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TESIS DOCTORAL:

Machine Learning Applied to Non-Deterministic Actions Affecting Slender Structures and Their Active Cancellation

Presentada por César Peláez Rodríguez para optar al grado de
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ABSTRACT

Vibration problems in slender structures pose a significant challenge in modern structural engineering, leading to problems such as structural fatigue, discomfort and safety risks. These undesired vibrations arise from various nondeterministic sources such as dynamic loads, turbulent winds, human activities, and machinery. Understanding and characterizing these actions is crucial for structural design and safety and represents a central research topic in structural engineering. In this context, data-driven methods have emerged as a valuable addition to traditional structural engineering techniques. They use extensive data collection, sensor networks and advanced analytics to provide real-time insights into structural behaviour and accurate forecasts of potential excitations, etc.

This doctoral thesis aims to develop and apply data-driven techniques to address vibration challenges in slender structures. Its objectives involve identifying, predicting and characterizing non-deterministic actions affecting these structures by means of data-based non-parametric models as Machine Learning, as well as developing methods to actively mitigate them based on evolutionary computation.

The doctoral thesis encompasses three works, where various issues related to different facets of structural vibration analysis have been successfully addressed following the subsequent methodologies.

In first place, the focus is on the prediction and characterizing stochastic forces that dynamically influence structures, with particular emphasis on extreme events with potentially significant impacts. Specifically, the work involves the prediction of extreme wind speeds. An intrinsic challenge in predicting such extreme events lies in dealing with highly unbalanced datasets. To address this, in addition to the application of conventional data balancing techniques, a novel three-level Hierarchical Classification/Regression methodology was developed, yielding highly satisfactory results in forecasting extreme wind events while minimizing false alarms. The prediction of stochastic events was conducted across various time prediction horizons, spanning short to long term, ensuring the methodology's robustness and optimal performance across different scenarios.

The second work is focused on characterizing non-deterministic forces impacting structures, specifically emphasizing the reproducibility of their temporal series using an electrodynamic shaker. This approach facilitates standardized testing of structural responses to dynamic loads in an objective and repeatable manner. The challenge of dealing with a naturally nonlinear electro-mechanical system, represented by a non-invertible model, was addressed in this work, where the goal was to derive an inverse model for replicating time series signals. To overcome this hurdle, an iterative neural network framework for replicating human-induced ground reaction forces was developed. Within this framework, an inversion-free offline control approach was applied to the electrodynamic shaker, ensuring repeatability and accuracy in dynamic load tests. This proposal was successfully validated, achieving reliable reproduction of ground reaction forces produced by different types, amplitudes, and frequencies of human motion or locomotion activities.

The final work involves the successful development, implementation, and experimental validation of an Active Mass Damper control system for a full-scale structure. A genetic evolutionary algorithm was utilized to optimize both the state estimator gain and the feedback gain controlling the actuator in the active control methodology. This demonstrated that the data-based optimization of the control law serves as a viable alternative to classical methods. Various optimization criteria were assessed for this purpose. Additionally, the validation of the control system was carried out by evaluating different parameters in both the time and frequency domains.

In terms of the obtained results, the accomplishments achieved throughout the development of this doctoral thesis represent notable contributions to the research field in which it is framed. Developing and successfully applying machine learning and artificial intelligence methods to address challenges arising from structural engineering.

KEY WORDS: Vibration mitigation, Artificial Intelligence, Time series forecasting, Human-induced vibrations, Active Mass Damper.

RESUMEN

Los problemas causados por vibraciones suponen un desafío significativo en la ingeniería estructural moderna, donde las estructuras son cada vez más ligeras y esbeltas. Estas vibraciones dan lugar a problemas como fatiga estructural, disconfort y potenciales riesgos de seguridad. Las vibraciones no deseadas surgen de diversas fuentes no determinísticas como cargas dinámicas, vientos turbulentos, actividades humanas y maquinaria. Comprender y caracterizar estas acciones es crucial para el diseño y la seguridad estructural, representando un tema central de investigación en ingeniería estructural. En este contexto, los métodos basados en el análisis de datos han surgido como un valioso complemento a las técnicas tradicionales de ingeniería estructural. Estos métodos utilizan una amplia recopilación de datos, redes de sensores y análisis avanzado para proporcionar información en tiempo real sobre el comportamiento estructural y pronósticos precisos ante posibles excitaciones.

Objetivos

Esta tesis doctoral tiene como principales objetivos el desarrollo y aplicación de técnicas basadas en el análisis de datos y el aprendizaje máquina para resolver problemas causados por las vibraciones en estructuras esbeltas. El trabajo involucra tanto la identificación, predicción y caracterización de acciones no determinísticas que afectan estas estructuras mediante modelos no paramétricos basados en datos, como el desarrollo de métodos para mitigar activamente las vibraciones basados en la computación evolutiva.

Metodología

La tesis doctoral abarca tres trabajos, donde se han abordado con éxito varios problemas relacionados con diferentes facetas del análisis de vibraciones estructurales. Estos trabajos incluyen el desarrollo de nuevos algoritmos de aprendizaje máquina para la predicción de series temporales relacionadas con acciones no deterministas que inducen vibraciones en las estructuras, la caracterización y replicación de fuerzas dinámicas inducidas por humanos, y el desarrollo y validación experimental de un sistema de control activo para la mitigación de vibraciones. Para ello, se han implementado diversas metodologías relacionadas con el aprendizaje máquina que se resumen a continuación.

Resultados

En primer lugar, el enfoque del primer trabajo se centra en la predicción y caracterización de fuerzas estocásticas que influyen dinámicamente en las estructuras, con especial énfasis en eventos extremos con impactos potencialmente significativos. En concreto, el trabajo implica la predicción de velocidades extremas del viento. Un desafío intrínseco en la predicción de este tipo de eventos extremos radica en trabajar con conjuntos de datos altamente desbalanceados. Para lidiar con este inconveniente, se ha desarrollado una metodología de clasificación y regresión jerárquica de tres niveles, que ha proporcionado resultados altamente satisfactorios en la predicción de eventos extremos de viento minimizando el ratio de falsas alarmas. La predicción de eventos estocásticos se realizó considerando diferentes horizontes de predicción temporal, desde el corto hasta el largo plazo, asegurando la robustez y el rendimiento óptimo de la metodología presentada en diferentes escenarios.

El segundo trabajo se centra en la caracterización de las fuerzas no determinísticas que impactan en las estructuras, haciendo hincapié en la reproducibilidad de sus series temporales mediante un shaker electrodinámico. Este enfoque facilita la estandarización de los tests dinámicos estructurales, permitiendo su realización de manera objetiva y repetible. En este trabajo se abordó el desafío de lidiar con un sistema electromecánico no lineal, donde el objetivo era obtener un modelo inverso para replicar las señales de series temporales. Para superar este obstáculo, se desarrolló una arquitectura iterativa de redes neuronales para replicar las fuerzas de reacción al suelo (GRF) inducidas por humanos. Dentro de esta metodología, se aplicó un esquema de control offline al shaker electrodinámico, logrando una reproducción fiable de las series temporales de fuerzas de reacción al suelo producidas por diferentes tipos, amplitudes y frecuencias de movimiento o actividades de locomoción humana.

El trabajo final presentado consiste en el desarrollo, la implementación y la validación experimental de un sistema de amortiguador de masa activa para mitigar las vibraciones en una estructura a escala real. Se utilizó un algoritmo genético evolutivo para optimizar tanto la ganancia del estimador de estado como la ganancia de retroalimentación que controla el actuador en la metodología de control activo.

Esto enfoque demostró que la optimización de la ley de control utilizando algoritmos evolutivos es una alternativa válida a los métodos de control clásicos. Se evaluaron diversos criterios de optimización con este propósito. Además, la validación del sistema de control se llevó a cabo evaluando diferentes parámetros en los dominios de tiempo y frecuencia.

Conclusiones

Los resultados obtenidos mediante la realización de estos trabajos representan contribuciones notables al campo de investigación en el cual se enmarca esta tesis doctoral. Se han desarrollado y aplicado con éxito diversos métodos de aprendizaje automático e inteligencia artificial para abordar desafíos derivados de la ingeniería estructural. En primer lugar, se ha propuesto un nuevo algoritmo para la predicción de eventos extremos relacionados con acciones no deterministas que afectan a las estructuras esbeltas. Además, se han caracterizado las fuerzas dinámicas a las que están sometidas las estructuras durante su fase operacional, estableciendo protocolos para la realización de test dinámicos sobre las mismas basados en la replicación de acciones no deterministas inducidas por peatones. Por último, se han empleado técnicas de optimización heurísticas como alternativa a los métodos clásicos para el diseño de sistemas de control activos, realizando su desarrollo y validación experimental sobre una estructura real.

PALABRAS CLAVE: Mitigación de vibraciones, Inteligencia artificial, Predicción de series temporales, Vibraciones inducidas por humanos, Amortiguador de masa activa.

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Chapter 1

Introduction

Vibration issues in slender structures pose a significant challenge in contemporary structural engineering. These undesired vibrations can be triggered by various sources such as dynamic loads, turbulent winds, human activities or nearby machinery. In slender structures, which are inherently more sensitive to disturbances due to their lower stiffness and relative mass, uncontrolled vibrations can lead to a range of concerning problems. These include structural fatigue, which can significantly shorten the structure's lifespan, as well as discomfort for occupants, negatively impacting the quality of life in residential or office buildings. Moreover, in extreme cases, uncontrolled vibrations can pose a risk to public safety. Therefore, the effective mitigation of vibrations in slender structures is a crucial goal in modern structural engineering and is a central topic of research and development in the field [1, 2, 3, 4, 5, 6].

