SIMULATION OF STRAIN HYSTERESIS LOOPS IN SHAPE MEMORY ALLOY ACTUATORS USING NEURAL NETWORKS

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Abstract. *Shape Memory Alloys (SMA) are considered intelligent materials with the special capacity of recovery a plastic deformation during heating. Therefore, the shape recovery associated with plastic deformation of these materials is intrinsically associated with the application of a controlled temperature field. This shape memory phenomenon is directly related to a solid state phase transformation, which is responsible for a lot of changes in the physical and mechanical properties of SMA. As a consequence, actuators based on the SMA technology are being increasingly studied due to its large number of possible engineering applications. On the other hand, Artificial Neural Networks (ANN) are connectionist systems based on the biological neuron and its synaptic connections. Intelligent systems resulting from the use of ANN can learn how to interpret given information, such as human learning, without having to say what the system should do. In this sense, this work present the simulation of hysteretic loops of strain as a function of electrical current in Ni-Ti SMA wire actuators using ANN. For this, an experimental test bench was designed and assembled for application of constant loads (dead weights) in a single Ni-Ti SMA wire actuator where activation is controlled by passage of electrical current. The LabVIEW® software was used to control the resistive heating and cooling of the Ni-Ti SMA wire in addition to store data of displacement and electrical current. A multilayer neural network is trained using the same data generated from the test bench that are used to train the SMA actuator model. For this purpose, the neural network toolbox of Matlab® software was utilized. Comparisons between experimental data and neural network outputs have shown very good concordance.*

Keywords*: Shape Memory Alloys, SMA actuators, Artificial Neural Network, Intelligent Materials, Simulation.*

1. INTRODUCTION

The research area of Artificial Intelligence (AI) is composed of several methods and systems that try to mimic specific portions of the human intelligent behavior, such as learning, parallel processing of information, assimilation of patterns, among others (Ludwig Jr. and Costa, 2007). Among the various areas of study in AI, the Artificial Neural Networks (ANN) are considered connectionist systems based on the functioning of the human nervous system. ANN are based on the fundamental unit of biological information processing (neuron) and its synaptic connections. Intelligent systems resulting from the use of ANN can learn to interpret given information, such as human learning, without having to say what the system should do.

In parallel, smart materials have been subject of numerous studies aiming applications in various areas of everyday human. These materials have the important property of reacting to impulses from the external environment by application of electric and magnetic fields, temperature variation, light, among others parameters. In this context, the Shape Memory Alloys (SMA) are considered smart materials that have the amazing ability to return to an original form existing before a plastic deformation introduced at low temperature. The shape recovery associated with deformation of these materials is intrinsically related with the application of a temperature field by heating (Otsuka and Wayman, 1998; Lagoudas, 2008).

SMA manufactured in the form of wires, ribbons and coil springs are considered linear actuators in nature and have great potential for applications in robotics, dentistry, medicine and production of miniaturized electromechanical systems. This potential for applications is a result of its great capacity to generate force and displacement in comparison with its mass and dimensions. SMA thin wires are also very interesting for the manufacture of active composites according to the recovery forces that these actuators may develop inside the structure during heating (Paine and Rogers, 1991; Jang and Kishi, 2005; De Araújo et al, 2008).

Therefore, the use of ANN for simulation and control of SMA actuators can expand the limits of applications for these smart materials, resulting in more intelligent structures. Recently, Asua et al (2009) used ANN combined with proportional-integral control to compensate the hysteresis in Ni-Ti wires. These authors have shown the viability of using SMA-based actuators without the need to place an extraordinarily large burden on the control system. Another study was carried out by Eyercioglu et al (2007) which used ANN with backpropagation algorithm to predicted martensite start (M_s) and austenite start (A_s) temperatures of Fe-based SMA.

