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INCREASING ROBUSTNESS OF CRITICAL INFRASTRUCTURES ASSESSMENT USING ARTIFICIAL INTELLIGENCE AND STRUCTURAL MONITORING

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“According to the laws of chance.”

J.A.

Resumo

A avaliação da segurança estrutural de estruturas operacionais, como pontes e barragens, depende da disponibilidade de uma estratégia adequada de monitorização da saúde estrutural (SHM). Embora estas estruturas sejam avaliadas periodicamente através da SHM tradicional e de inspeções visuais, estes métodos são por vezes limitados, envolvem uma intervenção humana significativa e são propensos a erros. Novas aplicações de SHM têm surgido, motivadas pela urgência de ultrapassar estas limitações e de otimizar o processo, apoiadas pelos recentes avanços nas redes de sensores e na Inteligência Artificial (IA).

Neste contexto, a presente dissertação propõe novas estratégias para melhorar a robustez do reconhecimento de padrões e da deteção de novidades, acrescentando valor às abordagens tradicionais de SHM através da adoção de ferramentas de IA. Para demonstrar a implementação destas ferramentas, foram escolhidos como casos de estudo duas infra-estruturas operacionais e monitorizadas com diferentes complexidades estruturais: a ponte suspensa 25 de abril e a barragem de betão do Feiticeiro, ambas localizadas em Portugal.

Os dados de monitorização em tempo real são normalmente conjuntos de dados grandes e complexos, muitas vezes contaminados com ruído, o que dificulta a sua análise, aumenta a incerteza relacionada com a previsão do comportamento estrutural esperado e, consequentemente, torna o desenvolvimento de metodologias para a identificação precoce e fiável de danos uma tarefa desafiante. O foco desta dissertação é contribuir para ultrapassar esta limitação, tirando partido da grande quantidade de dados previamente recolhidos para um reconhecimento fiável de padrões e deteção precoce de novidades.

Para o efeito, foram exploradas abordagens baseadas em dados de IA, supervisionadas e não supervisionadas, e foram propostas metodologias que integram ferramentas de Machine Learning e Deep Learning. A disponibilidade de redundância de modelos, a caracterização do efeito das cargas na resposta estrutural através da realização de análises de sensibilidade, a implementação de uma estratégia de reconhecimento de padrões em constante melhoria e a definição de limiares foram passos fundamentais incluídos e combinados com as abordagens de aprendizagem para aumentar a sua robustez na avaliação estrutural, melhorar o reconhecimento de padrões e reduzir os falsos alertas.

As metodologias propostas apresentam um potencial significativo para o reconhecimento de padrões e a deteção de novidades em tempo real quando aplicadas a dados SHM de infra-estruturas críticas. Os resultados confirmaram a sua capacidade para aumentar a robustez da deteção de novidades, representando um passo em frente numa estratégia de identificação automática de danos. No entanto, é de salientar que, apesar destes contributos, as conclusões sobre a condição estrutural devem ser retiradas da análise dos resultados do modelo, em combinação com o julgamento de engenharia e o conhecimento da história da estrutura.

Palavras-chave: Monitorização do estado de saúde estrutural, Aprendizagem automática, Aprendizagem profunda, Redundância de modelos, Análise de sensibilidade, Reconhecimento de padrões, Definição de limiares, Identificação de novidades, Ponte suspensa, Barragem de betão.

Abstract

The structural safety assessment of operational structures, such as bridges and dams, depends on the availability of a suitable Structural Health Monitoring (SHM) strategy capable of detecting novelties with the aim of identifying potential damage at an early stage. Although these structures are assessed periodically through traditional SHM and visual inspections, such methods are sometimes limited, involve significant human intervention, and are prone to error. New SHM applications have emerged, motivated by the urgency of overcoming these limitations and to optimise the process, supported by recent advances in sensor networks and Artificial Intelligence (AI).

In this context, the present dissertation proposes new strategies to improve the robustness of pattern recognition and novelty detection by adding value to traditional SHM approaches through the adoption of AI tools. To showcase the implementation of these tools, two operational and monitored infrastructures with different structural complexities were chosen as case studies: the 25 de Abril suspension bridge and the Feiticeiro concrete dam, both located in Portugal.

Real-time monitoring data are usually large and complex data sets, often contaminated with noise, which renders their analysis more difficult, increases the uncertainty related to the prediction of the expected structural behaviour, and, as a consequence, makes the development of methodologies for early and reliable damage identification a challenging task. The focus of this dissertation is on contributing to overcoming this limitation, taking advantage of the large amount of data previously collected for reliable pattern recognition and early novelty detection.

AI data-driven approaches, both supervised and unsupervised, were explored for this purpose, and methodologies that integrate Machine Learning and Deep Learning tools were proposed. The availability of model redundancy, the characterisation of the effect of loads on structural response by performing sensitivity analysis, the implementation of a continuously improving pattern recognition strategy, and the definition of thresholds were key steps included and combined with the learning approaches to increase their robustness for structural assessment, enhance pattern recognition, and reduce false warnings. By leveraging the observed SHM data, the methodologies proposed in this dissertation demonstrate great versatility across infrastructures with different structural behaviours.

The methodologies considered in this study exhibit significant potential for pattern recognition and real-time novelty detection when applied to SHM data from critical infrastructures. The effectiveness of these methodologies was tested and validated in the selected case studies. The outcomes confirmed their capacity to increase the robustness of novelty detection, representing a step forward in an automated damage identification strategy. However, it must be stressed that, despite these contributions, conclusions about structural condition should be drawn from the analysis of the model results, in combination with engineering judgment and knowledge of the structure's history.

Keywords: Structural Health Monitoring, Machine Learning, Deep Learning, Model Redundancy, Sensitivity Analysis, Pattern recognition, Threshold Definition, Novelty Identification, Suspension Bridge, Concrete Dam.

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Acronyms

Acronym	Meaning
AANN	Auto-associative neural networks
ADAS	Automated data acquisition system
ADC	Analog-to-digital converter
AI	Artificial intelligence
AR	Autoregressive
ARIMA	Autoregressive integrated moving average
BDT	Bayesian decision tree
CI	Computational intelligence
CNN	Convolutional neural network
DAC	Digital-to-analog converter
DBN	Deep belief networks
DBSCAN	Density-based spatial clustering of applications with noise
DL	Deep learning
DP	Damage prognosis
DWT	Discrete wavelet transform
FNN	Feedforward neural network
FRF	Frequency response function
GAN	Generative adversarial networks
GDBSCAN	General density-based spatial clustering of applications with noise
GPS	Global positioning system
GRNN	Generalized regression neural network
GRU	Gated recurrent unit
HST	Hydrostatic, seasonal, time
HTT	Hydrostatic, thermal, time
ICOLD	International Commission on Large Dams
LNEC	Portuguese National Laboratory of Civil Engineering
LSTM	Long short term memory
LVDT	Linear variable differential transformer
MAE	Mean absolute error
ML	Machine learning
MLP	Multilayer perceptron
MLR	Multiple linear regression
MPCA	Multiway principal components analysis
MSE	Mean squared error
MWL	Maximum reservoir water level
NDE	Non-destructive evaluation

Acronym	Meaning (continued)
NDT	Non-destructive testing
NLPCA	Non-linear principal component analysis
NN	Neural networks
PCA	Principal component analysis
PR	Pattern recognition
RMSE	Root mean squared error
RNN	Recurrent neural networks
SD	Standard deviation
SHM	Structural health monitoring
SPC	Statistical process control
SVR	Support vector regression
SVM	Support vector machine
UPN	Unsupervised pretrained network

Chapter 1

Introduction

Artificial intelligence (AI) born within computer science, is covering more and more spaces in our lives and societies. In the field of civil engineering, AI techniques provide an additional alternative to traditional methods for a wide range of complex civil issues, including structural health monitoring which is the focus of the present dissertation. Nowadays, through the use of digital twins and AI-based models, the structural analysis and safety assessment have improved in terms of computational cost and accuracy. However, despite the increasing popularity and continuous innovation of AI techniques it is essential to pay attention to how to learn and apply these new techniques. The learning process, as proposed by the chemist Isabelle Stengers, must be dependent on the creation of ‘artifices’, ways of staging an event that rely on social, technical, and material constraints that make it possible to relate, instead of relying on straightforward and assumed interpretations (Debaise and Stengers, 2017).

The proposed dissertation follows this line of thought by applying AI predictive data-driven models with real time data of critical operational structures, focusing on the attentive analysis of the models, results and considering all the novelties with the potential to become damage, while taking care of the consequences these novelties might entail.

This chapter introduces the main concepts of structural health monitoring for damage identification and its transition from traditional visual inspections to intelligent monitoring systems. Data-driven techniques are presented as advanced sensing and computational methods to detect and predict novelties with accuracy. The motivations and main objectives are presented after, followed by the thesis outline and brief description of the case studies.

1.1 Structural health monitoring for damage identification

Structural Health Monitoring (SHM) can be defined as the process of implementing a damage identification strategy for any civil, aerospace or mechanical structural system (Farrar and Worden, 2012). The in-service health assessment through automation is a key element of cost-effective SHM strategies, that prioritise the real-time detection of abnormal behavior as a preventive measure of failure states that may compromise the structural performance and safety (Posenato et al., 2010; Santos et al., 2016; Chen and Ni, 2018).

Damage can be defined as a change in a structural system that affects its current or future performance concerning both, structural safety and serviceability (Santos et al., 2013). Still, while damage occurrence implies a structural novelty, a novelty may not necessarily imply damage that compromises the structural performance. The same way, damage does not always indicate a complete failure, but only a comparative deterioration of the system functionality (Avci et al., 2021). Failure, on the other hand, can be understood as a direct consequence of damage and the exceedance of the structure's capacity, disabling it from performing as specified in the design and construction requirements.

Catastrophic failures that end in collapse, defined as a substantial loss of structure, entail consequences that can take different forms: from material/structural damage and human injuries/fatalities, to functional downtime and environmental impact, as well as loss of reputation and collateral damage that can have greater consequences than the reconstruction cost (Santos, 2014; Gehl and D'Ayala, 2018; Chryssanthopoulos et al., 2012; Thons et al., 2018). Damage detection is usually carried out in the context of one or more closely related disciplines that include: structural health monitoring (SHM), condition monitoring (CM), and non-destructive evaluation (NDE), also commonly called non-destructive testing (NDT), statistical process control (SPC) and damage prognosis (DP) (Farrar and Worden, 2012) and can be attended from all those perspectives. In the case of the present dissertation, the perspective is going to be from the SHM field.

Following Cury and Cremona (Cury and Cremona, 2010), damage occurrence can be classified by its location and its duration. In the case of location, damage generally starts at a single element and, depending on different scenarios and applied loads, it can spread up until the partial or the entire collapse of a structural system occurs. According to its duration, damage can be classified as progressive (such as fatigue, corrosion, excessive creep, deformation, etc.), sudden, such as that generated by accidents (such as vehicle collisions, construction accidents, seismic events) or unusual weather activity.

An SHM system for damage identification can be classified into five levels according to the level of information that can be delivered: (i) the determination of damage existence, (ii) the determination of damage location. The authors in Santos and, Chen and Ni (Santos, 2014; Chen and Ni, 2018), propose a level identified as the (iii) type of damage, that should be detected after the determination of the damage location. This is followed by (iv) the quantification of damage severity, and finally (v) the prediction of the remaining service life of the structures. As such, the SHM strategy can be outlined in the following five levels:

- Level I: Damage detection; Is damage present?
- Level II: Damage localization; Where is damage located?
- Level III: Damage classification; What type of damage is present?
- Level IV: Damage quantification; What is the severity of the damage?
- Level V: Damage prognosis; What is the residual lifetime?

The first two levels can be achieved using only structural monitoring data. Type, severity and residual lifetime depend on the density of the sensor grid, and predictive model, meaning that more sensors distributed across the structure lead to better spatial resolution, greater sensibility to subtle changes in vibration, strain or displacement can be captured. For level III, data related to specific types of damage must be available for correlation with the measured data. For levels IV and V, analytical and numerical models able to interpret the observed data are needed, the knowledge of the previous levels is needed too. According to Santos (Santos, 2014), sensor monitoring systems can only detect the first three levels presented above, not in terms of damage, but in terms of novelties (related to a pattern different to the classified as the normal one), making it possible to define damage only reaching the fourth level. In this sense, recasting: the first three levels of an SHM strategy involve novelty detection and not damage detection; determining the presence of damage is only possible by completing the analysis of the five levels

The detection of novelties and the evaluation of the life cycle of a structure is a powerful tool for the assessment of damage and the evaluation of the performance of civil structures. The process involves the observation and evaluation of a structure over time using periodically sampled measurements from a sensing system. Several civil engineering structures have been equipped with SHM systems in the last decades, namely bridges, dams, wind turbines, sports facilities,

buildings, offshore platforms, and underground facilities. The monitoring systems are generally envisaged to (Tome, 2019):

- monitor the construction phase and loading phase;
- monitor the life-cycle;
- monitor repairs;
- monitor reconstructions or reinforcements in order to evaluate the effectiveness of maintenance;
- provide a detailed understanding of the structural mechanisms and loadings;
- obtain massive amounts of in situ data for leading-edge research in structural engineering and / or optimisation of the SHM system;
- validate design assumptions and structural analysis methodologies with the potential benefit of improving design specifications and guidelines for similar structures in the future;
- ensure structural and operational safety using real-time information on anomalies in loading and response at an early stage;
- provide a decision support tool for safety assessment and residual capacity immediately after disasters and extreme events;
- provide evidence and instruction for planning and prioritising inspection, maintenance, repair and rehabilitation;
- predict the remaining life of the structure.

Despite the design codes and methodologies used for design and maintenance, civil engineering structures deteriorate over time. The reasons range from failure caused by cyclic traffic loads, effects of environmental factors (e.g. steel corrosion) and ageing in the construction materials, among others. In addition, deterioration can be caused by a range of natural hazards, cascading events, or multi-hazard events interactions (Gehl and D'Ayala, 2018). Therefore, structural health will be affected by operational and environmental factors, including normal load conditions, current and future environments, and expected hazards during the lifetime. All these factors are variables with uncertainties. Therefore, to ensure the safety and serviceability of the structure, a reliable structural health assessment and continued monitoring are essential.

Concerning damage effects and the development of strategies for their identification, it is important first to establish the difference between generators of linear and nonlinear effects. According with the type of structure, if after the occurrence of damage, the structure's behaviour remains in the elastic domain, we can conclude that the damage has a small magnitude (early damage). Its occurrence is not expected to greatly increase maintenance and repair costs (Santos et al., 2016). Early damage detection, in this sense, has always been one of the main concerns of SHM applications.

SHM techniques for damage detection can follow two different approaches: inverse or forward. Inverse damage detection, also known as a model updating approach, is based on fitting analytical or numerical responses to experimental data to infer structural quantities that cannot be directly measured. Forward damage detection instead, relies on pattern recognition techniques to extract sensitive information from data acquired on site (Santos et al., 2016). Because of the computational complexity, inverse approaches are more demanding than forward approaches which are more suitable for real-time monitoring and early damage detection.

Real-time monitoring can be effective in controlling the safety of existing structures and/or the repair interventions or post-accident situations through a baseline-free novelty detection, based on permanent data acquisition. Nevertheless, real-time diagnosis is usually sensitive to environmental and operational effects, and acquired data need to be processed so that novelty/damage detection and localisation techniques can be employed.

High in-service reliability of large critical systems is essential to meet the global competitive demands for increased warranties. For such systems, Wang et al. (Wang et al., 2018) state it is necessary to effectively predict future reliability indicators. For this purpose, data gathered by the SHM systems should be stored for safety evaluation, reliability analysis, and for the implementation of future new and more effective damage detection strategies.

1.2 From traditional inspections to intelligent monitoring

Traditionally, visual inspection played an important role in detecting structural defects. However, it is labour-intensive, time-consuming, subjective and dependent on well-trained inspectors. Moreover, it is unable to exactly track condition variations in real time (Sun et al., 2020a). To address this problem, Housner et al. (Housner et al., 1997), refers to the use of sensing techniques to detect structural damage or degradation, while Farrar and Worden (Farrar and Worden, 2007), relate SHM techniques to the damage detection process. According to Worden and Delieu-Bardon

(Worden and Delieu-Bardon, 2004), the use of intelligent monitoring systems allow structures to operate at the margin of safety without extended periods of inspection. Nowadays, SHM is a popular and still growing research field in the civil engineering community.

Structural damage identification based on changes in the structural response has been practised qualitatively for decades, since the time of the tap-testing for fault detection became common (e.g., on train wheels). However, it was not until 1980 that it started being addressed by the research communities. Recently, quantitative SHM methods have been developed to reduce costs, by using digital computing hardware and sensing systems (Sohn et al., 2002; Doebling et al., 1996). Advances have been made in various branches of technology, such as sensing instrumentation, signal acquisition and transmission, data processing and analysis, numerical simulation and modelling.

The damage-tolerant approach, based on the assumption that structural damage is inevitable, considers that, through load sequences and numerical models, it is possible to know the location of the damage. However, the control of the initiation and severity of the damage requires reliable monitoring methods. In response to this requirement, more comprehensive SHM capabilities have emerged (Farrar and Worden, 2007), the most popular approach being the so-called intelligent monitoring. Intelligent SHM depend on two key factors: sensing technologies and signal analysis. Since sensors cannot measure damage, feature extraction through signal processing and statistical classifications are necessary to convert sensor data into damage information (Farrar and Worden, 2007).

Numerous improvements in computational power and advancements in chip and sensor technology have enabled the use of Machine Learning (ML) techniques in engineering applications. ML techniques are focused on the development of intelligent algorithms capable of acquiring knowledge automatically from the available data to provide machines with a human-like ability of learning (Avci et al., 2021). There are two types of machine intelligence: hard and soft computing. The first one is based on binary logic and the second one can deal with ambiguous and noisy data incorporating stochastic information and allowing parallel computation. Soft computing is commonly known as computational intelligence (CI), a concept explored by the author in Bezdek (Bezdek, 1998), that also considers that CI is a subset of AI sciences. AI can be defined as the ability of a machine to mimic intelligent human behaviour, thus seeking to use human-inspired algorithms to solve difficult problems (Salehi and Burgueño, 2018; Avci et al., 2021).

AI methods have been used to deal with uncertainty problems in the context of damage detection and system identification through data analysis and numerical model updating. The use of AI

methods can also result in significant time and cost savings, as well as increasing computational efficiency in many structural engineering tasks (Salehi and Burgueño, 2018).

Intelligent SHM had to deal with two main issues; the lack of efficient and reliable methodologies coupled with signal processing and big data, and the lack of inexpensive sensors, as referred by Azimi and Pekcan (Azimi and Pekcan, 2020). With the recent technological advances, a relatively large number of sensors and sensor networks can now measure large volumes of response data. In this sense, data-driven ML techniques have been proposed by different authors to assess the global health condition of critical infrastructures (Santos et al., 2015; Liang et al., 2016; Bao et al., 2019; Mishra, 2020; Avci et al., 2021). The powerful capability of ML and pattern recognition (PR) techniques to extract information and develop predictive models from large data, have become a predominant approaches for SHM. Furthermore, ML algorithms are able to learn the complex interrelation among influencing factors, thus performing predictions without the need for empirical models. This combined with the advancements in self-powered sensors has promoted the development of the energy-efficient network technology that is allowing to address the constraint of communication power budget for SHM sensors, thus leading to an intelligent, reliable and efficient SHM system (Salehi and Burgueño, 2018).

1.3 Data-driven SHM techniques

Data-driven SHM techniques can be divided into two main typologies (Posenato et al., 2010): static and vibration-based. Static-based monitoring aims to obtain the structural response and environmental effects in the form of time series which are not sufficiently discretised in time to capture dynamic effects. This type of monitoring provides measurements that can be easily associated with phenomena of local character, being useful to identify novelties at their onset (Hu and Shenton, 2006).

Since the early 1980's civil engineering community has started to study and develop vibration-based detection methods for critical infrastructures (Chen and Ni, 2018). Initial studies examined damage using conventional modal properties like frequencies and mode shapes. Lower frequencies, already harder to detect and measure, are sensitive to operational and environmental conditions, which limits their use as damage indicators. However, during the last two decades, different Machine Learning (ML) tools have been utilised to develop a wide array of parametric and non parametric vibration-based structural damage detection systems in an attempt to optimise the process (Avci et al., 2021).

Vibration-based methods are widely used in research and practical applications, for its capacity to assess health by measuring the dynamic response of the structure and for being able to rely only on absolute quantities, such as acceleration and velocity records, an advantage that renders this type of monitoring less dependent on baseline references and on the installation of sensing systems. However, for large and critical infrastructures vibration-based techniques need an excitation capable of producing changes in the output signal resulting from localised damage, which is very difficult, as well as expensive (Hu and Shenton, 2006).

Santos (Santos, 2014) suggests an overall tendency to prefer static acquisition in practical applications for its convenience and ease of implementation. The same author cites some examples of instrumented bridges around the world: from twenty-five monitored bridges in China only one uses a system solely based on vibration measurements, while six of the thirteen major South Korean monitored bridges count with both, static and vibration-based monitoring systems. From the USA, it refers three applications that are mainly based on static strain measurements, also with acceleration sensors for global monitoring. In European countries, both typologies are widely used. It is possible to find examples in Germany, Switzerland, and France of monitoring applications that use static and dynamic data acquisition separately or simultaneously.

In Portugal, examples of acceleration-based monitoring systems are the ones installed on the Pedro e Inês pedestrian bridge and the Infante D. Henrique Bridge (Magalhães et al., 2012). An online early damage detection system proposed by Tome (Tome, 2019) uses multivariate analysis applied in SHM data from the Corgo's suspended concrete cable-stayed bridge. Static-based acquisition systems can be found in the Guadiana International Bridge, in the Salgueiro Maia Bridge and in the São João framed bridge.

