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Model reference Neural Network-based methodology for vibration control in a five-story steel structure.

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***Abstract*—The recent natural hazards that have taken place around the world led to the development of structures that can truly adapt to the ever-changing operational conditions. One of the main goals that an adaptive structure is to mitigate the vibrations that a civil structure is being subjected to, where artificial intelligence-based proposals are one of the active research topics, since they have been demonstrated noticeable results in vibration mitigation in civil engineering. Bearing this information in mid, this work proposes a reference-based vibration controller using a neural network implementation to reduce the negative impact of such conditions and, consequently, avoid damages into the structure. In this regard, a recurrent topology network is employed to implement the model reference and the controller, respectively. A magnetorheological damper is chosen to provide the actuator device, as it offers the best compromise between the required power and has the flexibility to still offer a protection when it is not powered. A simulation scheme is developed in this work, where the obtained results show a 18%-reduction in the vibrations measured at the second story of a five-story steel building, demonstrating the capabilities that the proposal could have for vibration control in real-life scenarios.**

***Keywords*—vibration controller, neural network, model reference, civil structures.**

I. Introduction

In the last years, the occurrence of diverse earthquakes and other natural hazards has attracted the attention of engineers and researchers for developing or generating civil infrastructure (e.g., working and habitable spaces, bridges, among others) with the capability of adapting to changing operational conditions. In this regard, the development of compact and powerful sensors and actuators has allowed the design and construction of civil structures known as smart structures that can truly adapt to external conditions and perturbations that may cause a damage into the structure [1-2]. A smart structure is characterized by sensing the operational conditions that interact with a structure such as displacements, wind, ground motion, among other factors, in order to adapt the mechanical properties of structure through actuators (e.g., stiffness and damping) for compensating excessive displacements or vibrations that can produce a damage into the structure [3]. Hence, a smart structure allows reducing a possible damage that can occur in the structure, avoiding long closure periods of structure because of inspections, which will benefit the economy and save human lives.

A smart structure can employ passive, semi-active and active actuators or devices to modify the mechanical properties of a structure [3]. In particular, passive devices (e.g., tuned mass dampers (TMD), particle TMD, tuned liquid particle damper, tuned liquid column damper (TLCD), eddy-current TMD, viscoelastic and friction dampers, among others) have been employed for compensating the excessive vibrations in civil structures [4-5]. They increase within a predefined range either the stiffness or damping of the structure, with the benefit of no requiring any power to perform this task [6-8]. Unfortunately, if the external perturbations require an out-of-range increase of the mechanical properties, the protection the devices provide might not be the strong enough [4-5, 9]. For this reason, active devices such as active mass dampers, active tuned mass dampers, distributed mass dampers, among others, have been employed to lessen the undesirable vibrations in a civil structure [4-5, 9]. These devices offer an increased range of variation of the mechanical properties, i.e. damping or stiffness, compared with the passive ones, but their degree of variation depends on the amount of power available [9]. Hence, if the structure is power-limited, they might not be the best solution [5]. On the other hand, semi-active devices (e.g., tuned liquid damper with floating roof, resettable variable stiffness TMD, variable friction dampers, semi-active TMD, magnetorheological dampers (MR), and semi-active friction tendons combine the best of previous devices, that is, the addition of a fixed value of either damping or stiffness when no power is applied and the ability to regulate the value of the damping or stiffness the actuator offers when an electrical current is applied [5]. However, despite the great advantages of semi-active devices, they require of a reliable control strategy with the capability of estimating the device parameters to lessen the excessive vibrations in the structure adequately [10].

