are arranged randomly to decrease the sensitivity of the NN to the order of the tests.

All the designing, training, and evaluating processes of the NN are done in *Matlab* software using the *Neural Network Toolbox*. After some trial and error, a network with two hidden layers is adopted to learn the SMA spring behavior. Similar to the input layer, each hidden layer contains 5 neurons with *tansig* activation functions. The output layer consists of a single neuron which predicts the force exerted by the SMA spring using a linear activation function.

The proposed network uses *Levenberg-Marquardt* back-propagation algorithm for off-line learning of the SMA spring model. This algorithm is designed to approach second-order training speed and implemented in Matlab as function *trainlm*.

Based on the descriptions provided in Demuth and Beale (2002), the Levenberg-Marquardt algorithm approximates the Hessian matrix as

$$\mathbf{H} = \mathbf{J}^T(\mathbf{x}_k)\mathbf{J}(\mathbf{x}_k) \quad (4.1)$$

computes the gradient vector as

$$\mathbf{g}_k = \mathbf{J}^T \mathbf{e} \quad (4.2)$$

and updates the network weights in the following way

$$\mathbf{x}_{k+1} = \mathbf{x}_k - [\mathbf{J}^T \mathbf{J} + \mu \mathbf{I}]^{-1} \mathbf{J}^T \mathbf{e} \quad (4.3)$$

In these relations $\mathbf{J}(\mathbf{x}_k)$ is the Jacobian matrix that contains first-order partial derivatives of the network errors \mathbf{e} with respect to the network weights \mathbf{x}_k . The value of the scalar parameter μ is decreased after each successful iteration to shift toward Newton's method because of its better speed and accuracy near the error minimum (Demuth and Beale, 2002).

Presenting the training data to the designed network, after 45 iterations the error becomes small enough and the training process is stopped. To demonstrate how well the network has learned the training data, the actual force of the spring is compared to the network output for some training tests. As shown in Figs. 6a and 6b, the network output is in a good agreement with the test results indicating that the network has successfully stored the information of the training data.

As the next step, the generalization ability of the NN model should be evaluated. Therefore, some new input sets are built upon fixed-stress tests. The new unlearned input sets are presented to the NN and the experimental results are compared to the NN model output as shown in Fig. 6c. It can be seen that the NN model has successfully predicted the spring force which in turn indicates that the NN has stored an almost exact and general model of the SMA spring.

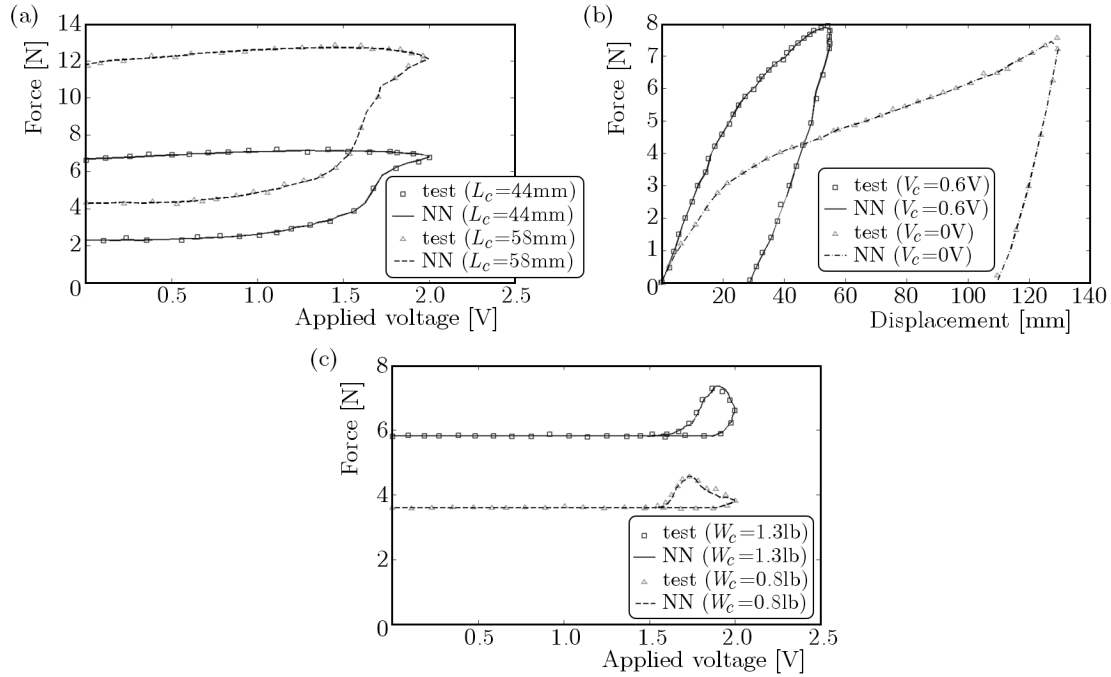


Fig. 6. Some samples of evaluating the NN model performance: (a), (b) remembering the learned data for some samples of fixed-length and fixed-voltage tests respectively, (c) generalization ability of the NN model for some samples of unlearned fixed-stress test results

