JCAMECH

Vol. 49, No. 1, June 2018, pp 9-17
DOI: 10.22059/jcamech.2017.234999.151

Modeling SMA actuated systems based on Bouc-Wen hysteresis model and feed-forward neural network

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ARTICLE INFO

Article history:
Received: 06 June 2017
Accepted: 25 September 2017

Keywords:
Shape memory alloy (SMA)
Hysteresis behavior
Bouc-wen model
Artificial neural network (ANN)

ABSTRACT

Despite the fact that shape-memory alloy (SMA) has several mechanical advantages as it continues being used as an actuator in engineering applications, using it still remains as a challenge since it shows both non-linear and hysteretic behavior. To improve the efficiency of SMA application, it is required to do research not only on modeling it, but also on control hysteresis behavior of these materials which are the fundamentals of several research opportunities in this area. Having considered these requirements, we have introduced a mathematical model to describe the hysteresis behavior of a mechanical system attached to SMA wire actuators using Bouc-Wen hysteresis model and feed-forward neural network. Due to inability of linear mass-spring-damper equations of classic Bouc-wen model to explain the hysteresis behavior of SMA actuators, in this paper we have applied changes in the mentioned equations of classic Bouc-Wen model to describe hysteresis loops of model. We also have used flexibility of the neural network systems to describe Bouc-Wen output in the main equation. Parameters of the developed model have been trained for a real mechanical system using simulation data after selecting proper configuration for the selected neural network. Finally, we have checked the accuracy of our model by applying two different series of validation data. The result shows the acceptable accuracy of the developed model.

1. Introduction

Generally, there are two methods for modeling and identifying the hysteresis [1]. First method is based on hysteresis physical characteristics and some experimental coefficients. This method is rarely used as it is unable to detect some of the physical properties that affect the hysteresis and likewise its lack of generalization among different cases. Second method is based on hysteresis phenomenology and describes the phenomenon merely by mathematics. Among research studies conducted based on phenomenology, due to the need to describe the hysteretic behavior of SMA, phenomenological models based on thermo-mechanics of crystalline-phase-transition has been developed for SMA materials [2]. In these type of models, Boyd and Lagoudas model which is developed based on Gibbs free energy [3] and Brinson model which is based on Helmholtz free energy, are more popular. Brocca et al. also introduced a 3-D model using microplane and one dimensional Brinson model [4]. In addition, there are numerous models developed based on thermo-mechanics and Gibbs free energy and Helmholtz free energy [5]. Due to widespread applications of (one-dimensional) shape memory alloy actuators, many constitutive models are developed to describe 1-D actuators. Including in these models are Tanaka, Liang and Rogers and modified Brinson models [6] , [7]. Among these models, Brinson, Liang and Rogers model are developed based on Helmholtz free energy. Poorasadion et al. improved Brinson model for asymmetrical hysteresis behavior and implemented it in modeling of a two-dimensional beam element [8]. Dutta et al. developed hysteresis differential model to describe phase transition in crystalline forms and heat transfer of the SMA's actuator [9]. Among purely mathematical methods that models the SMA hysteresis behavior, the models based on play hysteresis operator can be mentioned. Zakerzadeh et al. modeled a cantilever beam with SMA actuator wires using Krasnoselskii-Pokrovskii (KP) hysteresis model [10]. In addition, they modeled hysteresis behavior of the mentioned dynamic system using Preisach model and neural network. The model was validated by experimental data [11]. In another paper the generalized Prandtl-Ishlinskii (PI) method was used by them to model the mentioned dynamic system and used the inverse of the developed model in a feed-forward controller to control the deflection at the end of the beam [12]. Another method based on mathematics to model hysteresis of smart materials is combination of Fuzzy Logic and Neural networks or ANFIS.