Among the main non-deterministic effects that can potentially affect structures susceptible to vibration problems, introducing uncertainty in their behaviour, the following can be outlined, which can be grouped into three distinct type:

1. <u>Effects resulting from the utilization of the structures</u>:
   - **Human activity**: In buildings and pedestrian walkways, the loads generated by people occupying the space or walking through them are inherently non-deterministic. The location, movements and amplitudes of occupants loads cannot be accurately predicted and affect the live loads of the structures [7, 8].
   - **Traffic Loads**: In bridges and transport structures, traffic loads from vehicles and trains create variable and non-deterministic loads. These loads depend on the type of vehicles, their weight, speed and traffic patterns, and constitute an essential factor in the dynamic behaviour of these structures. [9, 10].
2. <u>Effects derived from environmental and meteorological causes</u>:
   - **Wind**: Wind is one of the primary sources of non-deterministic loading on structures, especially in tall buildings and bridges. Wind speed and direction can vary significantly with time and location, affecting lateral loads on the structure [11, 12]. The Weibull distribution is a frequently employed statistical model for describing measured wind speed data [13].
   - **Environmental Loads**: Other environmental factors such as ice loading, corrosion, moisture, and extreme temperatures can introduce uncertainty into structural behavior and impact the durability of the structure. [14, 15]
   - **Wave and Tide Loads**: In coastal structures, waves and tides can generate variable and non-deterministic loads, especially in ports, docks, and maritime structures [16, 17].
3. <u>Effects due to accidental causes</u>:
   - **Seismicity**: Earthquakes are highly non-deterministic events that generate significant seismic loads on structures. The geographical location and magnitude of earthquakes are difficult to

predict accurately, making seismicity a major source of uncertainty over time and place, affecting the structures [18, 19]. Characterizing these phenomena represent a complex challenge, not only in terms of predicting when they will occur but also in discerning their frequency components.

Understanding and analyzing these non-deterministic actions are fundamental to the design and assessment of structures. In this context, a proper characterisation of the ranges and distributions of non-deterministic phenomenon that may affect flexible structures throughout their life cycle is of vital importance to ensure the integrity of the structure. It provides an essential basis for robust structural design, ensuring that these buildings can withstand the full spectrum of unpredictable forces that they may encounter during their operational life. By quantifying potential variations in loads, engineers can conceive more resilient designs, optimise the use of materials and implement effective risk management strategies

Furthermore, the ability to replicate (to the greatest extent possible), during the design phase, these non-deterministic actions that a structure will encounter is of utmost importance in structural engineering and construction. It serves as a critical step in ensuring that the resultant structure is robust, safe, and capable of withstanding the dynamic and unpredictable forces it may confront over its operational lifetime. By accurately simulating non-deterministic actions it is possible to gain invaluable insights into how the structure will respond under various scenarios. This proactive approach not only helps identify potential weaknesses but also enables the optimization of materials, design parameters, and safety measures [20].

After identifying and analyzing the potential adverse elements that the structure may encounter to ensure its dynamic behavior remains within optimal service limits, it becomes crucial to explore and incorporate strategies for preventing structural damage arising from these non-deterministic phenomena. According to prominent authors in the field, this consideration spans from the initial design phase through to the operational phase:

1. Design the structure with the objective of, to the greatest extent feasible, avoiding its natural frequencies aligning with those that may become susceptible to excitation from the potential factors affecting the structure.
2. Increase the stiffness of the structure. Research has demonstrated that when the stiffness exceeds 8 kN/mm, vibrations do not present a threat [21]. Nevertheless, attempting to raise this stiffness value during later stages of the design process would result in prohibitively high costs.
3. Increase the weight of the structure to reduce the influence of exciting phenomena, a proportional increase in stiffness being then necessary.
4. Structural reinforcement by strengthening critical structural components or adding additional mass in strategic locations can enhance a structure's resistance to vibrations [22, 23].
5. Using vibration isolation systems, such as base isolators, negative-stiffness-mechanisms or resilient materials, can decouple the structure from external vibrations. This prevents vibrations from being transmitted into the building or structure [24, 25].
6. Vibration absorption devices, these systems consist of the addition of a subsidy system consisting of a moving mass that will transmit forces to the structure in response to its movement, thus dissipating the energy that produces the vibrations and reducing the dynamic responses of the structure [26, 27].

Among these strategies, the use of vibration absorption devices should be highlighted, being the most widely used in real structures, as it is the least expensive and easiest solution to apply to already built structures. These devices are integrated in structural control systems, and can be classified, according to the energy required by them, into four categories [28, 29]:

- **Passive control systems:** This is a self-contained control system that operates independently of external energy sources. The mobile mass is linked to the structure via springs and dampers, allowing forces to be transferred in response to the structure's motion, while the dampers reduce the system's energy [30, 2, 31].

- **Active control systems:** This is an active control system that relies on an external energy source to energize the actuators responsible for applying forces to the mobile mass and, subsequently, to the structure through the action-reaction principle. In an active control system with feedback, the signals sent to the actuators are determined by the system's response, as detected by physical sensors (including optical, mechanical, and electrical sensors, among others)[32, 33].
- **Hybrid control systems:** This control system uses a combination of active and passive control systems. In a hybrid control system, active elements like sensors, actuators, and control algorithms work in tandem with passive elements such as Tuned Mass Dampers (TMD) or base isolators. This combination allows for a dynamic response that can adapt to varying environmental conditions and load factors[34, 35].
- **Semi-active control systems:** These are control systems for which the external energy requirements are of a lower order of magnitude than is usual for active control systems. In addition, these control systems do not add mechanical energy to the structural system, so that stability is guaranteed for system input and output values bounded within limits. [36, 37, 38]

Another significant development in the field of structural engineering over the past few decades has been the rise of data-driven methods. Data-driven methods have revolutionized the various phases related to structural vibration, offering an alternative and providing additional support to conventional methodologies. These methods harness the power of extensive data collection, sensor networks, and advanced analytics to provide real-time insights into the dynamic behavior of structures. They enable the prediction and monitoring of potential excitation sources, such as wind gusts [39] or seismic activity [40], with a high degree of accuracy. Moreover, data-driven techniques facilitate the implementation of active control strategies [41, 42], allowing structures to dynamically adapt and counteract vibrations as they occur.

Data-driven methods encompass a wide spectrum of techniques used in various domains to extract insights and make predictions from data. Within the field of this techniques, there are several approaches that have become noteworthy due to their effectiveness and broad applications in a variety of domains. Some of the most prominent types of data-driven techniques include:

- **Machine Learning:** This approach uses algorithms and statistical models to learn patterns from historical data and make predictions in classification or regression tasks. Popular machine learning methods include linear regression, decision trees, support vector machines and neural networks.
- **Deep Learning:** It consists of a particular area of machine learning that relies on neural networks with multiple layers to model complex patterns and relationships in data. It is widely used in computer vision, natural language processing and speech recognition. Convolutional neural networks (CNN) and recurrent neural networks (RNN) are examples of popular deep learning architectures.
- **Time Series Analysis:** These techniques focus on the analysis and prediction of sequential data over time. Autoregressive integrated moving average models (ARIMA) and long-term memory neural networks (LSTM) are common examples of time series methods.
- **Optimization Algorithms:** Optimization algorithms are used to find optimal or near-optimal solutions to a variety of problems, including machine learning, planning, decision-making, and solving complex problems. In particular, evolutionary heuristic algorithms draw inspiration from natural selection and evolution to navigate complex search spaces [43]. These algorithms rely on the principles of population-based optimization, where potential solutions evolve and adapt over generations. By combining elements of exploration and exploitation, they offer a versatile means of tackling a broad spectrum of optimization problems.
- **Reinforcement Learning:** This subset of machine learning focuses on training agents to make sequential decisions by interacting with an environment and receiving rewards. It is therefore applicable to dynamic, real-time decision-making tasks such as active control. [42]

- **Unsupervised Machine Learning:** Instead of using labelled data, unsupervised learning seeks to find hidden patterns and structures in unlabelled data. Notable techniques include Principal Component Analysis (PCA) and clustering.

- **Complex Network Analysis:** In this approach, relationships and connections between elements of a dataset are studied. Techniques such as graph analysis and complex networks algorithms are used to extract relevant information from data.

- **Explainable Artificial Inteligence:** As machine learning applications become more critical, the ability to interpret and explain model decisions is essential. A new emerging research stream has arisen in recent years trying to bring explainability to these techniques [44]. Methods such as decision trees and interpretive attention are used to improve the transparency of Machine Learning.

In this doctoral thesis, a variety of data-driven methods have been employed to address diverse problems of varying natures. Particularly, this methods encompass evolutionary approaches to tackle optimization problems, specialized techniques for time series analysis and prediction and the use of supervised Machine Learning algorithms as regressors to solve specific problems within the field of vibration engineering.

1.1 Background and scope of work

This thesis is situated at the intersection of two distinct research lines. The first one focuses on the development of new data-driven approaches tailored to address specific challenges of classification and regression problems; while the second concerns the development and application of vibration mitigation techniques for slender structures.

Subsequently, the main elements of both lines of research are shown, beginning with the line relative to research on machine learning methods.

1. Development and application of machine learning algorithms for solving time series prediction problems in classification and regression contexts.

2. Development and application of heuristic evolutionary algorithms in different types of optimisation problems.

3. Development and application of specific methodology for dealing with highly unbalanced databases in solving prediction problems.

4. Development and application of Deep Learning methodology for the prediction of time series applied to the diferent problems.

On the other hand, the main areas of research of the structural vibration mitigation research are summarize as follows:

1. Dynamic identification and calibrated modelling using Finite Element or reduced models.

2. Development of protocols for dynamic load testing, particularly focusing on the comfort of walkways and floors during pedestrian traffic.