Lee et al. (2001) compared the angle control performance of a SMA active catheter by ANN and PID control. There is advantage in using the measurement of electrical resistance to obtain the information of SMA position. However, the control is difficult by traditional methods because SMA response is non-linear. Song et al. (2003) used ANN to compensate hysteresis in SMA actuators. The control tests showed that required movement of the SMA actuator was quite closed to its ANN simulation.

This work aims to simulate displacement – current hysteresis loops of SMA thin wires actuators using ANN. For this one, an experimental test bench was specially assembled to deform a SMA wire under constant load (dead weight) and subsequent activation by a controlled electrical current waveform. For each applied load, the contraction and expansion of the SMA wire as a function of electrical current lead to the apparition of a hysteresis for complete loops and partial ones (sub loops) which were simulated using a backpropagation ANN.

2. EXPERIMENTAL PROCEDURE

For this study, Ni-Ti wires with 0.29 mm in diameter and 80 mm in length were supplied by Memory Metalle (Germany). This Ni-Ti SMA is named alloy M. Figure 1 shows the phase transformation temperatures of the Ni-Ti SMA wire measured by DSC (Differential Scanning Calorimetry). As M_s and M_f temperatures during cooling are located below room temperature (~ 27 ^oC), the transformation of Ni-Ti wire is only partial, corresponding to the region between the R phase and austenite (Otsuka and Wayman, 1998; Lagoudas, 2008). Thus, the potential displacement by expansion and contraction of the Ni-Ti SMA wire actuator will be only partial.

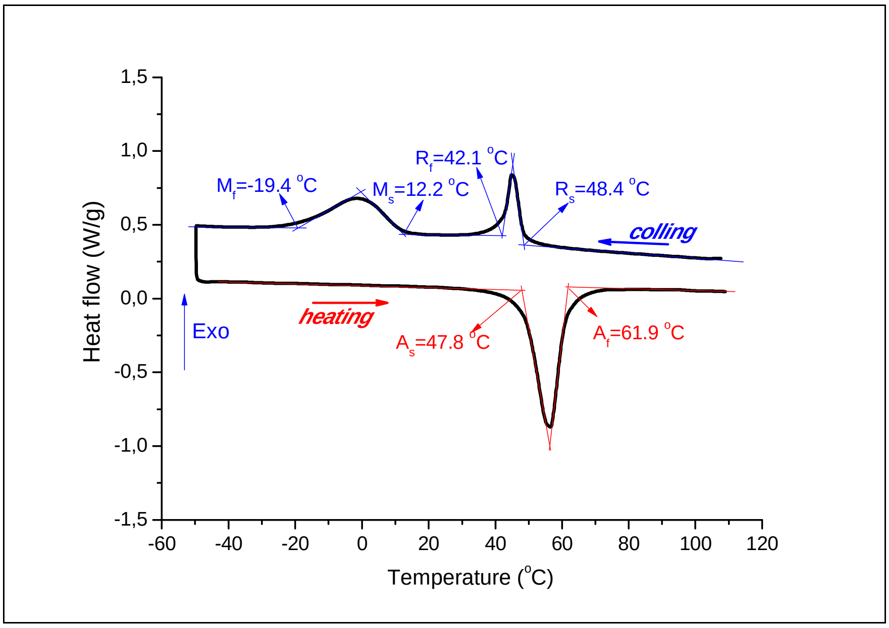

Figure 1. Phase transformation temperatures of the studied Ni-Ti SMA wire (alloy M).

Figure 2 show a schematic drawing of the experimental set-up, which is composed by an analog-digital acquisition card from National Instruments (1) (NI USB-6009), a printed circuit board (2), a Linear Variable Displacement Transducer (LVDT) (3) (Solartron), a mechanical frame to attach SMA wires under load (4) and a power supply (5) (Agilent, E3633A) for resistive heating and cooling of the SMA wire. A microcomputer (6) with LabVIEW® software and tools in Matlab® is used to drive the test system and store the measured data. Figure 3 shows a photograph of this experimental test bench illustrated in Fig. (2).