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Tafazoli et al. used ANFIS method to model hysteresis of a morphing wing with SMA actuator [13]. Rezaeeian et al. modeled system including SMA actuator with ANFIS method and controlled it with feed-forward controller [14]. There are other mathematical methods that employs differential models to describe the hysteresis behavior. Because this paper focuses on this type of methods, in the rest of this paper the history of this type of hysteresis modeling as well as identification and control of these methods (not SMA only) will be stated. One of the most important differential methods for hysteresis modeling is Duhem rate-independent model [15-17]. Generalization of this model is used as a basis to develop other hysteresis models such as Dahl, LuGre and Maxwell-Slip [18] friction models as well as Bouc-Wen hysteresis model. Xie et al. used Duhem model and neural network to design a state-observer to control Piezo-electric actuator [19]. Zhou et al. used the same hysteresis model to describe the piezo-electric actuator behavior [20]. Jayawardhana et al. used the dissipativity approach to analyze dynamic stability of electromagnetic-based actuators by Duhem method [21]. In addition to the above mentioned research studies, in Aiki et al. Duhem differential equations are used to illustrate the correlation of stress and strain in SMA wires [22]. One of the other hysteresis differential models is Jiles-Atherton (J-A) model which is independent of input rate (namely rate-independent model). This model was presented first for the modeling of hysteresis behavior in ferromagnetic materials. Annakkage et al. presented a new model based on the J-A model for modeling the hysteresis in magnetic materials at low frequencies and accurately described the asymmetric interior hysteresis loops [23]. In addition, modeling and identification of magnetic behavior in magneto-electric composite material by J-A model was performed by Pop and Călţun [24]. Further research in this area include identifying the model parameters by using identification method based on Genetic Algorithm (GA) [25], Particle Swarm Optimization (PSO) [26] and Differential Evolution [27]. As noted previously, Bouc-Wen differential model [28], [29] is a Duhem type model. Due to its ability in describing hysteresis loops with different trigonometric features it has widespread applications. One of the modification made and developed on this model is asymmetric Bouc-Wen model and Bouc-Wen-Baber-Noori (BWBN) to explain pinching hysteresis behavior [30]. Ikhouane et al. studied on dynamic specifications of Bouc-Wen hysteresis model including domain stability, free response and energy loss and have categorized model parameter [31]. Li et al. analyzed the model in terms of dynamics in order to explain non-linear behavior of SDOF oscillator [32]. In another research, Awrejcewicz et al. introduced a model to describe hysteresis behavior in Magneto-rheological Damper (MR Damper) and Ni-Ti poly-crystal (SMA's super elastic feature) by using Massing-Bouc-Wen framework [33]. Peng et al. used Bouc-Wen hysteresis model to predict hysteresis behavior of non-linear systems with lag (such as magneto-rheological damper). They discretized the model to configure it in a multi-layer feed-forward neural network system and trained the neural network with experimental data [34]. Zhu et al. analyzed parameter specifications in normalized Bouc-Wen model and introduced offline identification method based on LS (Least-Square) method to identify model parameters by using experimental data at constant frequencies for a mild steel damper [35]. Zhu et al. used asymmetrical Bouc-Wen model with offline identification method based on LS to identify a real system parameters including piezo-ceramic actuator [36]. In another research, Wei used asymmetric Bouc-Wen model with online identification method based on LS to precisely identify hysteresis behavior of a rate-dependent piezo-ceramic actuator (at inconstant frequencies) [37]. Sengupta et al. modeled structural hysteresis behavior of a reinforced concrete beam-column by Bouc-Wen-Baber-Noori (BWBN) model and identified model parameters by using Genetic Algorithm (GA) using experimental data (earthquake) [38]. One of the research studies in the field of identifying the Bouc-Wen model parameters is performed by Charalampakis et al., They introduced identification method based on Greedy Ascent Hill Climbing (GAHC) and Saw-tooth GA model for identifying the parameters of a non-linear mass-spring-damper model (elastic-plastic spring) described by Bouc-Wen model . They tested the ability of the method by using data accompanied with noise and without noise [39]. To improve the efficiency of SMA application, it is required to perform research on SMA modeling as well as control its hysteresis behavior. Having considered these requirements, In this paper, a mathematical model is proposed to describe the hysteresis behavior of a mechanical system attached to SMA wire actuators using Bouc-Wen hysteresis model and feed-forward Artificial Neural Network (ANN). Due to failure of linear mass-spring-damper equations of classical Bouc-wen model to explain the hysteresis behavior of SMA actuators, we have also applied significant changes in the equations of classic Bouc-Wen model to accurately describe the SMA hysteresis loops. In addition, we have used flexibility of the neural network systems to describe Bouc-Wen output in the main equation. To evaluate the developed model, the simulated data sets from a real system are used. The result shows the acceptable accuracy of the developed model with respect to the validation data. The paper is organized as follows. Section 2 is dedicated to the Bouc-Wen hysteresis model. In this section the mathematical equations and application of this model are described in details. In section 3, an SMA hysteresis modeling method based on the Bouc-Wen and feed-forward ANN is presented. Parameters calibration and identification of the developed model are described in section 4. In section 5, a real system simulation data are used in order to verify the modified model. The presented model is evaluated using simulated data sets in section 6. Finally, the concluding comments are provided in section 7.

2. Bouc-Wen Hysteresis Model

Bouc-Wen model is considered to be a differential method of general hysteresis modeling techniques. As it is a Duhem-type, it inherently is rate-independent model. Moreover, this model is honored due to its mathematical characteristics which is capable of indicating remarkable resilience in describing hysteresis behavior governed in hysteretic systems. However, the general model only can describe symmetric hysteresis loops and just expresses hysteresis loops in hardening and softening shapes.

Since the Bouc-Wen model can describe non-linear and hysteresis part of a dynamical system, its non-linear output is usually interpreted using linear function in a linear dynamical system. The equations of this model and the mentioned dynamical systems are given in the following coupled equations:

$$\ddot{x} + 2\xi\omega_n\dot{x} + \delta\omega_n^{\,2}x + (1-\delta)\omega_n^{\,2}z = u(t) \tag{1}$$

$$\dot{z} = A\dot{x} - \alpha|\dot{x}||z|^n\, sign(z) - \beta\dot{x}\,|z|^n \tag{2}$$

where equation (1) denotes a mass-spring-damper system while equation (2) or Bouc-Wen equation represents non-linear part of the spring and its output for the expression of non-linear response of springs has been used in the equation (1). In equation (1), x, $\dot{x}$ and $\ddot{x}$ are the displacement, velocity and acceleration of the mass in mass-spring-damper system respectively. In addition, z is the parameter related to the non-linear part of the system which is obtained from equation (2). In addition, $u(t)$ is system's input or external stimulus to the system. ω_n and ξ are natural frequency and damping ratio of the linear system, respectively. δ is a parameter which is used to determine whether the spring behaves linearly or non-linearly. Therefore, its value is variable from [0 1] interval. It means that when spring acts purely linear δ=1 and when it acts purely non-linear δ=0.