3. Static and dynamic simulation, including fluid-structure-citation interaction.

4. Structural Health Monitoring (SHM).

5. Design and installation of active and passive vibration mitigation systems.

Therefore, this work arises with the ambition to combine these two areas and tackle structural dynamics challenges through the utilization of artificial intelligence and machine learning techniques. In this domain, prior research has been conducted within the University of Valladolid's research group, where this thesis is situated, including the use of evolutionary optimization algorithms and data analysis to address and resolve challenges associated with vibration mitigation in slender structures[45, 46, 47].

1.2 Objectives and scope

After outlining the context of this study, the subsequent paragraphs delineate the specific objectives of this thesis.

The main objective will be the development and application of data driven methods for the resolution of problems derived from the analysis of vibrations in slender structures. Specifically, work will be performed with the aim of identifying, predicting and characterising different non-deterministic actions that affect slender structures, along with the development of techniques for actively mitigating them.

The specific objectives of this thesis are outlined below.

1. Application of machine learning algorithms for the prediction of non-deterministic actions affecting slender structures, considering different time prediction horizons in the forecasting process.
2. Characterisation of the dynamic forces that a structure will experience during its operational phase.
3. Development of protocols for dynamic load testing based on the replicability of the non-deterministic actions discussed above.
4. Development, application and implementation of active vibration control systems, with the aim of mitigating the vibrations induced by the dynamic actions commented in the previous points.

Simultaneously, a set of secondary goals are established to accomplish the defined objectives.:

1. Develop specific machine learning methods to deal with the problem of handling highly unbalanced databases when forecasting non-deterministic actions related to wind.
2. Undertake Experimental Modal Analysis (EMA) for the purpose of characterizing and acquiring the modal properties that describe the dynamics of both the structure and the actuator that will be used.
3. Characterization of the actuator responsible for inducing to the structure the forces applied during the dynamic load testing protocols developed that simulate human activity. This analysis aims to understand its behavior under various input signals and its corresponding dynamics as accurately as possible.
4. Employ evolutionary algorithms to optimize both the state estimator gain and the feedback gain that drives the actuator in the active control system designed for active vibration cancellation.
5. Development of software in different programming languages to obtain the necessary functionalities. The learning these programming languages, together with the search for new libraries suitable for the problem being faced, will also be an important part of the research work of this project:
   (a) In order to implement the different Machine Learning and Deep Learning algorithms and methodologies, the Python programming language will be used, with libraries both basic (pandas, scipy, matplotlib, numpy) and specific to machine learning (sklearn), deep learning (tensorflow, tsai), libraries for reading variables with temporal and spatial distribution (xarray), or others focused on extreme events (smogn).
   (b) Use of Matlab to obtain and simulate the reduced models of the structure and actuator used, as well as to design the active control algorithms.

(c) Use of specific Matlab functions to obtain the frequency response functions of the system, as part of the data analysis and processing process in the analysis of the system.

(d) Implementation of the active control systems in Simulink to conduct the corresponding simulations. simulations.

(e) Development of the Labview program for the real-time implementation of the final control system in the real structure. Making use of the MyRio Toolkit add-on to calculate the outputs of the system as a function of the inputs using the defined control law.

(f) Use of the Dewesoft data acquisition software to obtain the temporal signals in the different experiments carried out.

1.3 Content development

The elaboration of this doctoral thesis has been divided into three work packages, each of which has been published in a prestigious research journal after undergoing a peer review process:

- Article 1: A hierarchical classification/regression algorithm for improving extreme wind speed events prediction (DOI: 10.1016/j.renene.2022.11.042)
- Article 2: Human-induced force reconstruction using a non-linear electrodynamic shaker applying an iterative neural network algorithm (DOI: 10.24425/bpasts.2023.144615)
- Article 3: Evolutionary Computation-Based Active Mass Damper Implementation for Vibration Mitigation in Slender Structures Using a Low-Cost Processor (DOI: 10.3390/act12060254)

The bibliometry of these papers is depicted in Table 1.1:

Article	Journal	Impact Factor (2022)	Quartile (2022)	Rank (2022)	Cites
1	Renewable Energy	8.7	Q1	26/119	2
2	Bulletin of the Polish Academy of Sciences Technical Sciences	1.2	Q4	72/90	1
3	Actuators	2.6	Q2	62/136	2

Table 1.1: Bibliometry of published articles throughout the development of the doctoral thesis.

In the first of these articles, entitled "A hierarchical classification/regression algorithm for improving extreme wind speed events prediction", the first objective of this thesis is undertaken, in which machine learning algorithms are applied for the forecasting of wind speeds in different time horizons of prediction. Specifically, the work is focused on the correct prediction of Extreme Wind Speeds (EWS). These events are often responsible for the worst damages caused by wind, especially in wind farms facilities. In fact, wind farms must be restrained from operating during such events, in order to minimize the hazards involved with them. Thus, it is of crucial importance for the wind power sector, to have a proper knowledge as well as robust and reliable assessments to estimate the frequency and intensity of extreme events, not only to avoid wind turbines damage, but also to minimise cut-out events [48].

Wind represents a key source of stochastic loading for structures, particularly tall buildings, bridges and wind turbines. The velocity and direction of the wind can fluctuate significantly over time and across different locations, impacting the lateral loads experienced by the structure. Extreme wind speeds and gusts induce intense vibrations that can jeopardize the structural integrity of this kind of buildings, specially wind turbines. These vibrations can lead to fatigue and stress on the materials, potentially resulting in structural damage or, in the worst cases, catastrophic failure. Therefore, understanding, mitigating and anticipating the effects of extreme winds on these structures are crucial for ensuring their safety and longevity.

One of the inherent issues in forecasting the atmospheric extreme events (including EWS) resides in dealing with highly unbalanced databases, since the number of instances with extreme wind speeds often represents a minimum percentage of the total data. This problem has been mostly explored in the context of classification tasks [49]. However, the challenge we faced in this work concerned a continuous predictive domain, where in addition to forecasting the presence or absence of EWS, to provide a reasonable estimation of its magnitude was also important. The main strategy to deal with such challenge consists in the preprocessing of the datasets in order to balance the training data [50], either by performing a random undersampling of the majority classes or generating new synthetic samples for classification [51] or regression [52].

The methodology proposed in this paper for EWS prediction consisted of a Hierarchical Classification/Regression (HCR) approach, where the time series training data is divided into separate subsets (or clusters) depending on the wind speed value. Each cluster of training data is employed to fit a specific regression model. The HCR methodology proposed in this paper consisted on a three-level architecture. The first level consists of a data preprocessing step, where training data are divided into clusters and labels are added accordingly. Then, balancing techniques are applied to increase the significance of clusters with EWS, which are represented poorly in the original data. At the second level, the classification of each sample into the corresponding cluster is carried out. A variety of classifiers are trained with preprocessed labeled data after different balancing techniques are applied. Finally, this pool of classifiers is integrated into a voting classifier ensemble using a majority-voting rule. Once determined to which cluster a sample belongs to, the third level of the architecture forecasts the wind speed value, by applying the regression model that corresponds to that particular cluster. The proposed HCR approach was implemented and tested for prediction of extreme EWS events at a wind farm in Spain. Specifically, ten years of hourly wind speed data are available at a wind farm in Western Spain, where the proposed HCR was applied, obtaining excellent results reported in the experimental section of the paper.

In the second published paper presented in this work, titled “Human-induced force reconstruction using a non-linear electrodynamic shaker applying an iterative neural network algorithm”, an iterative neural network framework is proposed for the human-induced Ground Reaction Forces (GRF) replication with an inertial electrodynamic mass actuator (APS 400). This represent the second and third main objectives of this thesis, and it represents a first approach to the systematization of dynamic load tests on structures in a purely objective, repeatable and pedestrian-independent basis. To this end, an electrodynamic shaker [53] was used to recreate the Ground Reaction Forces (GRFs) produced by humans, whose temporal signals were previously acquired with a pair of instrumented insoles. This shaker consists of an inertial actuator, which works by generating inertial forces on the structure on which it is placed.

The inertial shaker employed represents an inherently nonlinear electro-mechanical system [54] whose dynamics are modeled with a non-invertible model [55]. This causes the inverse problem of obtaining the shaker drive target signal (the one which makes the actuator behaves as desired) to be not straightforward. The approach adopted in this paper consisted of the development of an iterative ML data-driven framework, where an inversion-free, offline control methodology was applied to the electrodynamic shaker. The proposed approach aims to obtain the optimal drive signal to minimize the error between the experimental shaker output and the reference force signal, measured with a pair of instrumented insoles (Loadsol©) for human bouncing at different frequencies and amplitudes. The optimal performance, stability and convergence of the system are verified through experimental tests, achieving excellent results in both time and frequency domain.

In the ML data-driven framework implemented, an Artificial Neural Network (ANN) was used as a regressor to generate off-line the optimal drive signal that makes the shaker follow a specific reference force signal. As the shaker was an inertial mechanical system, in order to output the voltage signal at each temporal instant, the ANN was fed with data relative to both the future reference force and the conditions of the moving mass at previous instants. Iteratively, the simulated force signal was compared to the reference, and the most optimal points (those whose error was below a previously defined threshold) are selected as training data for the following iteration. This way, the ANN weights are updated at each iteration, allowing the drive signal to converge to an optimal value, as demonstrated via experimentation. Since the network was only trained with data within the optimal operating range of the shaker, its output will be constrained within this range, ensuring the stable operation of the system.

Finally, the third paper titled “Evolutionary Computation-Based Active Mass Damper Implementation for Vibration Mitigation in Slender Structures Using a Low-Cost Processor” pursues the implementation of an active control system to mitigate human-induced vibrations in a pedestrian footbridge.

The work is devoted to design, implement and validate an active mass damper (AMD) for vibration mitigation in slender structures. The control law, defined by means of genetic algorithm optimization, is deployed on a low-cost processor (NI myRIO-1900), and experimentally validated on a 13.5-meter lively timber footbridge.

