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Application of Machine Learning in Developing a Predictive Tool for Modeling Shape Memory Alloy-Based Connections in Self-Centering Steel Moment Frames

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ABSTRACT

Steel beam-column connections with shape memory alloy (SMA) bolts provide self-centering behavior and eliminate permanent deformations in earthquake-resilient steel moment frames. This paper presents the development and frame modeling application of a freely available Graphical User Interface (GUI) for predicting the cyclic and self-centering response of extended endplate steel connections with superelastic SMA bolts. A database of moment-rotation response is created from the results of seventy-two 3D finite-element simulations and seven experimentally tested specimens. The study trains different machine learning algorithms, including Artificial Neural Networks (ANN), Decision Tree (DT), Random Forest (RF), Extreme Gradient Boosted Trees (ExGBT), Light Gradient Boosted Trees (LGBT), TensorFlow Deep Learning (TFDL), and Keras Deep Residual Neural Network (KDP). The accuracy of the algorithms is compared in terms of two performance metrics, root mean square error (*RMSE*) and coefficient of determination (R^2). The trained ANNs, which show the highest accuracy with an R^2 ranging from 0.92 to 0.99, are chosen to develop a Graphical User Interface (GUI). To demonstrate the application of the developed predictive tool, a phenomenological model of moment frames with SMA connections is developed and verified in OpenSees based on experimental test results. A two-stage validation study is performed to assess the accuracy of the proposed phenomenological model. The validation study uses the predictive tool to develop the phenomenological model for SMA-based beam-to-column connection. It is shown that the results of the predictive tool, the phenomenological model, and the 3D finite-element models in ANSYS are in line with each other with high accuracy. By using the developed tool, the prediction of the cyclic and self-centering response of a typical SMA connection can be performed rapidly – taking three minutes in OpenSees compared to seven hours in ANSYS.

Keywords: Machine learning, Earthquake resilience, Shape memory alloy (SMA), Self-centering endplate connection, Artificial neural networks.

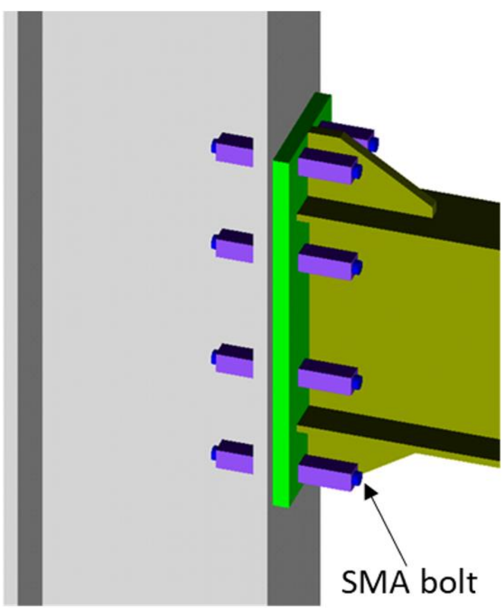
INTRODUCTION

Shape Memory Alloys (SMA) are metallic alloys with two favorable mechanical behavior: 1) undergoing large deformations; 2) recovering their original shape upon unloading or heating with minimal residual deformation. The exposure of the SMA materials to stress or temperature results in solid-to-solid phase transformations, which in turn can result in shape recovery. The unique behavior of the SMA materials, i.e., deformation capacity and shape recovery, convinced many researchers to use SMA materials in structural systems to provide a self-centering behavior ([1–4], among others). Self-centering structures are defined as structures that have the capability to return to their plumb position following lateral loading, such as earthquake loading.