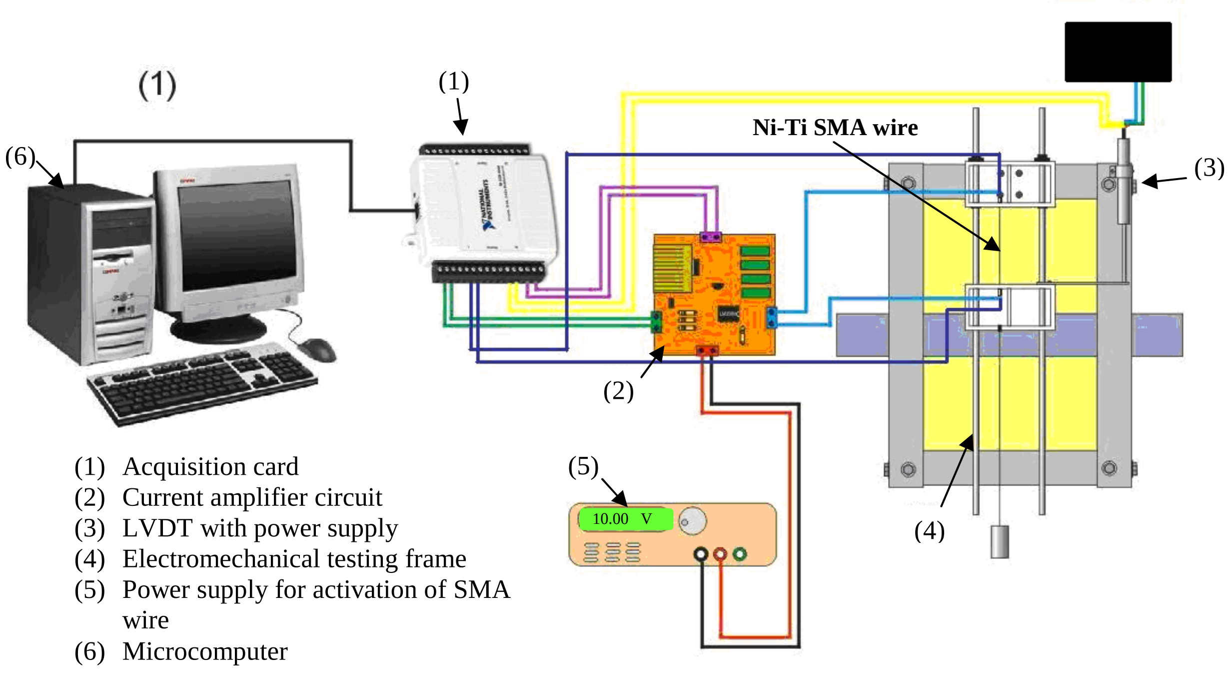

Figure 2. Experimental set-up developed to determine the hysteretic response of SMA wires under load.

In the system shown in Fig. 2, the control signals processed by LabVIEW® software (computer) to analog-digital card (1) are amplified by the printed circuit board (2) using a 10 V power supply (5). This electrical circuit (2) imposes on the Ni-Ti SMA wire a voltage proportional to the electrical current needed to generate the heat necessary to the complete transformation of the actuator.

Then, the applied electrical current (triangular or triangular reduced waveform) heats the Ni-Ti SMA wire by Joule effect, causing its phase transformation and consequently contraction and expansion moving the dead weight. Concomitantly, the signal of voltage drop on the Ni-Ti SMA wire is sent by analog-digital board for the LabVIEW® software that processed these data. The LVDT displacement sensor is used in order to obtain the variation of the SMA wire length. For this, the LVDT characteristic displacement signals is sent to the acquisition card and then processed by LabVIEW® software. During all tests, the SMA wire was loaded by a dead weight corresponding to about 200 MPa.