The strengths of the presented work lies in: (1) the use of genetic evolutionary algorithms to optimize both the state estimator gain and the feedback gain that commands the actuator using different fitness functions related to both time and frequency domains

After the dynamic identification of the actuator, the procedure consisted of the experimental characterization and identification of the modal properties of the structure (natural frequencies and damping ratios). Once the equivalent state space system of the structure was obtained, the design of the control law was developed, based on state feedback, where an genetic evolutionary algorithm was employed to optimize both the state estimator gain and the feedback gain that commands the actuator using different fitness functions related to both time and frequency domains. This control law was then in a low-cost controller. Finally, experimental adjustments (filters, gains, etc.) were implemented and the validation test was carried out. The system performance was evaluated using different metrics, both in the frequency and time domain, and under different loads scenarios, including pedestrian transits to demonstrate the feasibility, robustness and good performance of the proposed system.

Throughout these three papers, different problems related to various aspects of vibration analysis in structures have been solved, including: (1) the prediction and characterization of the stochastic actions that will dynamically perturb the structure, with special focus on extreme events that have the potential to exert a more significant impact on the structure; (2) the characterization of these non-deterministic actions affecting the structures, focusing on the replicability of their time series by means of an electrodynamic shaker. This approach allows the systematization of dynamic load tests on structures in a purely objective and repeatable way; and (3), the design, implementation and validation of an effective active vibration mitigation control system on a full-scale structure.

In addition, during the development of these works, the following challenges have been faced, for which an approach based on data driven methodologies has been adopted: (1) we have dealt with severely imbalanced databases within the context of a time series regression problem, and in response, a three-level hierarchical methodology that relies on model ensembles has been proposed; (2) we have encountered the problem of working with an inherently nonlinear electro-mechanical system whose dynamics were modeled with a non-invertible model, when the goal was to derive the inverse model of the system in order to replication time series signals. The approach adopted to solve this inconvenient consisted of the development of an iterative ML data-driven framework, where an inversion-free, offline control methodology was applied to the electrodynamic shaker; and (3) a genetic evolutionary algorithm was used to optimize both the state estimator gain and the feedback gain that commands the actuator in the active control methodology implemented.

Chapter 2

Background and state of the art

In this chapter, we will theoretically delve into the topics to be addressed in this study, including a review of the theoretical content developed during the thesis, as well as an examination of the state of the art in solving similar problems.

2.1 Artificial intelligence

Artificial Intelligence (AI) represents the cutting-edge field of computer science dedicated to creating systems that can mimic human-like intelligence and decision-making [56]. It encompass a wide range of approaches, including those based on logic, neural networks, statistical analysis, and natural language processing, among others. Within the realm of AI, Machine Learning (ML) stands out as a pivotal subset, where algorithms are designed to enable computers to learn and improve from data, making autonomous decisions and predictions.

ML is dedicated to enabling computers to acquire knowledge and problem-solving capabilities autonomously, without the need for explicit programming. ML relies on computational techniques rooted in mathematical algorithms. The core functionality of an ML algorithm hinges on the availability of data with a particular structure. This data serves as input to the model, facilitating the adjustment of one or more output variables, thereby yielding desired outcomes [57]. The learning process of the algorithm is developed by adjusting the internal parameters of the model using historical input and output data examples, in order to ultimately deliver optimal results. To ensure the accuracy of the model, two distinct phases are carried out independently. For this purpose, the data is divided into training data, which is the one used by the algorithm in its learning process, and validation data used to verify the model accuracy. This enables the good predictive performance on classification, regression and pattern identification problems.

In broad terms, ML can be categorized into three categories: supervised learning, unsupervised learning, and reinforcement learning; with Deep Learning playing a pivotal role in enhancing these areas (Figure 2.1).

Supervised ML is a fundamental paradigm within the field of artificial intelligence, wherein algorithms are trained to learn patterns and relationships between input data and their corresponding target outputs [58]. Unlike unsupervised learning, supervised ML relies on labeled training data, where each input is associated with a known, correct output. The primary objective of supervised ML is to build a predictive model that can generalize from the training data to make accurate predictions or classifications on unseen or future data points. This process involves adjusting the model's internal parameters iteratively through training to minimize the difference between its predictions and the actual target values.

Unsupervised ML, in contrast to supervised learning, does not rely on labeled input data. Instead,

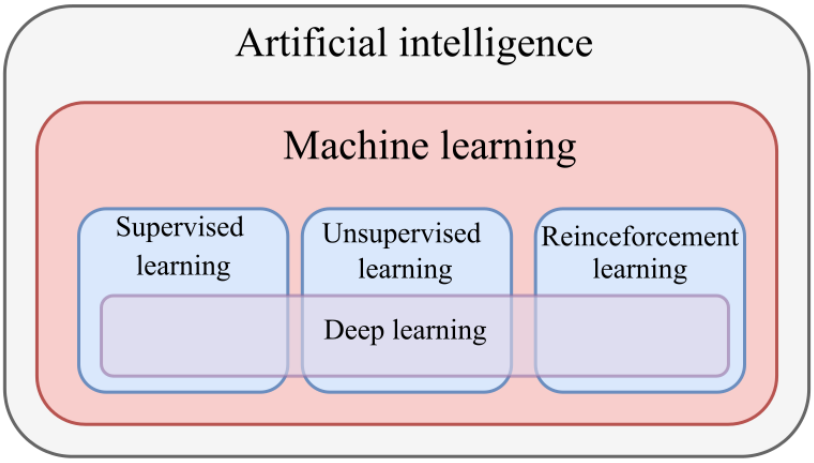


Figure 2.1: Division of ML areas.

algorithms within this framework aim to discover patterns or relationships within the data without any foreknowledge of the expected output. Here, the primary objective is to extract hidden patterns, relationships, or structures that exist within the data itself, often unveiling novel insights and facilitating data-driven decision-making. This branch of machine learning is particularly valuable when dealing with copious amounts of unlabelled information, as it autonomously identifies intrinsic structures and contributes significantly to various domains, including clustering, dimensionality reduction, and anomaly detection.

Finally, in this field of reinforcement learning, the goal is to teach algorithms through experimentation with input data. In this scenario, there is no predefined output label; instead, the algorithms directly interact with the data until they achieve the desired behavior. Subsequently, they reinforce this behavior through the repetition of actions that enable them to accomplish this task effectively. At its core, reinforcement learning is inspired by the principles of trial and error, mirroring the way humans learn through experiences. Agents, equipped with the ability to sense their surroundings and take actions, strive to maximize cumulative rewards, making decisions that are both informed by immediate consequences and long-term objectives.

Furthermore, DL represents the most complex branch of ML. DL seeks to emulate the human brain's ability to process and learn from vast amounts of complex data. It achieves this by employing neural networks composed of multiple layers of interconnected nodes, allowing it to automatically extract intricate patterns, features, and representations from raw data.

2.1.1 Multivariate time series

A time series can be defined as a set of measures collected at even intervals of time and ordered chronologically [59]. Although the time is a variable measured on a continuous basis, the values in a time series are sampled at constant intervals (fixed sampling frequency). Time series models can be either univariate (meaning that there is only one time dependent variable) or multivariate (where several time dependent variables are involved).

Mathematically, the problem can be formulated through the matrix presented in Equation (2.1), where y_i represents each time series variable, where $y_i(t-m)$, for $m = (0, \dots, L)$, stands for the historical and current data. The forecasting process consists of estimating the value of $y_i(t+h)$, where h denotes the time-horizon of prediction.

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \left(\begin{array}{cccc|c} y_1(t-L) & \cdots & y_1(t-1) & y_1(t) & y_1(t+h) \\ y_2(t-L) & \cdots & y_2(t-1) & y_2(t) & y_2(t+h) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ y_n(t-L) & \cdots & y_n(t-1) & y_n(t) & y_n(t+h) \end{array}\right) \tag{2.1}$$

An essential point in the creation of a predictive model involves the determination of the time sequence length that is entered into the system as inputs. Therefore, the preprocessing step of the time series before being passed to the system involves their splitting into sequences of length equal to the defined timestep, applying overlapping to preserve the number of samples. These sequences are then concatenated into a three-dimensional tensor. Thus, each sequence represents an input of the model. The dimension of this tensor is set at: (*number of samples*, *timestep*, *number of variables*). Figure 2.2 shows the time series preprocessing procedure, where no overlapping has been displayed to increase the readability of the image.

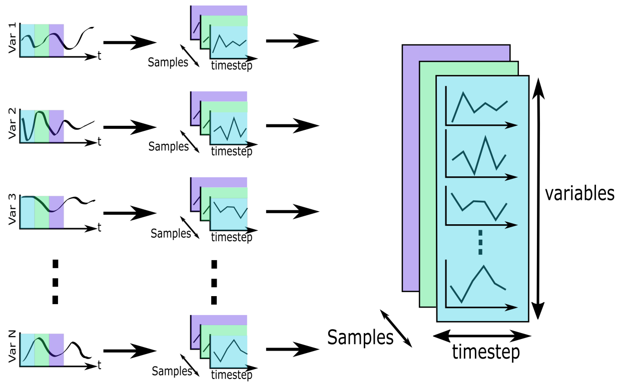


Figure 2.2: Time series data processing for a forecasting scenario.

2.1.2 Evolutionary optimization algorithms

Evolutionary optimization algorithms are a family of powerful computational techniques inspired by the principles of natural evolution and selection [60]. They play a significant role in the realm of artificial intelligence (AI) and optimization problems. These algorithms, inspired by the principles of natural selection and genetics, are employed to find optimal solutions in complex, multidimensional spaces. Within the field of AI, they are utilized for various purposes, including hyperparameter tuning in machine learning models, feature selection, neural network architecture optimization, and reinforcement learning. Their ability to efficiently explore large solution spaces, adapt to changing environments, and discover high-quality solutions has made them a valuable asset in the development and fine-tuning of AI systems. Within these algorithms, genetic algorithms stand out as one of the most used approaches.