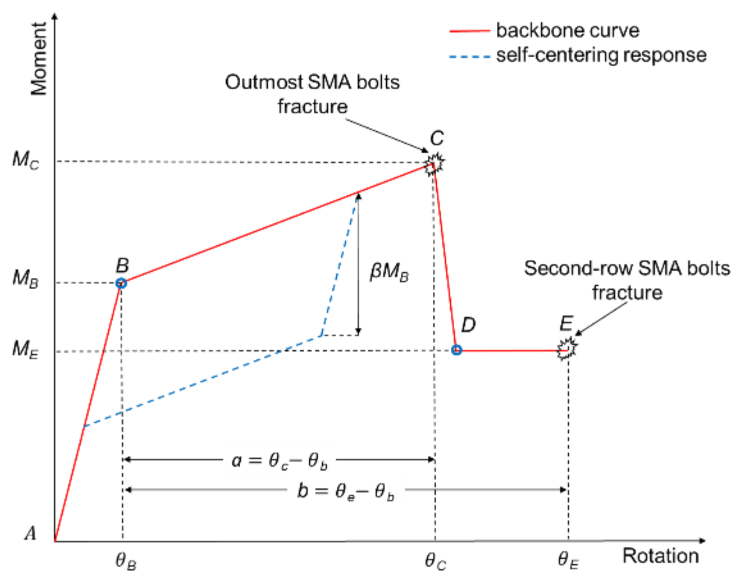
While there exist different applications of the SMA materials in structural systems, bolted SMA-based beam-to-column connections have shown effective self-centering behavior (e.g., [5–8]). Leon et al. [10] are among the earliest researchers who proposed the application of SMA materials in beam-to-column connections. In their study, two full-scale connections were tested according to the SAC testing protocol. Their results showed that the connections exhibit stable and repeatable hysteresis loops for rotations up to 4%. In a study by Ocel et al. [5], following testing two-full scale connections with large SMA tendons, the SMA tendons were heated to remove residual deformations, and then the connections were subjected to loading. The connections exhibited repeatable and stable hysteretic behavior while up to 76% of the residual deformations were removed by initiating the Shape Memory Effect of the SMA tendons, i.e., by heating the SMA tendons. Ma et al. [11,12] proposed proof-of-concept superelastic SMA-based extended endplate connections in which the high-strength bolts were replaced with superelastic SMA bolts. Based on the results of their numerical studies, SMA-based extended endplate connections exhibited a self-centering behavior while a moderate level of energy dissipation capacity was observed in the proposed connections. Following the Ma et al. studies on the proof-of-concept SMA-based connections, Fang et al. [6] performed eight experimental tests, including seven SMA-based and one regular extended endplate connection. In the tested specimens, superelastic SMA bolts were used in the extended endplate connections. Their results confirmed that while in the conventional extended endplate connections, the ductility and energy dissipations were accommodated by deformations in the beam, column, and endplate, in the SMA-based extended endplate connections, the ductility and energy dissipations were provided by SMA bolts; therefore, other parts of the beam-to-column connections, including endplate, beam, and column were within their elastic range. Confining the plastic deformations in the SMA bolts results in developing a superelastic hinge in the SMA-based extended endplate connections that reduces the repairs in structural members and, consequently, downtime of the building after a seismic event. The tested specimens by Fang et al. [6] showed a great recentering capability with a moderate energy dissipations capacity. While there exist other research efforts aimed at examining the seismic behavior of the extended endplate connections with SMA bolts ([9,13,14], among others), this research intends to characterize the seismic properties of the SMA-based extended endplate connections using Machine Learning (ML) algorithms particularly Artificial Neural Networks (ANN).

SCOPE AND METHODOLOGY

In this study, the database developed by the authors [15], which contains seventy-two detailed finite element simulations, along with seven experimentally tested specimens were used to propose a predictive tool for the backbone curve parameters of the SMA-based extended endplate connections. Schematic views of the bolted SMA-based beam-to-column connections and also developed backbone curve are shown in Figure 1. The considered backbone curve herein can be associated with the generalized backbone curve of the ASCE 41-17 [16]. As shown in Figure 1, from *A* to *B*, the connection has an elastic behavior. After point *B*, the SMA materials enter their forward transformation phase. At point *C*, the outmost SMA bolts reach their fracture strain, which in turn results in a drastic reduction in the moment capacity of the connections (line *CD* in Figure 1). Following point *C*, the loading continues to achieve the fracture strain in the second row of the SMA bolts. Post-yield deformation capacity of the connections is defined with parameters *a* and *b* (Figure 1b). In fact, *a* and *b* are post-yield rotations up to θ_c and θ_e, respectively.