In the last years, diverse strategies to control both active and semi-active actuators have been proposed in literature. For example, classical algorithms (e.g., the proportional-derivative-integral (PID) controller) have been employed in a 15-story building with linear behavior using a rubber bearing device for performing a vibration reduction in the first story [11]. Although the PID controllers have noticeable results, a fine-tuning stage is required. For this reason, other approaches such as the Linear quadratic regulator control and Linear quadratic Gaussian control have been proposed and utilized in a 10-story structure, a numerical model, and a benchmark 4-story symmetrical building [12-13] using an active tuned mass damper and base isolation for vibration-induced displacement. The obtained results show both controllers are feasible to be implemented as vibration reduction strategies for civil structures; but, the high

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computational burden required to solve the equations has limited their application for real-life scenarios [5]; moreover, it should be noticed that when the structure has non-linear features this controller degrades its performance [14]. To lessen the effects of structures with nonlinear behaviors, optimal controllers have been used [15-20]; even when the presented results show a significant reduction of the measured vibrations in the stories, the high computational burden required to estimate the parameters of the actuator still limits their application in real-life scenarios. In this sense, other approaches are still needed. In this regard, artificial intelligence (AI) algorithms can be a suitable alternative because they offer the ability to deal with highly changing situation and the unavoidable uncertainty that a real-life situation might have [14]. In particular, neural networks-based controllers have proved to be effective as they are better-suited to deal with non-linear systems and discover the hidden relationship that the input variables can have [2, 14]; further, the computational time required to determine the output is smaller than optimal controllers since it is not required to perform matrix manipulations [5].

Considering the benefits of AI algorithms, this paper presents the development and simulation of a controller based on neural networks to mitigate the excessive vibration in civil structures using a semi-active actuator. In order to evaluate the controller effectiveness, the vibrational responses obtained experimentally of a five-story steel structure subjected to earthquakes are employed. This structure is selected as it is one of the most common types that can be found in real-life applications. The obtained results show that the proposal can be a suitable solution for performing vibration control in civil structures.

II. Theoretical Background

This section introduces briefly the mathematical concepts used to implement the proposed controller.

A. *Model Reference Neural Controller*

Civil structures are constantly subjected to changing operational conditions, which limit to the structure designers

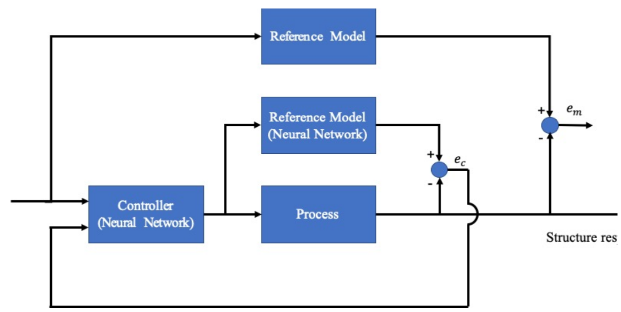

Fig. 1. Model Reference Neural Controller Block Diagram.

guarantee a safe operation of a civil structure under these conditions. Hence, to lessen these possible scenarios the development and application of vibration controllers are necessary. In general, a controller is characterized by its adaption to changing the operating conditions of a dynamic system as in the case of a civil structure, which will help avoiding catastrophic consequences. In particular, the neural networks have been widely used to model non-linear systems [21-22] and the inverse dynamic of a system of effective manner [22]. These important features can be combined to provide a solution that has the flexibility of adapting rapidly changing conditions without requiring convergence time and an efficient computation time to estimate the solution [22-23].

In particular, the model reference neural controller (MRNC), an AI controller, presents a higher adaptability and reliability to changing conditions than other controllers such as the Neural Network (NN) Predictive Control and NARMA-L2 Control algorithms, which allow an efficient vibration control since it does not depend on linearizing potential non-linear features the structure can have [24]. Fig. 1 illustrates a MRNC scheme, where it can be observed that two neural networks are employed: one for generating the plant model (in this case the civil structure prediction response model) and the other one to perform the control action using both the predicted response and the measured one. On the other hand, Fig. 2 shows a detailed block diagram of the MRNC. The process network uses the response