In Bouc-Wen equation (eq. (2)), $\dot{x}$ acts as input to the equation while z is the hysteresis output of the equation. In the mentioned model, A, α, β and n are dimensionless coefficients that determine the shape and slope of hysteresis loops. Therefore, these coefficients should be identified by the experimental measured data. Overall, A, α and β are used to illustrate hysteresis loop's dimensions and n is used to determine the sharpness of the hysteresis loops. Generally, for the set of real numbers the shape and dimensions of hysteresis loops could be identical for different sets of the mentioned coefficients. Therefore, for avoidance of duplication, the equations have been used under conditions in which, $A = 1$ and $|\alpha|+|\beta| = 1$, $n \geq 1$.

Fig. 1. illustrates the output of the Bouc-Wen model (i.e. z) as a function of mass displacement input (i.e. x) when $A = 1$,α =0.4 , β = 0.6 and $n = 1$.

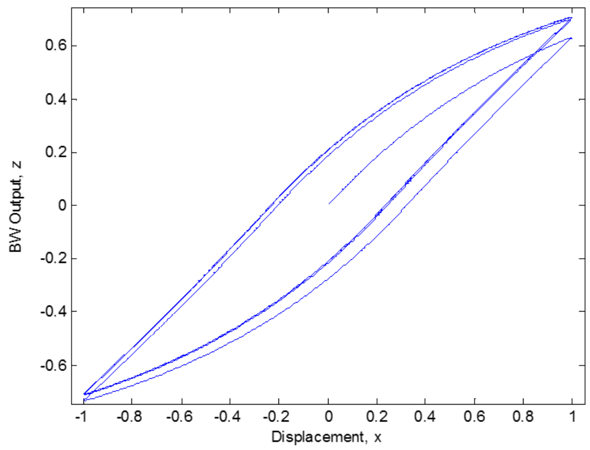

Figure 1. Output of Bouc-Wen model z verses input x.

3. SMA Hysteresis Modeling

As mentioned in the introduction section, Bouc-Wen model has been developed to describe the hysteresis behavior of mechanical structures and dynamical systems. However, the classical version of Bouc-Wen model (equation (2)) is incapable of describing the hysteresis behavior of SMA materials. As a result, this version of the model has not been yet directly used to describe the behavior of systems actuated by SMA actuators, precisely. Hence the classical version of the Bouc-Wen model needs to be changed accordingly.

In systems with SMA actuation, SMA temperature, the voltage or electrical current are literally system input and strain of the SMA actuator or displacement of the body attached to the actuator is system output. Therefore, in a developed model in this study, we try to decrease the correlation of system's input to dynamic of system, using some mathematical tricks.

In the following coupled equations, the single input-single output (SISO) developed model based on the classical Bouc-Wen model is introduced in order to describe the hysteresis behavior of systems actuated by SMA actuators:

$$\ddot{x}+2\xi\omega_n\dot{x}+(2\delta-1)\omega_n^{\,2}x=net(x,z)+k(u(t)-u_{\min}) \qquad (3)$$

$$\dot{z}=A\dot{x}-\alpha|\dot{x}||z|^n\,sign(z)-\beta\dot{x}|z|^n \qquad (4)$$

In equation (3), ω_n and ξ are in accordance with the previous definitions given previously. However, since they do not present physical characteristics in the current developed model, their values have been set arbitrarily and are user-defined. It is recommended that the values of ω_n and ξ be chosen in a way that the dynamic system responds to the input in the fastest way and the transient response of the equation becomes damped as fast as possible. Hence, it is desired to choose $\xi = 0.7$ and ω_n assigns a high value [40].

It has been suggested that the value of δ which is introduced to determine the major hysteresis loop be selected in [0, 1]. It is evident that the hysteresis loop gets smaller as the value of δ reaches the lower limit of the mentioned interval.

The term $net(x ,z)$ expresses the feed-forward Artificial Neural Network (ANN) having two inputs, x (system displacement) and z (Bouc-Wen's output). In other words, our feed-forward neural network has replaced the linear function in classical Bouc-Wen model to assist describing the hysteresis behavior of SMA. In the developed model we try to use the ability of ANNs in explaining sophisticated non-linear functions straightly and make the system's hysteresis part to appear in equation (3) (mass-spring-damper) non-linearly. Same as the classical model, $u(t)$ states the system's stimulus input which is SMA temperature for the SMA actuated systems. Also, u_{min} is as well the initial temperature of the SMA actuator.