The genetic algorithm (GA) is a well-established optimization algorithm inspired by natural selection, which was first proposed by [61]. It is a population-based search algorithm, which makes use of the concept of survival of fittest. The basic idea is to maintain a population of chromosomes (representing candidate solutions to the specific problem being solved) that evolves over time through a process of competition and controlled variation. A GA starts with a population of randomly generated chromosomes, and advances toward better chromosomes by applying genetic operators based on the genetic processes occurring in nature. The population undergoes evolution in a form of natural selection. During successive iterations, called generations, chromosomes in the population are rated for their adaptation as solutions, and on the basis of these evaluations, a new population of chromosomes is formed using a selection mechanism and specific genetic operators, such as crossover and mutation. An evaluation or fitness function must be devised for each problem to be solved. Given a particular chromosome, a possible solution, the fitness function, returns a single numerical fitness, which is supposed to be proportional to the utility or adaptation of the solution represented by that chromosome [62, 63]. The chromosome representation, fitness function computation, selection, crossover and mutation are the key elements of GA. The procedure of GA is depict in the pseudo-code shown in Algorithm 1.

Algorithm 1 Genetic algorithm (GA)

Input:
  Population size, n
  Maximum number of iterations, MAX
Output:
  Global best solution, Y_b

begin:
  Generate initial population of n chromosomes $Y_i (i = 1, 2, \cdots, n)$
  Set iteration counter, $t = 0$
  Compute the fitness value of each chromosomes
  while($t < MAX$):
    Select a pair of chromosomes from initial population based on fitness
    Apply crossover operation on selected pair with crossover probability
    Apply mutation on the offspring with mutation probability
    Replace old population with newly generated population
    Increment the current iteration t by 1
  end
  return the best solution,Y_b
end

2.2 Non-Deterministic Actions: Characteristic and related problems

Non-deterministic actions affecting structures represent an emerging and complex area within structural engineering and computational sciences. These actions, often arising from uncertain external factors or stochastic processes, introduce a level of unpredictability that can significantly affect the behavior and integrity of structures, either by varying in a non-deterministic way the loads imposed upon the structure, or by inducing vibrations that can cause fatigue failures or adverse effects on the users of the structure.

One of the defining characteristics of non-deterministic actions is their inherent variability, which challenges traditional deterministic models that assume perfect knowledge and predictability. The consequences of non-deterministic actions on structures can manifest in various forms, ranging from structural failures due to unforeseen loads or environmental conditions to causing a negative impact on the comfort quality of occupants.

Among the numerous sources of stochastic actions affecting structures, two have been studied in this thesis: those generated by high wind speeds and those generated by human activity.

2.2.1 Extreme wind speeds

Wind energy stands out as one of the fastest-growing and potentially useful energy sources worldwide [64]. This is attributed to its notable efficiency, abundant resource availability, and the minimal pollution generated by wind farms [65]. Furthermore, it ranks among the most promising renewable energy sources concerning its integration into the electrical grid, economic implications, and annual growth rate [66, 67], owing to its inherent natural, cheap and clean nature. Moreover, wind energy holds the advantage of being continuously producible by wind turbines throughout the day, making it particularly suitable for applications requiring a constant energy supply [68].

Like other renewable sources, wind energy is susceptible to inherent drawbacks such as uncertainty and intermittence [69]. These factors can contribute to grid instability and result in either insufficient supply during peak hours or wasteful energy consumption during periods of low demand. Therefore, the accurate forecasting of wind power assumes a pivotal role in the successful integration of a substantial share of wind energy into the electricity system [70]. In addition, a factor of crucial importance for the wind power sector lies in the inevitable occurrence of extreme events, i.e. Extreme Wind Speeds (EWS), which represent a relatively brief but a highly intensive peak in wind speed, often responsible for the worst damages caused by wind, especially in wind farms facilities [71, 72], but also in other slender vertical structures [73] such as church towes, roof structures [74] or traffic signal structures [75]. Indeed, wind farm operations must be halted during these events to mitigate the risks they pose. Therefore, possessing a comprehensive understanding and employing dependable, robust assessments to gauge the occurrence and severity of EWS is vital. This is not only essential for preventing damage to wind turbines but also for reducing instances of forced shutdowns [48].

Several methods can be found in the literature to address the prediction of EWS, from the application of classical techniques [76, 77] to modern techniques [78, 79] and these methods include Machine Learning (ML) approaches as well [80]. A first review of classical techniques for EWS prediction was reported in [76]. More recent reviews of modern techniques, including NWM and also Machine Learning (ML) approaches have been presented in [78, 79, 80].

One of the inherent issues in forecasting the atmospheric extreme events (including EWS) resides in dealing with highly unbalanced databases, since the number of instances with extreme wind speeds often represents a minimum percentage of the total data. This problem has been mostly explored in the context of classification tasks [49].

However, an important challenge arise when a continuous predictive domain is concerned, since in addition to forecasting the presence or absence of EWS, it is also important to provide a reasonable estimation of its magnitude. The most popular strategies to deal with such challenge can be categorized into three types: preprocessing, cost-sensitive learning, and ensemble learning. The preprocessing of a dataset consists in dealing with the data in order to balance the training data [50], either by performing a random undersampling of the majority classes or generating new synthetic samples for classification [51] or regression [52]. Cost-sensitive learning is an aspect of algorithm-level modifications for class imbalance [81]. Here, rather than relying on conventional error-based evaluation, this approach incorporates misclassification costs to mitigate conditional risks. By imposing significant penalties for errors in specific classes, it enhances their significance in the training process. Consequently, this shift results in the displacement of decision boundaries away from instances of these classes, ultimately contributing to enhanced generalization performance. Finally, the ensemble learning involves a decision-making process that combines the individual learning algorithms and their outcomes in parallel to obtaining the ultimate accurate result. In a way that each individual model can be specialized in a particular range of the data.

2.2.2 Human activity

The effects of human induced forces over structures are increasingly gaining importance as modern structures become lighter, slenderer and with lower natural frequencies, that are excited by regular human activities, such as walking or running [82, 83]. Furthermore, within the field of structural engineering, the influence of human-induced forces assumes critical importance. This influence extends to the assessment of vehicle vibrations [84] and aircraft vibrations [85], as well as the analysis of Human-Structure Interaction (HSI) in structures subjected to human occupancy [86, 87]. It's essential to recognize that human occupants can exert considerable influence on the dynamic properties of slender structures, including their mass, stiffness, and damping characteristics [88, 89]. Neglecting these effects during the design phase can lead to various issues, including structural damage, reduced structural lifespan, and serviceability problems affecting the safety and comfort of occupants.

In order to simulate human-induced vibration, various approaches have been documented in the literature for modeling both the structure and the human element [90]. The bridge can be modelled using either modal analysis (MA) – a formulation in modal coordinates, or Finite Element (FE) methods. When considering the impact of pedestrians on the bridge, different strategies are available. The simplest model treats pedestrians as moving forces (MF), essentially concentrated loads moving at a constant walking velocity. However, this MF model may lead to an overestimation of the bridge's response, as it does not account for the interaction between pedestrians and the vibrating bridge [91]. Taking a more comprehensive approach, a realistic model can be achieved by incorporating a moving mass, which considers the mass interaction of pedestrians, known as the moving mass (MM) model, originally introduced by

Biggs [92]. Nevertheless, for an even more accurate representation, it is becoming increasingly common to model the human as a spring-mass-damper (SMD) system, given the separation between the human center of mass and the bridge surface [93]. Consequently, this approach has started to gain prominence in recent literature [94]. Forecasting the dynamic reactions of these civil engineering structures subjected to loads induced by human subjects has consequently emerged as a crucial facet of structural design [95].

In this thesis, a preliminary approach to the systematization of dynamic load tests on structures in a purely objective, repeatable and pedestrian-independent basis is established. To this end, an electro-dynamic shaker [53] has been used to recreate the GRFs produced by humans, whose temporal signals were previously acquired with a pair of instrumented insoles. This shaker consists of an inertial actuator, which works by generating inertial forces on the structure on which it is placed.

2.3 Dynamic structural analysis

The primary goal of structural analysis is to ascertain the defining characteristics of a structure's behavior under specific loading conditions, enabling the prediction of the system's response to a given excitation. In typical structural calculations, it is assumed that the applied loads vary slowly, reaching their final values (design values) over a sufficiently extended period of time such that the acceleration at any point within the system does not generate inertial forces that need to be considered (quasi-static process). However, there are certain loadings on structures for which this consideration cannot apply due to their rapid incidence, resulting in the emergence of inertial forces that must be factored into the equilibrium of forces at every instant for all points in the system. In such cases, a dynamic analysis becomes necessary. In these cases, the loads acting on the structure consist of impacts or vibrations. Furthermore, the system's response, while evolving over time, is damped, meaning that the structure's vibration gradually diminishes.

Before delving into the detailed analysis, it is essential to provide context for the various phases of this theoretical process (Figure 2.3). This image illustrates the three typical phases that constitute a dynamic vibrational analysis. Firstly, it commences with a description of the physical characteristics of the system, such as mass, damping, and stiffness, resulting in what is termed the physical model. Subsequently, after conducting a theoretical modal analysis of this physical model, a description of the structure's behavior as a set of modal properties (frequencies, mode shapes, and damping coefficients) is obtained. These properties depict the various ways in which the structure can naturally vibrate, and this model is referred to as the modal model. Finally, the third phase of the analysis involves obtaining the most accurate possible estimate of the structure's response to specific excitations. This is known as the response model and comprises a set of frequency response functions (FRFs) applicable within a particular frequency range, indicating the relationship between applied excitations and the system's response (both phase and magnitude) [96].