An interesting example of both static and dynamic data acquisition is the suspended 25 de Abril bridge (LNEC, 2012) in Lisbon, Portugal. During the construction in the 1960's, the monitoring system installed in the bridge had as a first objective the safety control during the construction phases. The monitoring system provided measurements of stress variations and displacements, using electric strain gauges, static and dynamic clinometers to characterize continuously the actions imposed on the bridge; Wind gauges also measure the wind action and one macro seismograph that allowed to obtain the unique record of the earthquake of 1969. Nowadays, the monitoring system installed in the bridge can measure strains, displacements and actions imposed to the bridge, similar to the one implemented during the construction phase but in addition, it includes the automatic and continuous identification of natural vibrations for novelty identification

(Oliveira and Santos, 2020). The 25 de Abril bridge is one of the bridges in Portugal that has a long-term monitoring system that certifies the structural health of the infrastructure. However, the demand for new processing strategies that can efficiently extract useful information from data collected by monitoring systems is evidenced by the lack of robust interpretation of the results provided by the monitoring systems (Magalhães et al., 2012).

1.4 Motivation

The scale and the spatial extend of most critical infrastructure systems, together with the multitude of elements that compose those systems, make them exposed to multiple cascading events or multi-hazard interactions that have the potential to exceed the demands of the design and compromise their safety and serviceability (Gehl and D'Ayala, 2018). Structural deterioration also represents a substantial threat for existing structures, the effects of which can easily lead to failures, if they are not assessed in time. In this context, real-time SHM systems with the ability to identify structural changes at their onset using the minimum amount of information from the previous structural conditions are useful and needed.

SHM technologies are a tool to ensure the safety, serviceability, durability, and sustainability of structures by employing, ideally, long-term real-time monitoring to detect novelties in real-time and at their early stage to prevent critical damage and minimise negative impacts. For these purposes, SHM methods should be able to deal with any combination of structural loads and identify the consequences of multiple hazards on a single structure. In addition, advanced algorithms should be capable of managing the entire workflow, thus contributing to the standardization of SHM systems.

During the last decades, the SHM of critical infrastructures has become more popular. However, despite the multiple technological advancements, SHM systems still struggle with the lack of efficient and reliable methodologies to address signal processing and the analysis of large amounts of data (Azimi and Pekcan, 2020). On the other hand, the low probability of collapse of civil engineering structures (essentially due to the high safety margins adopted in design) leads to the erroneous perception that the investments involved in the structural maintenance activities are unnecessary. Research has been the greatest application activity of structural monitoring for the last decades, which allowed increasing and deepening the knowledge about the performance of structures. But, can the critical infrastructures assessment be improved using AI and SHM?

As confirmed by the research developments in the field, AI and SHM offers significant potential to enhance the robustness of critical infrastructure assessment. By leveraging advanced data analysis, modelling, and real-time monitoring, these technologies address several key challenges in infrastructure management. From the side of the structural monitoring, the predictive modelling allows automated novelty detection and the sensor technologies permit early warning systems and long-term recording. Regarding AI applications, the advancements in supervised and unsupervised learning and the development of ML and Deep Learning (DL) increased the accuracy of the prediction models.

In this sense, AI and SHM enable advanced uncertainty quantification by analysing large volumes of sensor data, identifying patterns, and estimating the likelihood of various failure modes. AI-driven approaches assist in defining dynamic thresholds for novelty identification based on real-time observed data, while the adaptivity of those thresholds allow to improve the sensitivity to early signals, reducing false alarms. The use of AI algorithms enhances pattern recognition analyses, since they can learn from complex, high dimensional SHM data and automatically detect novelties, classify them and predict future events. Based on observed data gathered by the monitoring system, AI-based assessment strategies can manage multiple predictive models simultaneously and this model redundancy allows cross-validation of the results. In addition, with a proper sensitivity analysis, it is possible to identify which are the variables that influence the structure behaviour the most, aiming to target monitoring and maintenance. In the present dissertation, those topics and their benefits are tested in order to show that AI and SHM technologies collectively improve the robustness of critical infrastructure assessment.

1.5 Objectives

In line with the motivation described in the previous subsection, the major goal of the present dissertation is to increase the robustness of the structural assessment of critical infrastructures subjected to multi-actions using artificial intelligence and monitoring data. This global objective involves a set of intermediate objectives:

- Apply Machine Learning and Deep Learning models to SHM data acquired continuously on-site;
- Assess the methods with the best performance considering site conditions, structural complexity and singularity, actions, hazards and sensor limitations;

- Use only structural response data, thus avoiding the need to characterize complex actions acting in large structural systems (temperature, wind, traffic);
- Define the best SHM strategy based on ML or DL methods;
- Benchmark against the most common strategies used nowadays.

In order to accomplish the objectives, the intermediate objectives are focused on increasing the accuracy and/or on enhancing the strategies for pattern recognition, sensitivity analysis and novelty identification as a key step in the increasing of robustness. For this purpose four general topics are covered in chapters 3, 4 and 5: model redundancy for the interpretation of the observed behaviour, sensitivity analysis for the identification of the effects in the observed structural response, improving pattern recognition through the combinations of ML and DL techniques and finally the definition of thresholds based on the observed behaviour for supervised and unsupervised data-driven analysis (see Figure 1.1).

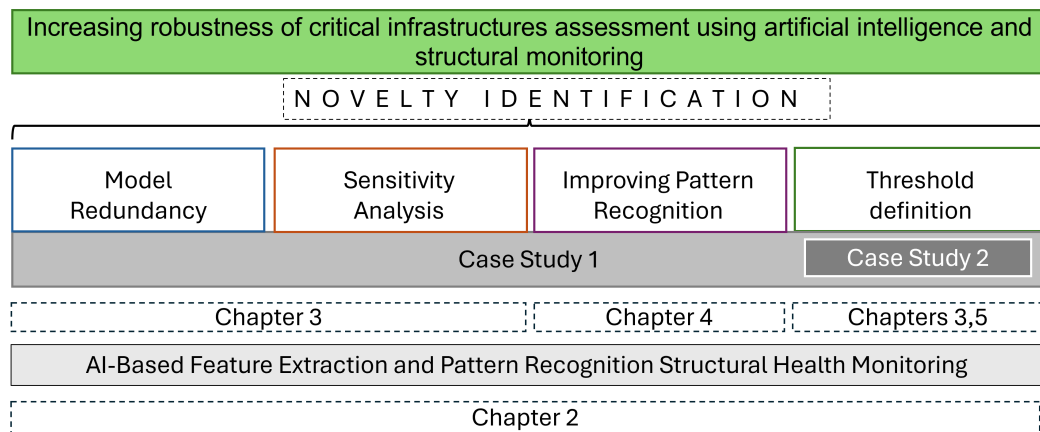


Figure 1.1: Flowchart representing the structure of the dissertation.

The present dissertation discusses the importance of SHM in addressing the structural health and safety of critical infrastructures. Over time, many SHM methods have been tested and studies have been published regarding different approaches that deal with damage detection and identification. In this sense, a comprehensive literature review of the different methods used for SHM was carried out. This review has covered ML methods, with special focus given to SHM and the new ML paradigm: DL concepts and applications. Based on the advantages and disadvantages of the reviewed methods, it was possible to conclude that DL methods allow overcoming limitations of ML approaches, such as the ability to efficiently deal with large size datasets composed of raw

data instead of features, the ability to analyse data without separating the effects generated by each structural action and the ability to perform the entire SHM workflow with a single algorithm.

The referred conclusions regarding the different methods allow to propose five milestones to be reached in the dissertation when fulfilling the objectives presented before:

- I. Increase the sensitivity of novelty identification methods (reduce false negatives);
- II. Increase of the robustness of novelty identification methods (reduce false positives);
- III. Contribute to the standardization of SHM systems;
- IV. Provide stakeholders with automatic procedures for safety assessment and decision-making based on predictive analysis of the structural condition;
- V. Contribute to the achievement of real-time damage identification in practical applications of critical infrastructures.

1.6 Thesis outline

Aside from the current chapter that introduces the general context of the dissertation, a bibliographic discussion on SHM systems, data-driven strategies for damage identification, pattern recognition, and novelty identification is presented in Chapter 2 covering the state of art of the present dissertation. The following chapters, namely 3,4 and 5, comprise practical experimentation and proposal of methodologies for structural assessment using real-time data of operational structures (a bridge and a dam). Chapter 3, presents a methodology based on real-time monitoring data of a suspension bridge for its structural characterization. The chapter explores the effects of model redundancy and the benefits of the proposed sensitivity analysis and threshold definition for novelty identification. In Chapter 4, a methodology is proposed to improve the currently most used pattern recognition technique based on Multiple Linear Regression (MLR) models by combining it with a deep learning approach, Long-Short Term Memory (LSTM) models. Chapter 5, presents an application of the methodology explored in Chapter 3 applied to a concrete dam including supervised and unsupervised learning approaches.

As described in Figure 1.1, the present dissertation covers both the theoretical background of the chosen AI-based feature extraction, pattern recognition techniques and the experimental analysis through the virtual representation of the dynamic simulation powered by real-time data

from sensors of two different instrumented critical structures; a suspension bridge and a concrete dam, both operational.

Chapter 6 is dedicated to the conclusions and achievements obtained from the work conducted in this dissertation as well as proposal for future works.

1.7 Case studies

Two kinds of critical infrastructures were chosen to analyse and assess: a suspended bridge and concrete dam, both currently operational and located in Portugal (see Figure 1.2).



Figure 1.2: Location of case studies: The Feiticeiro dam and 25 de Abril bridge.

Bridges and dams have different structural behaviour patterns; in the case of bridges, the main loads comes from the self weight, traffic, wind and temperature daily variations that impact the structural response. In the case of concrete dams, main loads come from the self weight and variation on the reservoir water level and air temperatures, just the annual variations of water are relevant for the structural response, daily variations do not have any impact. Consequently, because of the faster variations in the structural response of bridges, they need different observation

systems and measurement frequencies than concrete dams. The application of the same AI data-driven strategies for such different critical structures was considered an advantage since it allows showing their versatility while contributing to the objective of proposing a standardized SHM.

- **Suspended 25 de Abril bridge:** located in the estuary of the Tejo River connecting the cities of Lisbon and Almada. The bridge has a total length of 2277.5 m, with three suspended spans: the central suspended span of 1012.9 m and the two laterals suspended spans of 483.4 m each. The north access is made through a prestressed concrete viaduct comprising 13 spans while the South span is made by a railway tunnel and road access.

The bridge deck consists of a suspended rigid beam for 1344 vertical hangers that, at the same time, are suspended by four principal cables supported at piers P2 and P5 and at pylons P3 and P4. The deck's stiffening truss (12.0 m x 21.5 m) holds six car lanes at the upper chord level and a double electrified track railway at the lower chord level. All piers and pylons are made of steel trusses, with the exception of pier P7 which is built as a concrete hollow section. Piers P3 and P4, 180 m tall, support the suspended truss at the height of 60 m. Piers P2, P5 and P6 are supported by piles, while P3 and P4 have concrete foundations. The abutment P1 and the cable's anchorage structures are concrete hollow elements founded directly on the rock (see Figure 1.3).

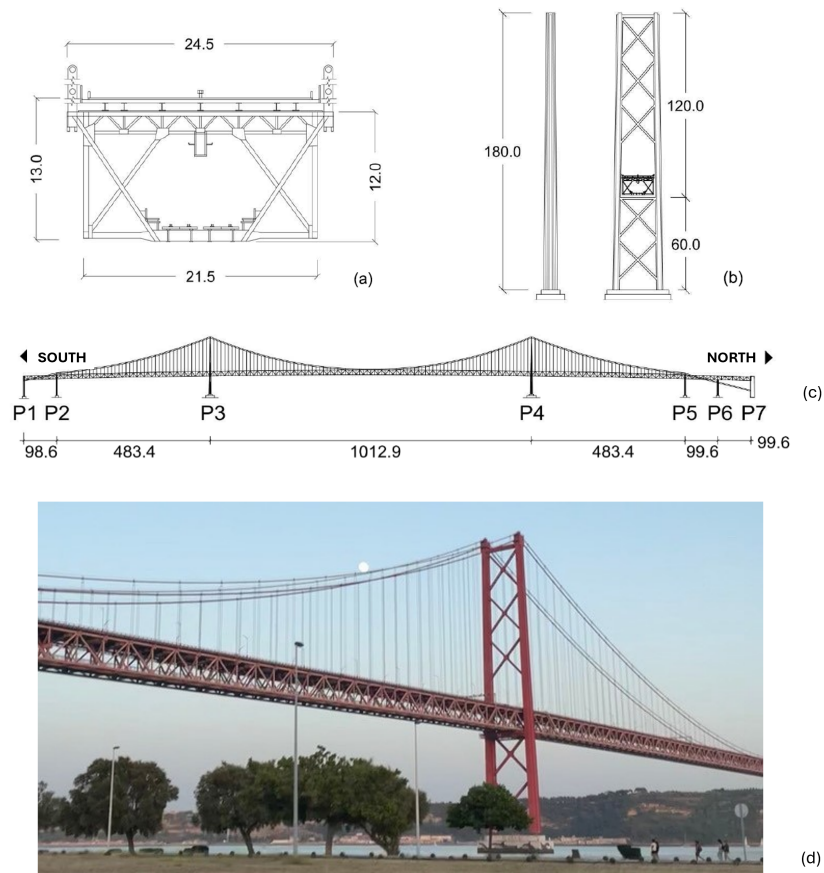


Figure 1.3: a) stiffening truss section, b) pier view, c) suspended bridge view, d) general view of the 25 de Abril bridge. Adapted from (LNEC, 2012).

The installation of the structural monitoring system comprises eight types of sensors able to acquire data that would allow the characterization of the structural behaviour of the bridge and the imposed actions, such as traffic and environmental. For the established system, sensors are understood according to their conceptual meaning, i.e. they are useful to identify the acquired variables; one accelerometer for three directions is not considered as unique sensor but as three. Following this premise, the data acquisition system is composed of 13 data concentrators which control 210 sensors, all connected through RS485 on fibre optic cabling. All the concentrators are connected by an Ethernet network built also on fibre optic with ring geometry for redundancy. An industrial computer located also on site controls the acquisition from the concentrator network and establishes the permanent link to LNEC's server, to ensure real-time availability and data processing. The sensors acquire measurements at a frequency of 500 samples per second. Data is stored in binary format

in different files, one per controller and one per hour of acquisition, that are then processed and analysed.

The sensors installed on the deck's stiffening truss consist of: therm compensated strain gauges installed on the chord to measure the strains, accelerometers to obtain the natural frequencies and mode shapes, displacement transducers to capture the displacements between the bridge and the piers, as well as those between the road stringers and the transversal suspended frames, thermometers installed together with the strain gauges.

Over the abutment P1, four railway pads detect trains travelling over the bridge. On sections 0 and 22S, two tri-axle ultra-sound anemometers estimate the wind distribution along the bridge. On the pylons, 6 strain gauges (three on each pylons leg) measure the strains, tilt-meters on the top of the towers, allow the indirect control of the cable's cell displacements, and the accelerometers installed on the foundations and the upper instrumented sections on the towers measure the natural frequencies and modes (see Figure 1.4). The data acquired continuously on the 25 de Abril bridge reflects numerous effects generated by simultaneous loads imposed on the structure. The information extraction strategy applied in the bridge is based on obtaining, from the time-series at certain predefined time-intervals (i) statistical features that can be directly and precisely correlated with the loads imposed on the structure, and (ii) vibration information such as natural frequencies, their corresponding damping ratios and mode shapes.

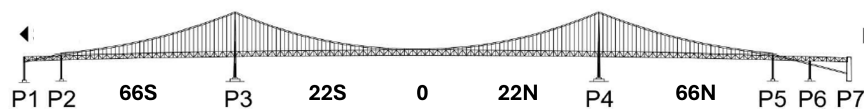


Figure 1.4: 25 de Abril bridge sections. Adapted from (LNEC, 2012).

- **Feiticeiro dam:** The Feiticeiro dam is located about 3.3 km upstream from the confluence with the Douro River and approximately 500 m upstream from the confluence with the Vilarica stream. In the central area, it is the concrete dam, including the safety hydraulics (flood spillway, its dissipation basin, and bottom discharge); and on the right bank, the two underground hydraulic circuits and (the circuits start at the water intake and end at the restitution structure) and their respective accesses. The dam is 45 m high and has a crest length of 315 m, which is divided into twenty-two blocks. The total concrete volume is equal to 130,000 m³.

The concrete dam is located in an area where the Sabor River valley is wide and has a relatively flat bottom. The overall construction maintains the geometric shapes of the initial solution, with a rectilinear axis of 45 m and a longitudinal axis of 140 m, it has length of around 315 m. The dam thus consists of 22 blocks, with developments varying between 21 m and 7 m, separated by 21 structural joints, defined as vertical surfaces perpendicular to the reference surface. The body of the dam consist of: i) the non-creep zone, which corresponds to the blocks on the banks, formed by 9 blocks on the left bank and 8 blocks on the right bank; ii) an overtopping zone, located in the centre, consisting of 5 blocks at the bottom of the valley, where the surface spillway is located, equipped with 4 shutters, controlled by segment gates, which are supported by pillars; and iii) the downstream foot of the dam, where the dissipation basin structure of the spillway is located (see Figure 1.5).

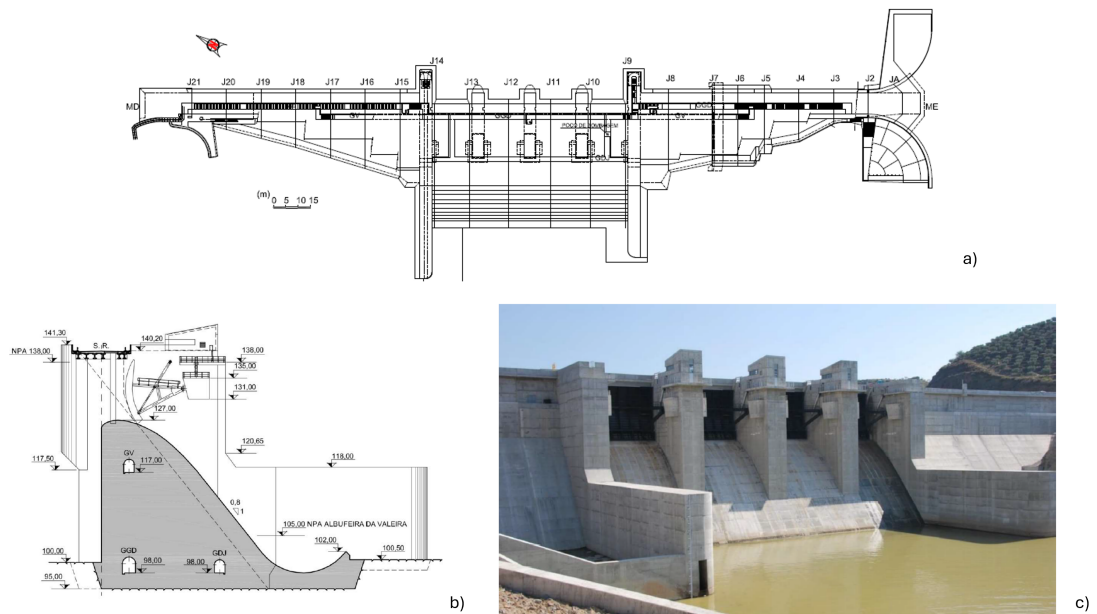


Figure 1.5: a) concrete dam plan, b) concrete dam section, c) general view of the Feiticeiro concrete dam. Adapted from (LNEC, 2013b,a, 2020).

In accordance with the best technical practices, the monitoring system of the Feiticeiro dam aims at the evaluation of the loads, the characterisation of the rheological, thermal and hydraulic properties of the materials, and the evaluation of the dam's structural response. The monitoring system of the Feiticeiro dam measures temperatures, reservoir water level, seepage and leakage, displacements in the dam and in its foundation, joint movements, strains and stresses in the concrete, and pressures, among others. High precision pressure meter,

provides a record of the water height over time, and a level scale. The air temperature and humidity are measured by an automated weather station placed on the right bank, approximately 100 m apart from the dam crest. The concrete temperature is measured in 76 electrical resistance thermometers distributed across the dam thickness of several blocks. The location of the thermometers was defined taking into account the set of the others electrical resistance devices (embedded joint meters and strain gauges) that also allow for the measurement of the concrete temperature. Displacements are measured using an integrated system that includes 3 pendulums, 8 rod extensometers and geodetic observations. The relative movements between blocks are measured by superficial and embedded joint meters. The concrete deformation is measured with strain gauges arranged in groups distributed in radial sections that allow the determination of the stress state through the knowledge of the deformation state and of the deformability law of the concrete. Drained water and infiltrated water are measured separately, with drains installed at the foundation of the dam and by weirs that differentiate the total quantity of water that flows in the drainage gallery in several zones of the dam. The drainage system comprises a set of 57 drains, distributed over the drainage gallery with 3 drains per block. All the water extracted from drains and leakages is collected in 4 weirs. Finally, the measurement of the uplift pressure in the foundation is performed by a piezometric network that comprises 26 piezometers.

The real time monitoring data is acquired by the auscultation instrumentation (ADAS) installed at the dam. In addition, the weather station has been integrated into the Automated Data Collection System. As a complementary system, a high precision Global Navigation Satellite System (GNSS) has been installed, controlling the horizontal and vertical displacements of the dam in three points, using an external pillar as reference, allowing to obtain post-process results with sub-millimetre precision every hour, 4 hours and 24 hours.

The communication between the instrumentation and automation box is performed with multi-wire shielded sheaths from each device to the box, thus avoiding interconnection boxes, all channelled in separate trays of the power supply sheaths, avoiding electromagnetic noise and guaranteeing the quality of the signals. All the instrumentation is conditioned to be able to make a parallel manual reading, allowing data contrast and validation of both systems.

Chapter 2

Structural health monitoring for pattern recognition and damage identification

Civil structures are prone to structural damage. Despite the existence of construction codes and maintenance schedules, deterioration of the structures are inevitable. Deterioration factors can depend on different environmental actions or hazards and of course, operational loads. In this sense, mitigation strategies need to be established to ensure the safety of these structures and to prevent costly economic, social and/or environmental impacts. For this purpose, data taken from in-situ measurements and long-term monitoring allows verifying the structural response and safe operation of the structures in real conditions (Biondini et al., 2025).

