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Behavioral Modeling and Experimental Verification of a Smart Servomotor Used in a Thermal Control Louver of a Satellite Using Dynamic Neural Network

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ABSTRACT: Louvers are powerful devices for the thermal management of satellites. Nevertheless, the high mass and power consumption and the low reliability of servomotors serving as the actuators of louvers, make the space applications of these technologies very restricted. To tackle this problem, this paper utilizes a shape memory alloy to build a smart servomotor for use in a laboratory louver. The major bottleneck of the use of thermal shape memory alloys is the existence of complex nonlinear hysteretic characteristics in the behavior of these materials. In this paper, a nonlinear autoregressive exogenous model is proposed to predict the nonlinear hysteric behavior of a shape memory alloy. This model is based on a dynamic neural network that its fine function is achieved by a suitable selection of the architecture and the transfer functions of the output and hidden layers. The proposed model is first trained with a batch of test data at the frequency of 0.01 Hz and then validated with another batch of data at the frequency of 0.008 Hz. The training and validation data are obtained from a laboratory louver equipped with a spring of shape memory alloy as the opening actuator of blades. The mean square error of the proposed model for the training and validation data is 1.0325 and 1.0835 degrees, respectively.

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1. INTRODUCTION

Due to high strain, high power to weight ratio, and easy compatibility with structures, Shape Memory Alloys (SMAs) are considered as one of the most attractive actuators in the field of smart systems and have attracted the attention of researchers in various fields of engineering including medical, robotics, space and vehicles [1]. These materials are used as an alternative to classic operators such as DC or servo- motors. This fact motivates one to utilize SMAs for satellite thermal control louvers wherein servomotors are the main bottleneck because of their high mass and power consumption and low reliability (due to using many parts). These disadvantages limit considerably the space applications of louvers despite their noticeable beneficiaries for thermal management systems. Therefore, the employment of SMAs for louvers as the substitution of traditional servomotors is an interesting idea raised in this paper and will be carefully investigated.

The major challenge of these materials when they are used as servo actuators is their complex nonlinear behavior and hysteric characteristics. The hysteresis phenomenon is a usual feature of many smart materials including piezoelectric, magnetostrictive, shape memory polymers, and magnetic shape memory alloys [2]. Despite the attractive features of smart materials, hysteresis restricts the use of these materials particularly for control applications. Therefore, one of the research areas in smart materials, especially SMAs, is the behavioral modeling of them to predict the performance and design model-based controllers for the systems equipped with these actuators. The modeling can be useful for decreasing cost and time in behavioral investigation and designing a good controller. Therefore, many researchers try to propose novel behavioral models for SMAs to develop their applications [3-5].

For modeling hysteresis in smart materials, there are three major categories, which include behavioral physics [6], phenomenological mathematical models [7, 8], and neural networks [9, 10]. In behavioral physics-based methods, the researchers focus on the interactions of the inherent behavior of the material with a material science point of view [11]. Also, phenomenological mathematical models such as Preisach, Krasnoselskii-Pokrovskii, and Prandtl-Ishlinskii [12] are capable to describe a part of the behavior of these materials [13]. In the neural network approach, the behavioral description of the material is established by considering the inherent property of hysteresis and dynamics for the network [14].

Among the three mentioned methods, a behavioral physics-based method is not suitable for control applications due to its complexity. While both neural network and phenomenological methods can provide a model to describe the behavior of smart materials regardless of the system's complete dynamics and only concerning the input and output results. Therefore, the extracted models eliminate unnecessary complexities and would be suitable for control applications. Be-

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sides, the dynamic neural network method, due to its ability to consider system delay dynamics, shows the ability to predict historic behavior better than phenomenological models [15]. Therefore, regarding the specific characteristics of SMAs, the dynamic neural network is the most preferable method for the modeling of these actuators.

The system scrutinized here is a satellite thermal control louver in which an SMA is served as a smart servomotor. This actuator is responsible for opening and closing the blades in accordance with the thermal situations of the orbit wherein the satellite operates. Therefore, the function of the system is considerably impacted by the hysteresis phenomenon. Regarding the above issues, a dynamic neural network model should be employed for the function prediction of the system to get reasonable performance.

There are various approaches to the dynamic neural network applied for systems modeling and identification. The approaches utilized depend deeply on the behavior of the system and so are exclusive to the system identified. For the system presented here, these approaches are never examined until now. Hence, a novel approach based on the dynamic neural network is proposed in this paper to predict the system's complex behavior.

The idea of the authors is to provide a Nonlinear AutoRegressive eXogenous (NARX) model based on a dynamic neural network to describe the complex hysteresis behaviors in the smart servo motor of the louver. This model can predict the complex behavior of the smart servo motor in the shortest time and using a simple model. Paper innovations are summarized as follows:

- Selection and implementation of shape memory alloys as a proper actuator in a laboratory louver instead of traditional servomotor
- Proposing a new neural network-based model to predict the thermal louver behavior equipped with an SMA spring

Section 2 explains the problem description by introducing a hysteresis phenomenon. In the third part of the article, the proposed model formulas and descriptions of its features are discussed. In section 4, the testbed and block diagram used for laboratory tests are indicated. The fifth part deals with the results of the trained model and its validation, and the last part is related to the conclusion of the research.