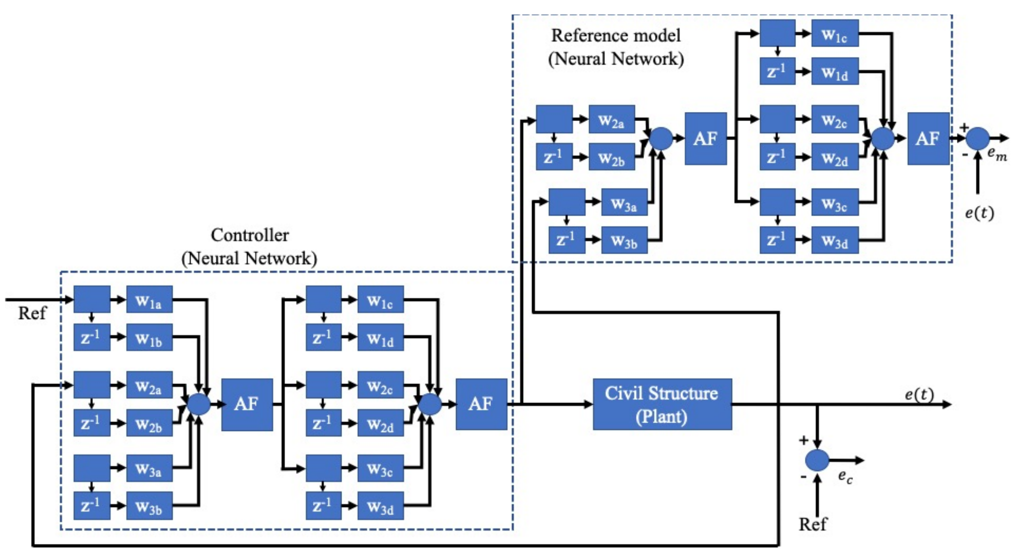

Fig. 2. Detailed Reference Neural Controller Block Diagram.

one step ahead of the civil structure response [25-26]. To this purpose, a recurrent neural network is employed, where its function is to minimize the error between the measured output and the one step predicted one as follows [26]:

$$e_m = \sum_{k=1}^{N}\left(y(k) - \hat{y}(k)\right)^2 \quad (1)$$

where N, $\hat{y}(k)$, and $y(k)$ are the number of samples, one step ahead response prediction, and the actual process output, respectively. It should be noticed that a recurrent configuration is more appropriate to process time-series signals due to the memory the model employs to store past values, denoted by z^{-1} in Fig. 2, of the input and output [27]. The superscript m denotes that the error is the one associated with the prediction model.

The controller is developed and trained to generate the required control variables for allowing the process to reach the reference or set-point desired; in this case, it is desired to mitigate as much as possible the vibrations amplitude of a civil structure. In this sense, for this network, the inputs are the reference or set point, the past controller responses, and the actual values of the controller. The training scheme for this network is done by finding the weights that minimize the following function [26]:

$$e_c = \sum_{k=1}^{N}\left(r(k) - \mathrm{y}(k)\right)^2 \quad (2)$$

where N, $y(k)$, and $r(k)$ are the number of samples, structure response, and the reference model output, respectively. The subscript c stands for the controller. In this way, the training scheme intents to mitigate the structure vibration response by minimizing the difference of the reference model neural network and the structure response. Hence, it is important that the reference model predicts the structure response with the lowest error possible, as this will determine the performance of the vibration controller.

B. *Training Algorithm*

Since the employed NNs are recurrent ones, the traditional backpropagation algorithm cannot be employed, as it will require an excessive training time [26]. For this reason, an adapted backpropagation algorithm known as backpropagation through time (BPTT) is employed for training the NNs, because it can handle efficiently the gradient operation required to reduce the network error using time-series signals [28]. BPTT is based on four steps to train a recurrent neural network, which are described as follows:

1. The time series signals are normalized, that is, the values are arithmetically divided between its maximum value, so their variation is located from -1 to 1 interval; then, they are accommodated in pairs (one sample and its corresponding output, respectively). This procedure allows avoiding the overflow problem derived from operating with samples whose values have a considerable numerical separation between them [28].
2. The network is unrolled depending the number of time lags; then, the corresponding data pairs are used to calculate and accumulate the prediction error.
3. The network is rolled to update the weights that minimize the prediction error.
4. This procedure is repeated until the minimal error or stop criteria is achieved.

A full depth of BPTT can be consulted in [28].