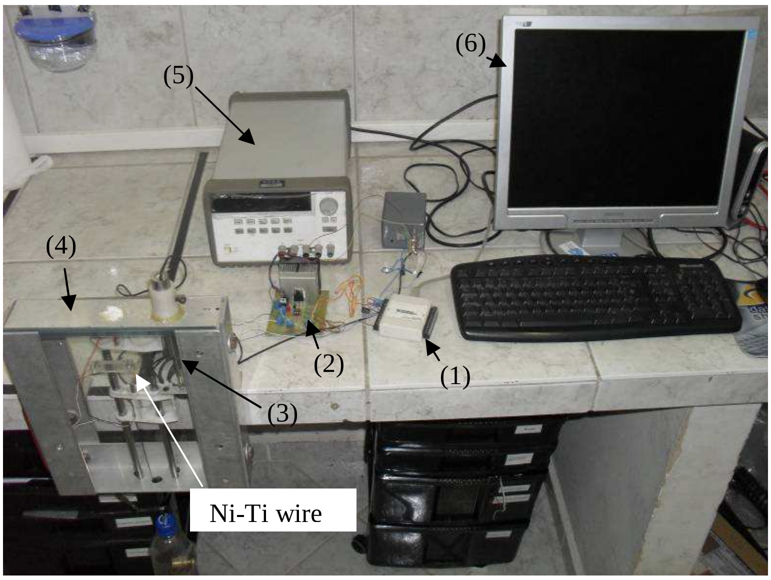

Figure 3. Photograph of the experimental test bench.

The data obtained using the experimental system defined in Fig. 2 were processed by the ANN backpropagation Levenberg Marquardt algorithm (*trainlm*) with 20 neurons in the hidden layer and one neuron in the output. This task was performed using Matlab® software. Random weights were released and carried by Matlab® network training. Figure 4 shows a schematic arrangement of the ANN architecture used to simulate the displacement – current hysteretic behavior of the SMA Ni-Ti wire.