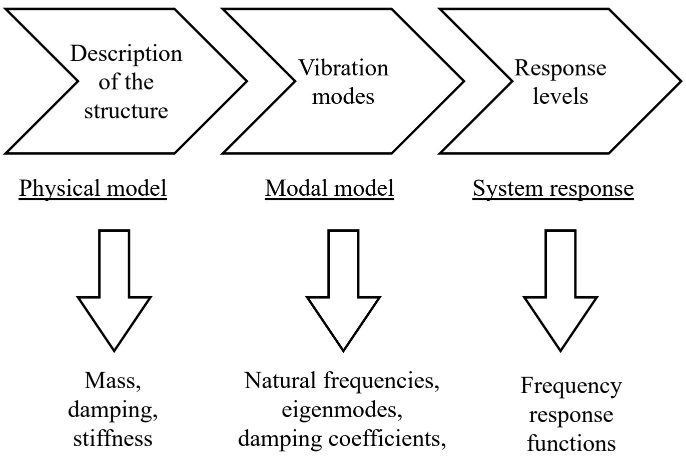


Figure 2.3: Theoretical process of dynamic analysis of structures.

Additionally, it is common not to have a reliable description of a structure in terms of its physical properties, as is the case in the system under investigation in this study. In such situations, the structural analysis can be performed by commencing with the experimental response of the system to known excitations, as depicted in Figure 2.4. This involves conducting an EMA of the structure to extract its modal properties and, based on these findings, deriving a new response model or updating an existing one.

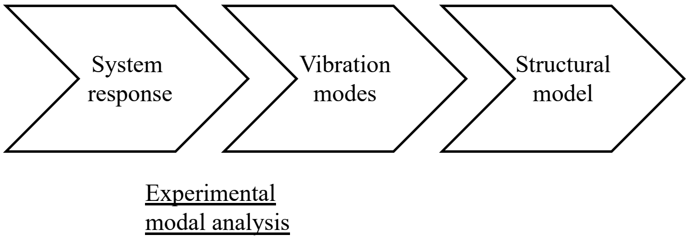


Figure 2.4: Experimental process of dynamic analysis of structures.

The analysis of the mechanical behavior of a structure is conducted through models of the structure. In this context, a model is an abstraction of certain aspects of the physical and functional reality of the structure. A comprehensive description of a structure for the purpose of its modeling and analysis would involve considering all defining aspects of its physical reality. However, this approach not only generates a vast amount of challenging-to-manage information but also does not guarantee higher quality conclusions in the analysis of the model. Hence, to create a model that faithfully represents the structure under analysis, while maintaining a manageable level of complexity, it becomes necessary to employ a set of simplifying assumptions. The goal is to abstract from reality those aspects that influence the behavior being analyzed, rather than striving for a complete depiction of the structure's physical and functional reality.

In physical models, physical variables like displacement, velocity, and acceleration are used to calculate forces, including elastic forces, damping forces, and inertia forces. A common simplification consists in focusing on discrete mass point models, using three essential components:

- **Springs:** These represent the stiffness of the structure, measuring its resistance to deformation.
- **Dampers:** They account for the energy dissipation capacity of the structure.
- **Masses:** These represent the inertia of the structure, measuring its resistance to accelerations.

With these components and external excitations, the equation of motion is derived to determine the position, velocity, and acceleration of various points in the structure at any given moment, Equation (2.2), where M, C, and K represent the mass, damping, and stiffness matrices of the system (respectively), and $f(t)$ is the vector of generalized forces that represent the external forces applied to the system. Therefore, this model allows us to determine the position ($u(t)$), velocity ($\dot{u}(t)$), and acceleration ($\ddot{u}(t)$) at any given moment for any material point of the structure, provided that the values of M, C, K, and $f(t)$ are known.

$$M\ddot{u} + C\dot{u} + Ku = f(t) \tag{2.2}$$

However, these models require precise knowledge of the structure's physical properties, which is often not available. Therefore, modal properties are employed to model the system without detailed physical information. Modal properties include:

- **Natural Frequencies:** These are inherent frequencies of the structure, determined solely by its mass and stiffness.

- **Mode Shapes:** They describe how the structure oscillates when excited at its natural frequencies.
- **Modal Damping Factors:** These specify the damping of each mode.

To obtain these modal properties experimentally without knowing the physical properties, EMA techniques are utilized. These techniques extract modal properties from the structure's response to known excitations.

2.3.1 Active vibration cancellation

Once the structure has been identified, and reliable models that accurately represent its behavior have been obtained and calibrated, the next step is to provide solutions for situations in which serviceability limit states are not met in vibration, or simply to extend the structure's lifespan by reducing its stress levels. It is important to note that vibration is associated with fatigue cycles, and decreasing these cycles can prolong the life of structures, leading to reduced maintenance or replacement costs.

Structural control systems are typically categorized into four distinct strategies based on the nature of control devices and methods: passive control, active control, semi-active control, and hybrid control [97]. Among these, passive control, often implemented as a TMD [98, 99, 100, 101], is a widely employed approach. A TMD is a single-degree-of-freedom mass-spring-damper system, designed with its natural frequency matched to one of the structure's natural frequencies. This effectively damps the response associated with that particular mode. This system is advantageous due to its cost-effectiveness, small size (typically representing 0.15 to 1% of the structure mass), and straightforward integration into existing structures. However, its effectiveness is limited to mitigating the response of the specific structural mode it's tuned to, allowing relatively large responses to loading with different frequency components, such as impulse or random forces.

For situations demanding high performance, active control devices are a more suitable choice [102]. These systems can dynamically adapt the structure's response by applying control actions in real-time, achieving highly efficient vibration mitigation. Moreover, active systems can concurrently mitigate the impact of several vibration modes with a single device. This feature makes them a compelling solution for reducing responses in low-damping flexible structures characterized by multiple contributing vibration modes. Additionally, active systems offer versatility, freedom from tuning issues, and the potential for unconditional stability when a well-designed control system is in place [103]. Nevertheless, active control may not be the most cost-effective solution, as it demands advanced technology and maintenance, often involving expensive devices and power supply systems. Additionally, it may face reliability issues under specific circumstances.

Designing an active control system involves addressing two critical concerns. The first is the development of a robust control algorithm capable of real-time computation of control forces to prevent instabilities and potential structural damage. The second concern pertains to the requirement for a high-performance actuator capable of applying the intended control force to the structure in real-time with an acceptable level of error [37].

Regarding the control strategy, most approaches are grounded in a feedback framework [104]. In a feedback control system, the core principle involves comparing the system output (y) with a reference signal ($\hat{y}$) and computing the error signal, denoted as e ($e = y - \hat{y}$). This error signal is then fed into a control device or compensator, which incorporates the necessary algorithm to convert the error values into a signal for controlling the actuator appropriately. The challenge in this control framework lies in identifying the right compensator to ensure the closed-loop system's stability and optimal performance.

Numerous active control strategies have been proposed and extensively reviewed in the literature [105, 38, 104]. Two of the most commonly utilized methods include Direct Velocity Feedback (DVF) [106, 107, 108] and Feedback State Control [109, 110, 111]. These methods leverage structural response information to generate a set of control forces that influence the dynamic response of the structure. An especially intriguing approach in this context is optimal control, wherein operational parameters are determined to optimize a specific performance metric [112].

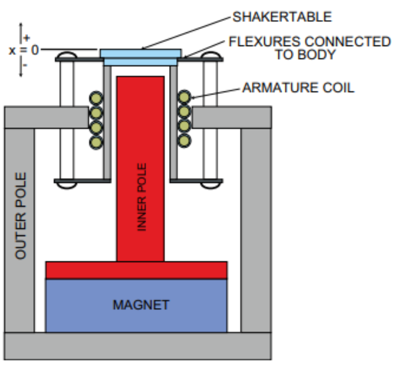
Most optimal control design techniques are founded on an optimization strategy aiming to enhance system performance. This can be achieved by either minimizing control energy under specific constraints or minimizing structural response magnitudes. In essence, the optimization procedure involves fine-tuning the control system parameters [62]. One of the most frequently employed methods is the linear-quadratic regulator (LQR), which has been extensively studied in the literature [113, 114, 115, 116, 117]. LQR designs a state-feedback gain by minimizing a performance index that combines weighted state and control input terms. Furthermore, several evolutionary computation and metaheuristic optimization algorithms have been employed to address the challenge of control parameter optimization [118, 119, 120, 121, 122, 123, 124, 125].

2.3.2 Inertial-electrodynamic-mass actuator dynamics

For developing an AMD system that operates optimally, it is essential to obtain a model that describes the behavior and dynamics of the inertial mass actuator that will be used to feedback forces into the system, allowing to accurately predict how it will behave according to the signal it is fed with.

An inertial mass electrodynamic shaker, specifically the APS 400 ELECTRO-SEIS (Figure 2.5(a)), was utilized in this thesis both to replicate Human GRF and to act as the actuator to mitigate the vibracion on the AMD. These devices are commonly employed for applying forces to structures during dynamic tests, typically using either a noise signal or a sinusoidal signal. The shaker consists of a moving reaction mass, denoted as m_A, attached to a current coil that moves within a magnetic field generated by a cluster of permanent magnets. The connecting of the moving mass to the frame is facilitated by a suspension system, which can be characterized by spring stiffness K_A and viscous damping c_A (as depicted in Figure 2.5(b)). To operate the shaker, an amplifier receives an electrical signal ranging between ±5 V and supplies the necessary power signal to drive the oscillation of the moving mass.

(a) APS 400 ELECTRO-SEIS.



(b) Sketch of typical electrodynamic inertial actuator [54]

Figure 2.5: Inertial electrodynamic mass actuator.