Most common causes of failure in bridges, worldwide are; i) floods (through scour effect), ii) train and vehicle collisions, iii) overload, iv) deficiencies in design and detail, v) earthquakes, vi) exceptional winds, vii) fire occurrences, viii) fatigue, cracking and corrosion of steel elements, ix) insufficient resistance or stiffness, mainly in steel elements or steel reinforcement, x) corrosion of pins, hangers, reinforcement and pre stress tendons, xi) design deficiency of structural bearings under the actions of creep, shrinkage and temperature, and xii) lack of maintenance (Santos, 2014).

In the particular case of Portuguese bridges, in Figueiredo et al. (Figueiredo et al., 2011), the authors refer that the most commonly observed damage scenarios are: i) corrosion in metal components, ii) generalized concrete degradation (cracking, delamination, and corrosion of the reinforcement bars), iii) degradation of corrugated metal culverts, iv) degradation of the expansion joints and v) construction defects. The corrosion in metal elements is normally observed in

beams, bearings, and railings, derived from defects of painting or protective coating. The concrete deterioration is mainly caused by debris, deficient drainage or leakage.



Figure 2.1: a) Collapse of the Silver Bridge, 1967. USA. b) Collapsed north section of the Minneapolis I-35W Bridge, Minnesota, USA. Adapted from (Figueiredo et al., 2011).

Following Sohn et al. (Sohn et al., 2002), the development of a robust detection and monitoring system for bridges can be seen to face several challenges. For example, bridges involve a significant number of uncertainties caused by environmental effects such as temperature, loading or humidity. Additionally, the uncertainty to estimate the strength and stiffness of structural components is significantly higher than for example that of truss members commonly used for space frame structures: bridges typically have more complicated geometry, many different materials, and greater structural safety margin is present in the design compared to spatial or mechanical constructs. These issues make accurate modelling very difficult, even with the possibility to conduct model updating and refinement techniques prior to damage detection; the dimension of the bridges requires the instrumentation of many, well located sensors and the excitation of higher modes, which demands a large economical investment. Moreover, the application of forced vibration tests, which are commonly used for system identification, can be difficult for operational bridges because of the economic and social impacts caused by service interruption.

Based on 750 bridge failure cases briefly summarised in Santos (Santos, 2014), it is possible to conclude that monitoring systems installed on bridges must be particularly sensitive to changes imposed by scour effects, vehicular collisions, as well as by damage in steel elements such as cables, tendons, pins, etc., which are difficult to inspect and prone to corrosion effects. Early damage detection once again is the way to prevent failure and/or collapse and potentially minimize the inherent damage costs.

Regarding concrete dams, a failure represents a catastrophic event, typically a breach followed

by a flood wave, which may result in significant loss of life and property. Even in cases where the reservoir's availability or the reliability of its operation is merely impaired, essential economic interests may be disrupted, and environmental damage may occur. For these reasons, dam owners and engineers have consistently placed dam safety as a paramount concern.

The ICOLD report *Deterioration of Dams and Reservoirs* compiles numerous incidents and failures (ICOLD, 1974). In the case of concrete dams, failures have been attributed to:

- Insufficient shear strength and discontinuities in the foundation;
- Excessive uplift pressure in the foundation due to inadequate or absent drainage;
- Structural instability of the dam;
- Lack of precautions to accommodate excessive or differential foundation deformations, among others.

Dam failure is generally a complex process, typically initiated by an undetected abnormality. Progressive deterioration, often unnoticed, may then lead to further damage and ultimately disaster. This highlights the critical role of systematic inspection and monitoring of dams, together with timely data analysis and interpretation. Documenting how deterioration and malfunctions have first been identified, or how failures have been averted, provides valuable guidance for the design of monitoring and warning systems.

ICOLD Bulletin 99 (ICOLD, 1995), on the statistical analysis of dam failures reported the following conclusions:

- Most dam failures occur in newly built structures, particularly within the first ten years, and most frequently within the first year of operation;
- The highest failure rates were observed in dams constructed between 1910 and 1920;
- In concrete dams, foundation problems are the predominant cause, typically linked to internal erosion and insufficient shear strength;
- In masonry dams, overtopping is the most common cause, followed by foundation erosion;
- Where appurtenant works were implicated, inadequate spillway capacity was the principal factor.

The causes of dam failure are diverse, and susceptibility varies with dam type. The global study of dam incidents and accidents has been the focus of various organizations, including ICOLD committees (ICOLD, 1974, 1983, 1994, 1995) and the U.S. Committee on Large Dams (U. S. Committee on Large Dams (USCLD), 1990a,b,c), among others. Most of the failures can be attributed in the foundations due to deformation and land subsidence, shear strength, seepage, erosion, tensile stresses at the upstream toe, grout curtains and other watertight systems and leak of drainage system. Due to the resistance to freezing and thawing, permeability or ageing of the concrete. Due to unforeseen loads or to loads of exceptional magnitude such as uplift, overtopping or deterioration of rock-concrete interface. Due to structural behaviour of the arch and multiple arch dams related with artificial abutments and foundation. Due to structural behaviour of gravity and buttress dams related with tensile stresses and facings.

For concrete dams, excluding failures due to appurtenant works, most recorded cases are linked to deficiencies in the foundation rock mass, such as erosion, dissolution of soluble rock, and inadequate shear resistance along unfavourable discontinuities. Because the foundation and abutments provide essential structural support, their instability directly compromises dam stability. For instance, seepage can induce erosion, dissolution, or excessive internal pressures, all of which may trigger dam failure. Similarly, leakage through concrete may give rise to comparable safety concerns.

The materials used in dam construction must withstand the stresses and pressures associated with impounded water. Material deficiencies can create zones of weakness that ultimately threaten dam integrity. In older structures, prolonged exposure to water erosion, cyclic loading from water level and temperature variations, and progressive material deterioration may aggravate vulnerabilities. Insufficient maintenance exacerbates these effects, creating unsafe conditions. Natural phenomena, such as floods and earthquakes, can also precipitate dam failure, particularly where ageing or deterioration is already present.

Since dams are constructed from materials whose properties evolve over time, it is necessary to account for such changes throughout their service life. Deterioration may occur from the earliest construction stages through operation and even up to demolition or abandonment. Dam safety, and consequently the safety of downstream populations, depends not only on sound design and quality construction but also on consistent maintenance and comprehensive surveillance (ICOLD, 2000).

Dam safety surveillance encompasses two main activities: periodic visual inspections of accessible surfaces, foundations, galleries, appurtenant structures, and the reservoir; and systematic

monitoring using instrumentation embedded in the dam to evaluate its safety. The primary tasks of dam monitoring include instrument measurements; data verification; data processing and analysis; and interpretation and reporting of results.

The central objective of monitoring is to generate reliable information for assessing the dam's continued performance and safety. During operation, monitoring serves two complementary purposes: short-term and long-term monitoring. In short-term monitoring is focused on detecting rapid anomalies in dam or reservoir behaviour that may compromise safety or operability, requiring immediate intervention (e.g., restrictions on operation, repairs, or, in extreme cases, emergency alerts). In turn, long-term monitoring: Identifying gradual changes in condition and behaviour, facilitating comprehensive safety assessments (including validation of design parameters) and supporting maintenance planning. Both functions are equally important. Although short-term monitoring is often viewed as sufficient, an understanding of long-term behaviour is frequently essential for explaining anomalies detected by critical instruments. Moreover, gradual trends can be as significant for safety as abrupt changes. These two functions, therefore, are interdependent, operating on different temporal scales of data analysis (ICOLD, 2000).

To monitor any structure in order to ensure their safety, it is important to follow an standard process: observation over a period using periodically spaced measurements, extraction of features from these measurements and the posterior analysis. These components are discussed in the following, along with a discussion about the choice of SHM strategy depending on the identified vulnerabilities, and the integration of forward novelty identification approaches.

2.1 Operational evaluation and data acquisition

Considering that the structure to evaluate is operational, the SHM strategy must consider the limitation (environmental variability, sensor related limitations, data size) of what will be monitored and how the monitoring will be accomplished (Farrar et al., 2001).

In order to define the most convenient sensor solution, operational evaluation takes advantage of each feature from the host structural system. Hence, social, economic and operational constraints must be taken into account together with designers, investors and authorities (Santos et al., 2013).

According to the authors in Sohn et al. and Farrar and Worden (Sohn et al., 2002; Farrar and Worden, 2007), operational evaluation should answer four main questions:

1. What are the life-safety and / or economic motivations for performing SHM?

2. What are the operational and environmental conditions under which the monitored structural system works?

3. What are the limitations of acquiring data in the operational environment?

4. What are the vulnerabilities of the structural system being investigated?

Questions 2 and 3 consider operational and environmental actions and effects acting on the structure and require analysis of data previously acquired from similar structures that in general comprise: temperature, wind and/or humidity. In bridges, traffic must also be considered. Question 4 represents the most challenging question of the operational evaluation since it must be considered not only during serviceability but also during construction or repairing works.

In Figueiredo et al. (Figueiredo et al., 2011), the authors mention that during the extraction phase the observed changes in the damage sensitive features, should be correlated with the level of damage present in the structure. However, environmental variations can mask those features, as well as the damage level and the correlation between them. On the other hand, the more sensitive the damage measurement is, the more sensitive it is to changes in operational and environmental conditions. To overcome this issue, an intelligent feature extraction by means, for example, of data driven techniques, early damage detection based on pattern recognition (Santos et al., 2017) and Machine Learning (ML) techniques (Santos et al., 2013; Anaya et al., 2014; Salazar et al., 2015, 2017; Sajedi and Liang, 2020) recommended.

Data acquisition involves selecting the types of sensors to consider, the location, the number, the data acquisition/storage/transmission hardware, and its programming. The rate of data acquisition and economic considerations play an important role in making decisions regarding the SHM approach (Farrar et al., 2001; Figueiredo et al., 2011). However, the greatest constraint for the implementation of a proper data acquisition strategy is, perhaps, the SHM typology. Depending on the outcome of the operational evaluation with respect to the vulnerability and the effect of the different loads, the selected SHM strategy to choose can be static-based or vibration-based (Posenato et al., 2010; Moon and Catbas, 2013; Chen and Maung, 2014). Both strategies can be used along with forward novelty identification approaches, and the choice of acquisition strategy depends on the vulnerabilities identified in the previous operational evaluation phase. Static-based monitoring aims at obtaining the structural response and environmental effects in the form of time-series without considering the dynamic actions, this type of monitoring generates smaller volumes of data, being easier to interpret. Furthermore, measurements of static or quasi-static quantities can be easily associated with phenomena of local character, which is important to identify novelties

at their onset. Vibration-based monitoring aims to assess the structural health by measuring the dynamic response of the structure, detecting any variation on the mass or stiffness in the structural materials or in the boundary conditions. This type of monitoring relies only on absolute quantities, such as acceleration or velocity. However, the global character of the acquired data greatly hinders the identification of structural changes at their onset. Therefore is considered more appropriate to identify changes in the global structural behaviour (Santos, 2014).

According to the authors in Avci et al. (Avci et al., 2018, 2021), a typical damage detection system consists of software and hardware components. The hardware part is composed of the sensing and data acquisition interface, which may include accelerometers, velocimeters, strain gauges, load cells, tiltmeters, relative displacement transducers and other types of sensors along with data acquisition modules (Adewuyi and Wu, 2009), as shown in Figure 2.2. The software part is instead dedicated to signal processing, to translate the signals acquired by the sensing interface into essential information that reflects the condition of the monitored structure.



Figure 2.2: Strain gauges used in civil testing. a) resistance-based glued, b) resistance-based welded, c) embedding resistance strain gauge inside the concrete element. Adapted from (Borosc hek and Santos, 2020).

A fundamental premise regarding data acquisition and sensing systems is that these systems do not measure damage. Instead, they measure the response of a system to operational and environmental loads or the response to inputs from actuators embedded with the sensing system. Depending on the sensing technology and the type of damage to be identified, the sensor readings may be correlated to the presence and location of damage. Feature extraction and data processing

for damage identification are then necessary to convert the sensor data into useful information for structural assessment (Farrar and Worden, 2012).

Data acquisition systems should be selected based on the number of sensors, type of sensors (generality), sensitivity, stability, robustness to environmental actions, and usage conditions. Reliability and longevity of data acquisition systems require robust hardware, protected from environmental threats like dust, overheating and moisture, as well as uninterruptible power supply protection. In Yuen-Wong and Qing-Ni, and Chen and Ni (Yuen-Wong and Qing-Ni, 2009; Chen and Ni, 2018) the authors present the most common layout of data acquisition units (see Figure 2.3). Those units are usually composed of signal conditioning components that convert electrical energy (analogical signals) obtained from the sensors, into data (digital signals); this central component is called analogical/digital converter (ADC). The ADC can also be used as buffer or long-term temporal storage. In addition, this subset can also include: several types of embedded signal conditioners for appropriate data input, circuitry for device control using digital or analogue output (the latter resorting to digital to analogue converters (DACs)) and multiplexers for sensor signals confluence.

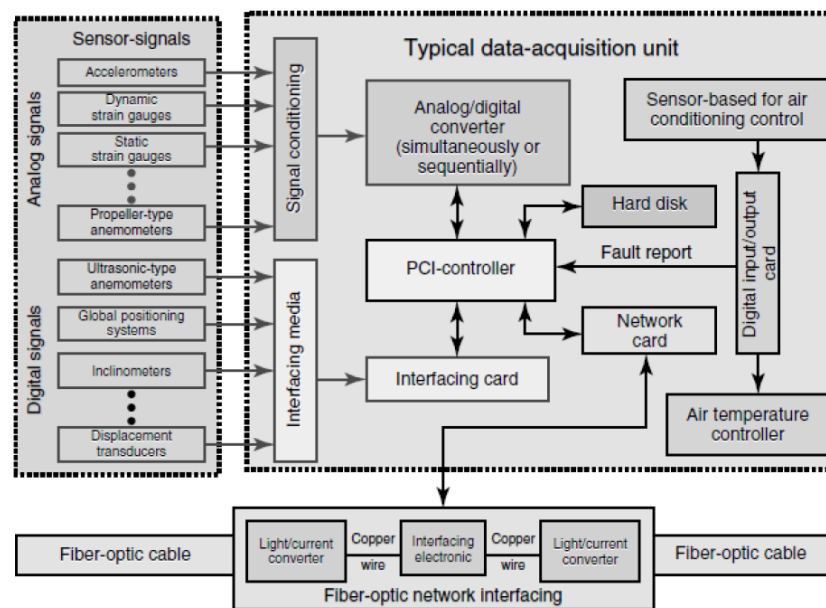


Figure 2.3: Schematic layout of a typical data-acquisition unit. Adapted from (Yuen-Wong and Qing-Ni, 2009; Chen and Ni, 2018).

In SHM applied to bridges, commonly used sensors include velocity sensors, which measure structural vibration speed and can be used as alternatives to accelerometers. Strain gauges are

based on several types of transducer principles and can provide accurate dynamic data output. Relative displacement sensors are generally deployed between the ends of joints, bearing supports, base isolation, or control devices to measure the vibrations imposed on them and also to capture the structural natural modes associated with the displacements imposed on them (see Figure 2.4.). Load cells generally consist of mechanical assemblies of strain gauges, either resistance-based or optical. Tilt-meters are used for measuring rotation in structural elements and foundations. Environmental sensors are used for civil testing to measure the effects of any demands that can influence the structural response (Borosc hek and Santos, 2020).

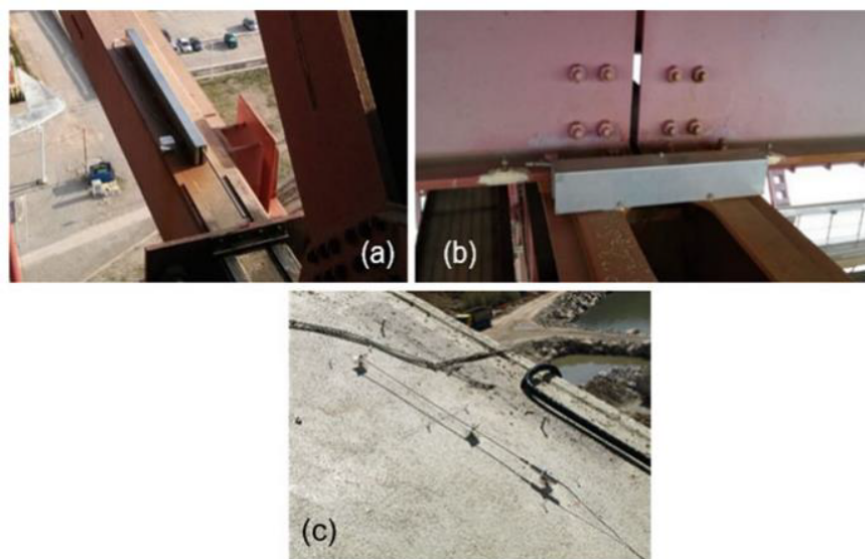


Figure 2.4: Relative displacement sensors used in civil testing: a), b) magnetostrictive sensor, c) linear variable differential transformer (LVDT). Adapted from (Borosc hek and Santos, 2020).

In the case of concrete dams, the variables to be measured, the general information about the devices to be installed, and the procedures to be followed in the installation and maintenance must be presented in the monitoring plan. According to Mata et al. (Mata et al., 2013), the monitoring of a concrete dam can be categorized according to three purposes: characterisation of the structural properties, measured by in situ tests and laboratory tests of samples of the materials used in the dam construction, forced vibration tests, and tests under fast loads or permanent loads over time using load cells installed in the dam.

Dam safety management begins with the preparation of a monitoring plan, ideally developed before construction starts. This plan should explicitly address the design assumptions and critical issues identified during project development, assess potential risks, allocate resources for safety and functionality, and ensure timely detection of anomalies. Although the monitoring plan spans

the entire service life of the dam, it is inherently dynamic and must be revised and updated as necessary.

During the operational phase, monitoring activities focus on analysing and interpreting dam behaviour. By this stage, extensive data and historical records about the structure and its site are typically available. Information collected in earlier phases is essential for identifying safety concerns in current operation (Myers and Stateler., 2008).

Assessment of dam conditions relies on maintaining up-to-date knowledge of its performance, ensuring that anomalies are detected in time to permit corrective interventions and prevent severe consequences. The monitoring system, as defined in the monitoring plan, must be designed with reference to possible accident and incident scenarios, considering:

- Dam safety and functionality;
- Characterisation of structural behaviour (actions, properties, and effects);
- Accuracy of instruments relative to the expected range of physical quantities;
- System reliability and redundancy;
- Accessibility of the dam under adverse conditions (e.g., winter).

Monitoring systems must be both adequate and dependable. Their long-term performance is critical, which is why instruments should be selected for ease of replacement or repair, ensuring continuity of data collection and compatibility across time. Redundancy in measurements is strongly recommended to avoid misinterpretation caused by the malfunction of a single device. Beyond economic considerations, practical aspects must also be accounted for; for instance, the use of high-precision, short-range instruments may be impractical in certain contexts. The monitoring plan also specifies the variables to be measured, general information about the devices to be installed, and the procedures for installation and maintenance. According to ICOLD (ICOLD, 1994), monitoring methods can be classified by their purpose:

- Characterisation of structural properties: in situ and laboratory testing of construction materials, forced vibration tests, and long-term or rapid load tests performed in dedicated cells within the dam.
- Monitoring of actions: observation of construction sequences and methods, water levels, air and water temperatures, and seismic events (including reservoir-induced seismicity), using

instruments such as limnimetric scales and water pressure sensors (see Figure 2.5) and, thermometers (see Figure 2.6), and seismographs.



Figure 2.5: Limnimetric scale for manual water level measurement (left). Hydrostatic pressure sensor for automated water level measurement (right).



Figure 2.6: Weather station, including thermometers for air temperature measurement (left). Electrical resistance thermometer to be embedded in the dam body during its construction (right).

- Monitoring of direct effects of actions and indirect mechanical effects: measurement of pore and crack pressures, seepage, leakage, and concrete temperatures (see Figure 2.6), with devices such as piezometers (see Figure 2.7), drains, weirs (see Figure 2.7), and thermometers; and measurement of absolute and relative displacements, joint movements, stresses, and strains, using survey methods, direct and inverted pendulums (see Figure 2.8), rod extensometers, jointmeters (see Figure 2.8), stress meters, and strain gauges.



Figure 2.7: Measuring weir for discharge measurements to evaluate the amount of water that flows through the dam (left). Apparent part of a piezometer to measure the uplift pressure placed on the rock mass foundation (right).



Figure 2.8: 3D jointmeter for manual and automated measurement of relative movements between blocks (left). Pendulum, measuring table and automatic system for horizontal displacement measurements (right).

2.2 SHM approaches: Forward and inverse

Inverse approaches also identified as model updating or system identification approaches consist in finding the parametric numerical or analytical models that best fit structural responses (Farrar and Worden, 2007). Model updating of structural systems has been an important field of research in civil engineering. Many computational methods have been developed on the subject, including

matrix-update methods, sensitivity-based methods, iterative optimization methods, Bayesian approaches, computational intelligence methods, among others (Hasançebi and Dumlupinar, 2013). Such techniques can provide precise information about structural changes, but their computational complexity makes them less suitable for real-time applications. As mentioned in Santos et al. (Santos et al., 2017), it requires the use optimization or stochastic search techniques for computational efficiency.

Traditional model updating of large-scale structures is time-consuming because the global structural model needs to be repeatedly re-analysed to match global measurements. In Weng et al. (Weng et al., 2012) the authors proposed an alternative substructural model updating method where the modal data measured on the global structure are disassembled to obtain the independent substructural dynamic flexibility matrices under displacement compatibility conditions. In another study, the authors of Lin et al. (Lin et al., 2020) proposed a time history analysis based on the non-linear finite element model updating method that establishes the objective functions based on the response time history and the associated acceptance criteria, to perform comprehensive sensitivity analyses in order to select appropriate non-linear updating parameters. In Esfandiari et al. (Esfandiari et al., 2020), the authors proposed a new sensitivity-based model updating method based on changes in principal components of the frequency response function (FRF) using principal component analysis (PCA). The methodology applied to a truss and a frame model proved to be a robust damage detection algorithm in the presence of measurement and mass modelling errors.