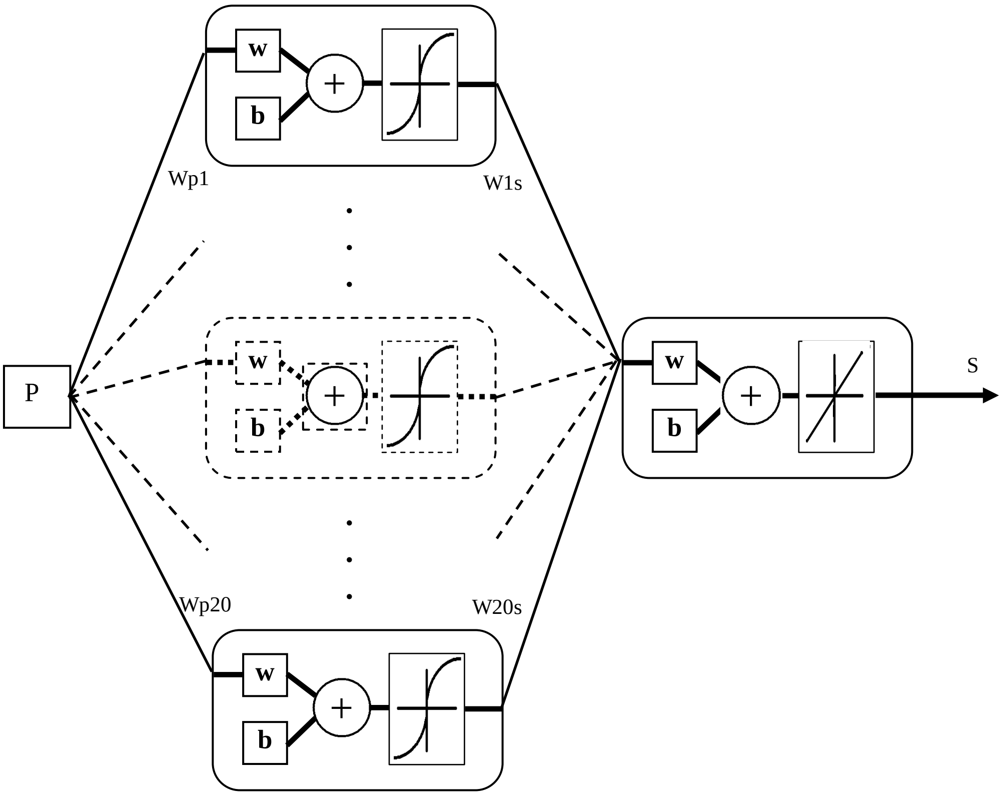

Figure 4. Schematic drawing of the ANN architecture used for the simulation of the SMA hysteretic behavior.

3. RESULTS AND DISCUSSIONS

Before obtaining the data of the behavior of Ni-Ti SMA wire actuator, a cycling procedure necessary to stabilize its thermomechanical response was performed. Figure 5 show a schematic drawing of this training procedure. For this one, 3000 activation cycles were performed under a load of 200 MPa. Figure 6 shows the evolution behavior with a tendency to stabilize the position of the Ni-Ti wire. At the end of cycling, it is observed that the Ni-Ti wire present a permanent deformation under load equivalent to 1.5 mm.

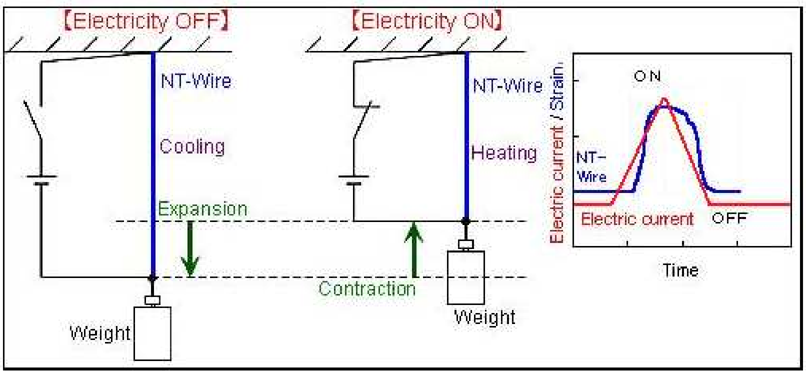

Figure 5. Training schema employed to stabilization of the Ni-Ti SMA wire.

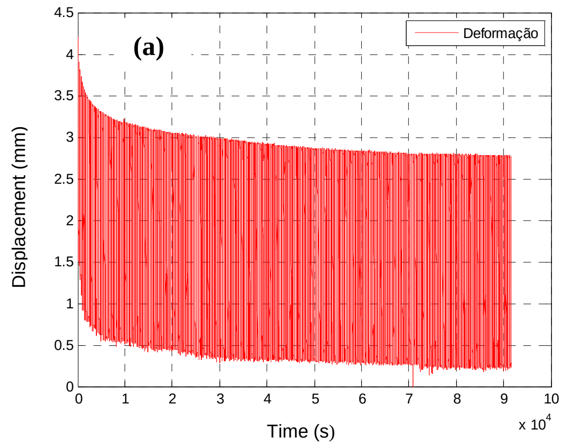

Figura 6. Cyclic displacement stabilization of the Ni-Ti wire for 3000 activation cycles. (a) Evolution as a function of time. (b) Evolution of hysteresis loops of the displacement as a function of electrical current.

Figure 6(b) shows the displacement – current hysteresis loops of the Ni-Ti SMA wire during the stabilization by training. It was observed the same trend of stabilization in Fig. 6(a), accompanied by a reduction of hysteresis in electrical current.

After the training of Ni-Ti wire, an analysis of its response under the load of 200 MPa with different triangular wave current activation was performed. Figure 7 shows the results of displacement due to the change in length of the actuator wire in response to a specific triangular electrical current waveform.