2. PROBLEM DESCRIPTION

Many smart materials, such as piezoelectric [16], magnetostrictive [17], magnet-based systems [18], and SMAs [3], have a phenomenon called hysteresis. Hysteresis refers to a loss between inputs and outputs of a system as shown in Fig. 1(a).

The presence of hysteresis in smart materials behavior complicates control applications of these materials. When the desired path is given to be tracked to such systems, due to the nonlinear behavior and delay caused by the hysteresis phenomenon, they cannot be controlled with common linear controllers such as PIDs (Fig. 1(b)). Therefore, behavioral modeling of these materials is of particular importance to researchers in the field of smart materials for identifying the effects of different parameters and designing model-based controllers.

There are two transition temperatures in SMAs: martensite or low temperature and austenite or activation temperature. When the temperature of the SMA element is increased by heat and reaches austenite, it tries to recover its defined shape if the SMA element is in a shape other than its defined shape. SMAs, like many smart materials, have a one-directional behavior, meaning they can only return to their defined shape when their temperature is increased. While sweep function is usually required in practical application. Return function is done in SMAs with different mechanisms, one of which is the use of conventional passive springs.

When heating an SMA element is interrupted, the element's temperature is lowered in interaction with the surrounding environment. In this case, the conventional passive spring can overcome the SMA-based spring force and return the SMA spring to its original position. This method can be considered to make a sweep behavior for the SMA-based actuator resulting in a smart servomotor (Fig. 2).

Fig. 2 shows that the louver blades are closed when the smart spring was stretched and the passive spring is at rest position. When the smart spring is heated, it overcomes the passive spring force and decreases its length. The blades are opened as the smart spring is retracted to achieve its defined shape. When the electric current is cut off, the passive spring overcomes the smart spring force and the blades are closed.

3. NARX NONLINEAR MODEL

NARX is a model based on the ARX linear model, which is commonly used in time series modeling. The characteristic equation for the NARX dynamic model is as follows [19]:

$$y(t) = f\,(y(t-1), y(t-1), \ldots, y(t-n_y), u(t), u(t-1), \ldots, u(t-n_u)) \tag{1}$$

In this model, the output values of each time step are calculated based on the input of that instant time step and the inputs and outputs of the previous time steps that makes a dynamic structure. In Eq. (1), f, $u(t)$ and $y(t)$ are a nonlinear function, input, and the network output at time t, respectively.

n_u and n_y are the input and output orders, which determine the system dynamics degree. In the NARX structure, the goal is to find a nonlinear function to describe the complex behavior of hysteresis.

For an approximation of the function, we can use various functions and methods such as fuzzy, neuro-fuzzy, neural network, polynomial functions, etc. The neural network is used to characterize SMAs behavior due to its high capability and flexibility in describing complex behaviors. In this research, a two-layer neural network model of NARX is considered. The first and second layers are known as hidden and output layers, respectively, as shown in Fig. 3.

In Fig. 3(a), a general block diagram of the NARX model is shown in which the output of the NARX model is derived