Forward or data driven SHM approaches instead, do not require the development of numerical or analytical models to be fitted with in situ data. These techniques extract sensitive information from the measured time-series, using data based learning methods (Sohn et al., 2002). Different from inverse approaches, forward SHM methodologies are more flexible, less computationally demanding, which is why these techniques have been the most reported in recent SHM literature. This issue is particularly relevant when applied to structures subjected to operational and environmental effects, since data-based algorithms can more easily reproduce these effects, when compared to numerical or analytical models (Santos, 2014). Forward approaches are going to be described in the following section, framed in the scope of civil infrastructure SHM.

2.3 Forward SHM

Forward SHM strategies start with the observation of the instrumented structure, followed by feature extraction, and finishes with the analysis (see Figure 2.9).

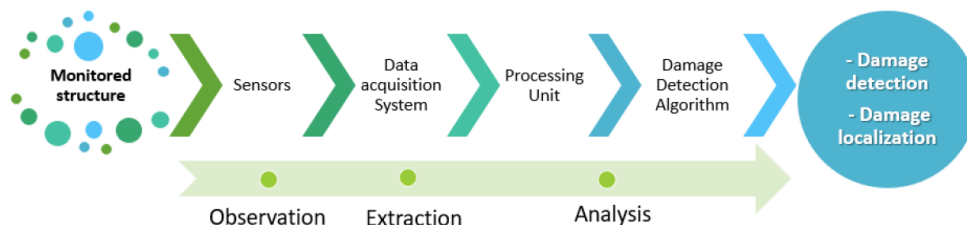


Figure 2.9: Flowchart for damage identification strategy.

Because SHM systems are operated in harsh and noisy environments, abnormal data is inevitable. The large variation in extracted features from massive SHM data causes conventional novelty detection techniques to perform poorly. Even with expert intervention, the parameter tuning associated with multiple data pre-processing methods is still a challenge and makes the procedure expensive and inefficient. In addition, novelty detection techniques that are focused on a single type of novelty miss other types of equally relevant novelties (Bao et al., 2019).

Normalization, defined as the process to suppress the structural changes caused by environmental and operational actions (Cury and Cremona, 2010) to establish a difference with the novel structural behaviour, was widely explored by many researchers as a first forward SHM step. Currently, there are two well-known approaches for normalizing data related with environmental and operational effects; the first one uses regression models between the environmental actions and the structural response (Cury and Cremona, 2010) and the second is based on latent variable statistical algorithms (Santos, 2014; Shokri and Tavakoli, 2019; Meixedo, 2021) that allows inferring the responses generated without measuring them.

Environmental and operational factors significantly impact structural responses, with temperature being the most consequential environmental load in bridges (Figueiredo et al., 2011; Loh et al., 2011). In the case of the concrete dams, the water temperature is also relevant. It exerts a pronounced influence on displacement and strain variations (Santos et al., 2013). Wind actions are also important to consider, especially for flexible structures like high buildings or long span bridges (Li et al., 2010). In concrete dams, the water level reservoir, the temperature and the time-dependent actions are the more relevant for the structural response.

Feature extraction is frequently referred as the next and most important step of forward SHM strategies. The term “feature” can be considered as a shortening of “distinguishing feature” or “sensitive feature” (Bishop, 2006) and is defined as the type of information that may expose structural novelties (Figueiredo et al., 2011; Worden et al., 2011). The process of extraction represents the transformation of the measured data into different types of information, that compared with raw data can inform about the structural condition. The multivariate outputs of this process are usually called “feature vectors”, whose length and dimension should be as small as possible, otherwise the statistical characterization or comparison with physical models can involve significant computational complexity (Worden et al., 2011).

Once the features have been established, the map between the features and the diagnosis rules and methods, or algorithms, can be constructed. Statistical learning, as an intersection of machine learning and statistics, is a process that aims to implement algorithms that can operate on the extracted features to discover patterns (novelties) or extract hidden knowledge to assess damage in the structure. It can be categorized in supervised and non-supervised learning and depends on the kind of data available to choose one of the categories. According to Farrar and Worden (Farrar and Worden, 2012), identifying and locating damage can be approached through unsupervised learning, which involves analysing data solely from the undamaged state or from a set of recognized structural states to detect changes. When data from both undamaged and damaged conditions are accessible, the supervised learning mode is suitable, as it not only discerns the existence of damage but also determines its type and severity, unlike unsupervised learning.

Feature classification is a direct application of statistical classification and is referred by authors in Figueiredo et al. and, Farrar and Worden (Figueiredo et al., 2011; Farrar and Worden, 2007), as the step receiving less attention in the literature. In Santos (Santos, 2014), the author states that this step reports three major approaches: i) definition of boundaries around features related to a known structural condition, ii) definition of frontiers between features belonging to several known structural conditions, and iii) definition of clusters corresponding to one or more known structural behaviours. The first two approaches are only applicable to supervised learning and the third one can also be applied to unsupervised learning.

2.4 SHM based on machine learning approaches

The transition from traditional methods to ML, is presented in this section, along with the conceptual framework of different techniques such as: i) damage-sensitive feature extraction from the

monitored response, ii) ML regression techniques for modelling the structural responses and iii) ML classifiers for classifying the extracted features of civil structures. The ML-based strategies that are reviewed comprise different methods for extraction, normalization and classification and are based on separating effects and actions.

Conventional ML-based approaches require the extraction of damage sensitive features to use them as inputs of ML models. In vibration-based approaches, novelty detection relies on modal characteristics (natural frequencies, damping ratios, mode shapes) as sensitive features. However, the reviewed literature suggests that such features might be affected by factors other than structural damage such as changes in temperature and moisture conditions. Furthermore, taking into account that the majority of signals impacting civil infrastructure are non-stationary (such as seismic and wind-induced activities), analysing these signals within the time or frequency domains using alternative features, such as auto-regressive methods, time-frequency analysis, PCA, clustering, and symbolic data, can frequently result in a more sensitive, robust, and effective damage identification process.

2.4.1 Feature extraction and data fusion

In Worden and Delieu-Bardon ([Worden and Delieu-Bardon, 2004](#)), the authors state that SHM is a multilevel and multi faced method dealing with data from single and multiple sources. In order to have a robust and more confident decision, multiple monitoring sensors are installed in the structure. The process produces multivariate datasets or feature vectors. Since reducing their dimensionality is essential, data fusion and feature extraction can be regarded as complementary approaches within the broader framework of information extraction from data. According to the author in Santos ([Santos, 2014](#)), feature extraction is based on the assumption that structural behaviour will reflect itself, at least in one of the five data descriptors: (i) vibrations (frequencies, spectra, etc); (ii) expected value (mean, median, etc.); (iii) variability (standard deviation, covariance and correlation); (iv) distribution's symmetry and (v) distribution's flatness.

Feature extraction and data fusion strategies can be classified according to their location in the SHM workflow ([Worden and Delieu-Bardon, 2004](#)) as shown in Figure 2.10 in: a) centralised strategy in which each sensor provides information to a central feature extraction unit that tries to remove the inter and intra-sensor redundancy, and it aims at describing vibration descriptors, b) pattern-level strategy, in which the feature extraction is carried out for each sensor independently

and it aims at describing the other four non vibration descriptors, finally c) combined strategy that is the result of the combination of strategy a) and b) (Worden et al., 2011; Santos, 2014).

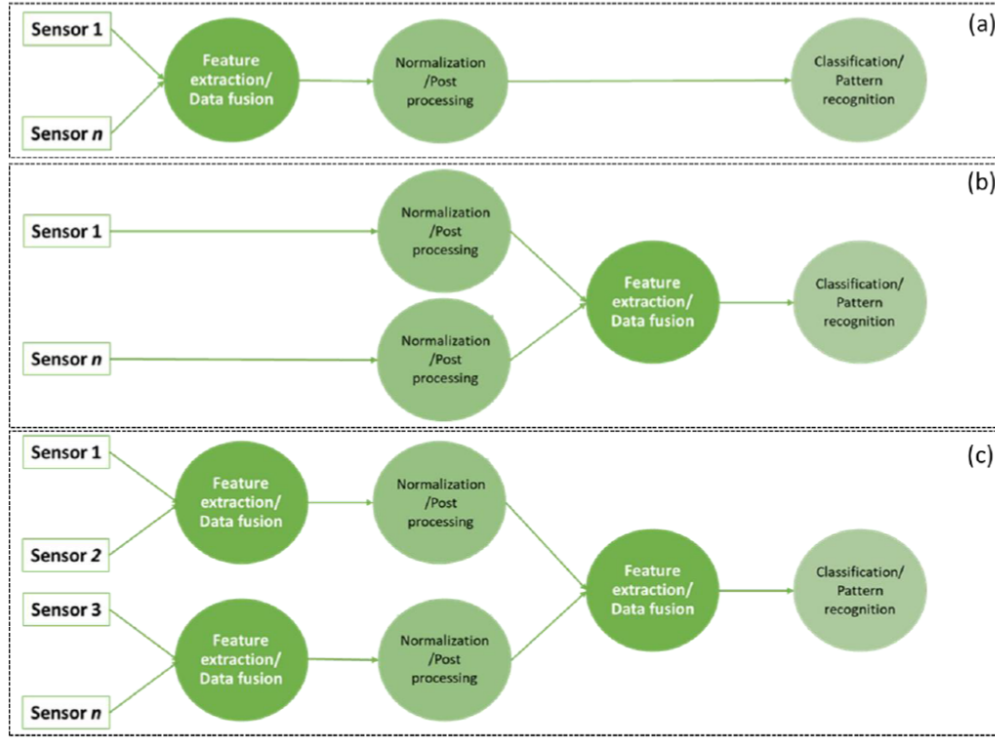


Figure 2.10: a) centralised strategy; b) pattern-level strategy and c) combined strategy. Adapted from (Worden et al., 2011; Santos, 2014).

As mentioned before, centralised strategies aim to describe vibration descriptors, which requires converting large amounts of acceleration data into sets of meaningful vibration feature, most common ones being the modal frequencies (Cury and Cremona, 2010; Zhou et al., 2011). In pattern-level strategies, instead there is a need to convert either vibration features or static-based measurements into compact information that can be statistically classified as "known" or "novel", in this sense, symbolic methods such as symbolic data analysis (Cury and Cremona, 2010; Santos et al., 2015), PCA analysis (Santos, 2014; Meixedo, 2021; Meixedo et al., 2022; Guedes et al., 2024) or autoregressive models (Bao et al., 2019; Bornn et al., 2016; Mosleh et al., 2023) are preferred for their ability to describe the variability present in multivariate data sets.

Feature extraction in a centralized-level is meant to convert fast-sampled responses into new types of information such as an expected value or a variability, which, for novelty identification purposes, can be handled in the same way as static data (Santos, 2014). Regarding the pattern level strategy, the final objective of feature extraction is to describe the data distribution in terms

of statistical moments: mean, standard deviation, skewness and kurtosis. Depending on the case each moment may exhibit different levels of correlation with structural novelties (Sohn et al., 2002; Farrar et al., 2001; Farrar and Worden, 2007; Figueiredo et al., 2011).

2.5 Statistical learning for feature modeling

Statistical learning can be applied to detect damage and provide quantitative and objective information regarding its existence, location, type and magnitude in a fully automated way (Santos, 2014). Statistical learning methods typically focus on preventing two kinds of classification errors: i) false-positives, also known as Type I errors, where damage detection is activated without the presence of damage, and ii) false-negatives, or Type II errors, which happen when damage is present but goes undetected. Type I errors are of economic concern and Type II errors are life-safety concern in SHM.

Statistical models aim to implement two types of SHM levels: i) protective and ii) predictive (Farrar and Worden, 2012). In the first case, the focus is to use damage-sensitive features to identify any alteration on the system that can lead to catastrophic failure, the definition of thresholds on acceptable levels of feature changes are used for this purpose. The second level, instead, refers to the cases in which trends in data are identified to predict when the damage will reach a critical level. In this case cost-effective maintenance planning are needed.

Predicting the structural performance is a key aspect for civil engineering, to ensure safety, efficiency and durability of the infrastructures. Data driven strategies for structural response prediction are now widely combined with advances in engineering for SHM applications. ML and artificial intelligence (AI) techniques for predicting structural behaviour are attracting the attention of researchers and investors for its multiple benefits. However, as emphasized by the authors in Afshar et al. (Afshar et al., 2024), ML approaches should be a complementary tool to classical structural analysis, enabling real/time monitoring and intelligent predictions that balance the data-driven learning with civil engineering experts knowledge to improve reliability and robustness in SHM applications.

2.5.1 Regression analysis

Regression analysis is widely used to model the relationship between input variables, such as sensor data or structural loads, with structural responses. In Berk (Berk, 2016) the author states that for many statistician's, regression models are just about conditional distributions. However,

the goal is to understand how the conditional distribution varies as determined by the predictor or predictors. That is, in a generic way, where the interest is centred: on the distribution of the response variable Y is conditioned by one or more predictors X . Regression analysis, therefore, is fundamentally about conditional distributions: $Y|X$.

Regression models are currently used in the suppression of changes related to environmental and operational effects present in SHM data (Cury and Cremona, 2010; Santos et al., 2013), by establishing regression models between measured operational and environmental variations along with the structural responses. According to the authors in Santos et al. (Santos et al., 2013), several suppression strategies are based in regression methods: multivariate linear regression (MLR), multi-layer perceptron (MLP), neural networks (NN), or support vector regression (SVR). However, when applied in an actual case study, they are dependent on an appropriate characterization of temperature effects on the structure.

2.5.2 Multivariate linear regression

Multivariate linear regression is one of the most direct regression methods used for data normalization. In its theoretical and computational simplicity along with the fact that most physical relations between environmental and operational actions and structural measurements have a linear nature, it is suitable for normalization (Santos, 2014).

In a study of the thermal effects on natural frequencies of the PI-57 Bridge due to temperature changes, the authors in Cury and Cremona (Cury and Cremona, 2010) test three regression and fitting models: multiple linear regression, parametric linear regression and neural networks in order to calibrate a model, so it can be capable of discriminating deviations of natural frequencies due to temperature changes from those caused by other factors, such as environmental factors or imposed structural modifications.

MLR model takes a subset of temperature profiles as inputs and delivers a vector output that represents the estimated (or predicted) natural frequencies. The results showed that even if the process can be well-approximated by the linear model, it might not be well suited for large datasets since it is very sensitive to the presence of unusual data points used to fit a model. To overcome these possible limitations, the authors refer that parametric linear and a non-linear regression models can be used. In Firat and Gungor (Firat and Gungor, 2009), the authors investigate the applicability and capability to predict the scour depth around circular bridge piers using NN methods

and a MLR. The authors tested a combined model with experimental data. Comparing the performance of the predictive models tested, namely Generalized Regression Neural Network (GRNN), Forward Neural Networks (FNN) (the tested NN methods) and MLR (see Figure 2.11), the results suggested that the efficiency of the MLR method is lower than that of the other two methods, the GRNN method being the most efficient one.

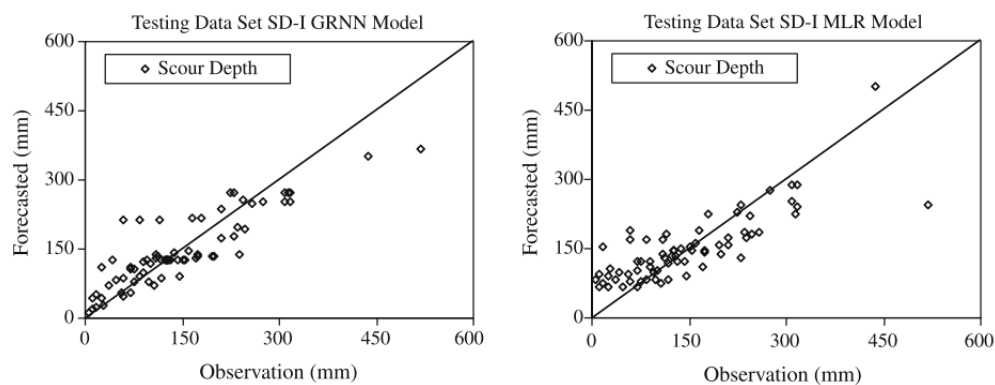


Figure 2.11: Comparison of the results from GRNN and MLR method applied on circular bridge piers for scour depth prediction. Adapted from (Firat and Gungor, 2009).

Even if MLR applications provide reliable approximations, numerous SHM applications refer the need to use non-linear methods to appropriately model relations between the structural data and structural responses.

2.5.3 Support vector regression

Support Vector Regression (SVR) is a statistical learning algorithm that employs the structural risk minimization principle, rather than the empirical risk minimization (Santos, 2014). According to the same author, SVR is based on minimizing the distance of two equally spaced boundaries of generalized errors, instead of minimizing the error of the entire training data set like the empirical risk minimization approach.

SVR uses a different risk function, motivated by the idea of robust regression. In Skiena (Skiena, 2017), the author describe three essential components of SVR: i) representation as a linear regression, ii) minimization with respect to the so called ϵ (intensive loss function) and iii) the complexity of the problem. The capacity to generalize, is controlled by keeping the weights as small as possible.

SVR are capable of modelling any relationship, linear and non-linear, being a more versatile method when compared with MLR. In Skiena (Skiena, 2017), the authors compared the performance of MLR and SVR models using data from a simulated three-story frame structure in aluminium proposed in Figueiredo et al. (Figueiredo et al., 2009). Both models were applied in a portion of undamaged data in which the signal predicted by SVR model provides a better fit to the actual signal, indicating more accuracy in the prediction. As the model must be sensitive to distributional changes in the data that result from damage, a control chart was calculated based on the fit to the undamaged data, and 99% confidence lines were drawn based on the undamaged residual error data and carried forward for comparison on the potentially damaged data. Since SVR confidence lines were much closer to the mean value of the residual errors than the MLR lines, it was, is possible to conclude that the SVR model is more precise at identifying small perturbations that produce changes in the residual error distribution than the MLR model (see Figure 2.12).

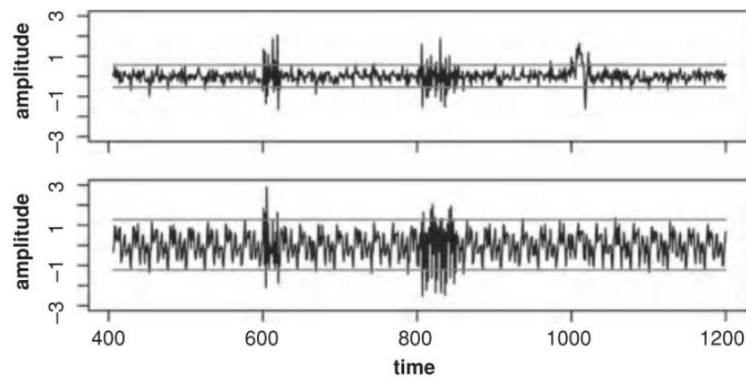


Figure 2.12: Residual errors from SVR model (top) and MLR model (bottom). Adapted from (Skiena, 2017).

In SHM tasks, SVR provide higher accuracy and sensitivity when compared with MLR due to its robust loss function and effective control of model complexity. The ability to model both linear and non-linear relationship allows SVR to capture subtle changes in residual model error distributions. Therefore, it can detect more reliably small structural perturbations. However, its efficiency is limited when applied to large and more complex data.

2.5.4 Neural networks

Neural networks (NN) are highly flexible models capable of capturing non-linear relationships between structural responses and underlying novelties. They are a general modelling framework that can be adapted according to the task (e.g., regression, classification, clustering, generation,

etc.). Following the review of (Santos, 2014), the application of NN for the analysis of SHM data has become attractive to use in intelligent control systems since the 1990s (Housner et al., 1997). Early applications in SHM primary used MLP for regression and classification tasks (Bishop, 2006; Worden et al., 2011), for damage detection or estimation of damage severity based on sensor data (Figueiredo et al., 2009).

MLP networks are widely used for outlier detection, neurons in the hidden layer of the network has impact in the dimensionality of the analysis and can be used to detect outliers as well as a clustering of the data (Chandola et al., 2007). The power resides in the interconnection of its neurons (input and output) and a set of weights associated with each interconnection, the weights are used to minimize an error function (Gomez-Cabrera and Escamilla-Ambrosio, 2022).

In Cury and Cremona (Cury and Cremona, 2010), the authors trained the algorithm based on a comparison of the output and the target, until the network output matched the target (see Figure 2.13). The feed-forward MLP neural network was chosen by the authors for classifying dynamic tests. The output values were compared with the correct answer and a predefined error-function adjusted the weights of each connection to minimize the error. After some iterations, the network will converge to a state where the error of the calculations is negligible and the network is considered to be trained. According to the applications of the authors in Cury et al. (Cury and Cremona, 2010), the supervised learning strategy for normalizing the temperature effect (T) in modal frequency (f) data proved to have better performance than MLR, accurately detecting the effects of retrofitting processes in two bridges.

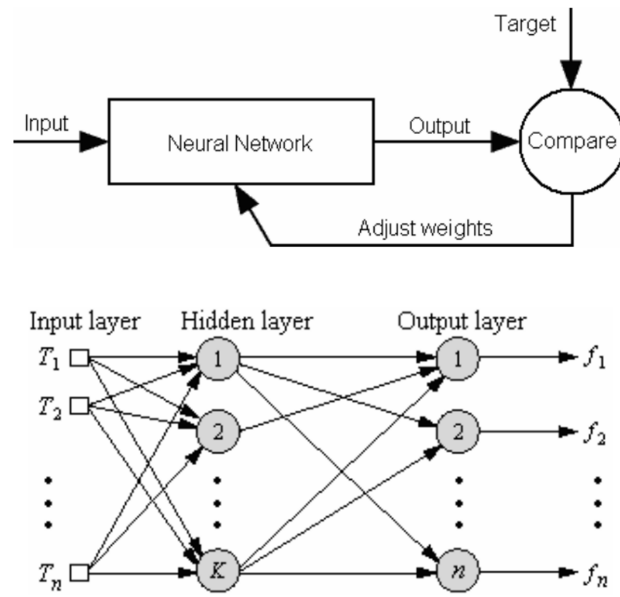


Figure 2.13: Supervised learning strategy for detection of retrofitting effect in bridges and one hidden layer MLP. Adapted from (Cury and Cremona, 2010).