(a)



(b)

Figure 1. Schematic view of: (a) the bolted SMA-based beam-to-column connections; (b) proposed backbone curve.

In this study, it is assumed that the SMA materials will fracture upon reaching a strain level of ε_{fr} [15] that is formulated as follows:

$$\varepsilon_{fr} = \varepsilon_L + \frac{\sigma_{Mf}}{E_{SMA}} \tag{1}$$

where ε_L is the maximum transformation strain of the SMA bolts, σ_{Mf} is the martensite finish stress, and E_{SMA} stands for Young Modulus of elasticity of the SMA materials.

Based on previous studies by the authors [8,9], ten factors were identified as influential factors on the seismic response of the backbone curves, which are listed in Table 1. Using these significant factors along with their ranges, a dataset of seventy-two factor combinations was developed using the Response Surface Methodology (RSM). Factor combinations used in this study can be found elsewhere [15]. For each factor combination, two finite element models are developed in ANSYS mechanical APDL [17]. In the first finite element model, the connection is loaded up to 0.07 rad rotation to capture the rotation at which the outmost bolts achieve their fracture strain as defined in Eq. 1. In the second finite element model, the first row of the SMA bolts is removed, and then the connection is loaded up to 0.1 rad rotation to capture the rotation at which the second row of the SMA bolts are fractured. A backbone curve similar to Figure 1 is obtained for each factor combination by assembling the backbone curves achieved from two finite element simulations. Further details on developing the dataset can be found in Ref. [15].

Table 1. Input factors and ranges.

	Factor	**Symbol**	**Minimum**	**Maximum**	**Unit**
1	Martensite start stress	σ_{Ms}	280	380	MPa
2	Martensite finish stress	σ_{Mf}	410	590	MPa
3	Austenite start stress	σ_{As}	170	250	MPa
4	Austenite finish stress	σ_{Af}	70	138	MPa
5	Maximum transformation strain	ε_L	0.07	0.13	-
6	Bolt pretension strain	ε_{pt}	0.005	0.015	-
7	Bolt length	L_{bolt}	300	350	mm
8	Bolt diameter	D_{bolt}	10	25	mm
9	Beam depth	h_{beam}	150	610	mm
10	Beam length	L_b	1500	4500	mm

MACHINE LEARNING FOR PREDICTING BACKBONE CURVE PARAMETERS

In this study, Artificial Neural Networks (ANN), Decision Tree (DT), Random Forest (RF), Extreme Gradient Boosted Trees (ExGBT), Light Gradient Boosted Trees (LGBT), TensorFlow Deep Learning (TFDL), and Keras Deep Residual Neural Network (KDP) were trained to predict the backbone curve parameters of the SMA-based extended endplate connections. Ten influential design parameters, as listed Table 1, are the inputs for the algorithms. For each backbone curve parameter, including θ_b, θ_c, θ_e, M_b, M_c, and M_e, a separate algorithm is trained. Finally, a single predictive model for backbone curve parameters is developed using trained ANNs, which gives us the backbone curve of the SMA-based extended endplate connections upon inserting ten input parameters.

Artificial Neural Networks

ANN are computational models that contain hundreds of single units, artificial neurons, connected with coefficients (weights) in which the human's brain working principles are emulated to conduct learning and then the prediction. ANNs can be trained to model a complex problem with many parameters where the training process is performed using proper exemplars [18]. ANN consists of interconnected neurons that are processing elements having similar characteristics, such as inputs, synaptic strength, activation outputs, and bias [19]. The processing units, i.e., input, hidden, and output units, are composed of a layered structure that carries the weights of the network. The training process of a network is associated with adjusting the weights in a network so that the optimum weight space of the network is achieved.