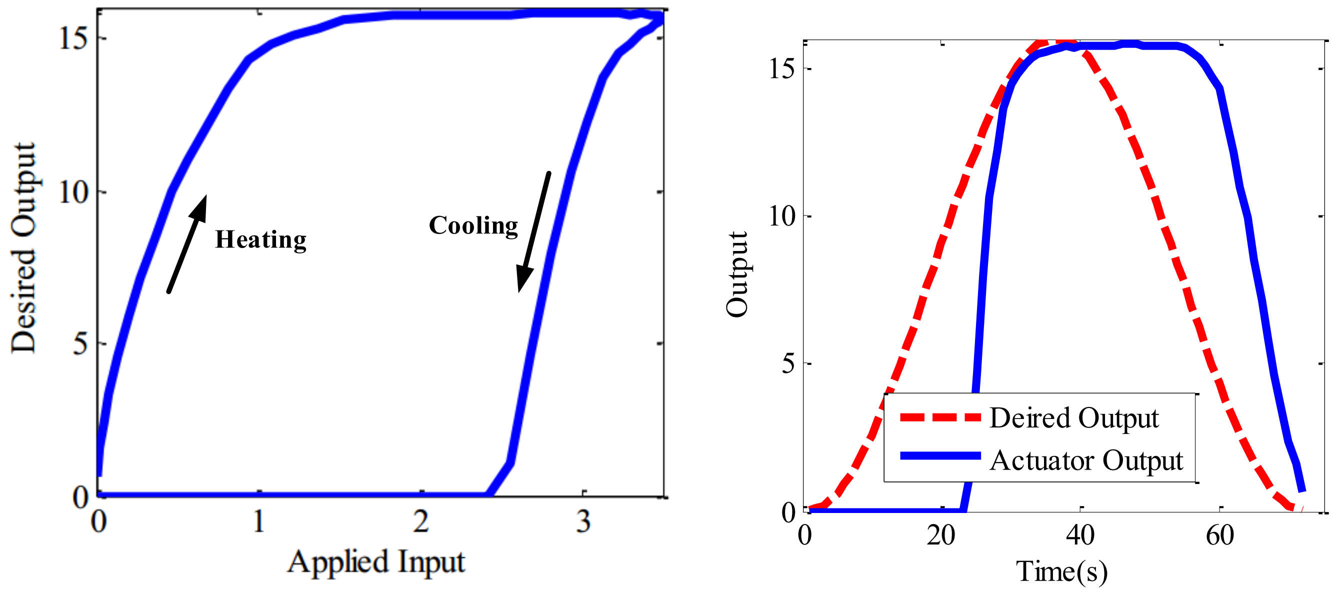
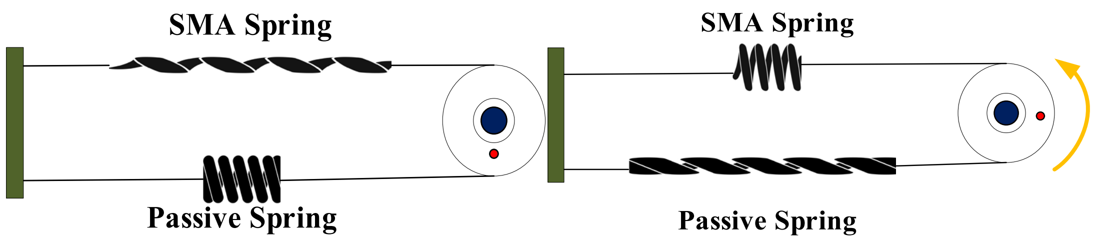
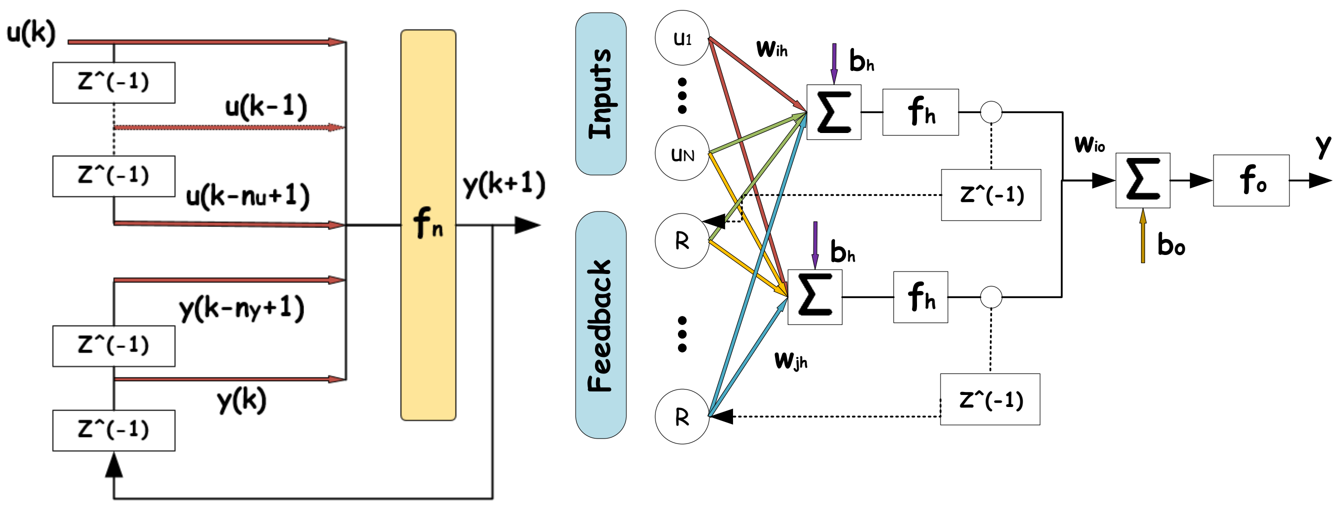


Fig. 1. (a) Hysteresis phenomenon between input and output (b) Complexity in control application



(a) (b)

Fig. 2. (a) Close and (b)open situations for blades in louver



(a) (b)

Fig. 3. (a) general General structure of NARX model b) NARX model based on neural network

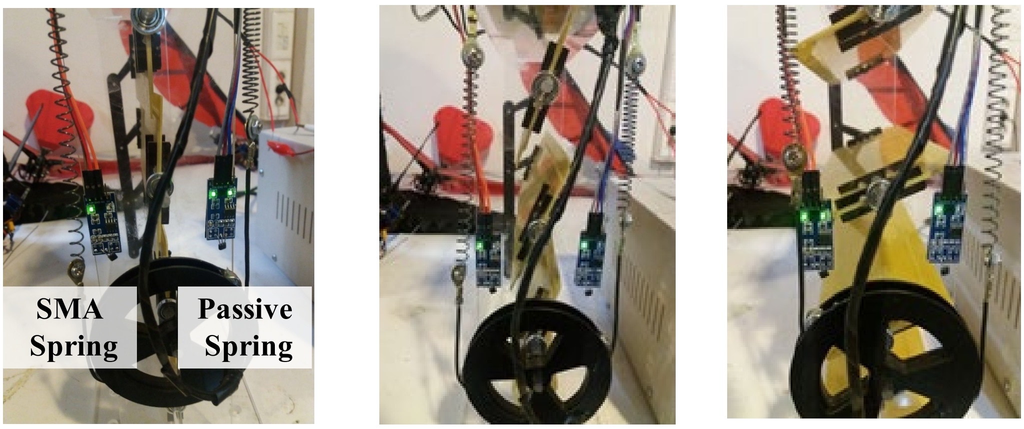
from the input in the same iteration and the previous inputs and outputs. Fig. 3(b) illustrates the NARX model based on a neural network that determines the nonlinear function f .