The authors in Santos et al. (Santos et al., 2015), tested the non-linear character of the relation between the first mode frequency and the temperature measured in a composite simply supported railway bridge in the South of France using linear regression and MLP. It was observed that MLP was more effective to remove the influence of temperature from the observed data (see Figure 2.14). Non-linear perceptron units located in the hidden layer are non-linear while the remaining ones are linear. The optimal number of hidden layers was defined by testing multiple architectures and choosing the one leading to the smaller average estimation error.

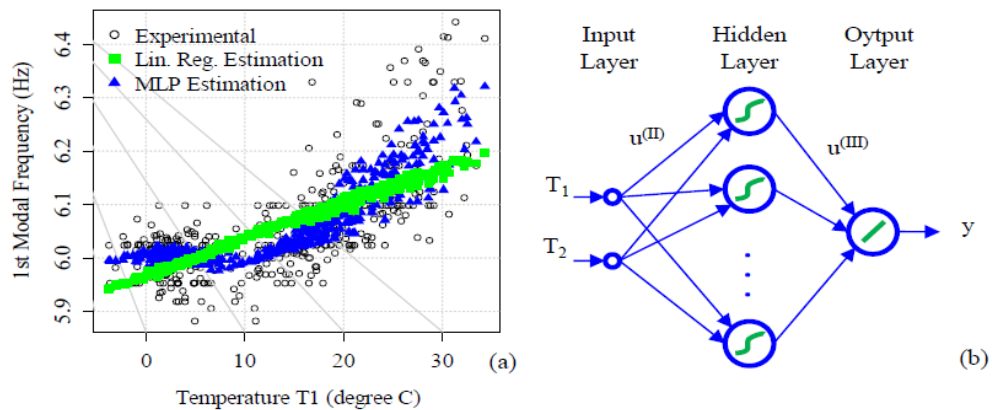


Figure 2.14: a) Comparison chart between experimental data and the results of linear regression estimation and the MLP model, b) MLP model. Adapted from (Santos et al., 2015).

MLP neural networks are an effective and computationally straightforward regression tools in SHM. NN architectures are able to overcome the limitations of traditional regression models due to their capacity to deal with large and complex datasets, interpreting the linear and non-linear relationships of the variables.

Auto associative neural networks (AANN) are a type of feed forward neural network trained to reproduce their own inputs at the output, effectively creating an identity mapping of the data. AANN can be seen as a non-linear principal component analysis (NLPCA) method, in concept very similar to PCA, and can be considered as generative models. Both methods aim at defining the optimal mapping between a set of original variables and a new set of uncorrelated variables. However, while PCA is restricted to mapping only linear correlations among variables, NLPCA can reveal the non-linear correlations present in the data set. AANN, on the other hand, is a particular type of MLP neural network.

The AANN-based architecture is described by two external layers (the input and output layer) comprising the variables of the original data set (Santos, 2014). The bottleneck layer, consisting of m variables, imposes an information bottleneck by forcing the original set to be described by $m < p$ dimensions instead of the original p dimensions (Bishop, 2006). When compared to the PCA normalization model, the AANN is different since it has two additional layers of hidden units, composed of non-linear activation functions: the mapping layer (with activation function h) and the de-mapping layer (with activation function g). The existence of these hidden layers gives this method non-linear capabilities and their activation functions are generally chosen as the sigmoid or the hyperbolic tangent (see Figure 2.15).

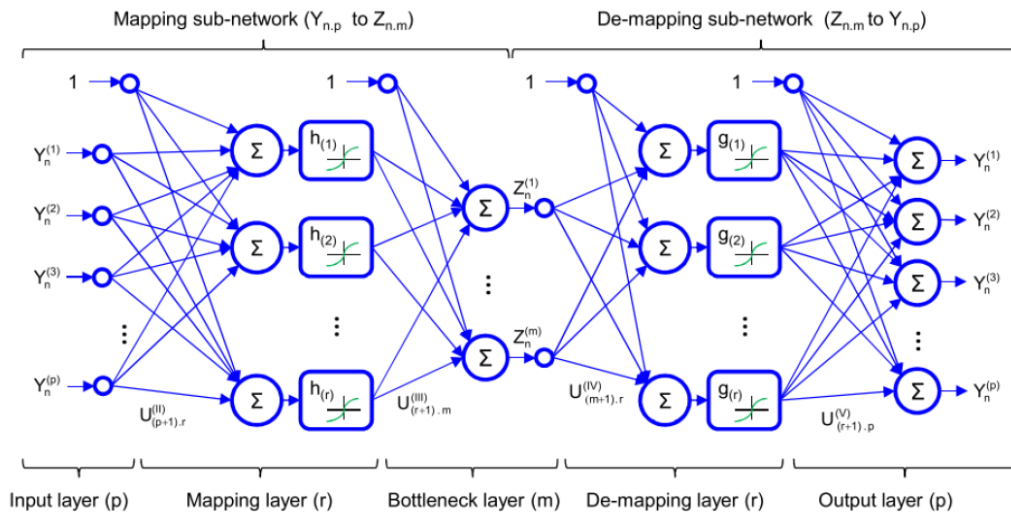


Figure 2.15: Auto-associative neural network architecture. Adapted from (Santos, 2014).

The application of AANN in Sohn et al. (Sohn et al., 2002) appears to be the first one in SHM studies. The authors used AANN for standardization of regression coefficients, and were able to confirm its effectiveness in normal environmental conditions. In Loh et al. (Loh et al., 2011), the authors used the AANN method to extract the underlying features of the static deformation of a concrete dam. The residual deformation between the estimated and the observed data was first generated so that a threshold level of the concrete dam static deformation could be determined. The authors concluded that the AANN method could capture the periodic variations (temperature, season) as well as the trends (creep), making the strategy suitable for long-term trend prediction. In Nguyen et al. (Nguyen et al., 2019), the authors analysed a simply supported beam considering the transmissibility method, in which the vibration response and the modal parameters change according to the severity of the novelty. The transmissibility indicators were taken as inputs of the AANN, and the network after being trained, showed accurate results in detecting and localizing damage.

In Santos (Santos, 2014), the author compared four methods applied to data normalization in order to find the most effective one: MLR, MLP, PCA and AANN, where the first two are regression based and the last two latent-variable based. All methods were applied under an unsupervised and supervised approach to understand their limitations. As a normalization performance indicator, the author analyses the ability of each method to remove the autocorrelation from the time-series of structural quantities acquired on site. The higher the autocorrelation' ratio, the better the performance. Under an unsupervised approach, the regression-based methods showed similar performance, but MLP revealed to be more effective to distinguish between changed and unchanged responses. On the other side, PCA showed a lower performance in both approaches and AANN proved to be the less effective method among the four, both in distinguishing between normal and novel conditions, and in computational efficiency. This latter aspect is the result of the method being forced to learn highly non-linear relations between the measured structural quantities which, in turn, forced the method to learn both the “regular” effects as well as the ones causing structural changes.

AANN networks are trained to reproduce their own input at the output. By forcing the network to compress the inputs and then reconstruct them, it learns an internal representation. Following the same principle, autoencoders appear to be a deep learning architecture which is an evolution of the AANN. The basic idea of an autoencoder is to have an output layer with the same dimensionality of the inputs to reconstruct each dimension exactly by passing it through the network. An

autoencoder replicates the data from the input to the output, and is, therefore, sometimes referred to as a replicator neural network (Aggarwal, 2018). In Fallahian et al. (Fallahian et al., 2018), the authors applied autoencoders for structural damage detection for the first time under the name of deep neural networks (Avci et al., 2021). The authors proposed an ensemble decision method that combined autoencoders with couple sparse coding, for the redefinition of the input vectors using a weighted linear combination of a small number of basis vectors. The authors tested the proposal numerically in a 2D truss bridge model and experimentally with the data of the I-40 bridge. The results showed robustness against incomplete measurements, measurement errors, modelling errors, and environmental variations.

2.6 Feature classification or discrimination

Classification or discrimination in the scope of forward novelty identification techniques are methodologies that organize sensitive features as belonging to known or novel structural conditions. As it was referred by the author in Santos (Santos, 2014), this step reports three major approaches: i) definition of boundaries around features related to a known structural condition, ii) definition of frontiers between features belonging to several known structural conditions, and iii) definition of clusters corresponding to one or more known structural behaviours. The first two approaches are only applicable to supervised learning and the third one can also be applied to unsupervised learning.

Supervised learning is applied to cases where a prior dataset exists. In case of SHM it is assumed to represent the structure's healthy state. The drawback of this approach is related with the limitations of data acquisition during the undamaged baseline period. This data acquisition is not always possible since, usually, SHM applications are based on aged structures, which may have already endured a structural modification or even damage. If, instead, and if it is applied to new structures the baseline information may not long enough to allow the establishment of a healthy reference state (Cardoso et al., 2019).

On the contrary, unsupervised learning methods do not need prior knowledge about long periods of the structure's response, nor target categories related to an assumed healthy reference state. Unsupervised methodologies establish the relation between monitoring data and the corresponding structural condition or health without having a prior knowledge of the structural health.

Clustering methods are widely used as unsupervised learning methods in SHM. The aim of any clustering method is to mathematically reduce the overall dissimilarities or distance of data

objects within each cluster, maximizing, in this sense, its compactness. In addition, by maximizing the distances between clusters it is possible to maximize their separation and enhance the method. Therefore, clusters can also be used for feature extraction, due to their capacity to classify data objects as members of different subsets.

2.6.1 Statistical-based discrimination

When considering boundaries around one known condition, supervised learning applies theoretical data distributions, such as the Gaussian distribution, to model the known structural condition. New acquired features are then placed in the feature space and their location is classified as within (inliers) and outside (outliers), the last being assumed to be a novel structural condition, different from the one that was used to define the boundaries. This process is called statistical process control (SPC) and can be applied to uni variate and multivariate analysis (Figueiredo et al., 2011; Posenato et al., 2010; Santos, 2014; Sohn et al., 2002).

In the case of univariate analysis, the use of autoregressive (AR) coefficients is documented in Sohn et al. and Figueiredo et al. (Sohn et al., 2002; Figueiredo et al., 2011), where the authors were able to detect several damage scenarios with a good sensitivity. A methodology proposed by the authors in Anaya et al. (Anaya et al., 2014), is also able to detect and classify structural novelties under different temperature scenarios through multiway principal components (MPCA) and wavelet approximation coefficients calculated using the discrete wavelet transform (DWT) from signals collected during several experiments on an aluminium plate and a stiffened composite panel. In the case of multivariate analysis, an SPC application to modal features acquired from bridge structures is referred by the authors in Zhou et al. (Zhou et al., 2011) where multivariate SPC is used to assess the effectiveness of AANN in the normalization of the modal frequencies.

2.6.2 Support vector machine

Support vector machines (SVM), MLR and bayesian decision trees (BDT) are supervised methods commonly used for multi-scenario SHM classification (Cury and Cremona, 2010; Cury et al., 2012).

In Burges (Burges, 1998), the authors present an early comprehensive tutorial for classification problems using SVM based on a linear and non-linear approach. In Berk (Berk, 2016), the authors revisit the tutorial and applied SVM, concluding that it is a worthy competitor to random forests and boosting. SVM estimate the coefficients of a linear regression with a binary outcome by

finding a separating hyperplane producing the maximum margin, subject to a constraint on the sum of the slack variable distances. With those estimates in hand, fitted values are produced (see Figure 2.16a). In the case that the values cannot be linearly separable one possible response permit violations of the buffer zone. One can specify some number of the observations that would be allowed to fall on the wrong side of their margin boundary. These are called “slack variables” (see Figure 2.16b). Some slack variables fall just across their margin boundary, and some fall far away. In response, the distance between the relevant fence and the location of the slack variable can be considered. The sum of such distances can be viewed as a measure of how permissive one has been when the margin is maximized.

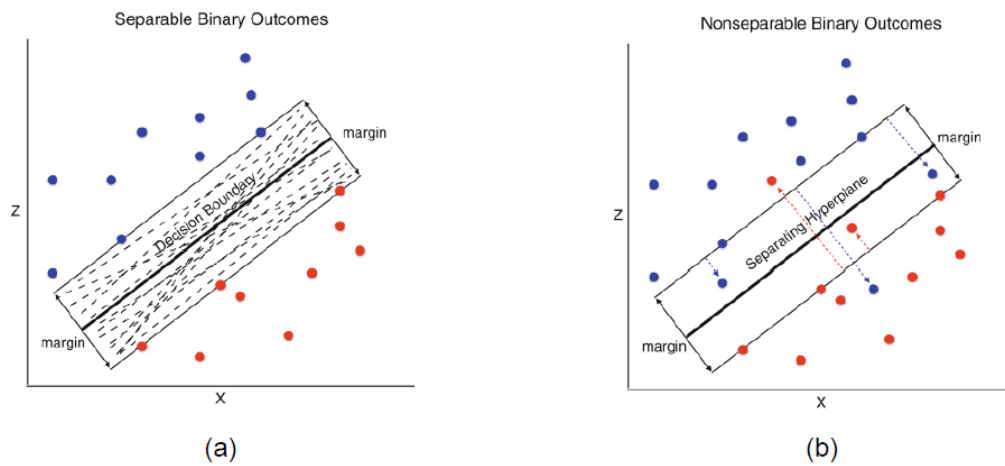


Figure 2.16: A support vector classifier with two predictors X and Z and a) two linearly separable classes shown as red or blue, or b) when there are two classes that are not linearly separable. Adapted from (Berk, 2016).

2.6.3 Clustering methods

Clustering methods can be classified in different families according to the way they address the problem of data partitioning. One of the most popular and simple clustering algorithms, K-means, was first published in 1955. After 50 years and several clustering algorithms published since then, K-means is still widely used (Jain, 2010). In Diez et al. (Diez et al., 2016), the authors describe K-means as: a clustering algorithm that performs a partition of data space into K clusters. Each cluster is represented by an object, named centroid or the mean point, whose initial value can be randomly set or estimated by applying some kind of heuristic. After iteration, each element is assigned to the partition with the least distance between it and the centroid of the partition.

Once all elements have been assigned into clusters, cluster centroids are recalculated using the information of the elements that belong to each partition.

The dynamic cloud algorithm is a partitioning-based clustering technique that can be considered a symbolic version of K-means, since it requires the input of an initial set of $K < N$ cluster prototypes that are defined, randomly. A prototype is a symbolic description model representing a cluster or, the average test of a cluster. Thus, the prototype is used as a reference to define each cluster (Cury et al., 2012). The process starts with a set of m random prototypes that are iteratively allocated in order to place each test into the cluster where the proximity between the test and the prototype is minimal. There are several possible allocation rules, but the most common is the one that consists in allocating each object to its closest prototype, based on the distance between each element and each cluster centroid. This rule is applied also in the well-known K-means clustering method (Cury and Cremona, 2010). The representation phase that follows the first iteration involves showing the new set of clusters' centroids, before repeating the process until the compactness and separations of the cluster partition can be confirmed. This criterion can be seen as the objective function of the described optimization strategy.

The dynamic clouds clustering algorithm can also be assumed to be a generalization of the K-means method (Cury and Cremona, 2010) since it uses as the objective function the squared of the overall within-cluster distance, measured across the K clusters defined at each iteration. In this sense, the dynamic clouds method, is based on the same objective function, taking into account the symbolic distance (dissimilarity) matrices defined in the initialization phase and also taking into account the objects allocation after the converged iteration.

As an alternative, hierarchical clustering methods create, a hierarchical decomposition of the given set of data, and can be classified either as agglomerative or divisive, based on how the decomposition is performed. Following the authors in Han and Kamber (Han and Kamber, 2006), when the merge or split is performed in these clustering methods, it can never be undone. This rigidity is useful for when dealing with smaller data sets where the scale of the error is not a particular concern, but it can be an issue when dealing with larger data sets. Hierarchical clustering can be applied to individuals and variables, and the principal objective is to find a hierarchy of partitions. Groups should be defined based on similarities among the elements within the group and dissimilarities between the created groups. Hierarchical clustering can be displayed in dendrogram plots, as referred by the authors in Hastie et al. (Hastie et al., 2011).

Finally, density-based methods allow discovering clusters with arbitrary shape, defining them

as dense regions of objects in the data space that are separated by regions of lower density (representing noise) (Han and Kamber, 2006). The general idea is to grow the given cluster until the density (number of objects or data points) in the “neighbourhood” exceeds some threshold. The neighbourhood radius of an object is determined by specific density measures and notions of connectivity (Sammur and Webb, 2011).

Density-based spatial clustering of applications with noise (DBSCAN) is a density-based algorithm that defines a cluster as a maximal set of density-connected points. The neighbourhood of a given object is called the neighbourhood of the object and each neighbourhood contains at least a minimum number of objects, termed the core-objects. In Figure 2.17 an object m (core object) is directly density-reachable from object p (core object) and q is directly density-reachable from m , so q is (indirectly) density-reachable from p because q is directly density-reachable from m and m is directly density-reachable from p . However, p is not density-reachable from q because q is not a core object. Similarly, r (core object) and s are density-reachable from o (core object), and o is density-reachable from r . In this sense, density reachability is the transitive closure of direct density reachability, and this relationship is asymmetric. Only core objects are mutually density reachable. Density connectivity, however, is a symmetric relation (Han and Kamber, 2006).

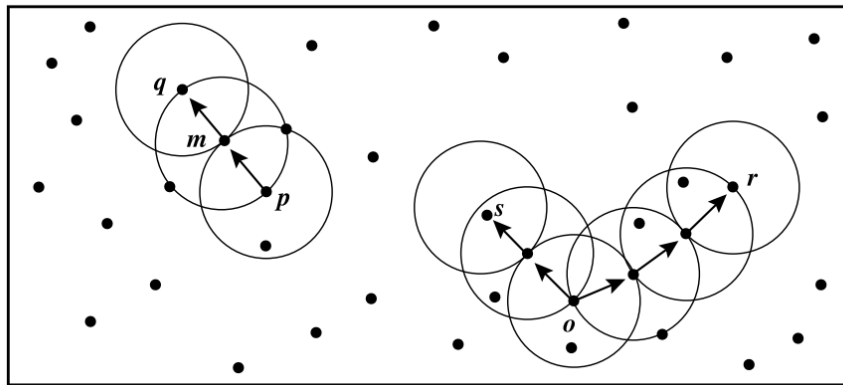


Figure 2.17: Density-reachability and density connectivity in DBSCAN . Adapted from (Han and Kamber, 2006).

The general density-based spatial clustering of applications with noise (GDBSCAN), generalizes the notion of a density-based clustering to that of a density-connected decomposition, assuming only a reflexive and symmetric neighbourhood relation for pairs of objects (direct links between some objects), and an arbitrary condition, called “MinWeight,” that is true for some neighbourhood sets of objects and false on others, so that a core object can be defined as an object whose

neighbourhood satisfies the MinWeight predicate. Then, a density-connected decomposition consists of the maximally connected components of the set of objects that are in the neighbourhood of some core object, and they can be computed with the same algorithmic scheme as density-based clusters by DBSCAN.

In Antunes et al. (Antunes et al., 2019), the authors proposed an approach that combines Manual Acquisition System measurements with DBSCAN and baseline methods (MLR and thresholds based on standard deviation) to create a method that is able to identify and remove most of the outliers in the Portuguese dam data sets used for demonstration and evaluation. DBSCAN is used by the authors to identify most of the outliers based on information from several predictors such as temperature and water level. The results showed that, between the three clustering methods tested, DBSCAN proved to be very useful for detecting outliers, having been able to identify nearly 90% of the outliers in every evaluated dataset (see Figure 2.18). However, since DBSCAN is a density-based algorithm, changes in the acquisition frequency or missing data (due inoperative or malfunctioning sensor) may cause it to behave differently throughout the dataset.

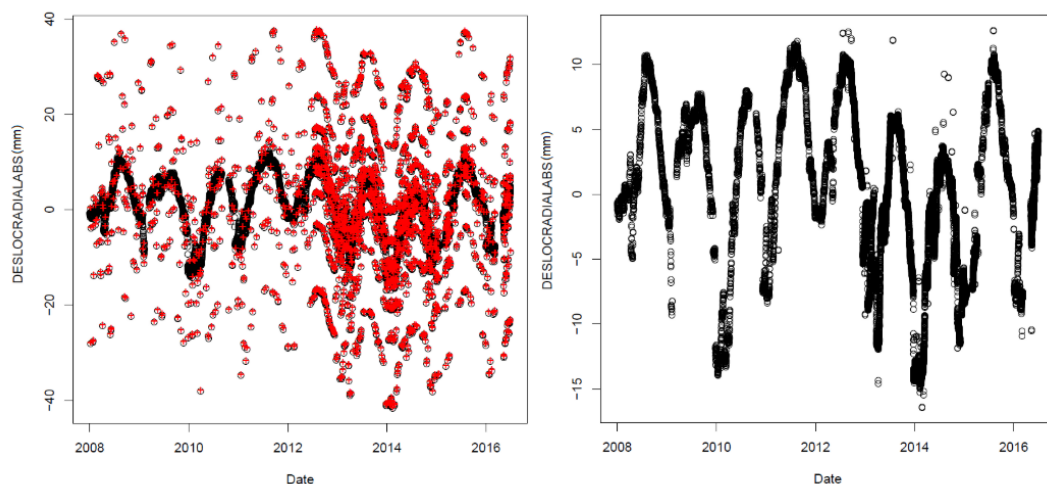


Figure 2.18: Impact of the Method on the Dataset with 10% of Outliers. Left - Original Dataset; Right - Final result after outlier removal. Adapted from (Antunes et al., 2019).