C. *Magnetorheological dampers (MR)*

A semi active actuator offers an appropriate protection level without consuming an excessive power level [29-30]; further, when the actuator is not powered, a limited protection level is still provided [29]. In particular, a MR damper device, a semi-active actuator, is filler with a magnetorheological fluid, whose properties, particularly the viscosity, can be modified using variable magnetic fields. To generate the variable magnetic fields, currents of different values are injected to the device; in this way, transitions from fluid to a semi-solid one is induced; thus, a change of the apparent stiffness is produced, leading to also modify the structure stiffness, which allows mitigating the excessive vibrations in civil structures [30].

Since a MR device uses magnetic fields to induce transitions in the fluid viscosity from solid to semi-solid, a hysteresis cycle is produced, making the device a strong non-linear one [24]. The Bouc-Wen model is employed because it allows modelling its non-linear behavior effectively [29-31]. For this model, the hysteresis is produced by the combination of a spring and its damping as well as the magnetic field applied. The force (F) the device will generate in the transitions of the fluid is estimated as follow:

$$F\left(x(\tau), \dot{x}(\tau)\right) = c_0\dot{x} + k_0 x + \alpha z \quad (3)$$

where x and $\dot{x}$ are the measured displacement and velocity, respectively, t is the time variable, and z is the hysteresis estimated using:

$$\dot{z} = -\gamma|\dot{x}||z|^{(n.-1)}z - \beta\dot{x}|z|^n + A\dot{x} \quad (4)$$

where γ, β and A are constants depending on the MR device physical properties. In this form, the required time to estimate the parameters to model the displacement is excessive. These equations have been employed in several works [29-31] to develop their approach, obtaining good results. This work uses the simplified version proposed in [29]:

$$F\left(x(\tau), \dot{x}(\tau)\right) = c_0(I)\dot{x} + k_0(I)x + \rho(I, \dot{x})z(x) \quad (5)$$

where I and $\dot{x}$ are the current and velocity, respectively. z is now estimated as:

$$\dot{z} = -\gamma|\dot{x}||z|z + \gamma\dot{x} \quad (6)$$

$c_0(I)\dot{x} + k_0(I)x + \rho(I, \dot{x})$ are the simplified constants, which are calculated as follows:

$$c_0\dot{(I)} = c_1 + c_2\sqrt{|I|} \quad (7)$$

$$k_0(I) = k_1 + k_2\sqrt{|I|} \quad (8)$$

$$\rho(I, \dot{x}) = \rho_1 + \rho_2\sqrt{|I|} + \rho_3\sqrt{|\dot{x}|} \quad (9)$$

Reference [29] proposes the adequate values of the constants required to evaluate the controller performance, which are enlisted as follows:

TABLE I. MR MODEL CONTROLLER PARAMETERS

Parameter	Value
c_1	40
c_2	550
k_1	350
k_2	2500
γ	15.8
ρ_1	30
ρ_2	230
ρ_3	45
λ	0.0032

It should be pointed out that these parameters are the typical ones for an MR damper used in scaled structures [29], as the one used in this article.

III. METHODOLOGY

The occurrence of earthquakes with diverse magnitudes as well as other natural hazards has led to the development of smart civil structures that can adapt to these changes quickly. One of the consequences that have these unintended hazards is the generation of vibrations that in most cases will produce excessive displacements or vibrations in the structure, which can lead to a rapidly deterioration of the physical integrity. Hence, the implementation of vibration control strategies is necessary because this will avoid having severe economic losses and saving human lives. In this sense, proposing or adapting strategies that have been successfully employed in other fields is a paramount necessity.

Fig. 3 shows the proposed methodology for controlling the vibrations in a 5-story steel structure. From the image, the proposed strategy uses three steps to perform the vibration control. In steps 1 and 2, the reference is set to a value of 0, as it is desired to reduce the vibration as much as possible and the controller can perform its tracking, which is composed, as seen in Fig. 2, of two NN that will perform the aforementioned task. Finally, in step 3, the controller output is fed to the MR device coupled with the structure, whose response is measured through using an accelerometer, so the controller can adjust the output. The goal is to reduce the amplitude of the measured vibration signals compared with the original structure response, as this will indicate that the controller performs its task. All the algorithms are implemented in Matlab; further, the MR model is also implemented as a Matlab function.

