



# Active vibration control design using the Coral Reefs Optimization with Substrate Layer algorithm



C. Camacho-Gómez<sup>a</sup>, X. Wang<sup>b</sup>, E. Pereira<sup>a,\*</sup>, I.M. Díaz<sup>b</sup>, S. Salcedo-Sanz<sup>a</sup>

<sup>a</sup> Department of Signal Processing and Communications, Universidad de Alcalá, Madrid, Spain

<sup>b</sup> E.T.S. Ingenieros de Caminos, Canales y Puertos, Universidad Politécnica de Madrid, 28040 Madrid, Spain

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## ABSTRACT

Active vibration control (AVC) via inertial-mass actuators is a viable technique to mitigate human-induced vibrations in civil structures. A multi-input multi-output (MIMO) AVC has been previously proposed in the literature to simultaneously find the sensor/actuator pairs' optimal placements and tune the control gains. However, the method involved local gradient-based methods, which is not affordable when the number of possible locations of actuators is large. In this case, the computation time to obtain a local solution may be huge and unaffordable, which limits the number of test points and/or actuators/sensors considered. This paper proposes an alternative approach based on a recently proposed meta-heuristic, the Coral Reefs Optimization (CRO) algorithm. More concretely, an enhanced version of the CRO is considered, the Coral Reefs Optimization with Substrate Layer (CRO-SL). The CRO-SL is a competitive co-evolution algorithm in which different exploration procedures are jointly evolved within a single population of potential solutions to the problem. The proposed algorithm is thus able to promote competition among different search methods to solve hard optimization problems. In terms of structural design, this work provides an important step to improve the applicability of AVC systems to real complex structures (with a large number of vibration modes and/or with a large number of test points) by achieving global optimum designs with affordable computation time. A finite element model of a real complex floor structure is used to illustrate the contributions of this paper.

## 1. Introduction

Improvements in design and construction have led to light and slender floor structures, which have in turn increased susceptibility to vibrations. These structures satisfy ultimate limit state criteria but have the potential of attracting complaints coming from excessive human-induced vibrations [1]. Active vibration control (AVC) via inertial mass actuators has been shown to significantly reduce the level of response, allowing structures to satisfy vibration serviceability limits [2].

Single-input single-output (SISO) strategies based on collocated control (i.e., the pair sensor/actuator are placed physically at the same point) are widely used. However, a better performance can be achieved if a multi-input multi-output (MIMO) control strategy is used. This was firstly shown in [3], in which an optimal direct output velocity feedback (DVF) MIMO controller was presented. This DVF-MIMO control strategy finds the optimal gain matrix and the optimal location for a predefined number of actuators and sensors. The optimal sensor/actuator placement and the gain matrix are obtained by minimizing a performance index (PI) that considers the amplitude and duration of the

vibration, and the maximum force imparted by each actuator. Simulation results were presented in [3], demonstrating the advantages of using MIMO control as opposed to SISO control.

In [4], the PI proposed in [3] was used to experimentally implement a MIMO AVC. Furthermore, the frequency bandwidth where humans perceive the vibration [5] was also considered in [4] to focus the control effort on the most important vibration modes. However, unlike [3], the MIMO AVC proposed in [4] takes into account practical considerations, such as the spillover effects due to high-frequency components [6], the actuator dynamics and its nonlinearities limitations due to stroke and force saturations. The spillover effects were reduced by considering low-pass filters and the stroke and force saturations were mitigated by including high-pass filters. This approach has been successfully implemented in practice on an indoor walkway sited at Forum building at the University of Exeter (Exeter, UK). The algorithm presented in [4], which is based on a local gradient-based method, is useful when the number of test points is small. However, problems in structural optimization are often characterized by search spaces of extremely high dimensionality and nonlinear objective functions [7]. In

\* Corresponding author.

E-mail address: [emiliano.pereira@uah.es](mailto:emiliano.pereira@uah.es) (E. Pereira).

these optimization problems, classical approaches do not lead, in general, to good solutions, or in many occasions they are just not applicable, due to the unmanageable search space structure or its huge size, which implies an extremely high computation cost (i.e., the computation time to obtain a local solution may be months). Then only a few of test points and/or actuator/sensor pairs can be considered within these optimization processes. In this context, modern optimization meta-heuristics have been successfully applied to an important number of structural optimization problems [8]. Meta-heuristic algorithms have been shown as a possibility to obtain an approximate solution to a given problem which cannot be tackled with exact algorithms.

Modern optimization meta-heuristics have been lately the core of a huge research work, focused on improving the performance and search capabilities of this class of optimization techniques. The application of these new optimization algorithms in almost all fields of Science, Engineering and Technology has been massive, generating even much interest on their study and improvement. Many of these meta-heuristics approaches have a *bio-inspired* origin such as evolutionary algorithms (EA) (Genetic Algorithms [9], Evolutionary Strategies [10], Evolutionary Programming [11], Differential Evolution [12], among others). These schemes are based on concepts borrowed from natural evolution and survival of the fittest individuals in Nature. Similarly, Ant Colonies Optimization (ACO) [13] are based on the social behavior of ants, Particle Swarm Optimization (PSO) approaches [15] imitate the behavior of birds flocks or fish schools, and Artificial Immune System (AIS) algorithms [14] are focused on imitating the behavior of the immune system in animals. Many alternative meta-heuristics have arisen in the last years, such as Artificial Bee Colony [16], which imitates the bees behavior when locating and bring food to the hive, the Gravitational Search Algorithm (GSA) [17], inspired by the law of the gravity, the Invasive Weed Optimization Algorithm (IWO) [18], based on weed growth and their invasive properties, the Hunting Search (HS) [19], based on how group of animals hunt, the Biogeography-Based Optimization algorithm (BBO) [20], based on the geographical distribution of living organisms, optimization based on virus infection [21], and on colonies of bacteria [22,23], the bat algorithm [25], based on the behavior of bats and its capability for echolocation of objects, or the so-called Cuckoo search approach [24], built upon the reproduction and breeding of the cuckoo bird.