In this figure, u, y, f_h and f_o are input, output, the hidden layer function and the output layer function, respectively. Parameters w_{ih} , w_{io} , z, b_h and b_o are the hidden layer weights, the output layer weights, the delay element, the hidden layer bias values, and the output layer bias values, respectively. The use of the neural network provides a NARX model with flexibility and capability to describe the hysteresis complexities of shape memory alloys, and the choice of two layers for it reduces the cost of computation.

4. EXPERIMENTAL TEST-BED

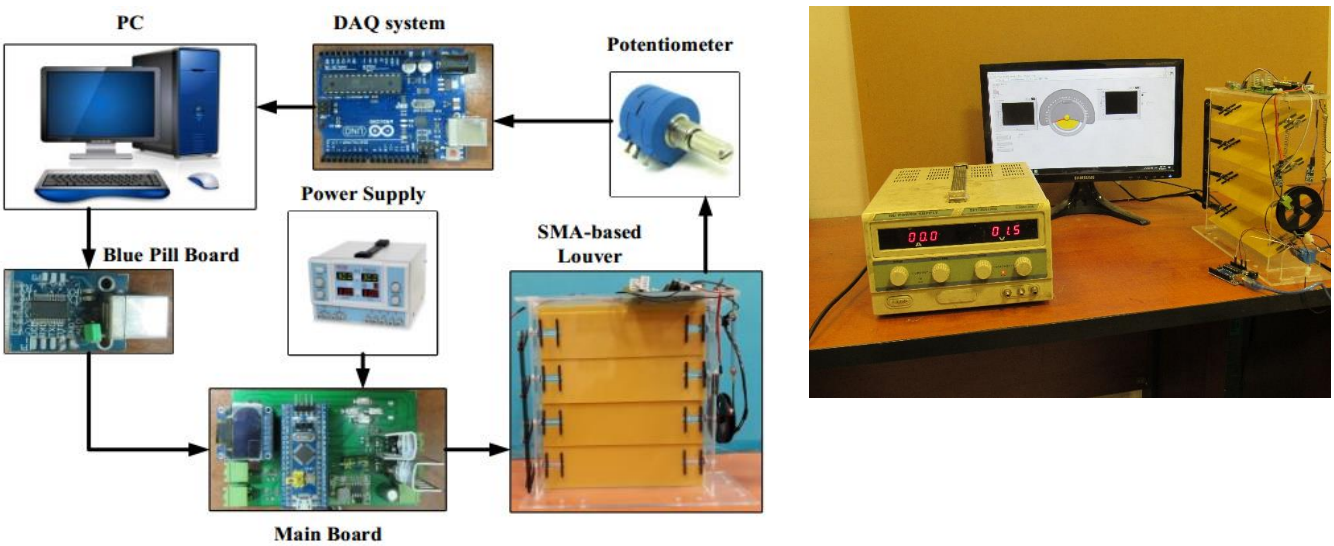
In this study, an SMA-based spring is used to construct a smart servomotor to open and close the blades of a thermal control louver of the satellite due to their lightness and high adaptability. Fig. 4 shows how the blade works with SMA-based servomotor.

This smart servo motor, due to its high resistance to corrosion and adaptability to temperature variations, is a



(a) (b) (c)

Fig. 4. Different situations of blades of thermal control louver (a) closed (b) starting to open (c) open



(a) (b)

Fig. 5. (a) Block diagram of testbed equipment connections (b)Lab setup and related equipment

good alternative to replace traditional actuators. In this study, the test data is obtained using the laboratory louver sample. The used equipment is shown in Fig. 5.

In this laboratory test-bed, the input signal is transmitted through the LabVIEW software (PC) into the electronic board, which is the interface between the computer and the mainboard of the SMA-based spring. The mainboard applies the appropriate input using the power supply to the smart spring. By applying the voltage to the smart spring, the spring is warmed up because of an applied electric current. Heating causes the smart spring to be entered into its active phase and then the spring tries to reach its defined shape. Finally, the position of the blade changes and the blades are opened. When the harmonic voltage decreases, the passive spring used as a return mechanism overcomes the generated force of SMA-based spring. Consequently, the blades are closed because of the force of passive spring. The panel blade angle is calculated using a potentiometer, transferred by an Arduino board, and stored in PC. The specifications of the equipment used are shown in Error! Reference source not found..

The smart spring specifications used to build the smart servo motor are shown in Error! Reference source not found..