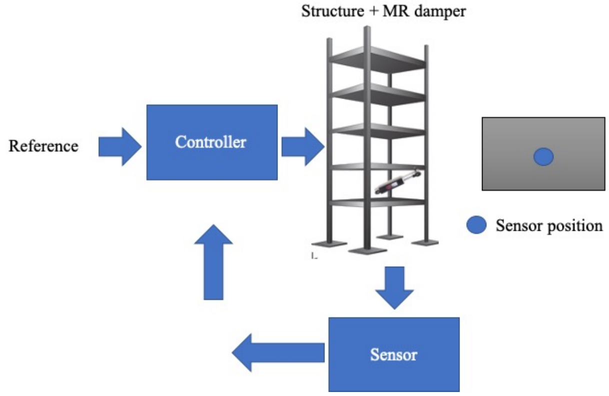

Fig. 3. Proposed Methodology.

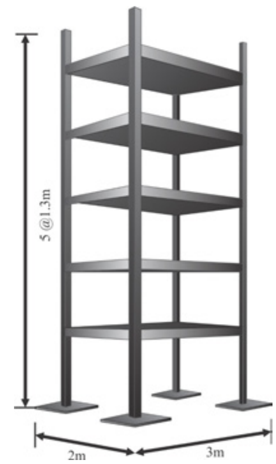

Fig. 4. 5-story steel structure

IV. APPLICATION OF THE PROPOSED METHODOLOGY

This section describes the technical characteristics of the employed structure and the obtained results.

A. *Structure employed.*

To validate the proposed controller, a scaled five-story steel frame, located and tested at National Center for Research on Earthquake Engineering in Taiwan is employed [32]. It consists of a five-story steel frame whose dimensions are: 2 m- width, 3 m-length and 6.5 m-height (each story has a 1.3 m- height) (see Fig. 4). The mass of every story is equally distributed and has a value of 3664 kg.

The structure is excited using the signals from the 1995 Kobe earthquake, scaled to induce only the 20% of the original amplitude with the purpose of avoiding a damage into the structure. The earthquake displacements are imposed to structure by means of a unidirectional shaker table and its response is collected by accelerometers, one the center of every story using a 1 kHz-sampling rate for 25 s, resulting in 25,000 samples per story. Fig. 5 shows the measured responses of the five stories, where Fig. 5a is the measured response of the first floor, Fig. 5b is the measured response of the second floor and so on. The complete explanation of tests performed. can be found in [32].

B. *Obtained Results*

Following the proposed methodology, the vibrational responses produced by the excitation signal (20%-reduced amplitude 1995 Kobe earthquake) are used to develop the controller. The structure is divided in 5 substructures (one for each floor), where in the second substructure the MR damper is assumed to be placed, in the horizontal (x) direction. This location is selected as it will have the influence of the vibrations of the 1st substructure (whose vibration amplitude is the highest, since the excitation system is located in this story) and the 3rd substructure, making the induced vibrations and displacements somewhat higher that the ones of the other substructures, which is confirmed by [32]. Hence, the measured vibrations of the

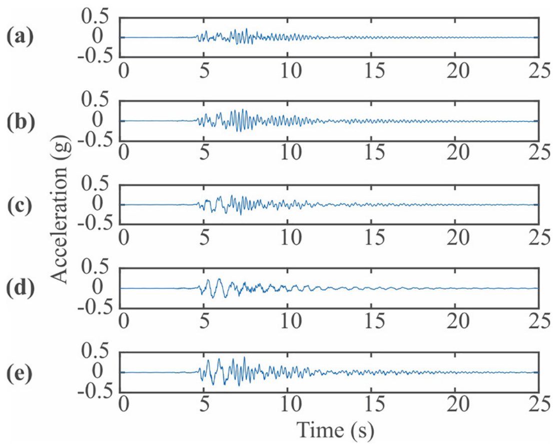

Fig. 5. Measured responses of the five stories (a-e)

second floor are expected to be mitigated, so the reference model uses as inputs the measured responses of the first and third stories.