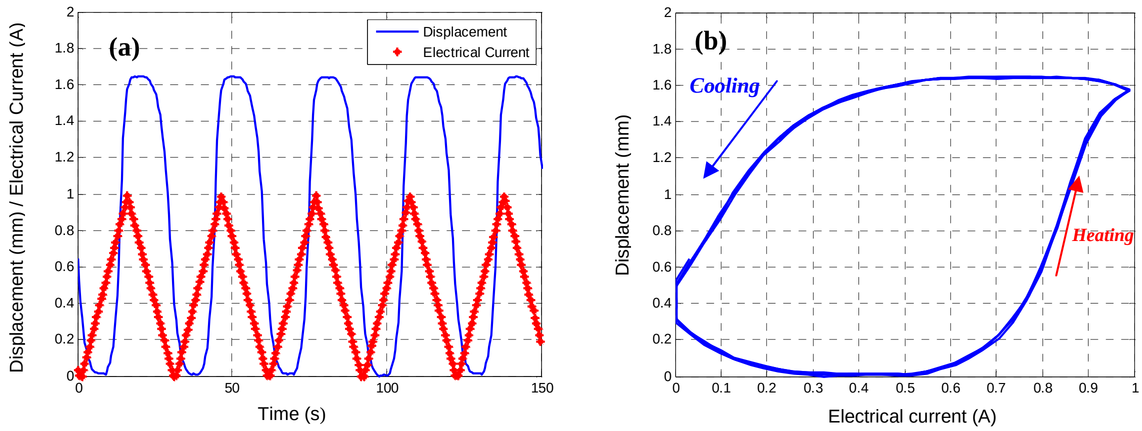

Figure 7. Response of the Ni-Ti SMA wire under 200 MPa and triangular electrical current excitation waveform. (a) Variation of wire length as a function of time. (b) Hysteretic displacement – current loop.

As can be seen in Fig. 7(a), it was observed a delay between the applied current and the response of the trained Ni-Ti SMA wire. It was also noted that the hysteretic loops in Fig. 7(b) present themselves exactly over each other, resulting from the application of electrical current. Comparing Figs. 6(b) and 5(b) it appears that the displacement obtained during the training procedure was higher, but this is because the length of Ni-Ti wire used for training was 100 mm.

To simulate the behavior of the Ni-Ti SMA wire actuator in response to the triangular current waveform using the ANN architecture defined in Fig. 4, it was employed random weights generated by the Matlab® software, as shown in Fig. 8.

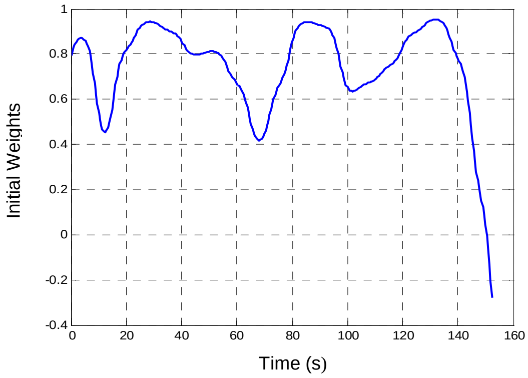

Figure 8. Random weights used for the simulation of experimental data using backpropagation ANN.

Figure 9 shows the results of simulation by ANN for 5 cycles of triangular electrical current excitation of the Ni-Ti SMA wire actuator.