To generate training and validation data, two harmonic inputs are applied to the smart servomotor at frequencies of 0.008 and 0.01 Hz, and the change of the blades angle is obtained by the potentiometer due to the applied input voltage. The main electronic board is designed for activation of the smart spring. The initial status of the panel is in a closed state. When the voltage rises, the smart spring that opens the panel is activated and the panel starts to be opened. This opening will continue until the input reaches its maximum range called a heating cycle. By reducing the input voltage amplitude, while the temperature of the smart spring starts to be decreased because of heat transfer with the surrounding environment, the passive spring force overcomes the smart spring force and the panel starts to be closed. The inputs and outputs of the training data and model validation are shown in Fig. 6.

Fig. 6 (c) shows that between the input and output in the heating and cooling cycle, there are loops that are known as hysteresis and are caused by the loss of thermomechanical behavior of smart material. This figure shows that by increasing the input frequency, the hysteresis loops between the input and the output of the smart servomotor are reduced, which is the opposite of the behavior of shape memory alloy wires [20]. When the frequency is increased, the heating time of the spring to complete the martensitic to austenite transformation will be decreased. Since part of the material loss is related to the phase transformation, the hysteresis will be reduced. Therefore, reducing losses in the phase transformation leads to the reduction of hysteresis loops width.

5. RESUTLS AND DISCUSSION

In this study, two categories of data have been used: for training and validation of the proposed model. For the learning of the proposed network weights, the gradient descent method

Table 1. specifications of test-bed equipment

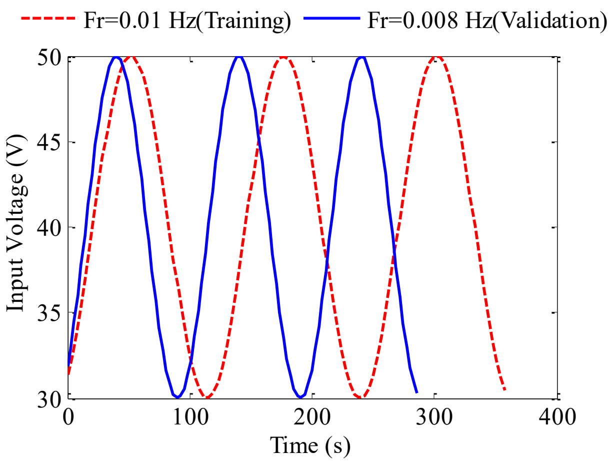
Characteristic	Description
Experimental setup	The louver is equipped with an SMA spring and a passive spring for opening and closing the blades, respectively
Protractor	Potentiometer 1-kilo ohm with 10 turns
Processing system	Dual-core computer, 2 GHz processor, 2 gigabytes of RAM
Software	LabVIEW 2013
DAQ system	Arduino UNO R3
Electronic boards	Electronic interface board for launching mainboard (blue pill), the mainboard

Table 2. smart spring specification of laboratory test-bed

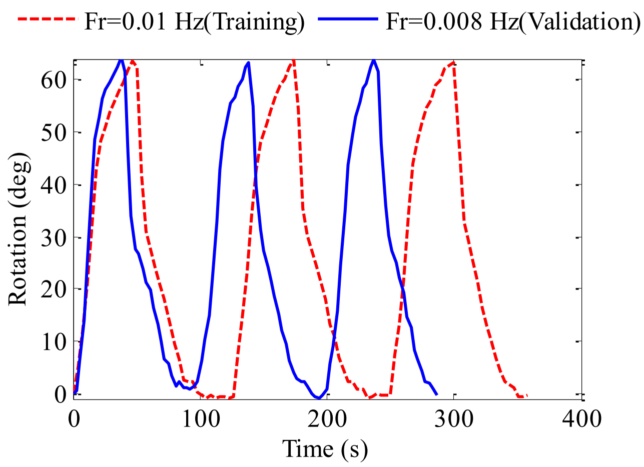
Characteristic	Parameter	Value	Unit
Inner diameter	d_i	5	mm
Spring wire diameter	t	0.2	mm
Total length of spring	l	35	mm
Maximum active spring length	l_t	100	mm
Martensite start temperature	M_s	50	℃
Martensite final temperature	M_f	55	℃
Austenite start temperature	A_s	70	℃
Austenite final temperature	A_f	90	℃

Table 3. Specification of proposed NARX model

Property	Parameter	Value
Order of input dynamic (delay in input)	*ID*	2
Order of output dynamic (delay in output)	*OD*	2
First layer size	*S1*	3
Second layer size	*S2*	1
Transfer function of the hidden layer	*TF1*	*"tansig"*
Transfer function of the output layer	*TF2*	*"tansig"*
Backpropagation network training function	*BTF*	*"trainoss"*
Backpropagation weight/bias learning function	*BLF*	*"learngdm"*
Learning rate	*lr*	0.01
Momentum constant	*mc*	0.9
Network performance cost function	*PF*	*"mse"*



(a)