It is noteworthy that for the sake of comparison some previously proposed neural networks are trained using the same training data sets. Besides the much more number of the iterations required by these models to learn the training data (comparing to our newly proposed model), it was observed that when the loading path is different from those in the training data, the NN will largely fail in predicting the SMA spring output force. Because of large differences between the output of these networks and the experimental data, these results are not shown here. Although it should be also noted that when the presented unlearned data have a loading path similar to the training data, the networks perform almost well. This observation could be explained regarding the aforementioned fact that the loading path is not considered by the previous NN models.

5. Conclusion

In this paper, a recursive neural network structure is proposed for the modeling of the behavior of shape memory alloy springs. The NN model takes in the current voltage and deflection of the spring in addition to the deflection, the applied voltage, and the spring force at the previous time step. The current force of the spring is predicted as the output of the network. The input set is chosen in a way that provides the network with sufficient information about the loading path. Comparing the successive inputs, the network is able to recognize the rate of changes in input signals as well.

The results indicate that the presented NN model can effectively extract the relation between the experimental training data and store a comprehensive model of the SMA spring. The network suitably works with almost all the possible tests even if the loading path is not included in the training set. In addition to more comprehensiveness, the proposed NN model learns the SMA spring behavior faster compared to its predecessors.

Even though the input set to the network is chosen such that the proposed NN model can deal with the rate dependency effect, this capability is not considered in this paper and all the

tests are conducted at a constant speed. The assessment of this capability of the model will be in focus of our future works.

References

1. AGUIAR R.A.A., SAVI M.A., PACHECO P.M.C.L., 2010, Experimental and numerical investigations of shape memory alloy helical springs, *Smart Materials and Structures*, **19**, 025008
2. ASUA E., ETXEBARRIA V., GARCIA-ARRIBAS A., 2008, Neural network-based micropositioning control of smart shape memory alloy actuators, *Engineering Applications of Artificial Intelligence*, **21**, 5, 796-804
3. BRINSON L.C., 1993, One-dimensional constitutive behavior of shape memory alloys: thermomechanical derivation with non-constant material functions and redefined martensite internal variable, *Journal of Intelligent Material Systems and Structures*, **4**, 2, 229-242
4. DEMUTH H., BEALE M., 2002, *Neural Network Toolbox for Use with MATLAB, User's Guide Version 6.5*, The Math Works, Inc., Natick, MA
5. GAO X., QIAO R., BRINSON L.C., 2007, Phase diagram kinetics for shape memory alloys: a robust finite element implementation, *Smart Materials and Structures*, **16**, 6, 2102-2115
6. HADI A.R., YOUSEFI-KOMA A., MOGHADDAM M.M., ELAHINIA M., GHAZAVI A., 2010, Developing a novel SMA-actuated robotic module, *Sensors and Actuators A: Physical*, **162**, 1, 72-81
7. KIM B., LEE M.G., LEE Y.P., KIM Y., LEE G., 2006, An earthworm-like micro robot using shape memory alloy actuator, *Sensors and Actuators A: Physical*, **125**, 2, 429-437
8. LAN C.C., LIN C.M., FAN C.H., 2011, A self-sensing microgripper module with wide handling ranges, *IEEE/ASME Transactions On Mechatronics*, **16**, 1, 141-150
9. LEE H.J., LEE J.J., 2000, Evaluation of the characteristics of a shape memory alloy spring actuator, *Smart Materials and Structures*, **9**, 6, 817-823
10. LIANG C., ROGERS C.A., 1997, Design of shape memory alloy springs with applications in vibration control, *Journal of Intelligent Material Systems and Structures*, **8**, 4, 314-322
11. SONG G., CHAUDHRY V., BATUR C., 2003, Precision tracking control of shape memory alloy actuators using neural networks and a sliding-mode based robust controller, *Smart Materials and Structures*, **12**, 2, 223-231
12. SUN Q.P., HWANG K.C., 1993, Micromechanics modelling for the constitutive behavior of polycrystalline shape memory alloys, part I: Derivation of general relations, *Journal of the Mechanics and Physics of Solids*, **41**, 1, 1-17
13. SUN Q.P., HWANG K.C., 1993, Micromechanics modelling for the constitutive behavior of polycrystalline shape memory alloys, part II: Study of the individual phenomena, *Journal of the Mechanics and Physics of Solids*, **41**, 1, 19-33
14. TANAKA K., 1986, A thermomechanical sketch of shape memory effect: One-dimensional tensile behavior, *Res Mechanica*, **18**, 3, 251-263
15. ZHANG X.D., ROGERS C.A. LIANG C., 1997, Modelling of the two-way shape memory effect, *Journal of Intelligent Material Systems and Structures*, **8**, 4, 353-362