As it is seen in equation (4), parameters of A ,α ,β and n are similar to the parameters for the classical model explained in the previous part. However, the key point in selecting these parameters depend on understanding the logic behind using the Bouc-Wen hysteresis model in the developed model. The main idea of using Bouc-Wen model in the developed model is to construct a new variable (i.e. z parameter) which is to be independent of x as neural network input. In the current developed model, due to the fact that ANNs illustrate a surface, by using Bouc-wen model, hysteresis output (i.e. x) has been arranged.

As a result, according to the given explanation and understanding the logic behind the Bouc-Wen model, it is recommended that Bouc-Wen parameters (A ,α ,β and n) be selected in such a way to have the least error between the output of the developed model and some simulation data of a real system. If the mentioned desire does not happen by changing the parameters, it then is suggested to multiply the input of Bouc-Wen model $\dot{x}$ into a relatively large coefficient v and to change the parameters again. It should be mentioned that the value of z is not real and makes no sense in physical terms. In order to have better insight about the model, in Fig. 2, the block-diagram of the developed model is shown.

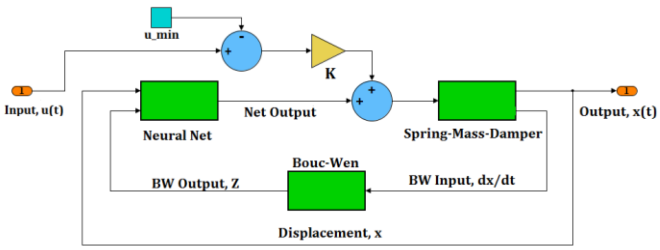

Figure 2. Block-diagram of SISO developed model for SMA wire

4. Identification of the Developed Model Parameters

In order to identify the parameters of the developed model, we need to have system states and their corresponding initial conditions. Therefore, we need to measure time history of system states including system displacement, velocity and acceleration (x , $\dot{x}$ and $\ddot{x}$) as well as SMA temperature (model input, $u(t)$) by proper sensors designated for the dynamic system. It should be noted that, it is required that initial conditions of dynamic states (x_0 and $\dot{x}_0$), as well as ambient temperature (i.e. system's initial temperature u_{min}) to be known.

It was noted before that how the parameters of the model should be selected. However, neural network structure and dimensions (i.e. number of layers, number of neurons and neurons function) are selected based on system's hysteresis behavior and it must be trained based on the measured experimental data of the real system. Block diagram of the training procedure of neural network based on measured data is shown in Fig. 3.

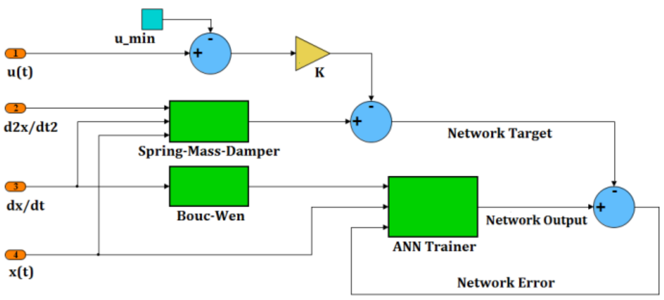

Figure 3. Block-diagram of training procedure of neural network

It should be noted here that initial states of the dynamic system including $x(0)$, $\dot{x}(0)$ and $\ddot{x}(0)$ are known. But after selecting parameters of the developed model we use some data related to $\dot{x}$ in order to determine the initial state value of z, (i.e. $z(0)$) and then we can solve Bouc-Wen equation by setting $z(0)$=0. As a result, the initial stable value of z for the main hysteresis loop is acquired and we use this value as $z(0)$ to train ANN.

5. Model Parameters Selection & ANN Training

In order to train the ANN used in the model and verify the model, data related to simulation of a real system in MATLAB 8.1 are used. This system consists of a mass (with mass m), a linear spring (with stiffness k) and a viscous damper (with damping coefficient c) that is actuated by an SMA wire (Fig. 4.). In this simulated system, SMA behavior has been demonstrated using Brinson phenomenological model [7].

System's equation of motion is expressed in equation (5):

$$m\ddot{x} + c\dot{x} + kx = F(t) \tag{5}$$

where $F(t)$ is the SMA force applied to the mass. This system is stimulated with a Nitinol (Ni-Ti) SMA wire having 180 *mm* length and SMA wire's initial strain is 4.6% when the dynamic system is in equilibrium. Mass, spring stiffness and viscous damping ratio are 5*kg*, 1000 *N/m* and 200 *N.s/m*, respectively. In addition, ambient temperature is 20 ºC.

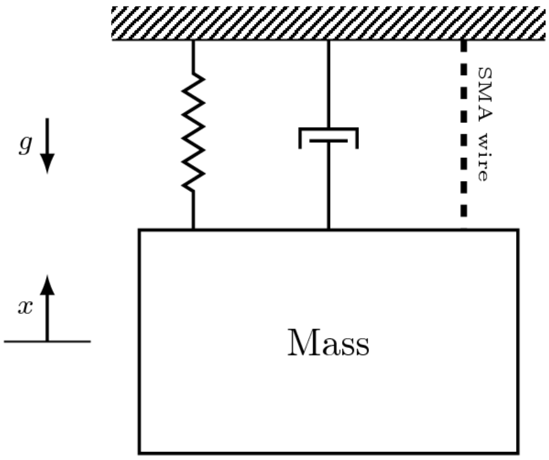

Figure 4. Dynamic system consists of mass, spring, viscous damper and SMA wire

Mass displacement (x in Fig. 6) of the simulated system is derived when temperature profile ($u(t)$) shown in fig. 5 is applied to the SMA wire. The hysteresis diagram between the SMA temperature and the mass displacement is plotted in Fig. 7.