ANNs are used to determine the nonlinear relationship between the input and output parameters of the backbone curve. In this study, a multilayer feedforward backward propagation of errors, i.e., backpropagation, the network is used. The reason for which the backpropagation network is selected is its capability to find complex relationships between inputs and outputs. In the backpropagation networks, the output errors are propagated back using the same connections used in the feedforward mechanism by the derivation of the feedforward transfer function [20,21]. The neurons are placed in three separate layers, including the input layer, hidden layer, and output layer. The input layer has ten neurons, reflecting ten design parameters. Neurons in the input layer pass the scaled input data to the hidden layer using weights. The hidden layer has different neurons for each response variable, obtained using hit and trial methods to have maximum accuracy. The output layer is comprised of a single neuron that represents the backbone curve parameter. In this study, the tangent sigmoid transfer (*tansig*), which generates an output between 0 and 1, is used as an activation function for the hidden layer, whereas pure linear (*purelin*) functions are used as activation functions at the output layer. It is worth mentioning that the goal of using nonlinear transform functions, e.g., the tangent sigmoid transfer, is to provide the network with the capability of learning the nonlinear behavior between input and output layers.

The design matrix, which was developed using *RSM*, is used as the input matrix while the finite element results were used as outputs. Multilayer perceptron architecture of feedforward ANN was developed. The developed design matrix using *RSM* contained seventy-two factor combinations from which fifty factor combinations, i.e., 70% of the dataset were used to train the network, eleven factor combinations (15% of the dataset) were used for validation, and the last eleven factor combinations (15% of the entire dataset) were used for the sake of testing the network. The performance of the networks was evaluated using the coefficient of determination (R^2) and root mean square error (*RMSE*). Note that the coefficient of correlation estimates the relationship between model output and actual values.

Data Preprocessing

The input data for ML algorithms were normalized to lie within a range of 0 to 1. The reason for which the input data has been normalized was to prevent the saturation region of the log-sigmoid activation function. The saturation problem can result in a low learning rate of the networks [22]. Eq. 1 was used to normalize the inputs of neural networks.

$$\varphi_m = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where φ_m is the normalized data, and x indicates the rough data.

ML ALGORITHMS' RESULTS

This section summarizes the results of the trained ML algorithms. For each backbone curve parameter, a separate algorithm was trained. The results of the trained algorithms are listed in Table 2. The coefficient of determination, R^2, and root-mean-square-error, *RMSE*, were considered as performance metrics to compare the performance of the trained ML algorithms.

As per Table 2, ANN outperforms other algorithms. It should be noted that except for ANN, other algorithms' hyperparameters were assigned according to the framework by suggested by Naser et al. [23]. Therefore, it might be a biased comparison if we compare the performance of ANN with other ML algorithms. Excluding ANNs and comparing the performance of other algorithms, it can be observed that no single algorithm outperforms other algorithms for all backbone curve parameters. By taking into account the overall performance of the algorithms, however, ExGBT and KDP are the first and second best-ranked algorithms, while TFDL and DT have the poorest performance.

GRAPHICAL USER INTERFACE PREDICTIVE TOOL

The trained neural networks were used to develop a predictive tool for the response prediction of SMA-based extended endplate connections. The developed tool will be helpful to eliminate the need for a detailed finite element modeling of the connections and consequently reduce computational expenses. With this goal, the trained ANNs were used to develop a Graphical User Interface (GUI) to predict the backbone curve and self-centering response of SMA-based extended endplate connections interactively. The developed predictive tool is freely available online [24]. As shown in Figure 2, ten significant parameters are required to be entered into the developed tool. An unloading path is also included to facilitate implementing the proposed response curve in other software programs, such as OpenSees (using *SelfCentering* material, for example). As shown in Figure 2, two switch keys are provided in the developed tool by which the return path and the moment rotation values at different points can be shown.

Table 2. Results of the trained ML algorithms using the developed database.

