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FUZZY COGNITIVE MAPS APPLIED TO ACTIVE MODAL CONTROL OF A MECHANICAL SYSTEM

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Abstract. *The present contribution is dedicated to the experimental application of fuzzy cognitive maps (FCMs) to the active vibration modal control of a simple mechanical structure by using electromagnetic to the structure without mechanical contact. In this case, the representative mathematical model of a two degree of freedom mass-spring-damper system was used. A model updating procedure based on the differential evolution optimization technique was used to determine the stiffness and damping coefficients of the considered test rig. Based on the identified parameters, it was possible to apply an active modal control technique to the structure. The vibration controller is based on FCMs, which combines aspects of the fuzzy logic and artificial neural networks. Moreover, the Kalman filter estimator was used to determine the modal states used by the controller and to filter the measured displacement signal. The numerical results demonstrated the effectiveness of the adopted control strategy dedicated to the reduction of the amplitude of the structure vibration response.*

Keywords: *active modal control, fuzzy cognitive maps, electromagnetic actuators.*

1. INTRODUCTION

An alternative to classic control techniques is to use heuristic methods that encode expert's knowledge and/or historical data, like fuzzy cognitive maps (FCMs) (Papageorgiou, 2014). FCMs allow the control of complex systems without the mathematical equations that describe the real relationships between the system's dynamic (Mendonça *et al.*, 2013). In this context, the modelling of complex systems using FCM is advantageous since the incomplete or incorrect initial mapping of the concepts can be adjusted adding new ones to the map (Ahmadi *et al.*, 2014).

Consequently, the use of FCMs do not require the mathematical model of the analyzed process, i.e. as higher the complexity of the system goes, the FCMs not necessarily expand in the same rate. In addition, the FCM concepts are not always the elements of the real system modelled: it can be individual parts of a physical system (temperature, volume, concentration), aggregated parts, concepts of the modelled system, and every kind of physical or logical concepts and its combinations that can be observed in the system (Štula, Maras and Mladenović, 2017). There are several scientific domains where FCMs are applied, such as business (Papageorgiou and Salmeron, 2013), information technology, industrial processes engineering and control (Mendonça *et al.*, 2013; de Souza *et al.*, 2017a; de Souza *et al.*, 2017b; Soares *et al.*, 2017). In addition, medicine (Papageorgiou, Stylios and Groumpos, 2006; Papageorgiou and Froelich, 2012; Amirkhani *et al.*, 2017), agriculture (Mourhir *et al.*, 2017), and behavioral sciences (Andreou, Mateou and Zombanakis, 2005).

Since undesired oscillations can be inherent in structures subjected to dynamic forces, several control techniques are used to minimize them. Thus, the modal active vibration control has been used due to its capability to reduce considerably the computational effort needed. This is caused by the reduction of the numerical model that represents the analyzed system. There are various ways to design modal controllers, including soft computing techniques. Thus, this work aims to contribute in the active modal control area using a novel FCM-based approach. This work will focus in the analysis of the vibration amplitude response of a two degrees of freedom (DoFs) structure using a FCM controller. We expect that the intelligent controller using the FCM soft computing technique lower the computational cost in comparison to other intelligent approaches.

This work is organized as follows. Sections 2 and 3 presents, respectively, the background for FCMs and the description of the mechanical system used for the controller implementation. Section 4 approaches the control scheme development using FCMs. The results are shown in Section 5, and we conclude the paper and present future work in Section 6.

2. FUZZY COGNITIVE MAPS

FCMs differs from traditional "if/then" rules systems due to its flexibility and capability to represent human knowledge (Ahmadi *et al.*, 2014). In short, FCMs combines aspects of fuzzy logic and artificial neural networks (ANNs). They derivate from cognitive maps (CMs), presented by Tolman (1948), and can be defined as a cognition network developed using experts knowledge (Kosko, 1986). A CM is a directed graph consisted of nodes (concepts) and arcs (relationships). Consequently, FCMs have three types of relationships between concepts: positive, negative and neutral (zero). In the first case, any change in the source concept will positively change the destination concept, and the reverse occurs with a negative relationship. In the last case, the two concepts do not have influence (Papageorgiou, 2014). The relationships are fuzzy values in the range [-1, 1], defined by a *n by n* connection matrix where *n* is the number of concepts (Kosko, 1986).