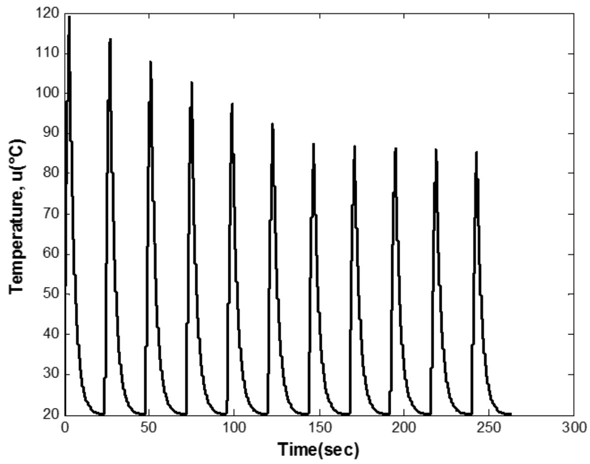

Figure 5. Temperature profile ($u(t)$) applied to the SMA wire in the simulation

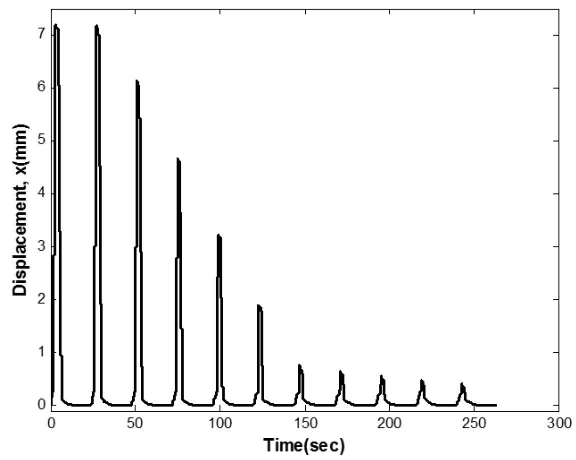

Figure 6. Simulated Mass displacement (x)

Table 1. Developed Model's Selected Parameters

Symbol	Quantity
Mass-Spring-Damper Parameters	
ξ	0.7
ω	10^{4}
δ	0.505
k	30.3
u_{min}	20
Bouc-wen Parameters	
A	1
α	0.5
β	0.5
n	1
$z(0)$	-1

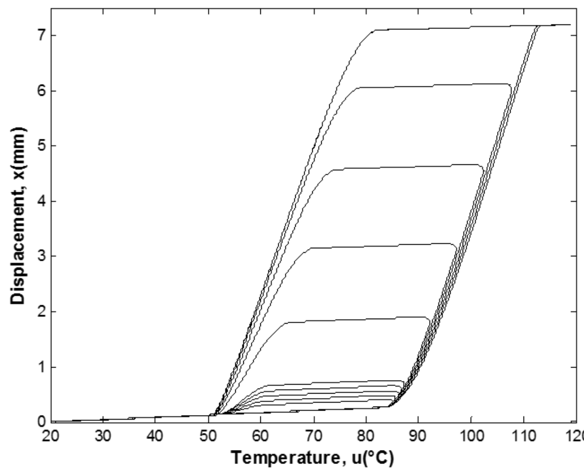

Figure 7. Hysteresis behavior between the SMA temperature and the mass displacement

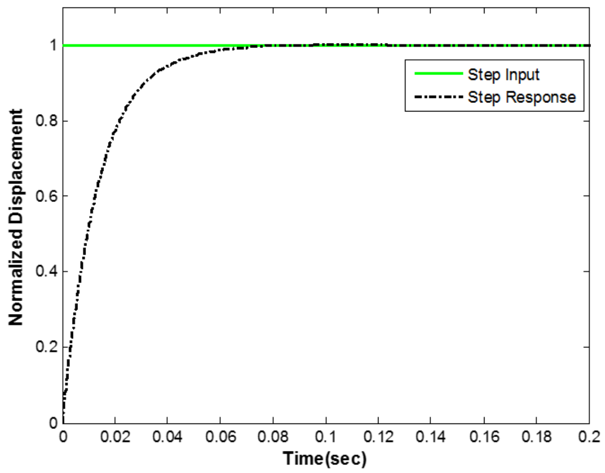

Figure 8. Normalized time response of model for step response

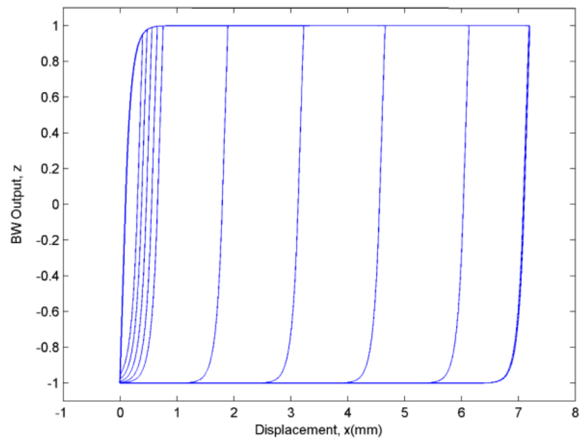

Figure 9. Bouc-wen hysteresis loops for $A = 1$,$\alpha = 0.5$,$\beta = 0.5$, $n = 1$ and $\upsilon = 10^{4}$