Parameter	metric	DT		RF		ExGBT		LGBT		TFDL		KDP		ANN	
		Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
θ_B	R^2	1.00	0.79	0.89	0.78	1.00	0.88	0.92	0.86	0.86	0.68	0.79	0.52	0.93	0.91
	RMSE	0.00	0.0010	0.0008	0.0014	0.0001	0.0010	0.0007	0.0011	0.0010	0.0016	0.0012	0.0015	0.0007	0.0010
θ_C	R^2	1.00	0.55	0.87	0.74	1.00	0.82	0.94	0.91	0.61	0.42	0.93	0.89	0.98	0.91
	RMSE	0.0006	0.0077	0.0041	0.0073	0.0007	0.0045	0.0031	0.0030	0.0087	0.0090	0.0030	0.0040	0.0020	0.0040
θ_E	R^2	1.00	0.76	0.91	0.91	1.00	0.86	0.95	0.93	0.64	0.28	0.93	0.92	0.99	0.96
	RMSE	0.00	0.010	0.005	0.005	0.00	0.006	0.004	0.004	0.008	0.018	0.005	0.004	0.001	0.004
M_B	R^2	1.00	0.98	0.97	0.92	1.00	0.99	0.98	0.97	0.92	0.90	1.00	0.99	0.99	0.99
	RMSE	0	33.4	35.5	60.5	1.2	23.3	32.3	42.1	58.4	70.3	12.4	17.2	14.9	17.0
M_C	R^2	1.00	0.94	0.98	0.96	1.00	0.99	0.98	0.98	0.87	0.71	1.00	0.99	1.00	0.99
	RMSE	0.37	72.9	37. 7	56.6	1.0	26.8	43.1	41.0	102.5	142.3	8.3	17.2	6.3	26.4
M_E	R^2	1.00	0.95	0.97	0.94	1.00	0.97	0.97	0.94	0.97	0.91	1.00	1.00	1.00	0.99
	RMSE	1	36.0	25.1	32.2	0.7	29.0	23.6	45.2	25.6	55.0	6.0	9.3	9.0	9.1
β	R^2	1.00	0.90	0.91	0.84	1.00	0.90	0.92	0.91	0.73	0.62	0.91	0.89	0.97	0.97
	RMSE	0.00	0.03	0.03	0.05	0.0	0.03	0.03	0.03	0.06	0.06	0.40	0.30	0.02	0.02