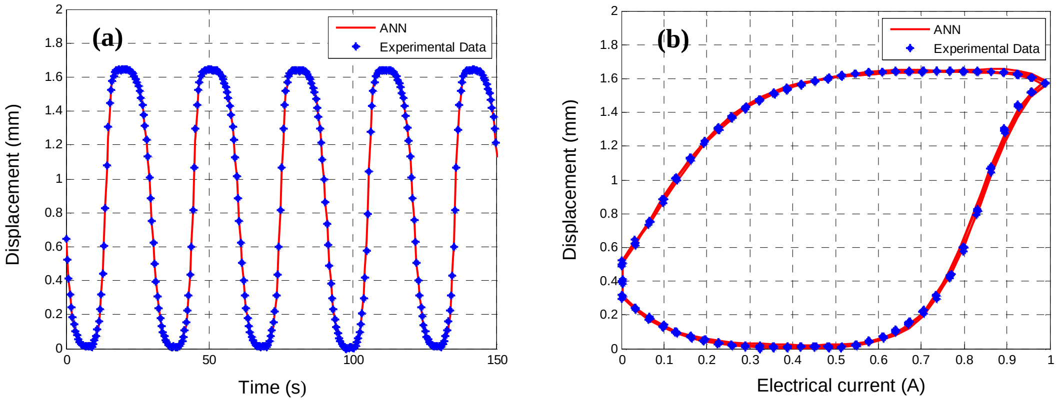

Figure 9. Simulation of the Ni-Ti SMA behavior by ANN. (a) Displacement versus time. (b) Hysteretic displacement – current loops.

For training the ANN it were used 1000 times (epochs). It may be noted that the ANN present a good approximation for both tests, displacement versus time and displacement versus electrical current.

Figure 10 show the experimental results of displacement produced by Ni-Ti SMA wire is response to the application of a reduced triangular electrical current waveform to generate incomplete loops (subloops).

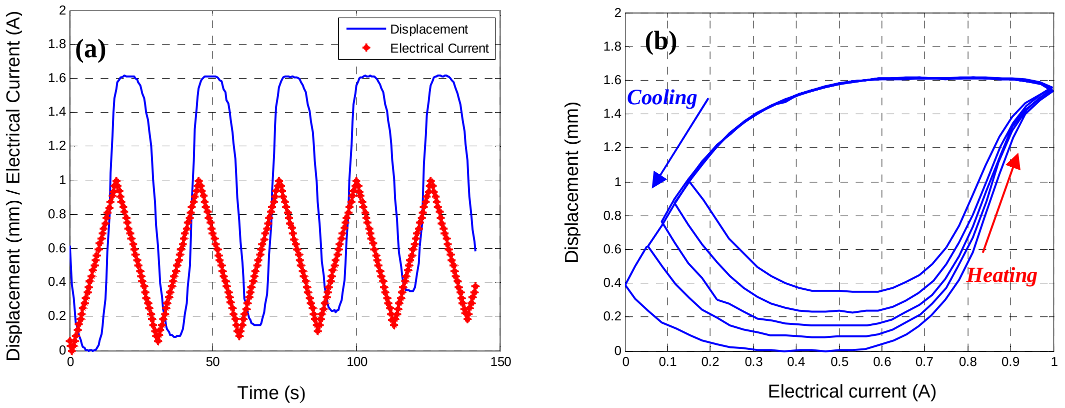

Figura 10. Ni-Ti SMA response under 200 MPa and reduced triangular excitation waveform. (a) Variation of wire length as a function of time. (b) Hysteretic displacement – current subloops.

To simulate by ANN the experimental behavior of the Ni-Ti SMA wire presented in Fig. 8, it was used random weights generated by the Matlab®, as shown in Fig. 11.

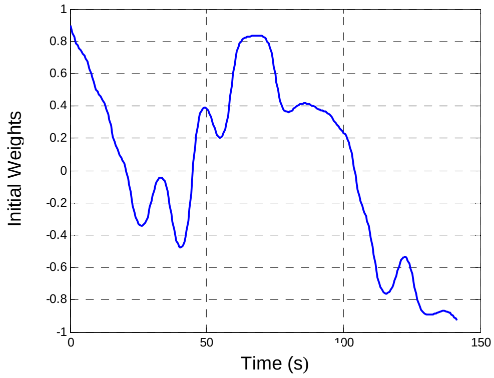

Figura 11. Random weights used for the simulation of experimental data using backpropagation ANN for the case of a reduced triangular electrical current waveform.