In particular, the following five definitions are used to describe FCMs (Ahmadi *et al.*, 2014):

1: A FCM is a 4-tuple (C, W, A, f);

2: $C = \{C_1, C_2, ..., C_n\}$ is the set of *n* concepts;

3: W_{ij} is an *n by n* connection (weight) matrix, which shows the causal relationship between concepts C_i and C_j.

4: $A= \{A_1, A_2, ..., A_n\}$ is a set of values in the range [−1, 1], which represent the values of *C*. The influence between concepts in several iterations is calculated by (1). $A_i^{(t+1)}$ represent the value of C_i at iteration $t+1$, and $A_j^{(t)}$ the value of C_j at iteration *t*. W_{ji} is the causal relationship between C_i and C_j.

$$A_i^{(t+1)} = f\left(\sum_{j=1}^{n} W_{ji}.A_j^{\ t}\right) \tag{1}$$

5: $f(x)$ is a threshold function. In this work, the sigmoid function (2) was used to convert the output to the interval [0, 1], and $\lambda>0$ is the slope of the function (defined 1). Other functions can be used, e.g. the hyperbolic tangent [-1, 1].

$$f(x) = \frac{1}{1+e^{-\lambda x}} \tag{2}$$

In general, FCMs can be classified by its learning approaches, concentrated on the weight matrix. The objective of the learning process is to find a set of FCM's weights that provides a desired steady state to the FCM. This is obtained through the minimization of a desired objective function (Parsopoulos *et al.*, 2003). Thus, the algorithms are divided in three types of knowledge: Hebbian-based, population-based, and hybrid approaches, derived from the other two learning types (Papageorgiou, 2012; Papageorgiou and Salmeron, 2013). In addition, there are several extensions of the Kosko's classic FCMs. These extensions generate better results according to its application. Usually, they are designed to solve the FCM drawbacks (Papageorgiou and Froelich, 2012): uncertainty modeling (e.g. FGCM (Salmeron, 2010)), dynamic issues (e.g. FTCM (Park and Kim, 1995)), and rule-based knowledge representation (e.g. RBFCM (Carvalho and Tomé, 2001) and TAFCM (Acampora, Loia and Vitiello, 2011)), among other extensions (DFCM (Mendonça *et al.*, 2013)).

3. MECHANICAL SYSTEM DESCRIPTION

The analyzed structure, presented by Fig. 1, consists of a two DoFs mass-spring-damper system. Where (1) represents mass m_1, (2) stiffness and damping of floor #1 (k_1, c_1), (3) mass m_2, (4) stiffness and damping of floor #2 (k_2, c_2), and (5) the electromagnetic actuators.

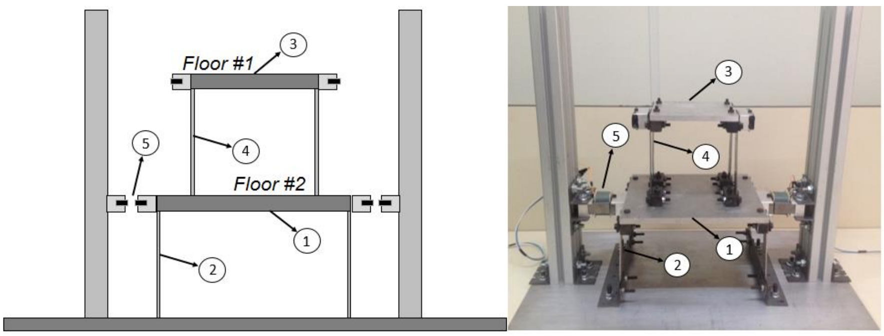

Figure 1. Mechanical system

The experimental test rig has two aluminum plates (masses) sustained by flexible stainless-steel rods (stiffness and damping elements), and two electromagnetic actuators are positioned on the side columns. The system is represented by Eq. (3), where $[M]$, $[K]$, and $[C]$ are the mass, stiffness, and damping matrices, respectively, $\{F_{exc}(t)\}$ is the excitation force, $\{F_{EMA}(t)\}$ is the electromagnetic force, and $\{\delta(t)\}$ is the displacement vector.