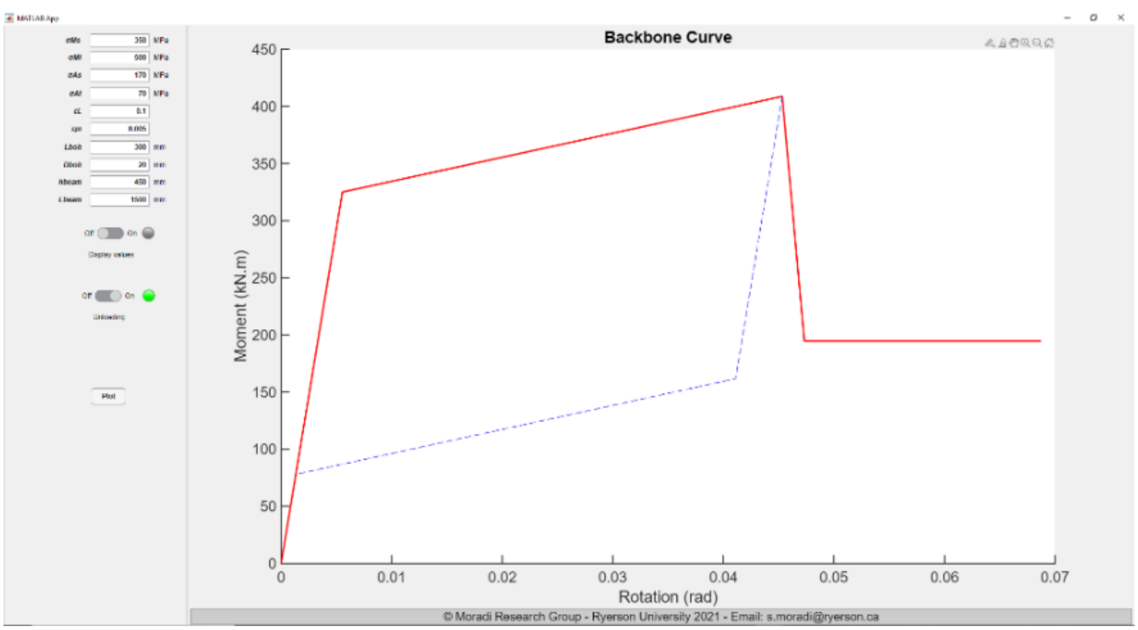


Figure 2. The developed MATLAB tool for predicting the backbone curve of SMA-based endplate connections.

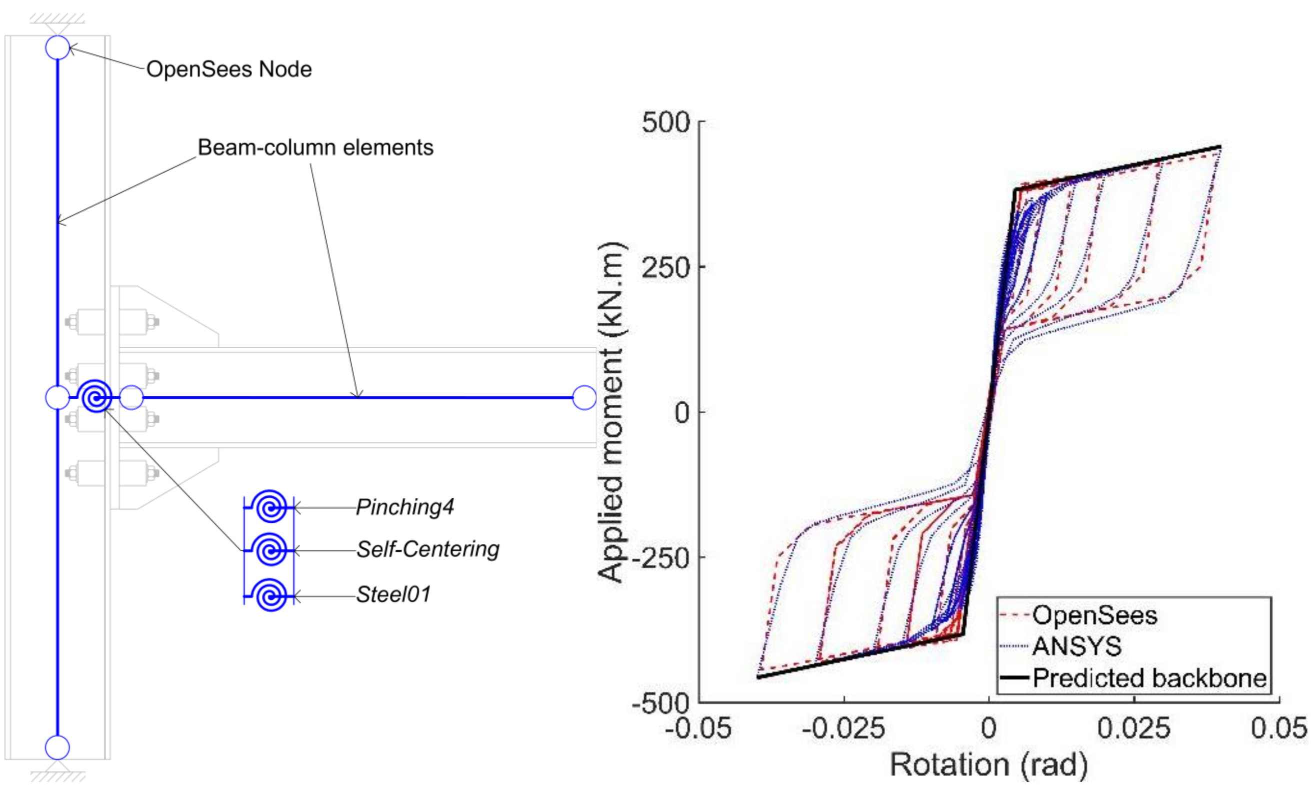
DEVELOPING HIGH-FIDELITY FE MODELS USING THE PROPOSED PREDICTIVE TOOL

In this section, the application of the developed predictive tool for developing computationally effective FE models of the beam-to-column connections is illustrated.