NN models use the architecture depicted in Fig 2. It should be pointed out the network performance (that is the error obtained for performing the response prediction or the reference track) depends on the number of hidden neurons used. In this sense, after performing several experiments to determine the number of neurons, it was found that 5 neurons allow obtaining the best results, that is the lowest error possible. A greater number did not show improvements in terms of the error between the model output and the responses measured. The obtained response using the model is depicted in Fig. 6, where it can be seen that the maximum errors are less than 0.03 g, demonstrating that the number of neurons used is sufficient to capture the structure dynamics. In addition, it also important to mention that both NN are trained with the BPTT and the reference value used is set to zero, as it is desirable to eliminate the vibrations that can be measured; hence, once the controller estimates the output (acceleration), this value is numerically integrated to estimate the velocity, because the simplified MR model requires its computation to estimate the required current to offer the necessary protection.

A limited current of 0.5 A is assumed to be applied to the MR damper model in order to evaluate an extreme low-power scenario, where only batteries are the main power supply. To estimate z, described by Eq. 6, the hyperbolic tangent function is employed, since it requires moderate computational resources [24]. Once the values of the required current are estimated, the MR model is set and can be used. In this regard, Fig. 6 shows the simulation results obtained, where the blue and orange traces are the original response and the one measured when the vibration controller is active. From the figure, it can be seen that a reduction of the estimated vibrations is obtained, as expected. This indicates that the reference model was trained correctly, since the underlaying relationships are captured adequately, allowing to affirm that the predicted response is very close to the real one. Moreover, the selected number of neurons in the hidden layer delivering reliable results. Specifically, a vibration reduction of over 18% is achieved, which is a good result considering that the MR damper is not allowed to employ more electrical current. This value is estimated taking the energies of the original signal and the controlled one and arithmetically subtracting them. It is hypothesized that if the MR damper can use more power, it is possible to achieve further reductions.

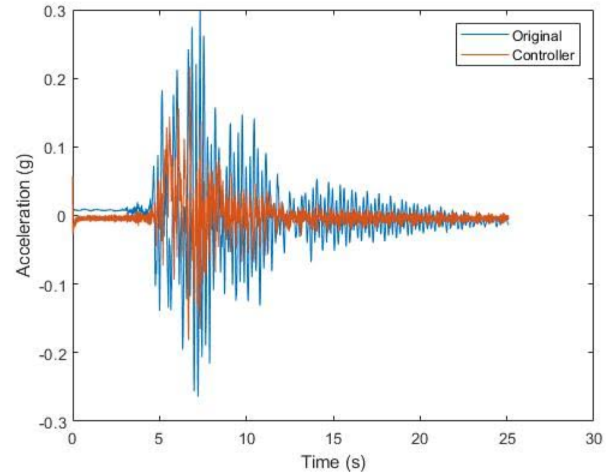

Fig. 7. Acceleration response from substructure 2: uncontrolled (blue trace) and controlled (orange trace) using the model reference controller.

V. Conclusions and Future Work

This paper explored the feasibility of employing the model reference-based neural network controller for vibration suppression in civil structures. The implementation of the reference model and the controller are done using a recurrent topology, whereas a simplified Bouc-Wen model is employed to simulate the behavior of the MR damper.

The obtained results show that the proposal can provide a feasible solution to perform the vibration controller in real-life civil structures in a low-power operation scenario, as a 18%-reduction in the vibration is achieved. This indicates that the topologies used to implement the reference model and the controller were trained correctly and efficiently, as only 5 neurons are employed in the hidden layer; moreover, the decision to divide the structure in subsection of 1 story allowed the computational resources optimization usage. This

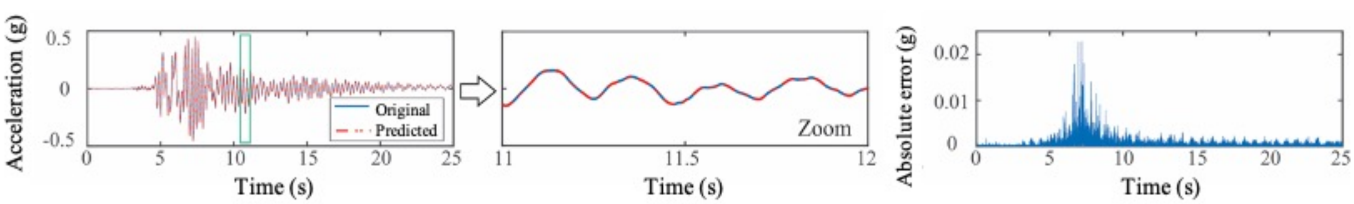

Fig. 6. Predicted response of floor 2 using the NN model

conclusion can be extended to the implementation of the simplified Bouc-Wen model.