Figure 12 shows the cyclic response of the Ni-Ti wire displacement for a reduced triangular electrical current waveform in comparison with the simulation by ANN. This simulation was performed with the aim of present reduced triangular electrical current waveform to test the learning ability of neural architecture. Since as the displacement amplitude is variable, the network learning process becomes more difficult. In practice, it was also required about 1000 epochs to obtain a good network response in relation to input data.

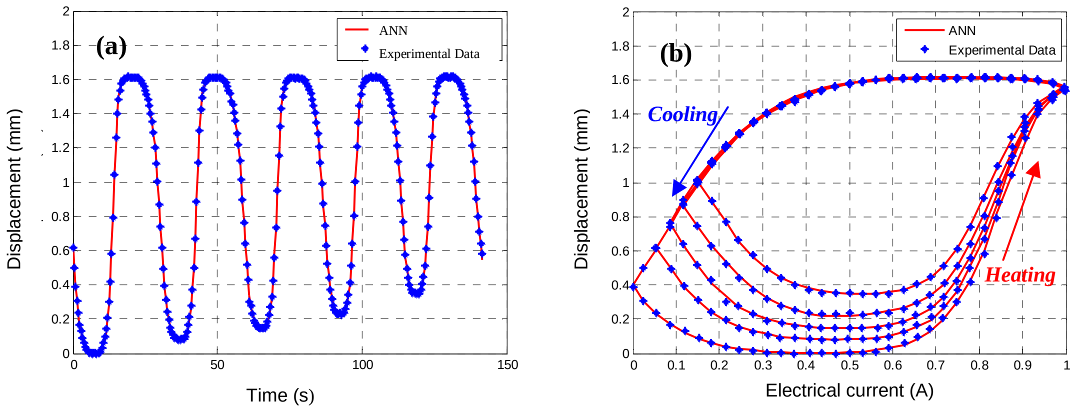

Figure 12. Simulation of the SMA behavior by ANN. (a) Displacement versus time. (b) Hysteretic displacement – current subloops.

Figure 12 (b) shows that during heating the SMA wire actuator does not start immediately its contraction, but only from a current of about 0.5 A. This behavior has nothing to do with physical aspects of the SMA actuator, since it is only a problem of thermal inertia. Thus, physical models available in literature (Lagoudas, 2008) would not be able to simulate this behavior, while the used ANN describes very well.

It can be observed, for both cases of electrical current triangular waveform (complete or reduced), by the good approximation between the experimental data and ANN simulation, that the network have learned very efficiently the behavior of the displacement of the SMA wire as a function of time and applied electrical current. This learning efficiency of the studied ANN can be used to control smart systems incorporating Ni-Ti SMA wire actuators. In this context, recently Nascimento et al (2009) developed a new simple mathematical model for the strain–temperature hysteresis of SMA actuators. These authors comments that limitations in the numerical implementation of mathematical models can generate discrepancies. However, simulation of hysteresis loops using ANN, as demonstrated in this work, can be a relatively easy task due to their ability to learn experimental data.

4. CONCLUSIONS

This work presented simulation of the hysteretic displacement versus electrical current behavior of Ni-Ti SMA wire actuators under load using artificial neural networks. For this, an experimental test bench was designed and assembled for application of constant load (dead weights) in a single Ni-Ti SMA wire actuator where activation is controlled by passage of electrical current. The LabVIEW® software was used to control the resistive heating and cooling of the Ni-Ti SMA wire in addition to reading and store the data of displacement and drop in electrical voltage. A multilayer backpropagation neural network with 20 neurons in the hidden layer and one neuron in output layer was trained using the same experimental data generated from the test bench. Comparisons between experimental and simulated ANN hysteretic loops have shown very good concordance.

5. ACKNOWLEDGEMENTS

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