The proposed backbone curve was used to develop a phenomenological model for SMA-based endplate connections in OpenSees [25]. *Self-Centering*, *Pinching4*, *Steel01* materials in OpenSees acting in parallel were considered to model beam-to-column connections. A rotational spring with a parallel material, including the *Self-Centering*, *Pinching4*, and *Steel01* materials, was considered to simulate the self-centering response of the bolted SMA-based beam-to-column connections. Using an iterative process, the percentage contribution of the *Self*-Centering, *Pinching4*, and *Steel01* were considered as 0.9, 0.05, and 0.05, respectively. In the proposed phenomenological model, the beam and column are modeled using elastic beam-column elements [26]. The verification of the presented phenomenological against experimental test data can be found elsewhere [27].

Application of the Developed phenomenological model

This section presents the applications of the developed predictive tool along with the proposed phenomenological model. Two-step verification was performed to demonstrate the efficiency of the developed predictive tool and also verify its accuracy. To this goal, a random factor combination, generated using a normal distribution, was considered. For the randomly generated factor combination, the backbone curve was developed using the predictive tool. The developed backbone curve was then used to create an OpenSees model. Additionally, an ANSYS model is developed based on the factor combinations to perform the two-step verification. A cyclic load is applied to both ANSYS and OpenSees models. Figure 3 shows the moment-rotation response of developed ANSYS and OpenSees models as well as the predicted backbone curve obtained from the predictive tool. As shown in Figure 3, ANSYS, OpenSees, and the backbone curve are in good agreement. It should be noted that the runtime for the OpenSees model, generated using the developed predictive tool, was about 3 minutes, while ANSYS runtime was about 7 hours with the same computer. Further details and discussions can be found in [27].



(a) *(b)*

Figure 3. The developed phenomenological model: (a) Schematic view; (b) Two level verifications.

CONCLUSIONS

This paper presented the application of artificial intelligence in structural analyses to develop high-fidelity finite element (FE) models while reducing computational time. To do so, an existing dataset for the backbone curve parameters of the Shape Memory Alloy (SMA) based extended endplate connections was combined with experimental test results. The enriched dataset was used to train different algorithms, including Artificial Neural Networks (ANN), decision trees (DT), random forest (RF), extreme gradient boosted trees (ExGBT), light gradient boosted trees (LGBT), TensorFlow deep learning (TFDL), and Keras deep residual neural network (KDP). Among the trained algorithms, ANNs were selected to create a graphical user interface (GUI) predictive tool to predict the backbone curve parameters of the SMA-based beam-to-column connections. A computationally efficient FE model was generated for the bolted SMA-based connections using a phenomenological model that was fed by the developed GUI. It was shown that accurate results could be obtained with less computational effort using the proposed predictive tool. The following conclusions were drawn from this study:

- The proposed predictive tool is capable of predicting the moment-rotation of the SMA-based extended endplate connections with acceptable accuracy. This accuracy was confirmed by close-to-one coefficients of determination from the comparison between actual and predicted values, ranging between 0.91 to 0.99 for ANNs.
- Among ML algorithms that were trained for the dataset, ANN, ExGBT, and KDP algorithms hold the top three rankings in terms of performance, with ANN being the highest, followed by ExGBT and KDP. Meanwhile, TFDL and DT algorithms show the weakest performance among all.
- The freely available MATLAB predictive tool is an efficient tool for modeling SMA-based endplate connections. Proper use of the developed predictive tool would be an efficient way to eliminate the need for detailed finite element analysis of SMA-based extended endplate connections.

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