As it was noted in the preceding section, parameters of the developed model are selected based on the hysteresis loops according to Table 1.

As mentioned before, transient response time of the differential equation (1) is important to have a total response without any delay (lag) and therefore it is crucial to analyze the response time of the equation. Therefore normalized step response of equation (1) with the selected parameters of Table 1 is shown in Fig. 8 and the result verifies this issue.

Therefore, as it can be seen in Fig. 8, response of the dynamic system is stabilized in less than 0.1 second and the transient response of the equation disappears after that time.

For this dynamic system, Bouc-Wen input ($\dot{x}$) is multiplied by the coefficient $\upsilon=10^{4}$. Bouc-Wen hysteresis diagram between the mass displacement and Bouc-Wen output (z) is shown in Fig. 9 for the parameters noted in Table 1 and as a result of the applied input plotted in Fig. 6.

According to the block diagram, shown in Fig. 3, neural network targets are obtained for hysteresis loops shown in Fig. 7. In order to select the neural network structure, it is required to analyze the dimensions and shape of the hysteresis loops in neural network target diagram with respect to input parameters of the network. The mentioned diagrams have been illustrated for the normalized values in Fig. 10.

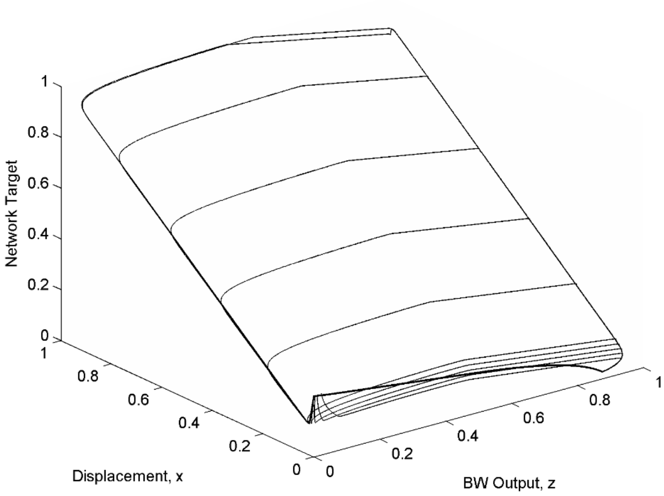

Figure 10. Neural network target vs. input parameters

After checking Fig. 10, a feed-forward neural network with two input and one output consisting of three layers with the following specifications is selected:

• 1st layer (Hidden) including 6 neurons with Tansig neuron function.

• 2nd layer (Hidden) including 14 neurons with Tansig neuron function.

• 3rd layer (Output) including one neuron with Purelinear neuron function.

Schematic configuration of the mentioned feed-forward neural network is shown in Fig. 11.

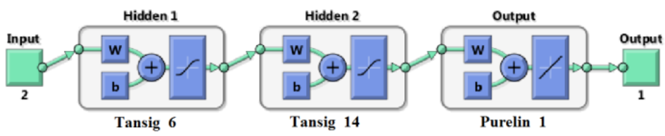

Figure 11. Schematic configuration of the noted feed-forward neural network

6. Validation of the Model

Now according to the neural network training and selection of the developed model parameters, it is required to test the model and have the model validated with different data sets. Since the training data was used to calibrate the model parameters and train the neural network, we first focus on the model estimation for the mentioned data (Fig. 5-7). Naturally, it is expected to have little error for the model estimation with respect to the training data obtained from simulation of the real model. In Fig. 12, the output of the model has been compared with this data (Fig.7).

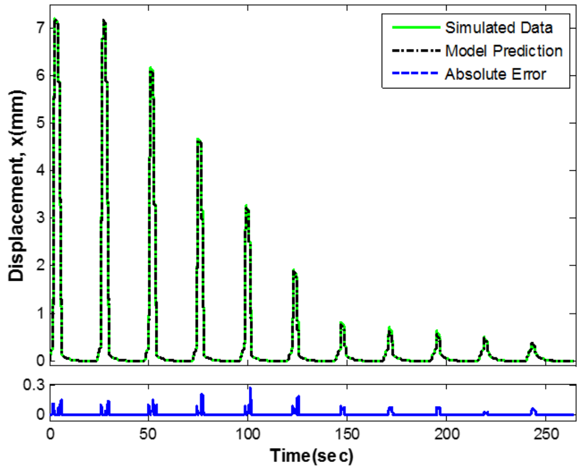

Figure 12. Comparison of the model output with the simulated data in the case of training data.