$$[M]\{\acute{\delta}(t)\} + [C]\{\acute{\delta}(t)\} + [K]\{\delta(t)\} = \{F_{exc}(t)\} + \{F_{EMA}(t)\} \tag{3}$$

The identification of the mechanical system's stiffness and damping coefficients consisted in the minimization of the difference between experimental and numerical frequency response functions (FRFs), a typical inverse problem. In addition, we used a Data Physics Quattro® acquisition board to measure the excitation force applied to the system by an impact hammer, and we measured its corresponding vibration responses through an accelerometer. Thus, the SignalCalc ACE® software was used to treat input and output signals. This procedure consisted in five tests in order to obtain average values for the FRFs. In this work, we obtained four FRFs measuring the impacts in the system caused by the impact hammer along floors #1 and #2.

We applied a differential evolution algorithm considering four configurations of initial population: 50, 100, 150 and 200 individuals) (Viana, 2008). Thus, the unknown parameters and its design intervals of the optimization are presented in Tab. 1, and the parameter set obtained in the optimization is shown in Tab. 2 (Repinaldo *et al.*, 2019).

Table 1. Design space adopted in the optimization process.

Parameter	Design space
Stiffness k_1 [N/m]	$9000 \leq k_1 \leq 40000$
Damping c_1 [N.s/m]	$0 \leq c_1 \leq 25$
Stiffness k_2 [N/m]	$8000 \leq k_2 \leq 20000$
Damping c_2 [N.s/m]	$0 \leq c_2 \leq 10$

Table 2. Parameters obtained through the optimization process.

Parameter	Value
Stiffness k_1 [N/m]	$2.15\text{x}10^{4}$
Damping c_1 [N.s/m]	14.43
Stiffness k_2 [N/m]	$3.18x10^{-8}$
Damping c_2 [N.s/m]	0.622
Mass m_1 [Kg]	4.38
Mass m_2 [Kg]	1.94

Table 3. Parameters of the actuators.

Parameter	Value
μ_0 [H/m]	$4\pi\ x\ 10^{-7}$
μ_r	688.27
a [mm]	9.5
b [mm]	38
c [mm]	28.5
d [mm]	9.5
e [mm]	2
f [mm]	21.5
N	237

Table 3 shows the parameters of the two electromagnetic actuators used to control the system. Thereby, we defined the electromagnetic force F_{EMA} as seen in Eq. (4), and the electric current *Ix* is obtained through the inverse model, as given by Eq. (5). The geometry of the solenoid is represented by *a*, *b*, *c*, and *d*. μ_r and μ_0 are the magnetic permeability and vacuum permeability, respectively. *N* is the solenoid's number of turns, *e* the gap, and corresponds δ to the displacement (Repinaldo *et al.*, 2019).

$$F_{EMA} = \frac{N\ .\ e^2\ .\ Ix^2\ .\ \mu_0\ .\ a\ .\ f}{2\ .\ [(e \pm \delta) + \frac{b+c+d-(2\ .\ a)}{\mu_r}]^2} \tag{4}$$

$$I_x = \sqrt{\frac{2 \,.\, F_{EMA} \,.\, \left[(e \pm \delta) + \frac{b+c+d-(2\,.\,a)}{\mu_r}\right]^2}{N^2 \,.\, \mu_0 \,.\, a \,.\, f}} \tag{5}$$

4. ACTIVE MODAL FCM CONTROL IMPLEMENTATION

Starting from previous research (Repinaldo *et al.*, 2019), we used a state observer to estimate the system's modal states. Thus, our control approach consists of a FCM in the two system's modes to control the vibration amplitude through an electromagnetic actuator. In this case, the main advantage of the proposed approach is to reduce the computational complexity (effort) of the modal control, since only one FCM (duplicated) can control the vibrations, instead of two slightly different controllers, such as in our past work. We present the proposed FCM in Fig. 2 and the control scheme is presented in Fig. 3, were *u* represent the controller's output signal.