Traditional ML methods might not perform well when the input data have a higher dimensional representation. Thus, a common approach to solve this problem is to reduce the data dimension before feeding it to a classification method or performing regression tasks, to make them more manageable (San Martin et al., 2019).

In Cury and Cremona (Cury and Cremona, 2010), the authors explore the use of three classification techniques: Bayesian decision trees (BDT), NN and SVM applied to experimental data

from a bridge in France in order to show the potentialities of these methods. BDT is a variant of classical decision trees where the uncertainty in the model parameters is handled using Bayesian inference and is used to solve classification problems. The general idea of this method is to classify a particular object into one of the classes (groups) previously defined, in this case for example, the “before” group and the “after” group of a strengthening procedure on the bridge.

The construction of a BDT starts with a first node called root and by using a “cut rule” the test of that node is separated in a left and right node, if the node cannot be split anymore, is called terminal. In the framework of the recursive algorithm, each node division step is performed based on a single variable (suitably chosen) and on “yes/no” answers to specific binary questions. The set of binary questions that will be useful for the recursive partition procedure is based on the Bayesian rule (Billard and Diday, 2006). The purity of each node is defined by the number of times that the node classification is correct (by leave-one-out and/or bootstrap methods). The conclusions of the authors in Cury and Cremona (Cury and Cremona, 2010), after exploring the three algorithms mentioned before, report that the results applied to the signals, natural frequencies and mode shapes of experimental data showed reasonable results, by the third simulation (validation) all the methods tested achieved 100% of correct classification considering either signals or modal parameters.

2.7 SHM based on deep learning techniques

Deep learning (DL) has emerged as a dominant paradigm within ML. It allows overcoming the existing limitations such as the ability to efficiently deal with large size datasets and raw data instead of features, to analyze data without separating the effects generated by each structural action, and to perform the entire SHM workflow with a single algorithm. In the field of SHM, DL can accommodate the increasing availability of large sensor data sets and the need for robust and automated models capable of dealing with non-linear relationships, environmental variability and noise (Zhao et al., 2019).

The deep learning concept dates back to the 1940s. Following the authors in Goodfellow et al. (Goodfellow et al., 2016), DL development followed three main branches: DL known as “cybernetics” in the 1940s–1960s, DL known as “connectionism” in the 1980s–1990s, and the current resurgence under the name “deep learning”, beginning in 2006.

The earliest algorithms intended as DL were simple linear models motivated by a neuroscience perspective, and based on two main ideas: one is that the brain provides a proof that intelligent

behaviour is possible, meaning that one only needs to reverse-engineer the computational principles behind the brain and duplicate its functionality to build intelligence. The second idea is that DL models that shed light on the principles that underlie human intelligence are useful apart from their ability to solve engineering applications (Goodfellow et al., 2016).

DL inspired by the brain are part of the first so-called cybernetics wave (McCulloch and Pitts, 1943; Wiener, 2019). The second wave, called connectionism, arose within the cognitive science, with the central idea that a large number of simple computational units can achieve intelligent behavior when networked together. In 1988, the authors in (Fodor and Pylyshyn, 1988) proposed the major philosophical issue in artificial neural networks and connectionism proposing a challenge: if connectionism will be able to reason, the only way it will be able to do so (since reasoning is inherently rule-based) is by making an artificial neural network able to produce a system of rules. However, if thinking and reasoning were not be completely rule-based, it would mean that they have aspects that are processed ‘intuitively’, and not derived by rules. Following by the author in Skansi (Skansi, 2018), connectionists in the 1980’s made a fundamental step in bridging in the development of AI and DL with developments that remain central until nowadays.

In 2006, the authors in Hinton et al. (Hinton et al., 2006), showed that a NN called a deep network could be efficiently trained using a strategy called greedy layer-wise pretraining, started the third wave of neural network research. Other research groups showed that that the same strategy could be used to train many other kinds of deep networks, and systematically helping to generalize on the concept using test examples. The term “deep learning” then started to be more popular and emphasized the capacity to focus attention on the theoretical importance of depth (Goodfellow et al., 2016).

DL allows computational models that are composed of multiple processing layers to learn representations of data with several levels of abstraction. They can learn not only to correlate the features to the desired output, but also to run the entire feature extraction process. Therefore, with proper training, they can find the direct mapping from the raw inputs to the final outputs, allowing the system to perform complex tasks by breaking them into smaller and simple parts (Avci et al., 2021).

According to the authors in LeCun et al. (LeCun et al., 2015), DL architectures can be categorized in four major groups: Unsupervised Pretrained Networks (UPNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Recursive Neural Networks. There are three further architecture types under UPNs: autoencoders (also known as deep autoencoders),

deep belief networks (DBN), and generative adversarial networks (GAN), can be seen in the scheme presented in Figure 2.19.

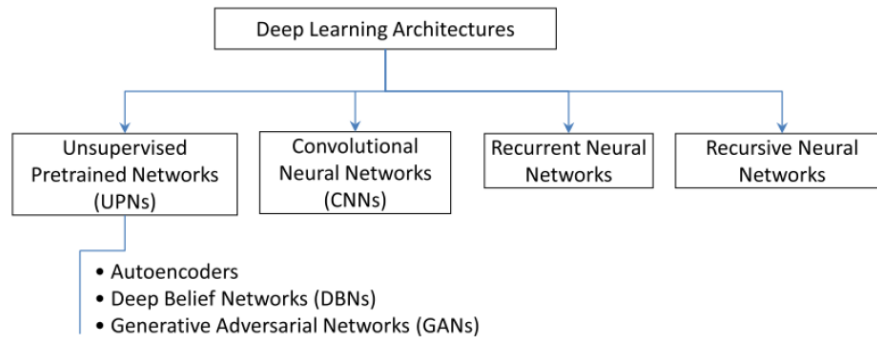


Figure 2.19: Deep learning architectures. Adapted from (Avci et al., 2021).

In Avci et al. (Avci et al., 2021), the authors presented a survey on vibration-based damage detection methods used in civil engineering, highlighting the growing role of DL methods. On vibration-based data sets, autoencoders and CNN stands over the other methods, due to their ability to describe the non-linear relationships and automatically reduce the dimension of the data sets without missing information.

However, recurrent neural networks RNN, considered to be sequential model, are well suited for sequential and time-dependent data. Considering that SHM often relies on vibration, strain, displacement signals, RNN became a relevant choice for damage detection and structural prediction in general, as detailed in the following.

2.7.1 Recurrent neural networks

RNN are the deepest of all neural networks, and are able to generate and address memories of arbitrary-length sequences of input patterns (Zhao et al., 2019). In contrast to feed forward NN, a RNN creates connections from posterior layer(s) to anterior layer(s) or connections among neurons in the same layer, so the networks become dynamic systems (Caterini and Chang, 2018). They overcome the limitations of simple NN by using information from the past networks results to produce the final output. A typical NN structure does not take into account the sequential structure in data for any observation; their corresponding hidden states are independent of each other. In RNN, instead, the hidden state at each step depends on the hidden state on the previous step (see Figure 2.20).

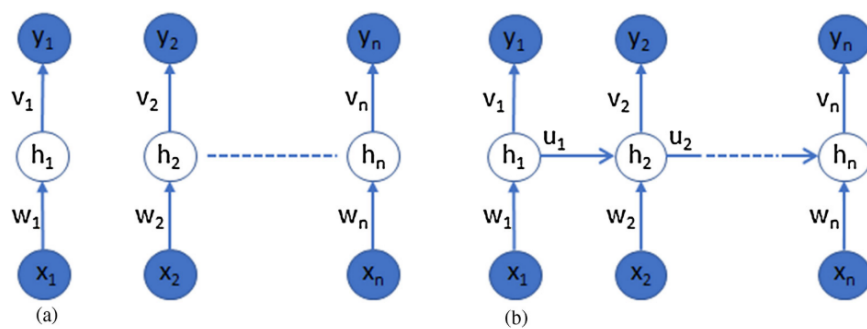


Figure 2.20: a) Sequential structure independence in a simple NN and in b) RNN structure, where x is the observed data, h are hidden states and U is a transition matrix that allows previous inputs to be kept in the networks internal memory . Adapted from (Khan and Yairi, 2018).

RNNs can be trained via backpropagation through time for supervised tasks with sequential input data and target outputs (Funahashi and Nakamura, 1993; Giles et al., 1992; Jaeger, 2002). The authors in Dang et al. (Dang et al., 2020), states that RNNs are suitable for sensor measurements learning due their ability to capture time-dependent characteristics. However, sensor data usually consist of long sequential samples, which is a limitation for RNNs that suffer from either gradient exploding or vanishing. To cope with this long-range dependencies, some derived RNN architectures such as Long Short Term Memory (LSTM) and its simplified version Gated Recurrent Unit (GRU) were presented to prevent back-propagated errors from vanishing or exploding. The core idea behind these advanced RNN variants is that gates are introduced to avoid the long-term dependency problem and enable each recurrent unit to adaptively capture dependencies of different time scales.

Alternatively, multi-layer structure can enable the hidden output of one recurrent layer to be propagated through time and used as the input data to the next recurrent layer (see Figure 2.21b). a bidirectional recurrent structure is another architecture that is able to process the sequence data in two directions, including forward and backward ways, with two separate hidden layers (see Figure 2.21c)(Zhao et al., 2019).

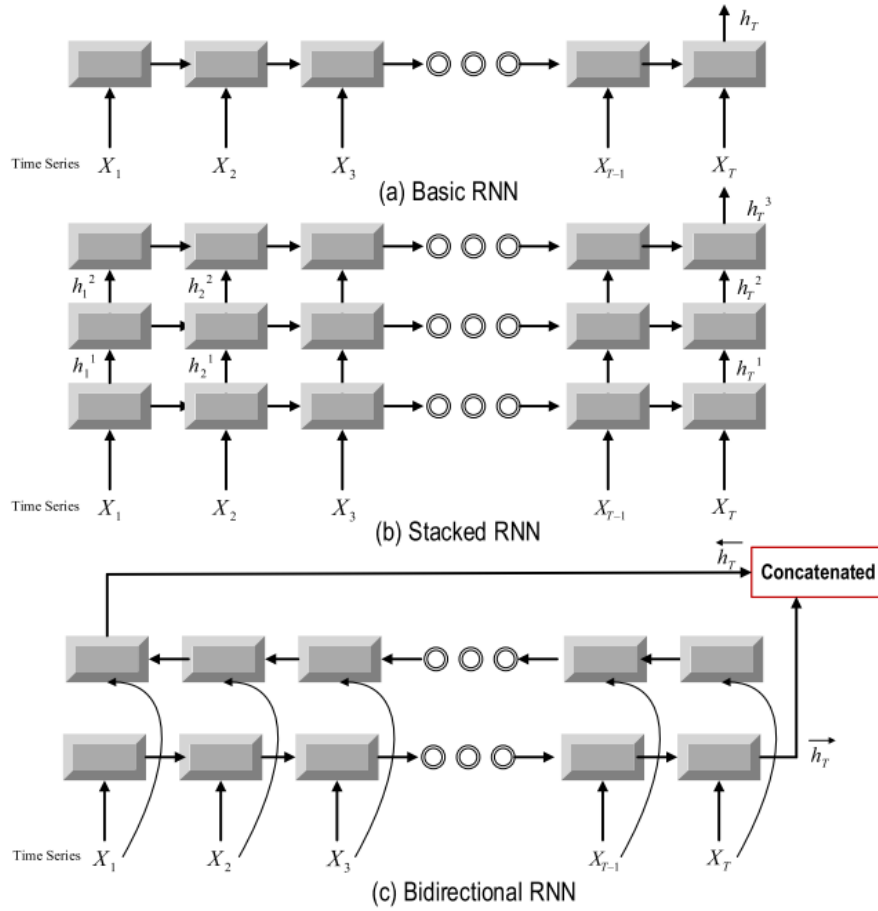


Figure 2.21: Illustrations of a) normal RNN, b) stacked RNN and c) bidirectional RNN. Adapted from (Zhao et al., 2019).

In Zhou et al. (Zhou et al., 2019), the authors proposed a deep RNN model consisting of two LSTM layers and one bidirectional LSTM (BLSTM) layer (see Figure 2.22), trained through a large number of dynamic responses and impact loads to learn the complex inverse mapping between structural inputs and outputs, and to identify the impact load of non-linear structures. The effectiveness and practicability of the proposed method was verified by three non-linear structures, including damped a Duffing oscillator, a non-linear 3-DOF system and a non-linear C/SiC composite plate. Results show that even if the impact location is unknown previously, the deep RNN model can identify well the impact load history acting at any position of the structure, and has a higher accuracy when compared with the traditional MLP model.

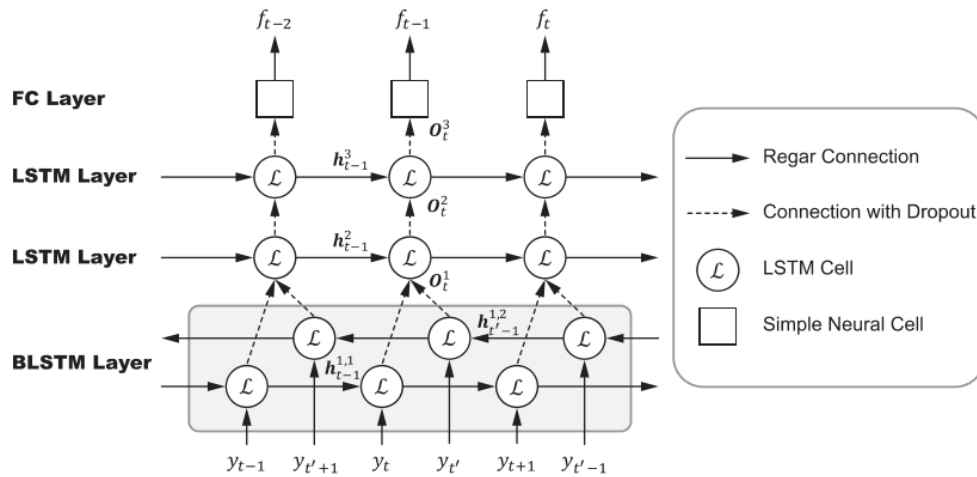


Figure 2.22: The architecture of the deep RNN. Adapted from (Zhou et al., 2019).

2.7.2 Long short-term memory

As was discussed in the previous subsection, RNNs can report problems associated with vanishing and exploding gradients. In this sense, the LSTM architecture provides a solution by incorporating memory units that allow the network to learn when to forget previous hidden states and to update them when new information is provided. The LSTM has an advanced RNN architecture, which can learn long-range dependencies due to its memory cell (Ding et al., 2018).

LSTM is an enhancement of the RNN architecture in which the recurrence conditions of how the hidden states are propagated changes. The authors in Hochreiter and Schmidhuber (Hochreiter and Schmidhuber, 1997), introduced for the first time LSTM architectures. This led to pioneering research in time series prediction, language translation, and video recognition since LSTMs contain memory cells that are composed of a chain of recurrent nodes. These memory cells helped the network to control the information by adopting an input gate, forget gate, and output gate (Gulgec et al., 2020). In Figure 2.23, a single memory cell and how data flow through it are shown. Each memory cell includes an input node, internal state and, input, forget, and output gates.

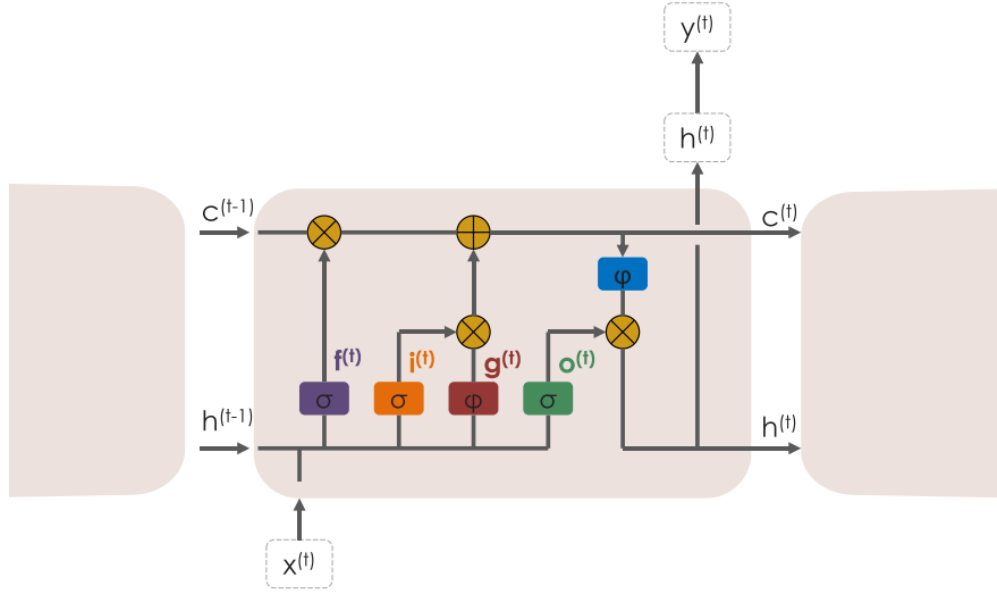


Figure 2.23: An LSTM memory cell. Adapted from (Gulgec et al., 2020).

The theoretical background of LSTM refers to the work of Hochreiter and Schmidhuber, 1997 (Hochreiter and Schmidhuber, 1997). The architecture consists of jointly connected repeating cells. Each cell has three gates: forget gate, input gate and output gate. Outputs of LSTM sequences are fed into a fully connected layer, which further provides the probability for each predicted class. Given x_t , the input at time step t , h_{t-1} the output of LSTM cell at time step $t - 1$, a linear transformation of the combination of x_t and h_{t-1} is expressed by:

$$\zeta(h_{t-1}, x_t) = W[h_{t-1}, x_t] + b \quad (2.1)$$

where W and b are the network's weight matrix and bias vector respectively. The three gates inside the LSTM cell are written as (Olah, 2015):

$$\begin{aligned} f_f &= \sigma \zeta_f(h_{t-1}, x_t) \\ f_i &= \sigma \zeta_i(h_{t-1}, x_t) \\ f_o &= \sigma \zeta_o(h_{t-1}, x_t) \end{aligned} \quad (2.2)$$

The subscripts f , i , and o indicate the forget gate, the input gate and the output gate, respectively, while σ is the sigmoid activation function.

At every time step t , the new candidate of information is created by applying the tangent activation function on a linear transformation of the combination $[h_{t-1}; x_t]$:

$$C_t = \tanh \zeta_c(h_{t-1}, x_t) \quad (2.3)$$

where ζ_c is a creation linear operator whose expression is similar to Eq. 2.1. Then the flow of information from the previous step is updated with the new candidate by the gates of the LSTM cell (Dang et al., 2020):

$$s_t = (f_f \odot h_{t-1} \oplus (f_i \odot C_t)) \quad (2.4)$$

where $\odot$ and $\oplus$ are element-wise product and element-wise summation, respectively. Next, the output of the cell at time step t is calculated based on the updated information and the output gate:

$$h_t = f_o \odot s_t \quad (2.5)$$

The authors in (da Costa et al., 2020) states that most of the previous data-driven methods assume that training (source) and testing (target) condition monitoring data have similar distributions. However, besides the different operating condition in terms of fault modes and noise, there are distribution and feature shifts across different domains. This assumption could, therefore, reduce the performance of predictive models when no target run-to-failure data is available. To address this issue, the authors proposed a new data-driven approach for domain adaptation in prognostics using LSTM, confirming that the proposed architecture for finding weights that can accommodate domain shift via adversarial learning can optimize the performance.

In Zhao and Ye (Zhao and Ye, 2016), the authors developed two LSTM-based methods, namely the basic LSTM, in which few gates are used to control the passing of information along the sequences that can capture long-range dependencies more accurately, and the deep LSTM, in which the input to the model can be passed through multiple LSTM layers and time series. The authors showed the relevance of the method by applying it for SHM of high-speed machines using sensory data. Their results confirmed the high efficiency of LSTM networks.

Chapter 3

Increasing robustness in structural behaviour assessment through model redundancy and sensitivity analysis

This chapter covers model redundancy, sensitivity analysis, and threshold definition for novelty identification, addressing three of the dissertation's four focus topics (see Figure 3.1).

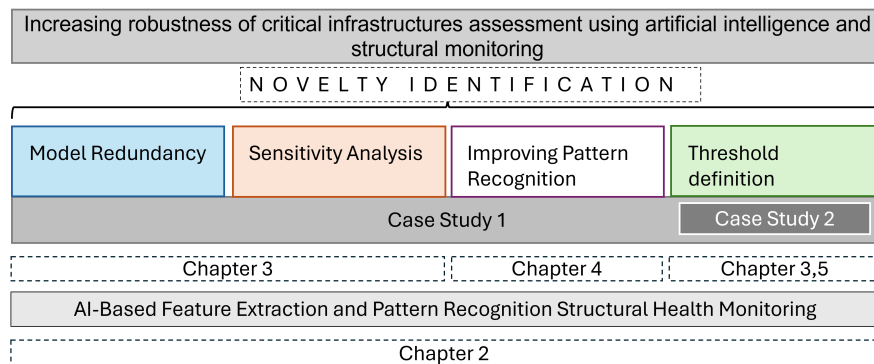


Figure 3.1: Flowchart of the dissertation's structure with the three topics addressed in the present chapter in color.

The challenge of early damage detection of large complex structures with high dimensional features is a determinant factor for SHM. Current technological advances contribute to the optimization of data analysis, aiming to make the process less demanding in terms of time and computational demand. ML models became popular due to their capacity to estimate structural behaviour based on the measurements gathered by the SHM systems. This chapter proposes a methodology

supported by ML models, for the characterization and prediction of the structural behaviour based on the main loads and the observed structural responses (see Figure 3.2). By comparing the observed values and predicted outcomes from the ML models, it is possible to identify new trends or pattern variations that can help the prediction of future observations. Additionally, a sensitivity analysis is proposed to confirm the model robustness and to characterize the influence of the inputs on the structural responses, as represented in Figure 3.3. Furthermore, it also helps characterizing the relation between the key response parameters under study and the definition of structural safety control thresholds to establish an accurate baseline of the structural behaviour based on monitored data.