The dynamics of an inertial mass actuator operating in voltage mode can be described as a third order transfer function relating the generated force F and the voltage input V as shown in Eq. 2.3 [55], where K_A corresponds to the transducer constant (in N/A), ω_A is the natural frequency associated with the suspended moving mass system, ξ_A represents the damping coefficient and the pole at ε accounts for the low-pass filtering property of these instruments, absorbing frequencies higher than the cut-off frequency ε (in rad/s).

$$G_A(s) = \frac{F(s)}{V(s)} = \left(\frac{K_A s^2}{s^2 + 2\xi_A\omega_A s + \omega_A^2}\right) \cdot \left(\frac{1}{s+\varepsilon}\right) \tag{2.3}$$

Chapter 3

Results

3.1 A hierarchical classification/regression algorithm for improving extreme wind speed events prediction

Title	A hierarchical classification/regression algorithm for improving extreme wind speed events prediction
Authors	César Peláez-Rodríguez, Jorge Pérez-Aracil, Dushan Fister, Luis Prieto-Godino, Ravinesh C. Deo and Sancho Salcedo-Sanz
Journal	Renewable Energy
Volume	201, Part 2, Pages 157-178
Year	2022
DOI	10.1016/j.renene.2022.11.042

Summary

A novel method for prediction of the extreme wind speed events based on a Hierarchical Classification/Regression (HCR) approach is proposed. The idea is to improve the prediction skills of different Machine Learning approaches on extreme wind speed events, while preserving the prediction performance for steady events. The proposed HCR architecture rests on three distinctive levels: first, a data preprocessing level, where training data are divided into clusters and accordingly associated labels. At this point, balancing techniques are applied to increase the significance of clusters with poorly represented wind gusts data. At a second level of the architecture, the classification of each sample into the corresponding cluster is carried out. Finally, once we have determined the cluster a sample belongs to, the third level carries out the prediction of the wind speed value, by using the regression model associated with that particular cluster. The performance of the proposed HCR approach has been tested in a real database of hourly wind speed values in Spain, considering Reanalysis data as predictive variables. The results obtained have shown excellent prediction skill in the forecasting of extreme events, achieving a 96% extremes detection, while maintaining a reasonable performance in the non-extreme samples. The performance of the methods has also been assessed using forecast data (GFS) as predictors.

3.2 Human-induced force reconstruction using a non-linear electrodynamic shaker applying an iterative neural network algorithm

Title	Human-induced force reconstruction using a non-linear electrodynamic shaker applying an iterative neural network algorithm
Authors	César Peláez-Rodríguez, Álvaro Magdaleno, Sancho Salcedo-Sanz and Antolín Lorenzana
Journal	Bulletin of the Polish Academy of Sciences- Technical Sciences
Volume	71, Part 3, e144615
Year	2023
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Summary

An iterative neural network framework is proposed in this paper for the human-induced Ground Reaction Forces (GRF) replication with an inertial electrodynamic mass actuator (APS 400). This is a first approach to the systematization of dynamic load tests on structures in a purely objective, repeatable and pedestrian-independent basis. Therefore, an inversion-free offline algorithm based on Machine Learning techniques has been applied for the first time on an electrodynamic shaker, without requiring its inverse model to tackle the inverse problem of successful force reconstruction. The proposed approach aims to obtain the optimal drive signal to minimize the error between the experimental shaker output and the reference force signal, measured with a pair of instrumented insoles (Loadsol©) for human bouncing at different frequencies and amplitudes. The optimal performance, stability and convergence of the system are verified through experimental tests, achieving excellent results in both time and frequency domain.

3.3 Evolutionary Computation-Based Active Mass Damper Implementation for Vibration Mitigation in Slender Structures Using a Low-Cost Processor

Title	Evolutionary Computation-Based Active Mass Damper Implementation for Vibration Mitigation in Slender Structures Using a Low-Cost Processor
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Summary

This work is devoted to design, implement and validate an active mass damper (AMD) for vibration mitigation in slender structures. The control law, defined by means of genetic algorithm optimization, is deployed on a low-cost processor (NI myRIO-1900), and experimentally validated on a 13.5-m lively timber footbridge. As is known, problems arising from human-induced vibrations in slender, lightweight and low-damped structures usually require the installation of mechanical devices, such as an AMD, in order to be mitigated. This kind of device tends to reduce the movement of the structure, which can be potentially large when it is subjected to dynamic loads whose main components match its natural frequencies. In those conditions, the AMD is sought to improve the comfort and fulfil the serviceability conditions for the pedestrian use according to some design guides. After the dynamic identification of the actuator, the procedure consisted of the experimental characterization and identification of the modal properties of the structure (natural frequencies and damping ratios). Once the equivalent state space system of the structure is obtained, the design of the control law is developed, based on state feedback, which was deployed in the low-cost controller. Finally, experimental adjustments (filters, gains, etc.) were implemented and the validation test was carried out. The system performance has been evaluated using different metrics, both in the frequency and time domain, and under different loads scenarios, including pedestrian transits to demonstrate the feasibility, robustness and good performance of the proposed system. The strengths of the presented work reside in: (1) the use of genetic evolutionary algorithms to optimize both the state estimator gain and the feedback gain that commands the actuator, whose performance is further tested and analyzed using different fitness functions related to both time and frequency domains and (2) the implementation of the active control system in a low-cost processor, which represents a significant advantage when it comes to implement this system in a real structure.

Chapter 4

Summary, Discussion, Future work and Conclusions

4.1 Summary

Vibration problems in slender structures raise a major challenge in contemporary structural engineering, causing structural fatigue, discomfort, and even safety risks. As a result, effectively mitigating vibrations in slender structures represents a pivotal objective in contemporary structural engineering and remains a central area of focus in research and development within the field. These induced vibrations arise from several sources of non-deterministic actions, as dynamic loads, turbulent winds, human activities, or nearby machinery. Understanding and characterizing these non-deterministic actions is crucial for structural design. Therefore, the ability to replicate these actions during the design phase and to forecast them during the operational phase constitutes an important part of the structural engineering of slender structures, providing insights into structural responses and weaknesses, as well as providing the capacity to anticipate the occurrence of extreme events that could have major consequences.

In this context, data-driven methods have emerged as an outstanding technology in the field of structural engineering, offering an alternative and providing additional support to conventional methodologies. These techniques leverage the capabilities of extensive data gathering, sensor networks, and cutting-edge analytics to offer real-time insights into the dynamic behavior of structures. They allow accurate forecasts and monitoring of potential excitation sources. Furthermore, data-driven approaches ease the implementation of active control strategies, enabling structures to dynamically adjust and counteract vibrations as they arise.

This thesis arises with the objective of developing and applying data-driven techniques to address challenges stemming from the analysis of vibrations in slender structures. Specifically, different approaches have been proposed for identifying, predicting and characterising different non-deterministic actions that affect slender structures, along with the development of techniques for actively mitigating them.

The thesis comprises three distinct works, each addressing diverse aspects of vibration analysis in structures. In the first work, the scope consists of predicting wind speeds, particularly extreme speeds, essential for minimizing damage in wind farms. The work introduces novel a three-level Hierarchical Classification/Regression methodology to predict EWS and achieve accurate forecast of extreme events. Then, in the second work, an iterative neural network framework for replicating human-induced GRFs using an electrodynamic mass actuator is presented. This approach allows the systematization of dynamic load tests, ensuring repeatability and accuracy in reproducing force signals. Finally, last work involves the implementation of an AMD to mitigate vibrations in a slender pedestrian footbridge using data-driven evolutionay algorithms. Specifically, genetic evolutionary algorithms optimize the control law for the AMD, deployed on a low-cost processor, with the system exhibiting robustness and performance.

4.2 Discussion

Throughout the development of this doctoral thesis, various issues related to different facets of structural vibration analysis have been successfully addressed. These include:

In first place, the prediction and characterization of stochastic forces that dynamically affect structures, with a particular emphasis on extreme events that can have a more significant impact on the structure. An intrinsic challenge of the prediction of this kind of events reside in the need of working with highly unbalanced datasets. To tackle this, standard data balancing techniques have been employed. Also, a novel architecture has been developed and has provided highly satisfactory results in the prediction of extreme wind events while minimizing the number of false alarms. The forescast of stochastic events have been performed considering different time prediction horizons, comprising from short to long term, ensuring the robustness and optimal performance of the presented methodology for different scenarios.

In second place, the characterization of non-deterministic forces impacting structures, with a focus on the reproducibility of their temporal series using an electrodynamic shaker. This approach enables the standardized testing of structural responses to dynamic loads in an objective and repeatable manner. In this problem, we confronted the challenge of dealing with a naturally nonlinear electro-mechanical system, which was represented by a non-invertible model. The objective was to derive the inverse model for replicating time series signals. To overcome this issue, we devised an iterative data-driven machine learning framework. Within this framework, we applied an inversion-free offline control approach to the electrodynamic shaker. This proposal has been validated achieving a reliable reproduction of the GRFs produced by different types, amplitudes and frequencies of human motion or locomotion activities.

Finally, in third place, the development, implementation, and validation of an effective active vibration control system for a full-scale structure has been successfully performed. Here, we employed a genetic evolutionary algorithm to optimize both the state estimator gain and the feedback gain that controls the actuator in the active control methodology implemented, demonstrating that this data-based optimization of the control law represent a valid alternative to the classical methods. For this purpose, different optimization criteria have been assessed. In addition, the validation of the control system has been conducted by evaluating different parameters in both the time and frequency domains.

These achievements represent notable contributions in the research line undertaken in the development and application of ML and artificial intelligence methods for the resolution of problems derived from structural engineering.

4.3 Future work

This doctoral thesis marks the beginning of a broad line of research, which will be continued and improved across its different branches in forthcoming studies. The planned future work can be summarized in the following points.

Regarding the EWS prediction, future work will focus on integrating state-of-the-art techniques into the proposed methodology. This involves incorporating more complex Deep Learning models and exploring other algorithms, such as variational autoencoders, for the detection of extreme events.