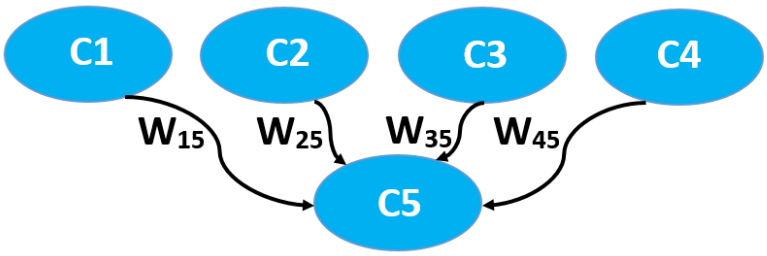

Figure 2. Proposed FCM controller

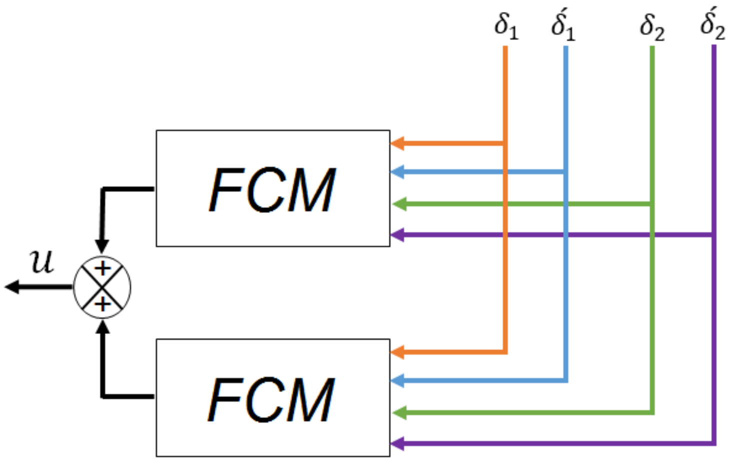

Figure 2. FCM control scheme

Regarding our development, there are two FCMs approaches in the literature: the automated ones, generated by historical data, and manual ones, developed by experts' knowledge (Yesil *et al.*, 2013; Mendonça *et al.*, 2017). In this work, the FCMs are manual, tuned from dynamic observation. We tuned the FCMs' weights heuristically according to our expert knowledge about the system. The fuzzy controller used in the previous work inspired the FCM's concepts. The input concepts are the modal displacements (*C1* and *C3*) and velocities (*C2* and *C4*). Concept *C5* is the control signal for the electromagnetic actuators. The weight vector is shown in Eq. (6).

$$W = [W_{15}, W_{25}, W_{35}, W_{45}] = [0.9, -0.7, 0.6, 0.8] \tag{6}$$

5. ACTIVE MODAL FCM CONTROL RESULTS

Figure 3 shows the results for the vibration control: the red and blue lines represent respectively the uncontrolled and the FCM controlled system over time (s). In this initial version, the main drawbacks from the FCM use are the control delay in the first 0.4s and a residual in permanent regime caused by the white noise implemented in the system simulations, in order to generate results closer to the future experimental control.