There are different meta-heuristics that have been specifically applied to structural engineering problems. Genetic and evolutionary algorithms have been applied to the discrete optimization of structures in [27]. There have been other works that applied genetic algorithms in structural optimization problems such as shape optimization [28], optimization of 3D trusses [29], impact load characterization of concrete structure [30], the plane stress problem [31] or welded beam optimization problems [32]. The particle swarm optimization algorithm [15] is another important meta-heuristic which has been successfully applied to structural optimization problems, such as truss layout [33] or truss structures optimization [34]. The Harmony Search approach [7,35] and the teaching-based learning algorithm [36,37] have also been used to solve mechanical design optimization problems. In the last few years, alternative modern meta-heuristics based on physics process have been applied to structural optimization problems, such as the Big-Bang Big-Crunch algorithm [38], the colliding bodies optimization algorithm [39], the Ray optimization [40], the charged system search algorithm [41] or the Thermal Exchange optimization [26].

In this paper, the recently developed co-evolution meta-heuristic, the Coral Reefs Optimization algorithm with Substrate Layer (CRO-SL) [42], is applied to design MIMO-AVC for structures subjected to human induced vibration. This optimization algorithm is particularly interested when vibrations on complex floor structures with several closely-frequency spaced vibration modes have to be cancelled. Thus, this algorithm promotes a powerful evolutionary-like search, ideal for solving high-burden optimization problems, which will be shown to be very effective in this particular problem of MIMO-AVC design. The proposed

algorithm's performance has been evaluated and compared with several reference algorithms in a finite element (FE) model of a complex floor structure.

The structure of the remainder of the paper is as follows: next section describes the generalized framework used to obtain the optimal design of MIMO AVC and location of sensors and actuators. This section also describes the structural model of the application example used in Section 4. Section 3 presents the main characteristics of the original CRO, including the different operators and the algorithm's dynamics. In addition, Section 3 also describes the proposed CRO-SL version, including the definition of *substrate layer*, and, in this case, how it represents the co-evolution of different searching mechanisms with the rules of the CRO. Section 4 presents the aforementioned application example, where the proposed algorithm's performance is evaluated and compared with a reference algorithm. Section 5 closes the paper by giving some conclusions and remarks on this research.

## 2. Problem definition

The problem tackled in this paper consists of finding the optimum locations and control gains of the AVC MIMO control strategy presented in [4]. This section explains the general scheme shown in Fig. 1 and how to formulate the cost function to use the CRO-SL as solver. In addition, the FE floor structure model, the AVC design methodology and the optimization problem are also described in this section.

### 2.1. Floor structure

The structure considered in this paper is a dining room floor of a primary-secondary school sited in Madrid (Spain). The general arrangement of beams and pillars is shown in Fig. 2. The FE model was created in ANSYS [43] using shell elements and 449 nodes. It is an irregular rectangular composite floor with the dimension of 25.5 m × 20 m × 0.3 m. As is shown in Fig. 2, the floor is supported by 33 columns. Different connections between the floor and columns are marked with different colors: red<sup>1</sup> ones represent those whose displacements in x, y and z directions are all restricted; cyan ones that are restricted in x and z displacements; blue ones that are restricted in y and z displacements; green ones are connections only restricted in z direction. None of the connections between columns and deck are restricted in rotations. The yellow lines show the meshing grids of the shell elements. The material properties considered are: modulus of elasticity  $E = 20 \times 10^9$  N/m<sup>2</sup>, Poisson's ratio  $\nu = 0.15$  and density  $\rho = 3000$  kg/m<sup>3</sup>. The density has been increased from 2500 kg/m<sup>3</sup> to 3000 kg/m<sup>3</sup> in order to include a portion of the imposed load (approximately 30%) and the total dead load, following the recommendation of [44] for analysis of floor vibrations. The modal shapes, natural frequencies, damping ratios and modal masses of the first ten vibration modes can be seen in Fig. 3.

For the sake of simplicity, the flexible structure and the integrators are grouped, so that the output of the resulting system is  $\mathbf{y}_s$ , which is the velocity at  $q$  locations. Thus, the standard state-space representation of the model for this flexible structure (with  $n$  vibration modes,  $p$  actuators,  $q$  sensors and  $r$  perturbations) is represented as follows (see Fig. 1):

$$\begin{aligned}\dot{\mathbf{x}}_s &= \mathbf{A}_s \mathbf{x}_s + \mathbf{B}_{s1} \mathbf{u}_s + \mathbf{B}_{s2} \mathbf{w}_s, \\ \mathbf{y}_s &= \mathbf{C}_s \mathbf{x}_s,\end{aligned}\quad (1)$$

If Eq. (1) is defined in modal coordinates, the state-space matrices are as follows [45]:

<sup>1</sup> For interpretation of color in Fig. 2, the reader is referred to the web version of this article.

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