Regarding the human-induced force reconstruction, the proposed framework represents a preliminary approach to the systematization of dynamic load tests on structures on a purely objective, repeatable and pedestrian-independent basis, leading to the possibility of performing serviceability tests without requiring skilled people. Future lines of work in this field encompass exploring human-structure interaction phenomena through a more experimental approach. This involves observing and learning from differences in structural responses when excited by a shaker as opposed to a pedestrian. Additionally, another future work will delve in enhancing the electrodynamic shaker with movement along the structure. This will enable the reproduction of not only stationary human activities but also other locomotion-related movements.

Regarding the implementation of an AMD, future lines of work will be directed in two areas. Firstly, there will be a focus on developing a more efficient and robust control system. This involves comparing various control algorithms and state-of-the-art optimization methods. Additionally, the adaptation of controller parameters to changes in the system or excitation will be explored to analyze the implications of this adaptation on the system's stability. In second place, forthcoming work will focus on the use of a multiple-degrees-of-freedom model. This would slightly complicate the modal analysis and platform modeling phase; however, it would allow knowing the expected behavior of more points of the structure, instead of only its midpoint, so that the control laws could be established knowing how the feedback will affect the overall structure, and eliminating instabilities due to platform torsion or high frequencies, as they would now be contemplated in the control system, so that the low-pass filter could be eliminated with the consequent reduction in data processing time for the system output. In addition, the influence of the actuator position will be analyzed, aiming at minimizing the response of the structure, thus converting the problem into a MISO scheme.

Furthermore, additional work is planned involving the application of ML techniques to address other challenges associated with the vibrational dynamics of slender structures. The anticipated research lines are outlined below.

1. Damage detection in slender structures using a supervised learning algorithms and model updating.
2. Generation of virtual ground reaction forces using fuzzy logic methodology.
3. Identifying motion patterns through the application of ML algorithms to acceleration data collected from wearable insoles.
4. Leveraging ML and deep learning techniques to predict other non-deterministic factors influencing slender structures, such as traffic loads, extreme temperatures, or wave and tide loads.

4.4 Conclusions

In this doctoral thesis, different data-driven methods have been developed and applied to effectively address three problems stemming from the analysis of vibrations in slender structures. Important efforts were were focused on identifying, predicting, and characterizing various non-deterministic factors that impact slender structures, as well as on the development of methodologies to actively mitigate their effects. The outcomes of this work represent a noteworthy progression in improving our understanding and capacity to address specific vibrations challenges in structures, thus potentially contributing to their long-term structural integrity and safety.

The specific objectives of this thesis have been successfully achieved, these included:

1. Utilizing ML algorithms to predict non-deterministic actions affecting slender structures across various time horizons, thereby enhancing the predictive capabilities.
2. Characterizing the dynamic forces that slender structures undergo during their operational phase, providing valuable insights into the structural behavior.
3. The development of protocols for dynamic load testing based on the reproducibility of non-deterministic actions, enhancing the reliability of such testing procedures.
4. The successful development, application, and implementation of active vibration control systems to effectively mitigate vibrations induced by dynamic actions, as discussed in the preceding objectives.

From the research work conducted in this doctoral thesis, the following conclusions can be drawn, divided into the three published articles:

Regarding the prediction of EWS:

1. In this thesis, a three-phase hierarchical methodology has been proposed for the accurate forecast of extreme wind events. This approach arises as a response to one of the main intrinsic problems of this type of problems such as the use of highly unbalanced databases, as the values that are most interesting to estimate accurately are those that are poorly represented on the dataset. The implementation of this methodology has yielded very satisfactory results, achieving higher EWS prediction ratios than those obtained with conventional data balancing tecniques.

2. Additionally, in this kind of problem, it is crucial to ensure that, besides delivering accurate predictions, there is a minimal occurrence of false alarms, which refer to predictions of high wind speeds when the actual speed is low. High false alarm rates can result in substantial economic losses due to unnecessary mobilization of emergency services and a potential loss of trust in the model among decision-makers in this field. In this sense, the proposed methodology achieves well-balanced predictions keeping the number of false alarms low.

Regarding the human-induced force reconstruction using a non-linear electrodynamic shaker:

3. A ML-based framework for human-induced forces replication using an electrodynamic shaker has been proposed and successfully implemented in this thesis. Its performance was assessed through the replication of 8 temporal signals acquired via a pair of instrumented insoles during bouncing at different frequencies and amplitudes. The methodology's accurate performance has been accounted both in the time and frequency domain. This means that, when introducing these forces as excitation in a structure, a similar response will be produced, which is the final objective of this work.

4. This approach contributes to provide an efficient alternative to classical control techniques for inverse problems. It provides an inversion-free solution and ensures the stability of the system, as long as the direct actuator model is stable, since the drive signal output from the neural network will always be within the voltage limits at which the shaker operates properly.

5. Furthermore, the proposed framework represent a preliminary approach to the systematization of dynamic load tests on structures in a purely objective, repeatable and pedestrian-independent basis, leading to the possibility of performing serviceability tests without requiring skilled people.

Regarding the implementation of an AMD employing evolutionary computitation:

6. In this thesis, the mitigation of human-induced vibrations on a lab-scale footbridge using an active control system has been addressed. Once the dynamic properties of both the structure and the actuator were identified after performing an experimental modal analysis, the design and implementation of an active control system were carried out based on a state feedback strategy. The design of a state estimator was also necessary. Evolutionary computation by means of GA was used throughout the whole article in order to fit the different models and obtain the optimum gains of the control architectures according to different criteria.

7. This work has focused on the mitigation of vibrations at low frequencies, which are those that can potentially be excited by humans. Therefore, the control strategy has been designed accounting for a range of frequencies below 5 Hz. Since only the first bending mode of the structure fell within this range, a reduction was made for considering the structure as a single-degree-of-freedom system. The performance of the presented AMD for mitigate the vibrations associated with this first mode was experimentally validated, achieving an impressive 99.09% reduction in the amplitude response at the first resonant frequency, as well as a 66.07% MTVV reduction when walking at this frequency. The efficiency of the system has also been validated by evaluating the settling time for a step input, obtaining a 96.54% reduction with respect to the uncontrolled system.

8. As a consequence of just modeling the structure performance in a frequency range around its first mode, it has been necessary to implement a low-pass filter in the controller in order to avoid instabilities due to the dynamics associated with the high frequencies that are beyond the designed model. This filter limits the controller's processing time, which affects the cycle time chosen in the system. Lowering this cycle time (currently, it is fixed to 1 ms) will make the system act faster, resulting in better performance. Future work in this direction will be to model the structure as a

multi-degree-of-freedom system, in order to remove the signal filter, as well as to make the control system able to mitigate several modes simultaneously.

9. Furthermore, this work has focused on using low-cost means, employing a NI myRIO 1900 controller, whose cost is 83% lower than other traditional systems of the same brand, such as the Compact RiO-9030 (608 EUR vs 3677 EUR). The accelerometers used (MEMS ADXL355BEZ) also represent an important saving of 87% with respect to piezoelectric accelerometers KS76C10 (44 EUR vs. 360 EUR). However, the exciter used is a high-cost commercial device (around 25,000 EUR), so that another future line of work is the development of a low-cost inertial mass exciter.

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Appendix A

Dissemination of Results

The research findings have also been presented at specific scientific forums, with the aim of disseminating them and obtaining feedback and advice from the international scientific community. Below, a summary of the contributions to various national and international conferences is provided:

1. C. Peláez-Rodríguez, A. Lorenzana, A. Magdaleno. "Human induced force reconstruction using a non-linear electrodynamic shaker applying ANN-based iterative learning controller." 7th European Conference on Structural Control (EACS 2022). Conference poster.
2. A. Magdaleno, J. Naranjo, A. Iglesias, C. Peláez-Rodríguez, I.M. Díaz. "Study of the interaction phenomena between a slender structure and its passive mitigation devices." 7th European Conference on Structural Control (EACS 2022). Conference poster.
3. A. Magdaleno, J. Pérez-Aracil, J.M. Soria, C. Peláez-Rodríguez, A. Iglesias. "A methodology to estimate the properties of a tuned mass damper installed on a slender structure." 6th International Conference on Mechanical Models in Structural Engineering. Conference paper.
4. C. Peláez-Rodríguez, A. Magdaleno, A. Lorenzana. "Damage detection in slender structures based on a hybrid system of supervised learning algorithms and model updating to analyze raw dynamic data". 6th International Conference on Mechanical Models in Structural Engineering. Oral comunication.
5. JM. García-Terán, C. Peláez-Rodríguez, A. Fraile, A. Lorenzana. "Ground reaction forces generation of virtual human subjects applying a fuzzy logic- based algorithm on statistical indicators extracted from experimental data." 6th International Conference on Mechanical Models in Structural Engineering. Conference paper.
6. A. Iglesias, C. Peláez-Rodríguez, A. Magdaleno, A. Lorenzana. "Influence of the friction effects on the efficiency of a tuned mass damper." 6th International Conference on Mechanical Models in Structural Engineering. Conference paper.
7. C. Peláez-Rodríguez. "Human-induced force reconstruction using a non-linear electrodynamic shaker applying ANN-based iterative learning controller." VIII Jornada de Doctorandos UVa 2022. Oral comunication.
8. D. Fister, J. Pérez-Aracil, C. Peláez-Rodríguez, M. Drouard, P.G. Zaninelli, D. Barriopedro-Cepero, R. García-Herrera, S. Salcedo-Sanz. "Towards the effective autoencoder architecture to detect weather anomalies." EGU General Assembly Conference Abstracts (2023). Conference paper.

Also, at the time of submitting this doctoral thesis, a new scientific article is undergoing the review process in a JCR indexed journal:

- An iterative neural network approach applied to human-induced force reconstruction using a non-linear electrodynamic shaker. Journal: Heliyon. IF(2022): 4.0 (Q2).