AI data-driven prediction models (ANN)	SHM real-time data			Sensitivity analysis
	Inputs	Outputs	Model's residuals	
Model 1	$load_1,$ $load_2,$ $\dots,$ $load_n$	$response_1$		
Model 2	$load_1,$ $load_2,$ $\dots,$ $load_n$	$response_1,$ $response_2,$ $\dots,$ $response_n$		
Model 3	$response_1,$ $\dots,$ $response_n$	$response_1$		

Figure 3.2: Model redundancy based on different input/output combinations.

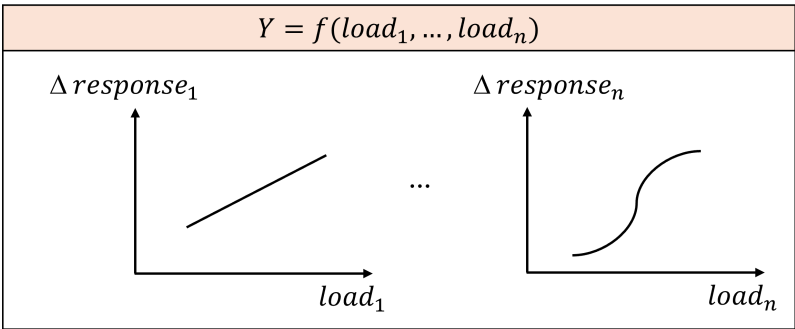


Figure 3.3: Sensitivity analysis representation.

3.1 Introduction

The occurrence of structural damage is intrinsic to civil engineering structures, and it is likely to propagate due to environmental or mechanical factors. In Santos et al. (Santos et al., 2013), the authors define damage as a change in a structural system that affects the current or future performance concerning both, structural safety and serviceability. Thus, while damage occurrence implies a structural change, the occurrence of this change may not necessarily imply damage that compromises the structural performance. Likewise, damage is not always an indicator of a complete failure, but can signal the occurrence of a deterioration of the functionality (Avci et al., 2021). As mentioned by Figueiredo and Brownjohn (Figueiredo and Brownjohn, 2022), the scientific community has adopted a damage identification hierarchy as a sequence of different levels of knowledge about damage and how it affects the structure. In this sense, damage identification can be divided into three areas: damage detection, damage diagnosis, and damage prognosis. Furthermore, characterizing the nature of any identified variation as a one-off event or something related to a trend in the data is particularly relevant. In case the variation corresponds to a trend, it is important to characterize the relationship between the observed structural responses in order to verify the presence of any anomalous behaviour. The monitoring of a structure to detect variations and assess the life cycle of the structure consists of a powerful tool for damage identification and performance evaluation of engineering structures. The process involves the observation and evaluation of a structure over time using periodically sampled measurements from a sensing system. Several civil engineering structures have been provided with structural health monitoring (SHM) systems in the last decades, and, according to Tome (Tome, 2019), those systems are implemented to ensure structural and operational safety by means of (near) real-time information that can help to detect anomalies in loading and response at an early stage.

SHM techniques can follow inverse or forward approaches for detecting damage. The former, also called model updating, are based on the fitting of analytical or numerical responses to experimental data with the objective of inferring structural quantities that cannot be directly measured. Forward SHM approaches rely, instead, on pattern recognition techniques for extracting sensitive information from acquired data on-site (Santos et al., 2016). Forward approaches, also called data-driven approaches, do not require the development of numerical or analytical models to be fitted with in situ data. Those techniques aim at extracting sensitive information from the measured time series, using statistical learning methods (Sohn et al., 2002). Because SHM systems are operated in harsh and noisy environments, the occurrence of abnormal data is inevitable. The large variation

in extracted features from massive SHM data causes conventional detection techniques to perform poorly. In addition, detection techniques that are focused on a single type of variation frequently miss other types of changes in the structure (Bao et al., 2019).

Structural condition assessment based on changes in the structural response has been practised in a qualitative manner for decades. Sensing techniques were initially proposed by Housner et al. (Housner et al., 1997), to detect structural change or degradation using intelligent monitoring systems that can allow structures to operate at the margin of safety without expended long periods of inspection. The advances in various branches of technology, such as sensing instrumentation, signal acquisition and transmission, data processing and analysis (Ribeiro et al., 2024), numerical simulation and modelling are now allowing the development of strategies that benefit from the technological precision for accurately evaluating the structural health of civil structures using real-time monitored data (Chen and Ni, 2018).

In particular, several improvements in computational power and advancements in chip and sensor technology have enabled the use of Machine Learning (ML) techniques in engineering applications. According to Avci et al. (Avci et al., 2021), those techniques are focused on the development of intelligent algorithms capable of acquiring knowledge automatically from the available data with the objective of providing machines with a human-like ability to learn. However, the formulation of reliable and efficient methodologies for data analysis and signal processing is still a challenge for SHM (Azimi and Pekcan, 2020). With the recent technological advances, a relatively large number of sensors and sensor networks can now measure large volumes of response data. In this sense, data-driven ML techniques have been proposed by different authors as an efficient way to assess the structural health condition of host infrastructures (Avci et al., 2021; Bao et al., 2019; Santos et al., 2015; Liang et al., 2016; Mishra, 2020). However, even considering the great advantages of ML tools applied to the assessment of structures, any tool, must be validated by experts in structural behaviour.

In this context, the present study proposes a structural behaviour characterization methodology based on neural networks, model validation and residual analysis to identify any variation in a specific zone of a structure. Since most physical relations between environmental or operational actions and structural responses are linear (Santos, 2014), applying regression models is common in SHM data analysis. In particular, Multiple Linear Regression (MLR) is currently used to interpret SHM data of operational structures, such as bridges worldwide, due to its capacity to explain the conditional distribution of responses and predictors. However, MLR has limitations

when explaining the non-linearity of the structural behaviour. For this type of problem, NNs have a better generalization capacity and can accurately represent the observed patterns of structural behaviour. MLR models use empirical functions to quantify the effect of the independent variables on the structural response. In NN models, the relationship between variables is established by the architecture and the synaptic weights of the network by taking advantage of the parallel processing of input variables. To enhance this capacity of NN, the authors propose the development of three models, whose integrated use will allow the specialist to validate the quality of each model in representing the observed structural behaviour as well as the database that is used, thereby increasing the understanding of the structural behaviour and the confidence in decisions regarding structural safety. NNs have demonstrated flexibility and superior predictive capacity, particularly in predicting structural behaviour for extreme temperatures (Mata, 2011). This is in stark contrast to the performance of MLR models. By adopting NN models, as proposed in this work, specialists can expect better model performance and residuals with a lower standard deviation, further underscoring the advantages of NN models.

The case study addressed in this research is the 25 de Abril bridge over the Tejo River in Lisbon, Portugal, which is monitored by an SHM system capable of measuring different physical quantities corresponding to fast loads, slow loads and structural responses. The prediction model is built with data, provided by the Portuguese National Laboratory of Civil Engineering (LNEC), gathered by the SHM system installed in the bridge, considering five years of data with an hourly frequency of measurements. This dataset allows to understand the governing thermal behaviour of the bridge and to establish a baseline for the structural characterization.

The implementation of moving average charts and the assessment of the standard deviation of the residuals of the models provide sensitivity measures about the results of the analysis that can be used for verifying and validating the predictions.

3.2 Main machine learning approaches for pattern recognition in structural health monitoring

The transition from traditional methods to ML represented an improvement in: (i) sensitive feature extraction from the monitored responses (Lin et al., 2017; Entezami et al., 2021; Mosleh et al., 2021), (ii) characterizing the pattern of the structural responses (Entezami et al., 2021; Salazar

et al., 2015; Nguyen et al., 2019), and (iii) classifying the extracted features of civil engineering structures (Jang and Smyth, 2020; Bull et al., 2020; Fallahian et al., 2018).

In Worden and Delieu-Bardon (Worden and Delieu-Bardon, 2004), the authors state that SHM is a multilevel and multi-faceted method capable of dealing with data acquisition from single and multiple sources, and further data processing. In order to have a more robust and confident decision, multiple sensors are installed in the structure to be monitored, thus, data fusion becomes an indispensable step. ML -based approaches applied to SHM data require extracting damage-sensitive features that later will be used as the input of the ML model. According to Braiek and Khomh (Braiek and Khomh, 2025), robustness refers to the ability of a system, model, or entity to maintain a stable and reliable performance across a broad spectrum of conditions, variations, or challenges, demonstrating resilience and adaptability in the face of uncertainties or unexpected changes.

Lately, SHM technology reflect the variations of structural parameters with the change of structural responses. Many field monitoring data indicate that structural responses are not only related to the characteristics of the structure, but also to the environmental conditions, such as humidity, wind, and temperature, among other factors (Han et al., 2021). Current procedures in bridge SHM have a considerable number of limitations and prevailing uncertainties due to non-stationary variability sources associated with operational and environmental conditions. Varying operational conditions include live loads such as traffic loads, speed of operation, and changing excitation sources. Varying environmental conditions are manifestations of weather in the form of temperature, humidity, wind, rainfall, and snow. Note that there are also other sources of variability in the measurement exist at the data acquisition stage such as instrumentation, random noise, estimation methods, and vibration source (Figueiredo and Brownjohn, 2022). According to de Battista et al.(de Battista et al., 2015), thermal effects due to temperature changes are an important factor in the serviceability limit state design of bridges. Daily and seasonal temperature changes result in thermal expansion and contraction cycles, which bridge designs need to cater for. The influence of ambient temperature will interfere with the estimate of the effects of other factors. To make a more accurate assessment, it is necessary to forecast and separate the temperature-contributions parts of the overall responses (Han et al., 2021).

Two main SHM approaches based on ML models are cited by Farrar and Worden (Farrar and Worden, 2012), for response modelling of structures: i) the protective approach, which refers to the case when damage-sensitive features are used to identify impending failure, that leads to the

adoption of changes in the normal operation of the system to avoid failure and; ii) the predictive approach, that, instead, is applied to the cases in which trends in data are identified to predict when the damage will reach a critical level. In this latter case, cost-effective maintenance planning is needed, and ML strategies are useful for this purpose. In order to identify such patterns, a learning process through the implementation of algorithms is proposed. Such a process can follow a supervised or an unsupervised learning (Farrar and Worden, 2012) as well as a self-supervised learning (Liu et al., 2021), being the supervised learning the most used approach.

Data-based models based on ML methods learn from past observed behaviour. Consequently, the obtained models are valid for the “domain/range” of the observed response and the corresponding loads used for the model development. From the different ML models, neural networks (NN) have caught the attention of the scientific community since the 1990s (Housner et al., 1997), due to their ability to learn the pattern of structural behaviour in large infrastructures with a good capacity for generalization (Fallahian et al., 2018; Mata, 2011; Mata et al., 2021; Shokri and Tavakoli, 2019; Aggarwal, 2018; Sun et al., 2020a; Salehi and Burgueño, 2018; Liu et al., 2018a). An NN model computes a function of the inputs by propagating the computed values from the input neurons to the output neurons using different weights as an intermediate parameter (Aggarwal, 2018). A Multilayer Perceptron (MLP) is a supervised feed-forward neural network that has neurons arranged in layers and is the most widely used model for cognitive tasks such as pattern recognition and function approximation (Mata, 2011). The specific architecture of feed-forward networks assumes that all nodes in one layer are connected to those of the next layer, and the input layer transmits the data to the output layer going through a set of hidden layers that perform computations that include refining the weights between neurons over many input-output pairs to provide more accurate predictions (Figure 3.4). Weights, after training, contain meaningful information, whereas before training they are random and have no meaning. The back propagation delta learning rule algorithm, one of the most famous training algorithms for the MLP (Bishop, 2006; Rocha et al., 2007), is a gradient descent technique intended to minimize the error or cost function, which adjusts the weights by a small amount at a time. The cost function C , usually considered, is defined by the mean square error.

The MLP learns by an iterative process of a weight adjustment that enables the correct learning using the training data so that, in a testing phase, it predicts the unknown data. The weights w are located in each connection between the input layer x with N neurons to the hidden layer l with Q neurons. The first layer receives the inputs, and the last layer produces the outputs. The middle

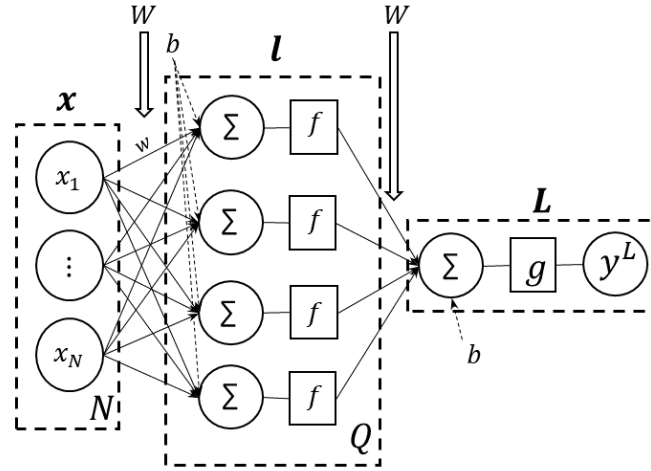


Figure 3.4: MLP architecture where x represent the input layer, l the hidden layer and L the output layer. Adapted from (Mata, 2011).

layer is called a hidden layer, and, within it, the information is constantly feed-forwarded from one layer to the next one having two values associated: the input value and the weight. For example, weights in the middle layer are showed in a matrix format W , where the number of columns contains the input dimensions (N) and the number of rows are the number of units in the hidden layer (Q). Another weight associated with the NN is the bias b . Bias is attached to every layer in the network, except for the input layer. Activation functions are applied to each of the neurons at the hidden layer and in the output layer. The activation function will map the linear combinations of the inputs and weights to the following layer, in the case presented in Figure 3.4 from the input layer to the hidden layer and, in a further step, to the final output of the network, L .

For regression problems, such as those found in the framework of SHM, the activation functions must be differentiable so that any non-linear model built from them can be derived with respect to the weights (Bishop, 2006). In this case, in the activation function from the input layer to the hidden layer, $f(x)$, a logistic sigmoid is adopted (Equation 3.1), and in the activation function from the hidden layer to the output layer, $g(x)$, a linear function is adopted (Santos, 2014).

$$f(x) = \frac{1}{1 + e^{-x}} \quad (3.1)$$

As mentioned before, NNs, and particularly MLPs, are widely used for pattern recognition and variation identification tasks. Applications for damage prediction and variation identification can be found in civil engineering such as in the case of Lee et al. (Lee et al., 2005), where the authors consider the difference of ratios of the mode shape components from damaged and undamaged

finite elements models as the input to the neural networks of the NN model. Other examples by Shokri and Tavakoli (Shokri and Tavakoli, 2019), that use NN to predict seismic damage in reinforced concrete bridges, and Pagani et al. (Pagani et al., 2021), that developed an autoencoder capable of reconstructing the contamination dynamics over real and artificial water distribution networks. In all these examples, NNs are seen to be versatile systems capable of changing their structure based on inner or outer information, thus being able to be rearranged to obtain different patterns in data or to model the multiple relationships between inputs and outputs. This is one of the reasons why NNs have been used to solve many engineering problems over the past few years.

As referred by Figueiredo et al. (Figueiredo et al., 2011), non-stationary sources of variability present in the structural response can be associated with operational and environmental conditions and may lead to variations in structural behaviour. Varying operational conditions include live loads (e.g., traffic loads on bridges), speed of operation, and changing excitation sources. Varying environmental conditions include thermal effects, wind-loading, and moisture content (Figueiredo et al., 2011). These variations can be equal to or greater than the ones that occur due to damage and it is fundamental to interpret them to prevent undesirable consequences (Fallahian et al., 2018).

In structural dynamics and earthquake engineering problems, NNs have experienced great advancements, which can be considered for determining the static and dynamic parameters of structures (Shokri and Tavakoli, 2019). In the particular case of bridges, response measurements comprise the effects of several types of loads including vehicular traffic and ambient conditions. According to Kromanis and Kripakaran (Kromanis and Kripakaran, 2014), an important step in the interpretation of these measurements involves characterizing the influences of the individual load components on the collected measurements. Long-term monitoring studies have illustrated that daily and seasonal temperature variations have a large influence on the structural response of bridges. In Hua et al. (Hua et al., 2007), the authors confirmed that environmental effects cause changes in physical parameters, thereby inducing changes in modal parameters, which may yield a false indication of damage when applying vibration-based damage detection algorithms. In Catbas et al. (Catbas et al., 2008), the authors observed that temperature-induced stresses on long-span bridges create responses that are very difficult to model due to unexpectedly high levels of stress. In Le and Nishio (Le and Nishio, 2019), by considering that the daily periodic air temperature change causes the characteristic global thermal deformation of a long-span cable-stayed bridge, the authors proposed a damage-sensitive feature extraction method through Autoregressive Integrated Moving Average ARIMA models from Global Positioning System (GPS) measurements of those

deformations, assuming that they are sensitive to changes on the global structural properties.

From these examples, the design of methodologies to improve damage identification including environmental and operational conditions can be seen to be an area of active research interest, motivated by the fact that there is an increasing number of new civil engineering, aeronautics, or mechanical designs that include increasingly more complex structures subjected to variable environmental and operational conditions that need to be assessed (Anaya et al., 2014).

Despite the design and maintenance codes and methodologies that are available, civil engineering structures deteriorate over time and structural health is affected by operational and environmental factors, including normal load conditions, current and future environments, and expected hazards during the lifetime (Gehl and D'Ayala, 2018). All these factors are variables with uncertainties, and to ensure the safety and serviceability of the structure, reliable structural health assessment, and continuous monitoring are essential.

3.3 Proposed methodology

Real-time monitoring can be effective for structural safety control activities and to facilitate decision-making regarding interventions in the monitored structure. However, real-time diagnosis is usually sensitive to environmental and operational effects. In this sense, the acquired data need to be processed so that pattern recognition techniques can be employed.

The main aim of this study is to define a baseline for the observed response pattern in a suspension bridge. For this purpose, the analysis based on NN models is carried out considering first the response at one point of a beam at the middle section of a suspension bridge as a function of temperatures measured in the same section. A second analysis is then performed considering the responses at four points of the beam's stiffening truss at that section as a function of all the loads and, finally, a third analysis is performed considering the response at one point of the beam as a function of the responses in the other three beams. Using these different models involving different inputs is also strategic to identify false positives. This approach facilitates their detection, therefore increasing the overall robustness of the model.

The NN models are developed with data gathered by the structural monitoring system during a time period where the structural behaviour is considered to be consistent with normal conditions. Interpretations about the structural behaviour are inferred from the model results and from the residual analysis, which describes everything that was not explained by the prediction model at first and contains information about errors, from the measurements or another unknown effect.

For the residual analysis, a moving average with a window of a week and a timestep of one hour is suggested in the current research. The standard deviation of the residuals is proposed to define a smoothed pattern behaviour in order to overcome the inherent randomness introduced by the traffic.

Two aspects are fundamental to support the informed structural assessment proposed herein; (i) the redundancy of the models, which are able to provide a general overview and a local detailed diagnosis about the structural behaviour and its evolution, and (ii) the validation of the analysis based on the accuracy and suitability of the models to represent the structural behaviour pattern through a sensitivity analysis that is able to describe the learned pattern (Figure 3.5).

The main steps of the proposed methodology, namely related to the prediction model, the residual analysis and the sensitivity analysis are presented ahead.

- **Prediction models**

By following a data-driven approach, the development of numerical or analytical models to be fitted with in situ data may not be required in a day-to-day basis. However, numerical models are very important for verification of damage scenarios that may be identified. Data-driven models rely on the discipline of ML or, more specifically, on the pattern recognition aspects of ML. The idea is that one can learn relationships from data, namely to recognize the relationship between the structural response and the temperatures, and also between the observed responses at the section under study. For this purpose, three different analysis models are proposed, based on the relationship between main loads (L) and structural responses (R) and between responses as referred in Table 3.1. In this sense, when the pattern recognition is performed during a time period that corresponds to a situation where the structure behaved normally, it will be possible to identify behaviour patterns that are different from the learned ones when new data are collected. Changes in the observed pattern behaviour can be identified, and experts, based on their knowledge and in a deep analysis, may decide if the changes observed are related to a potential damage scenario or to another type of scenario. In this context, the proposed models provide the ability to verify if the observed pattern is maintained, and if not, a timely detection is possible.