According to Fig. 12, estimation of the model has a good accuracy for the training data and it means that the developed model with the selected parameters and trained ANN can predict the system hysteresis behavior accurately. In order to have better sense it should be mentioned that mean absolute error and Mean Squared Error (MSE) for this data are 7.20×10^{-3} *mm* and 6.40×10^{-4} mm^2, respectively. In order to better validate the model output, the temperature profile, $u(t)$ (shown in Fig. 13) is applied to the simulated model and mass displacement (i.e. x) of simulated system has been extracted. Hysteresis behavior of the simulated system (named 1st validation data) is plotted in Fig. 14. In Fig. 15, the output of the developed model has been compared with 1st validation data.

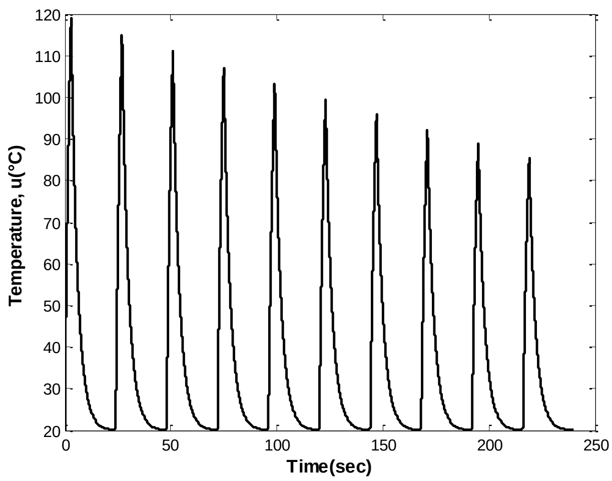

Figure 13. Temperature profile ($u(t)$) – applied in 1st validation data.

The output of the model has been compared with the 1st validation data in Fig. 15. According to this figure estimation error of the model has been increased in comparison to the training data. However, since the training data has been used to train the neural network and calibrating the model parameters, it is expectable. Mean absolute error and MSE for this 1st-validation data are respectively, 8.43×10^{-3} *mm* and 8.18×10^{-4} mm^2. In addition, it is obvious that the model also has presented a suitable estimation for small minor hysteresis loops.

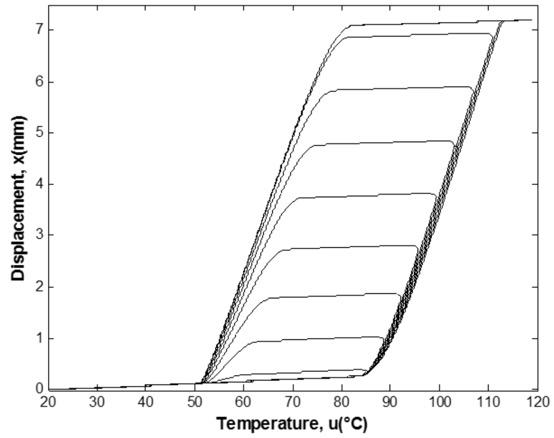

Figure 14. Hysteresis behavior between the applied temperature and mass displacement of the simulated model for data in the 1st case of validation

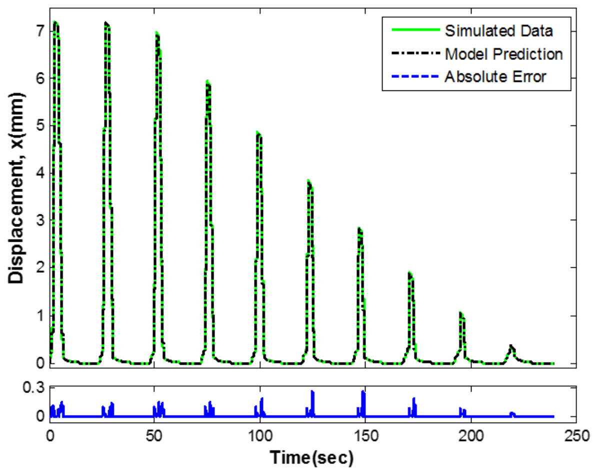

Figure 15. Comparison of the model output with the simulated data in data in the 1st case of validation data.

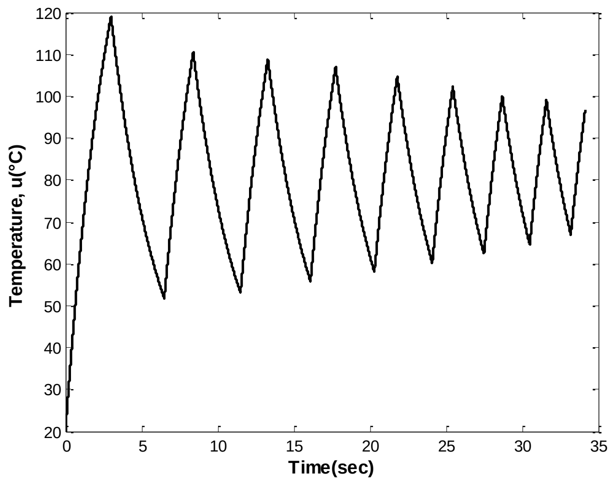

Figure 16. Temperature profile (*u(t)*) – applied in 2nd validation data.