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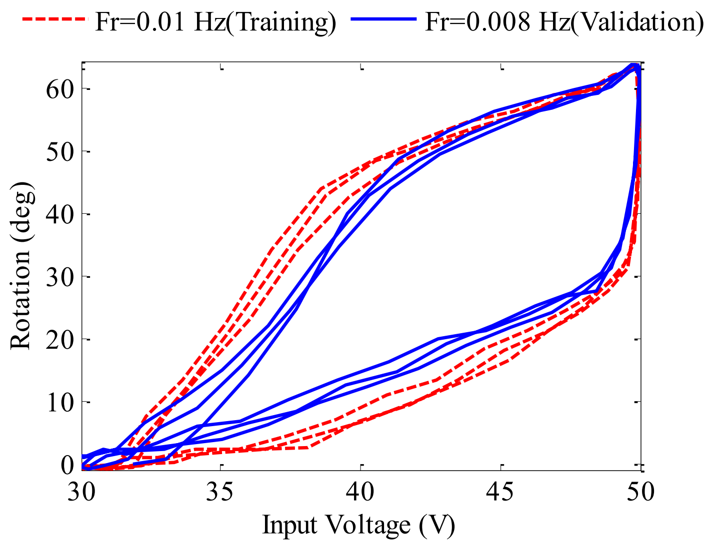


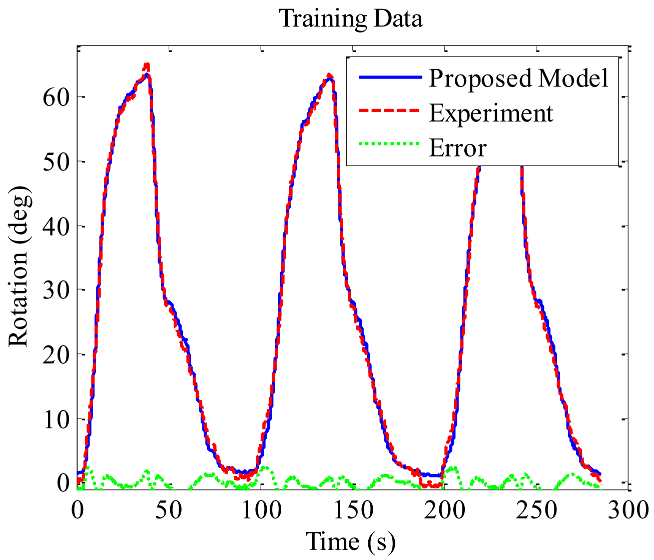
(c)

Fig. 6. (a) Input and (b) output of training and validation data (c) Hysteresis loops between input and output of training and validation data

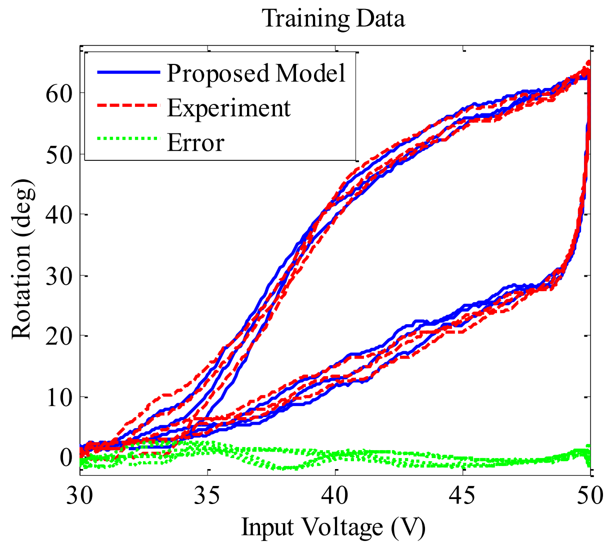
has been used which leads to an increase in the convergence rate of the feedforwarded networks. The momentum used in this approach, allows the network to respond to local changes and recent tendencies of the error plane. Like a low-pass filter, momentum allows the network to ignore small features on the error plane. Without momentum, a network may be limited to a local minimum and cannot determine the appropriate coefficients. Via momentum, the ability of the network to move to the other lowest points would be possible. The "*learningd*" function calculates the weight changes of the

Table 4. LSE of the proposed model for training and validation data

Data type	Value (deg)
Training	1.0325
Validation	1.0835



(a)



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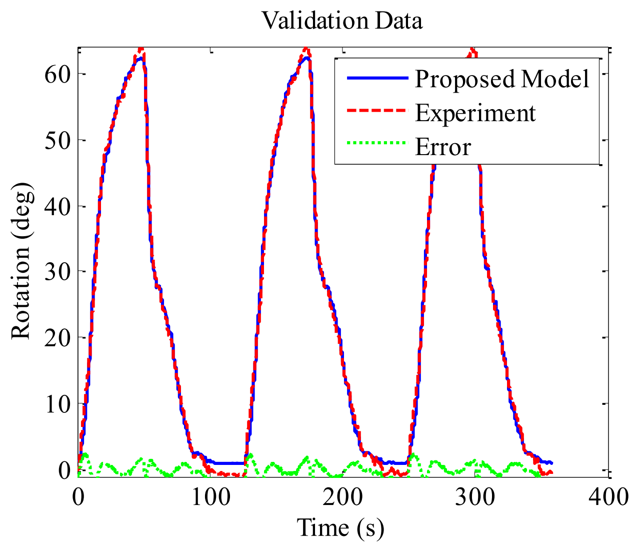