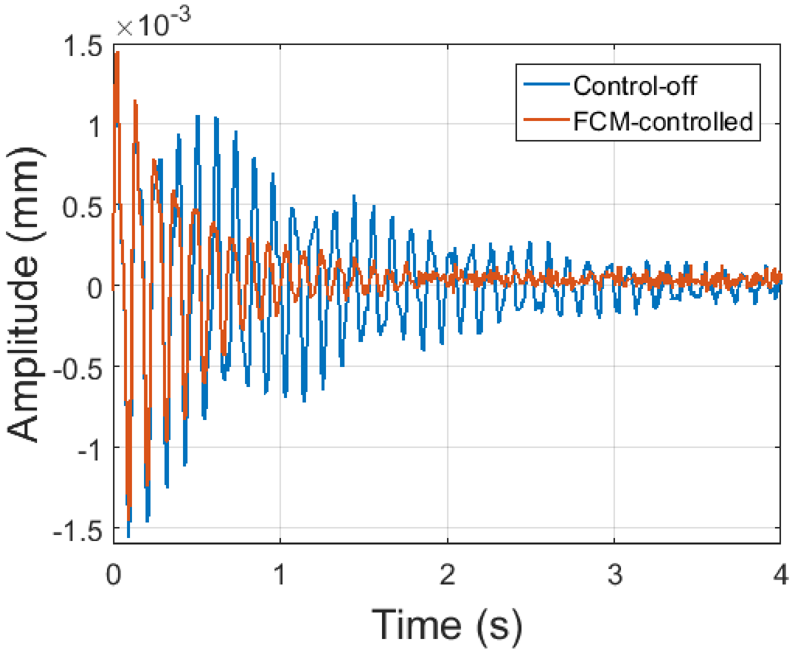

Figure 3. System's vibration – FCM controller

In this work, we used two criterions to evaluate the controller: the integral of absolute error (IAE) and the time-weighted integral of absolute error (ITAE). We used such criterions to refine the FCM's weights: since the system is underdamped, higher values in the IAE mean that the control action must be increased. Similarly, the ITAE values can show irregularities in the stationary condition. The final criterions obtained are IAE = 0.0794 and ITAE = 0.0730.

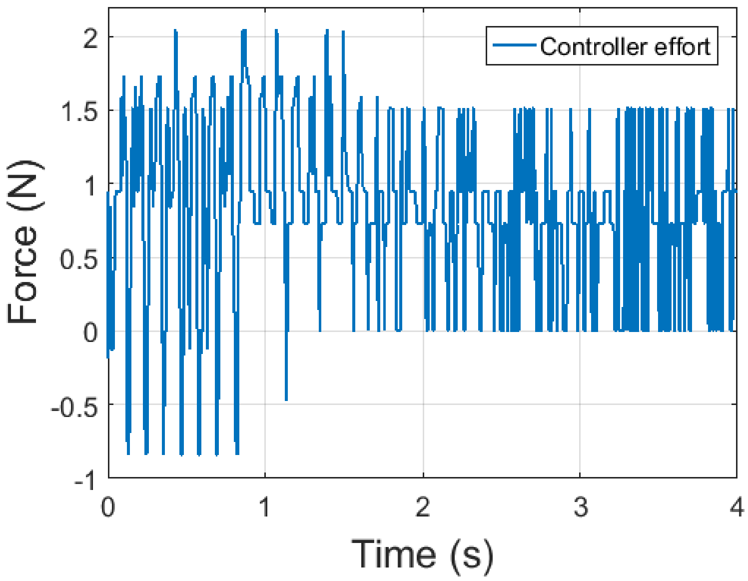

Figure 4. FCM controller effort

The controller's effort is shown in Fig. 4. The negative values indicate a change on the side of the force application. We can see that even after 2 s (were the system goes stationary), the controller effort continues to present non-zero values. However, this condition only changes its energetic efficiency, as can be seen in Fig. 5 through the currents for modes 1 and 2, respectively (Ix_1 and Ix_2). This behavior is caused since the FCM tends to a limit cycle from approximately 1.5 s. From Fig. 5, it is noteworthy that the first mode current Ix_1 has the main influence in the values obtained in Fig. 4. To outcome this behavior, we tested another control scheme using one FCM to control the first mode. In this investigation, we observed again the limit cycle in our results, with worst control criterions.