Like previous data, 2nd validation data was obtained by applying the temperature profile, *u(t)* (shown in Fig. 16) to the simulated model. The mass displacement (i.e. *x*) of the simulated system as a result of applying temperature profile has been extracted and hysteresis behavior of the simulated system has been plotted in Fig. 17. In Fig. 18 the output of the developed model has been compared with 2nd validation data.

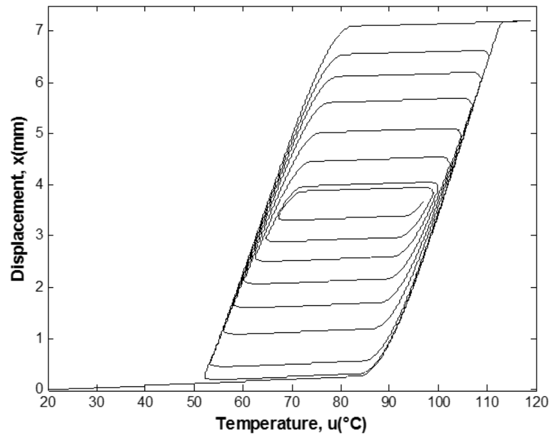

Figure 17. Hysteresis behavior between the applied temperature and mass displacement of the simulated model for data in the 2nd case of validation

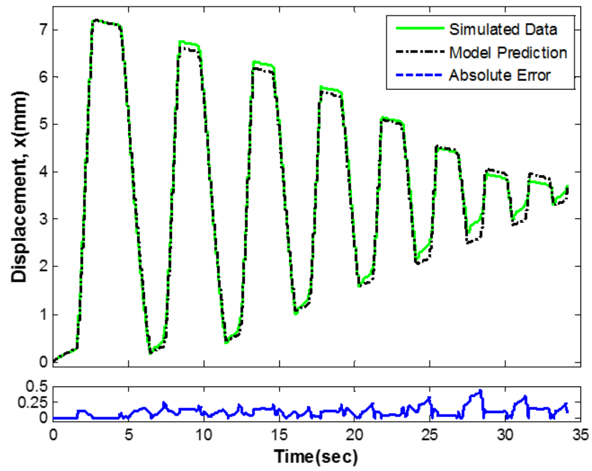

Figure 18. Comparison of the model output with the simulated data in the 2nd case of validation data.

Since hysteresis loops of the 2nd validation data (existence of high order minor loops) have more generality with respect to other two previous data, it is extremely important to validate this data for validation of the model prediction. According to Fig. 18, as hysteresis loops get more complicated, error values increase in comparison to training data and 1st validation data. However, the model estimation has a good accuracy even in the case of this complex hysteresis behavior while many phenomenological hysteresis models have difficulty to describe them. Mean absolute error and MSE for 2nd case of validation data are, 9.48×10^{-2} *mm* and 1.50×10^{-2} mm^2 , respectively. The values of MSE and mean absolute error of *x(t)* for all three sets of data used in training and validation are shown in Table 2.

Table 2. Error of validation

	Training Data	1st validation Data	2nd validation Data
Mean-Absolute Error	7.20×10^{-3} *mm*	8.43×10^{-3} *mm*	9.48×10^{-2} *mm*
Mean-Squared Error (MSE)	6.40×10^{-4} mm^2	8.18×10^{-4} mm^2	1.50×10^{-2} mm^2

7. Conclusion

In the current research, in order to describe hysteresis behavior of a dynamic system actuated by an SMA actuator, the mathematical equations of the Bouc-Wen hysteresis model was introduced. Due to inability of non-linear classical Bouc-Wen model, a modified Bouc-Wen model was used to describe hysteresis loops of the system. The developed model benefited from the flexibility of the feed-forward neural network to describe output of the Bouc-Wen model in system's dynamic equation in terms of non-linear complex functions.

Afterward, the parameter selection of the developed model and suitable configuration for the neural network were performed for a dynamical system using simulated data set of the system. The validity of the identified model was checked by using three different data sets. The prediction of the model output with respect to the mentioned data was validated by acceptable error.

It was seen that the maximum error of the model prediction is less than 10% of the real values and the MSE of the modeling output was a suitable value. Therefore, considering the objective of "output estimation of a hysteresis system", the identification of the developed model was successful with an accurate estimation and it is considered to be proper for the modeling of the SMA actuated dynamical systems with hysteresis behavior.

The advantages of the developed model are as the following:

•Due to model physical tangibility, it is easy to estimate displacement, velocity and acceleration of a dynamic system attached to an SMA actuator and to easily design a controller for the dynamic system afterwards.

• The developed model has flexibility for identifying the real hysteretic dynamic system as a result of considering the use of non-linear function in terms of neural network.

• Using neural network has caused less limitation in selecting parameters of the Bouc-Wen model. Also, the complexity for identifying the developed Bouc-Wen model parameters limits only to configuration and training of the selected neural network.

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