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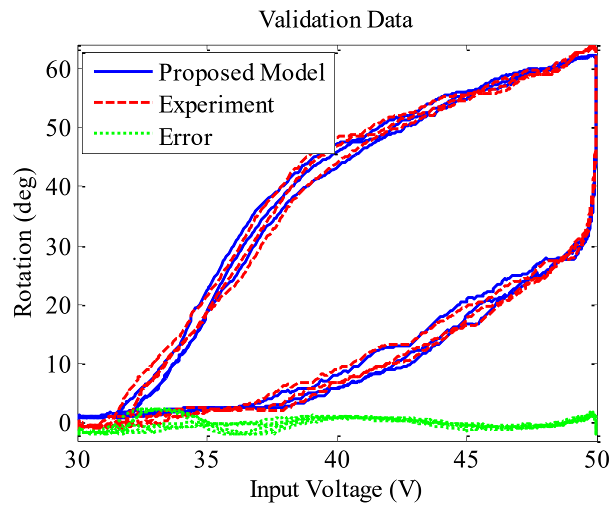

(d)

Fig. 7: . Comparison between the outputs of the proposed model and the smart servomotor based on training process: ((a) Voltage-time,(b)Voltage-Rotation(hysteresis loops)) and validation process: ((c) Voltage-time,(d)Voltage-Rotation(hysteresis loops))

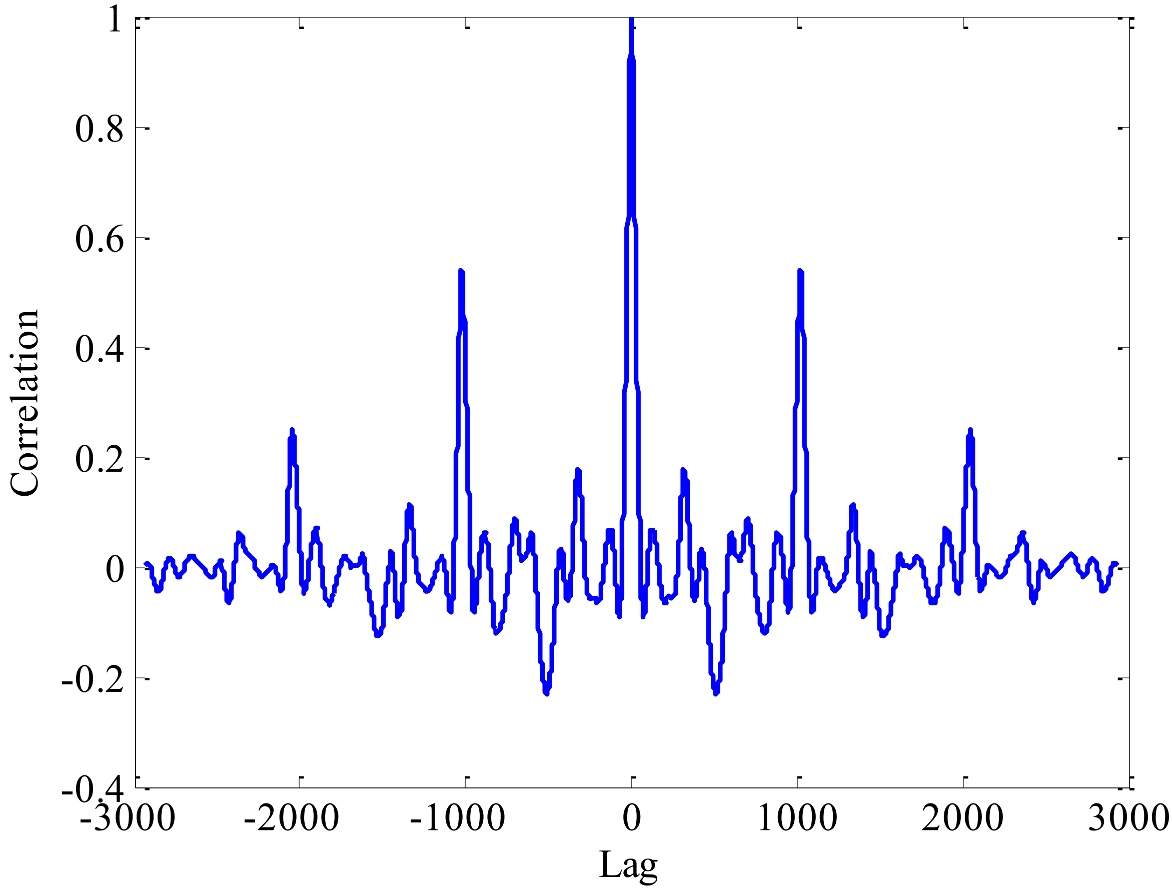

Fig. 8: . the The correlation of the proposed model error for the validation process

given neuron from the input, neuron error, weight (or bias), learning rate, and the momentum constant on the gradient descent with the momentum, as shown in Eq.(2).