As future work, the comparison between the used MR model and its real counterpart behavior should be done in order to verify the model accuracy; moreover, the acquisition of signals where the subsection has physically installed the MR devices can allow to generate even more accurate models, as the interaction between the device and the structure is captured and not inferred, as has been done in this work. On the other hand, more complex and asymmetrical structures should be used to explore the potentialities the proposal can have, in particular, by measuring, using displacement measurement sensors, the displacement reduction that the controller can achieve, considering the current restrictions that a real-life scenario have. In this sense, a complete solution could be tested in the first phase and delivered as a result in several constructions around the world.

REFERENCES

[1] Y.-L. Liu and J. He, Smart Civil Structures. Boca Raton, FL: CRC Press, 2017.

[2] J. P. Amezquita-Sanchez, A. Dominguez-Gonzalez, R. Sedaghatti, R. J. Romero-Troncoso, and R. A. Osornio-Rios, "Vibration Control on Smart Civil Structures: A Review," Mech. Adv. Mat. Struct., vol. 21, pp. 23–38, January 2014.

[3] N. R. Fisco and H. Adeli, "Smart structures: Part I—Active and semi-active control," Scientia Iranica, vol. 18, issue 3, pp. 275-284, June 2011.

[4] K. Ghaedi, Z. Ibrahim, H. Adeli, and A. Javanmardi, "Invited Review: Recent developments in vibration control of building and bridge structures," J. Vibroeng., vol. 19, issue 5, pp. 3564-3580, August 2017.

[5] Z. Li and H. Adeli, "Control methodologies for vibration control of smart civil and mechanical structures," Expert Sys., vol. 35, issue 6, pp. e12354, December 2018.

[6] N. Zhao, G. Huang, R. Liu, P. Zhang, C. Lu, and G. Song, " Novel Hidden Pounding Tuned Mass Damper for Vibration Control of a Cantilevered Traffic Signal Structure," J. Eng. Mech., vol. 146, issue 3, pp. 04020005, January 2020.

[7] N. Khodaie, "Vibration control of super-tall buildings using combination of tapering method and TMD system," J.Wind Eng. Ind. Aerodynamics, vol. 196, pp. 104031, January 2020.

[8] Y. Bigdeli and D. Kim, "Damping effects of the passive control devices on structural vibration control: TMD, TLC and TLCD for varying total masses," KSCE J. Civ. Eng., vol. 20, pp. 301–308, January 2016.

[9] F. Casciati, J. Rodellar, and U. Yildirim, "Active and semi-active control of structures – theory and applications: A review of recent advances," J. Int. Mat. Sys. Struct., vol. 23, issue 11, pp. 1181-1195, July 2012.

[10] J. Enríquez-Zárate, G. Silva-Navarro, and A. Cabrera-Amado. Semiactive Vibration Control in a Three-Story Building-Like Structure Using a Magnetorheological Damper. In: Caicedo J., Pakzad S. (eds) Dynamics of Civil Structures, Volume 2. Conference Proceedings of the Society for Experimental Mechanics Series. Springer, Cham, 2015

[11] R. Guclu, "Sliding mode and PID control of a structural system against earthquake," Math. Compt. Model., vol. 44, issues 1–2, pp. 210–217, July 2006.

[12] A.H. Heidari, S. Etedali, and M. R. Javaheri-Tafti, "A hybrid LQR-PID control design for seismic control of buildings equipped with ATMD," Front. Struct. Civ. Eng., vol. 12, pp. 44–57, March 2018.

[13] B. Mehrparvar and F. Khoshnoudian, "Efficiency of active systems in controlling base-isolated buildings subjected to near-fault earthquakes," Struct. Design Tall Spec. Build., vol. 20, issue 8, pp. 1019–1034, December 2011.