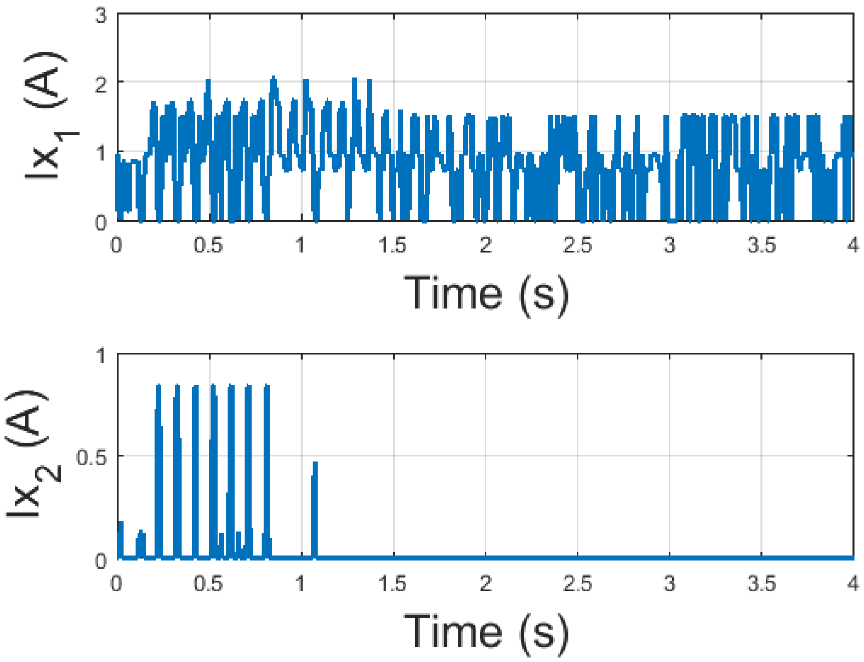

Figure 5. FCM controller currents for modes 1 and 2

Figure 6 shows the FRFs from modes 1 and 2, respectively. In the FCM-controlled system (blue-dashed response), the magnitude in the frequencies near 75 Hz is elevated, and the range from 150-200 Hz has an attenuated response in both modes.

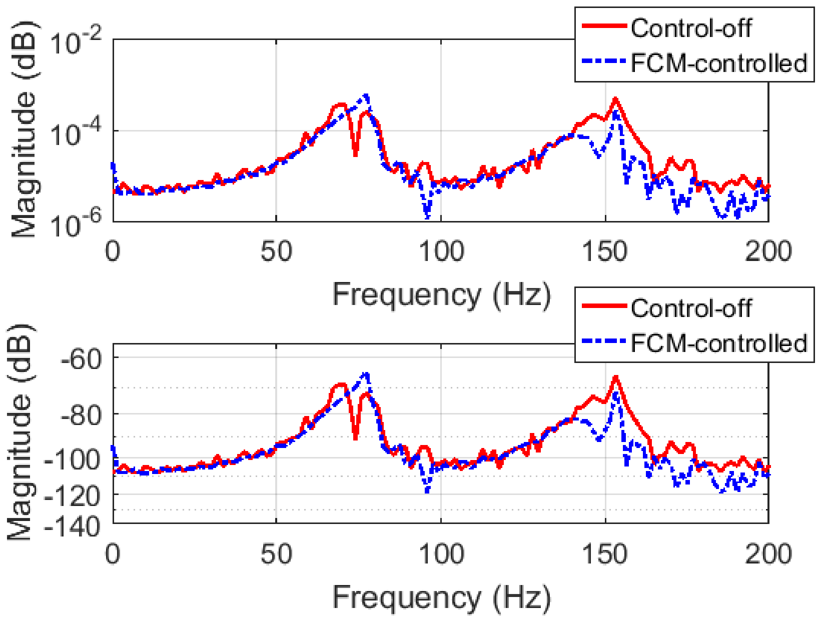

Figure 6. System's FRF for modes 1 and 2

6. CONCLUSIONS

This work presented a novel approach for the active modal control of a two DoFs mechanical system using a FCM controller. Our results in this case are promising despite the need for refinements in the controller's development.

The main expected contribution consists in the development of the FCM controller. With this technique, there are no need to know the entire mathematical model of the system: through experts' knowledge, and using the same input concepts, this FCM controller can be scalable for use in higher-order vibration systems by adapting the controller's weights according to the number of modes. Thus, this controller can be used in any mass-spring-damper system with two DoFs.

To outcome the FCMs drawbacks, we can design other FCMs, e.g. a PID-like using differential and integral errors as input concepts for the system's modes. In addition, the use of loops or self-loops to increase the FCM complexity in order to achieve better results will be studied.

Future work will focus on the comparison between the proposed FCM approach and other soft computing techniques, such as controllers based in fuzzy logic and adaptive neuro-fuzzy inference system (ANFIS) through simulations and using our experimental test rig, and the application in other systems. Further refinements in the FCM controllers will be made.

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9. RESPONSIBILITY NOTICE

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