$$d_{W_{k+1}} = m_c d_{W_k} + (1 - m_c) l_r g_w \tag{2}$$

In this equation, $d_{W_{k+1}}$ is the weight changes, m_c is the momentum constant, d_{W_k} is the previous weight changes, l_r is the learning rate and g_w is the gradient with respect to performance. In this research, the "*trainoss*" method is used to train the network. This method can train any network as long as there are weight derivatives, network input, and transfer functions. The "*backprop"* method is utilized to compute the derivative of the cost function relative to the weight and bias variables. Each variable is calculated by Eq. (3):

$$X = X + ad_X \tag{3}$$

In Eq. (3), d_X depicts the direction of the search and parameter *a* is selected to minimize the goal function along the search direction. The initial direction of the search is determined by the gradient descent of the goal function. In successive iterations, the search direction is calculated from the new gradient and the previous steps and gradients that are shown in Eq. (4):

$$d_X = -g_X + A_c X_{step} + B_c d_{g_X} \tag{4}$$

In Eq. (4), g_x , $X_{step,}$ and d_{g_X} are gradient, change on the weights in the previous repetition, and the change in the gradient of the last iteration, respectively. A_c and B_c are constant coefficients of the formula. Properties of the proposed NARX model are shown in Error! Reference source not found..

In the proposed model, a tangent function is used as transfer functions of the hidden and output layer, because the function is appropriate due to its proportionality with the behavioral properties of the shape memory alloys [7]. The results of the proposed model training are shown in Fig. 7 (a,b). As it is clear from the results of the training, the authors have been able to offer a model with the ability to describe the complex behavior of hysteresis, with a presentation of suitable network architecture, appropriate teaching and learning functions, and selection of exact transfer functions. In order to examine the performance of the trained model, it must have the ability to describe this behavior with new given data as validation. The results of the validation of the proposed model are shown in Fig. 7 (c,d).

based on the validation results of the proposed model, it is well able to describe the hysteresis behavior in an SMA-based smart servomotor. The Least Squares of the Error (LSE) for the two categories of training and validation data are shown in Error! Reference source not found..

Statistical analysis of the proposed model error is a good way to show the correctness of the proposed model. In this manner, a good prediction of the model obtains an estimation error similar to the white noise. In other words, the more accurate model can be achieved the more similarity to white noise. Therefore, in addition to comparing measured experimental data and the estimated results by the proposed model in the validation process, a statistical test has also been investigated on the estimated output error that is called the autocorrelation test. An estimate of autocorrelation is calculated as follows:

$$\hat{r}_{\varepsilon}(\tau)=\frac{1}{N}\sum_{t=1}^{N-\tau}\varepsilon(t+\tau)\varepsilon(t) \tag{5}$$

where N indicates the number of data samples and t shows the time shift parameter. If we have more data samples, we will have more accurate for the above function. In this model evaluation test, the autocorrelation of the proposed model output error is computed and compared with the white noise autocorrelation function. White noise has a non-zero autocorrelation value at zero lag and zero value at any other lags.

It means if the estimation error $\varepsilon(t)$ is white noise, then its covariance function is zero except at zero lag. Consequently, if N is large enough and estimation error autocorrelation has a relatively low value at other lags, therefore, $\varepsilon(t)$ is white noise and it is figured out that the estimation error is mostly concerned with data acquisition noise, not model inaccuracy. Normalized autocorrelation of the estimation error of the validation dataset is shown in Fig. 8.

Fig. 8 shows that the autocorrelation function of the proposed model error is maximum at zero lag and has a small value at other lags. Most of the autocorrelation function lies inside the range of [-0.2,0.2]. Therefore, it is figured out that the estimation error is similar to white noise which indicates the model correctness. In other words, the estimation error is mostly caused by measurement devices and ambient noise but not from model inaccuracy.

It should be noted that the autocorrelation function of white noise is obtained with the assumption of a very large number of data samples. It means if the number of data samples is increased, the autocorrelation function described in Eq. (5) becomes more accurate. Therefore, estimation error and white noise autocorrelation functions cannot be exactly the same in this case while the number of data samples is limited.

Also, one point should be taken into account that the proposed model cannot exactly characterize the hysteresis behavior of the servomotor actuator. However, this manner used in this study is a very suitable and relatively high precision model which turns it into one of the best manners to predict smart structures hysteresis.

6. CONCLUSIONS

Considering the attractive attributes of shape memory alloys in this research, an SMA-based servo motor was used as an actuator to open and close the thermal control louver of a satellite. The authors modeled the complex hysteresis behavior in the smart servo motor by a proposed NARX model based on a neural network. Two data sets were generated from the experimental test-bed of the thermal control louver for training and validation of the proposed model. In the first step, for the proposed model, suitable network architecture was designed and suitable training and learning algorithms, as well as accurate transfer functions, were considered. The proposed model was trained with an experimental data set. the results of training demonstrated the ability of the proposed model to describe the complex behavior of the smart servomotor. To validate the model, another data set was used for the investigation of the model performance. In the validation process, the model could predict hysteresis complex behavior well. Therefore, the proposed model could be used to describe the complex behavior of a smart servomotor.

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