[14] M.Gutierrez Soto and H. Adeli, "Recent advances in control algorithms for smart structures and machines," Expert Sys., vol. 34, issue 2, pp. e12205, April 2017.

[15] Z. Li and H. Adeli, "New discrete-time robust H_2/H_∞ algorithm for vibration control of smart structures using linear matrix inequalities," Eng. App. Arti. Intel., vol. 55, pp. 47-57, October 2016.

[16] N. Wang and H. Adeli, "Robust vibration control of wind-excited highrise building structures," J. Civil Eng. Manag., vol. 21, issue 8, pp. 967-976, November 2015.

[17] A. Yeganeh-Fallah and T. Taghikhany, "A modified sliding mode fault tolerant control for large-scale civil infrastructure," Compt.-Aided Civil Infra. Eng., vol. 31, issue 7, pp. 550-561, July 2016.

[18] Y. Wang, J. P. Lynch, and K. H. Law, "Decentralized $\mathcal{H}\infty$ controller design for large-scale civil structures," Earthquake Eng. Struct. Dyn., vol. 38, issue 3, pp. 377-401, March 2009.

[19] L. Fali, M. Djermane, K. Zizouni, and Y. Sadek, "Adaptive sliding mode vibrations control for civil engineering earthquake excited structures," Int. J. Dynam. Control, vol. 7, pp. 955–965, September 2019.

[20] O. Yaowen, F. Xiaodong, and M. S. Miah, "Active vibration control of tensegrity structures for performance enhancement: A comparative study," Earthq. Eng. Eng. Vib., vol. 18, pp. 679–693, July 2019.

[21] G. Danil, Principles Of Artificial Neural Networks (3rd edition). Singapore: World Scientific, 2013

[22] I. Douratsos and J. B. Gomm, "Neural Network based Model Reference Adaptive Control for processes with time delay," Int. J. Inf. Sys. Sci., vol. 3, issue 1, pp. 161–179, November 2007

[23] M. Khashei and M. Bijari, "An artificial neural network (p,d,q) model for timeseries forecasting," Expert Sys. App., vol. 37, issue 1, pp. 479–489, January 2010.

[24] M. T. Hagan, H.B. Demuth and M.H. Beale, Neural Network Design, Boston: PWS Publishing, 1996.

[25] V. Kasparian and C. Batur, "Model reference based neural network adaptive controller," ISA Transactions, vol. 37, issue 1, pp. 21–39, March 1998

[26] H. D. Patiño and D. Liu, "Neural Network-Based Model Reference Adaptive Control System," IEEE Trans. Syst., Man, Cybern. Syst., vol. 30, issue 1, pp. 198-204, February 2000.

[27] C. A. Perez-Ramirez, J. P. Amezquita-Sanchez, M. Valtierra-Rodriguez, H. Adeli, A. Dominguez-Gonzalez, and R. J. Romero-Troncoso, "Recurrent neural network model with Bayesian training and mutual information for response prediction of large buildings,", Eng. Struct., vol. 178, pp. 603-615, January 2019.

[28] P.J. Werbos, "Backpropagation through time: what it does and how to do it," Proc. IEEE, vol. 78, issue 10, pp. 1550-1560, October 1990.

[29] A. Dominguez-Gonzalez, I. Stiharu, and R. Sedaghati, "Practical hysteresis model for magnetorheological dampers," J. Intell. Mater. Syst. Struct., vol. 25, issue 8, pp. 967–979, May 2014.

[30] S. J. Dyke, B. F. Spencer Jr., M. K. Sain, and J. D. Carlson, "Modeling and control of magnetorheological dampers for seismic response reduction," Smart Mat. Struct., vol. 5, issue 5, pp. 565-575, October 1996

[31] F. Raeesi, B. Farahmand Azar, H. Veladi, and S.Talatahari, "An inverse TSK model of MR damper for vibration control of nonlinear structures using an improved grasshopper optimization algorithm," Structures, vol. 26, pp. 406-416, August 2020.

[32] S. H. Hung, C. S. Huang, C. M. Wen, and Y. C Hsu, "Nonparametric identification of a building structure from experimental data using wavelet neural network," Comput-Aided Civ. Infras. Eng., vol. 18, issue 5, pp. 356–368, September 2003