Multilayer Perceptron (MLP) models have been adopted due to their capacity for pattern recognition. The fully connected architecture of the MLP can consider several outputs (structural responses) in the same model. As such, the model can learn the response pattern considering all the responses at the same time, providing predictions that consider a

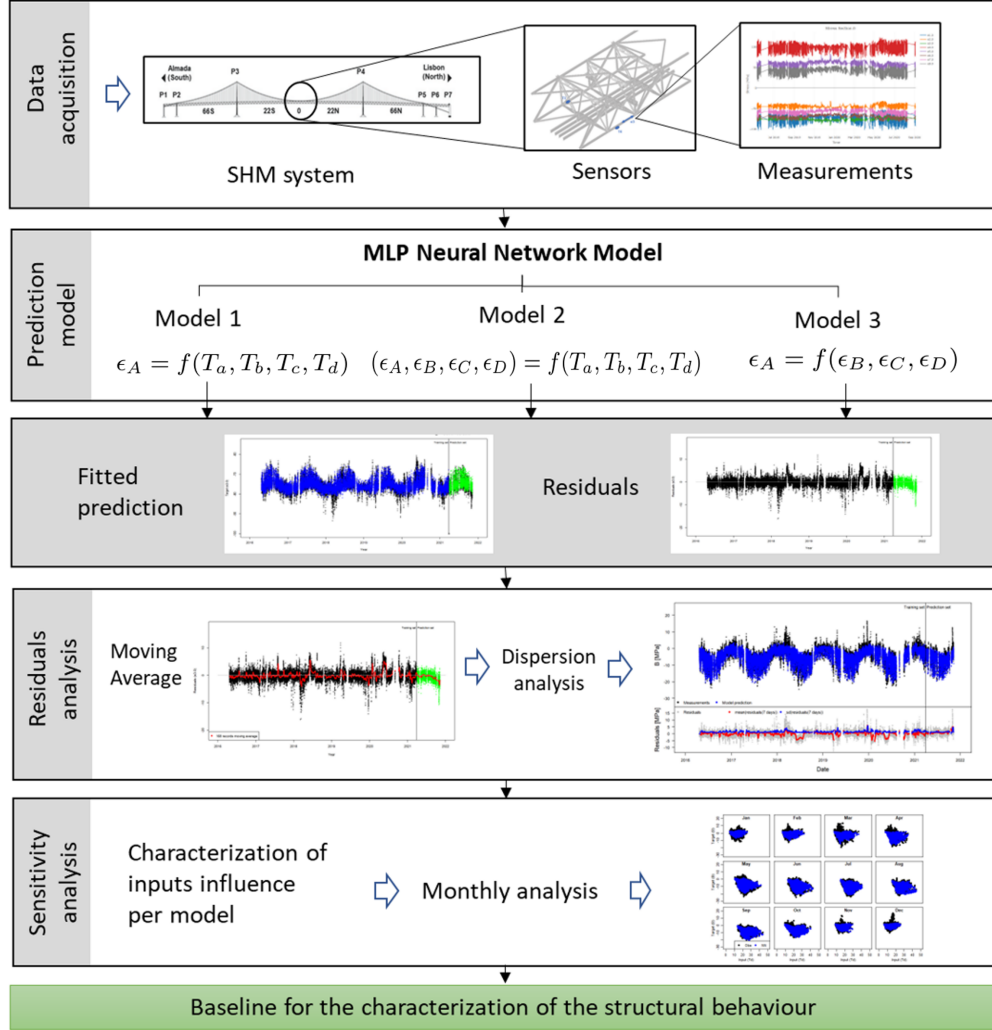


Figure 3.5: Proposed methodology for the observed structural behaviour characterization based on NN models.

Table 3.1: Proposed models, where R represents each of the quantities related to the structural responses and L represents each of the main loads.

Designation	Model: $Output = f(Input)$
Model 1	$R_1 = f(L_1, \dots, L_m)$
Model 2	$(R_1, \dots, R_n) = f(L_1, \dots, L_m)$
Model 3	$R_1 = f(R_2, \dots, R_n)$

broader observed pattern. For the learning strategy, the learning data must be divided into three subsets: the training, the cross-validation, and the testing sets. The training subset is used to build the learning model. The MLP might use different hyper parameters for the learning rate, and the same subset is used to build the model. The cross-validation subset is used for model selection and parameter tuning in order to select the best choice for the

architecture and for the parameters of the MLP model (Mata, 2011; Aggarwal, 2018). The cross-validation subset should be viewed as a strategic solution to find the NN with a better generalization capacity to avoid over fitting. Finally, the testing subset is used to test the accuracy of the final (tuned) model at the end of the process. In cases of complex and large available data sets, the biggest percentage of data must be dedicated to the training and cross-validation subsets.

The root mean squared error (RMSE) is used herein to assess the quality of the predictions and is defined as,

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_i - \hat{x}_i)^2}{n}} \quad (3.2)$$

where x_i describe the observed values and $\hat{x}$ the predicted values.

The resulting deviations between the observed and the predicted behaviour must be assessed with model validation.

- **Residual analysis**

Model deviations are generally systematic, producing consistent predictions under identical conditions. The suitability can be evaluated using different parameters such as the coefficient of determination or the standard deviation of the residuals. The residuals include different contributions such as measurement uncertainties, errors, and factors unexplained by the model. Although the pattern representing the behaviour of residuals is random, this pattern is expected to remain the same if the behaviour of the structure does not change. Therefore, the occurrence of any new or distinct pattern in the residuals suggests a situation that requires reassessment.

In light of this, the detection of the deviation between the observed and the predicted data that is not identified by the prediction model is one of the main objectives of the residual analysis. In order to reduce the intrinsic randomness of the data and identify as early as possible any deviation over time, a moving average analysis with a time window of one week and a time step of one hour is proposed.

A moving average control chart of the residuals (*m.a.r.*) is a type of memory control chart based on an unweighted moving average of the residuals r , that smooths out the data and

allows the analysis of the weekly evolution of the moving average. The *m.a.r.* is defined as (Liu et al., 2020):

$$m.a.r._i = \frac{m.sum.r._i}{w} = \frac{\sum_{j=i-w+1}^i r_j}{w}, i \geq w \quad (3.3)$$

where w is the width of the moving average at time i . For periods $i < w$, the moving average width must be smaller than this value. For these periods, the average of all observations up to period i defines the moving average. Once the SHM is defined to perform hourly records, four different *m.a.r.*, related to 6, 12, 24, and 168 records, corresponding to a quarter of a day, a half of a day, an entire day, and an entire week are potential options to be considered in this type of study. However, for clarity of visualization, only the results of a *m.a.r.* with a time window of one week and a time step of one hour are shown.

In order to describe the dispersion of residuals, the standard deviation of the *m.a.r.* ($sd_{m.a.r._i}$) is also presented in order to understand how the residuals vary or how they are dispersed over time. The $sd_{m.a.r._i}$ is defined as:

$$sd_{m.a.r._i} = \sqrt{\frac{1}{w-1} \sum_{j=i-w+1}^i (m.a.r._j - m.\bar{a}.r._{jto i})^2} \quad (3.4)$$

where $m.\bar{a}.r._{jto i}$ is the mean of the moving average between times i to j . Once the *m.a.r.* and the $sd_{m.a.r._i}$ are established, it is possible to define a baseline of the structural behaviour under normal conditions. The *m.a.r.* allows the identification of extreme values and trends along a time period. The $sd_{m.a.r.}$, on the other hand, allows the identification of any increment of variability and/or randomness along the same time period that might suggest, for example, a decrease of stiffness in the section under study. Based on the residual analysis, it is possible to identify any novel behaviour on the data that has not been explained by the model itself. In addition, residuals contain information related to errors, from the measurements and the model, and other unknown effects. In the particular case of the proposed study these effects can be indirectly related to the influence of traffic and train loads. The explanatory capacity of the residual analysis strengthens the accuracy of the baseline for the characterization of the structural behaviour.

- **Sensitivity analysis**

The importance of improving the understanding of the performance and inner working of the ML techniques is relevant in the SHM field since decisions regarding the structure under study must be grounded on robust conclusions. As such, the definition of an accurate baseline for the structural behaviour that can be used as a reference point in future studies needs to be validated and verified. In Saltelli et al. (Saltelli et al., 2008), the authors define a sensitivity analysis as the study of how the uncertainty in the output of a model can be assigned to the uncertainty sources in the model inputs. Different sensitivity analysis methods are proposed in the literature (Mata et al., 2021; Datteo et al., 2018; Mansourabadi and Esfandiari, 2019; Saltelli et al., 2008). In order to characterize the effects of the environmental loads on the structural responses and the robustness of the predictions, the proposed sensitivity analysis involves the evaluation of the predicted outputs evolution with respect to each of the inputs at the section under study according to the models presented before. The quality of the correlations between the quantities would confirm the reliability of the predictions. According to Mata et al. (Mata et al., 2021), this exercise would resemble the observed behaviour on the real system and can be used as a strategy for the validation and verification of the model.

3.4 Case study: The 25 de Abril bridge

The case study chosen for application of the proposed methodology is the 25 de Abril suspension bridge located in the estuary of the Tejo river connecting the cities of Lisbon and Almada, Portugal, (Figure 3.6). The bridge has a total length of 2277.5 m, with three suspended spans: the central suspended span has 1012.9 m and the two laterals suspended spans have 483.4 m each. The North access is made through a prestressed concrete viaduct comprising 13 spans while the South span is made by a railway tunnel and road access. The bridge deck consists of a suspended stiffening truss with 1344 vertical hangers that, at the same time, are suspended by four principal cables supported at piers P2 and P5 and at pylons P3 and P4 (Figure 3.7). The cross-section of the deck's stiffening truss supports six car lanes at the upper chord level, while, supporting a double electrified track railway at the lower chord level.

The structural monitoring system comprises eight types of sensors able to acquire data that allow characterizing the structural behaviour of the bridge, namely its displacements, rotations, strains, stresses; and the imposed loads, such as traffic and environmental loads (Figure 3.7).



Figure 3.6: The 25 de Abril bridge.

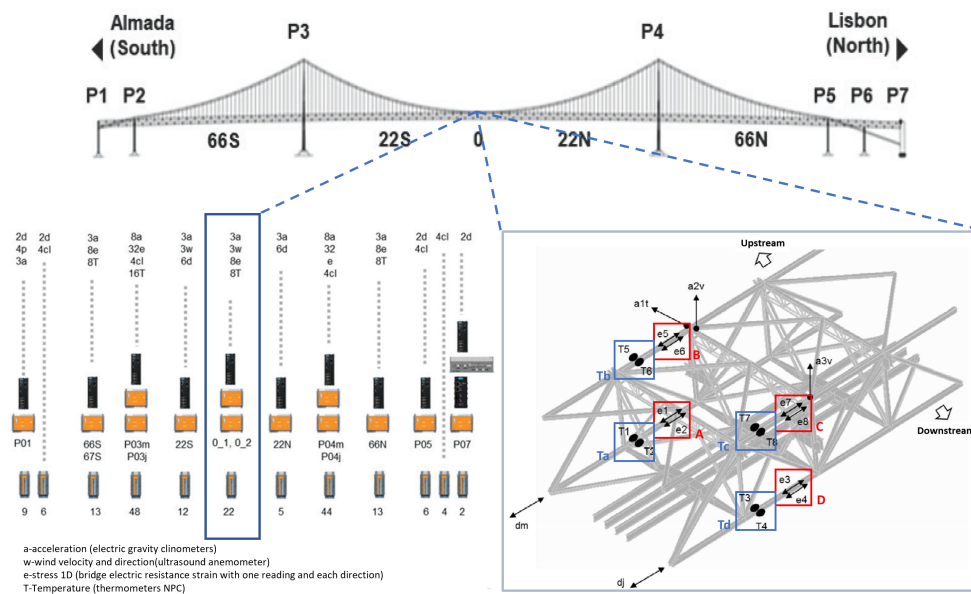


Figure 3.7: Schematic representation of the monitoring system of the 25 de Abril bridge. Adapted from (Oliveira and Santos, 2020).

The statistical features obtained from all the quantities measured at the bridge involve hourly maximum and minimum values, hourly medians, and hourly quartiles. The median values are

particularly important since they are expected to be free of the influence of extreme values related to traffic and other fast effects, thus reflecting only slow effects that can be analysed with higher precision. The data acquired continuously on the 25 de Abril bridge reflects numerous effects generated by simultaneous actions imposed on the structure. For SHM purposes, those data are divided into two subgroups: the imposed loads and the structural responses. The information extraction strategy applied to the bridge is based on time series obtained for certain predefined time-intervals from which the following are extracted: (i) statistical features that can be directly and precisely correlated with the structural behaviour, and (ii) vibration information such as natural frequencies and their corresponding mode shapes and damping ratios. The proposed methodology was applied to the statistical features extracted from the time series in a defined period of time and from the mid-span section of the bridge.

Strains are measured directly through strain gauges in 88 points located in the stiffening truss at the downstream and upstream chords and in the plates that make the sections of the towers. In this study, the strains measured at Section 0 (the mid-part of the central span) are the structural response parameters considered and temperatures are the environmental loads (Figure 3.8). The data considered in the present study is from a five-year monitoring period, from 20/04/2016 to 09/11/2021, with hourly measurements and a total of 45000 measurements per physical quantity. It is important to mention that the vehicular traffic loads and the train loads existing on the bridge were not considered in the present study, although they were indirectly included in the residual analysis. Since there are two strain gauges and two thermometers in each of the chords of the selected section of the stiffening truss (Figure 3.8), the mean value of each pair of the same type of sensors (i.e. strain gauges and thermometers) was considered in order to simplify the analysis. The corresponding mean value are $\epsilon_A = (\epsilon_1 + \epsilon_2)/2$, $\epsilon_B = (\epsilon_5 + \epsilon_6)/2$, $\epsilon_C = (\epsilon_7 + \epsilon_8)/2$, and $\epsilon_D = (\epsilon_3 + \epsilon_4)/2$ for the strain measurements (in $[\mu\epsilon]$), and $T_a = (T_1 + T_2)/2$, $T_b = (T_5 + T_6)/2$, $T_c = (T_7 + T_8)/2$ and $T_d = (T_3 + T_4)/2$ for temperature measurements (in $[^\circ\text{C}]$) (Figure 3.8). The strains are gathered from the strain gauges installed at the bridge and their time evolution is presented in Figure 3.9. The temperatures evolution is presented in Figure 3.10.

3.5 Results and discussion

This section presents the results of the application of the proposed methodology to characterize the structural behaviour of the 25 de Abril bridge. Three MLP models were developed to assess the evolution of the predicted responses and validate the modelling approach. As shown in Table 3.1,

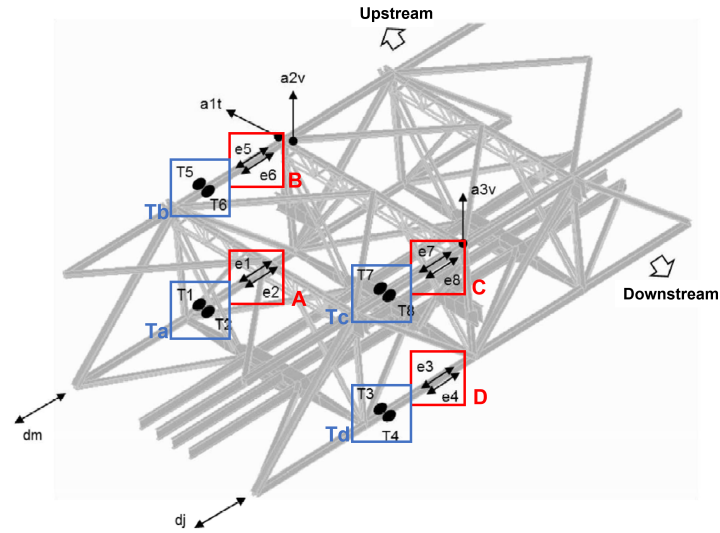


Figure 3.8: Location of thermometers and strain gauges in Section 0.

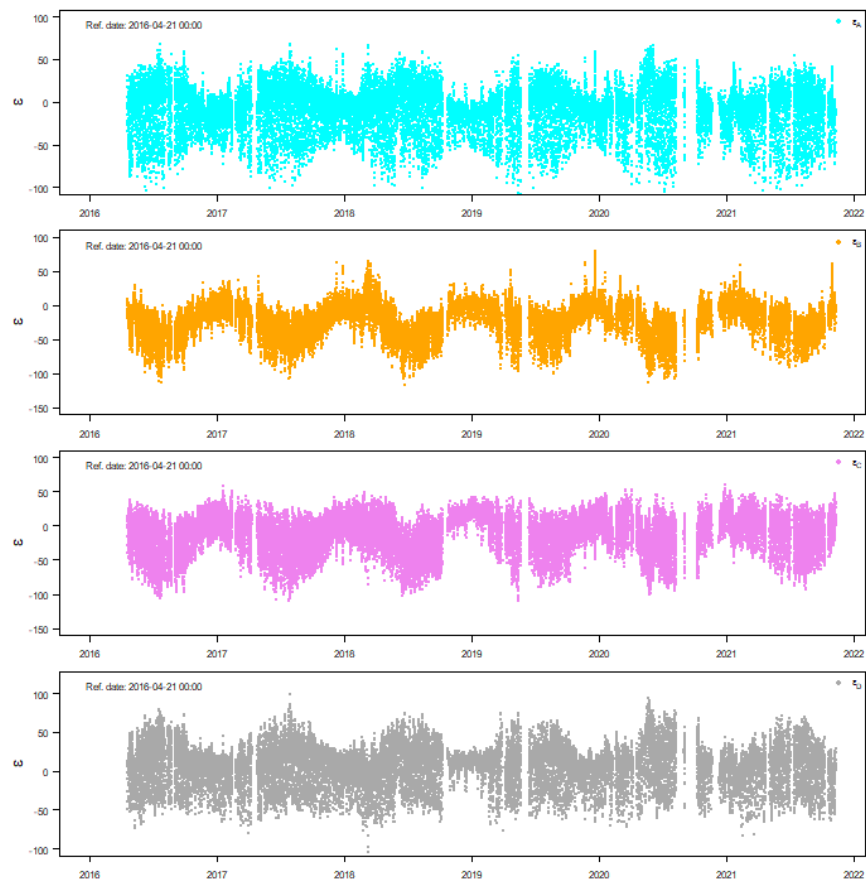


Figure 3.9: Time series of the strain measurements at Section 0, top to bottom A, B, C, D.

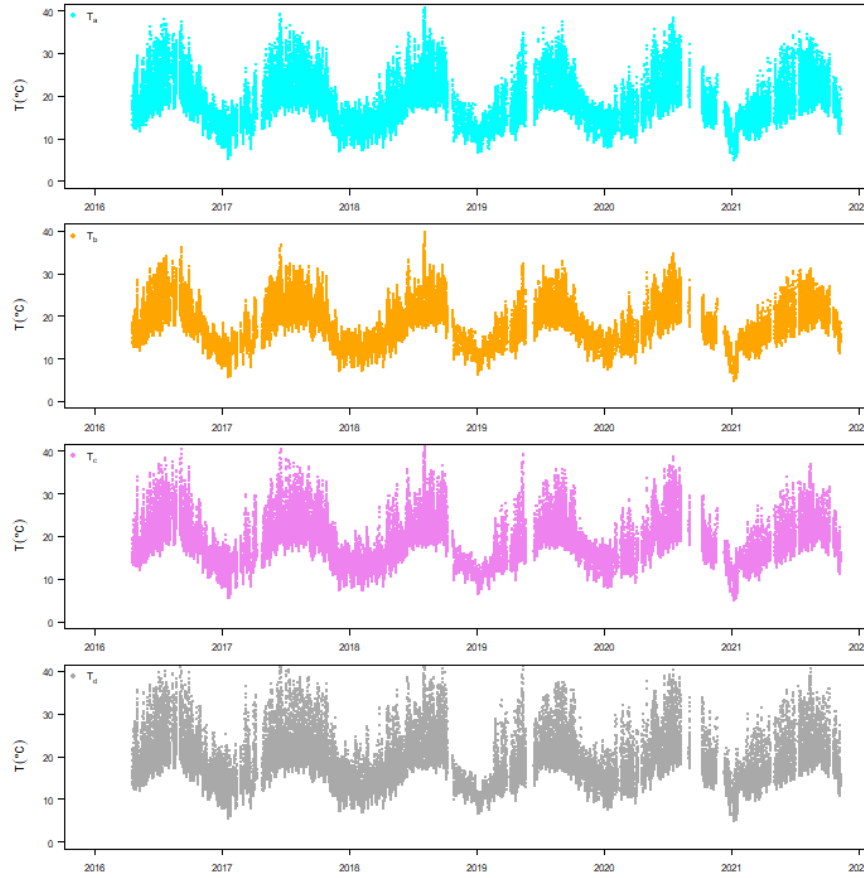


Figure 3.10: Time series of the temperature measurements at Section 0, top to bottom A, B, C, D.

the first model (Model 1) considers the influence of temperature on each response separately. This study presents the results obtained for the strains measured in point A, ϵ_A . In this scenario, nothing can be inferred from the other responses. The second model (Model 2) considers the influence of all the temperatures on the prediction of all the responses simultaneously. In addition, the third model (Model 3) addresses the relationship among the responses in the section under study. All of the models proposed herein were developed in R (Posit team, 2019) using the *nnet* package (Venables and Ripley, 2002a).

Table 3.2: Models for pattern recognition and novelty identification for strain measured in ϵ_A .

Designation	Model: $Output = f(Input)$
Model 1	$\epsilon_A = f(T_a, T_b, T_c, T_d)$
Model 2	$(\epsilon_A, \epsilon_B, \epsilon_C, \epsilon_D) = f(T_a, T_b, T_c, T_d)$
Model 3	$\epsilon_A = f(\epsilon_B, \epsilon_C, \epsilon_D)$

For all the cases, the learning dataset was established using 90% of the dataset, while the prediction dataset was defined by the remaining 10% of the data. The learning dataset was then

split into three subsets: the first 65% of the data, taken sequentially, are used as the training set, the next 15% are used for the cross-validation set and the remaining 20% are used as the testing set. The training and cross-validation sets can be seen as the learning data, and the test set as the data that allows evaluating the quality of the NN model. The training data set is randomized and, in each iteration, the training performance increases. It stops when the error for the cross-validation set increases, thus ensuring a better generalization (Mata, 2011). Regarding the residual analysis, the moving average and its standard deviation with a time period of 7 days ($7 \times 24 = 168$ records) are computed for all the cases. The results of the three models proposed are presented in the following sections.

3.5.1 Model 1: $\varepsilon_A = f(T_a, T_b, T_c, T_d)$

This model used as input values the environmental loads (temperatures T_a , T_b , T_c and T_d), and as output values, each strain at a time of the section under study at a time (ε_A , in this study), resulting in a NN of four inputs and one output. Values in the hidden layer were defined based on the input dimensionality due to the complex relationship between input-output and the large-size dataset. A hyperbolic tangent transfer function has been chosen to be the activation function for the hidden layer, and a linear function was chosen for the output layer. The generalized delta rule back-propagation algorithm was used in the training process. The chosen network architecture was the best of all the tested networks with 4 to 7 neurons at the hidden layer. To find out the optimum result, five initializations of random weights and a maximum of 35000 iterations were performed for each NN architecture. In this case study, the NN model with the best performance, i.e. involving the lowest error for the cross-validation set, was a 4-7-1 MLP (4 inputs - 7 neurons in the hidden layers - 1 output).

The RMSE values were calculated in order to evaluate the quality of the model representation. A RMSE value of $9.72 \mu\epsilon$ was obtained for the training subset, $9.76 \mu\epsilon$ for the cross-validation subset, and $9.57 \mu\epsilon$ for the test subset. Given that all the values are in the same range, a good quality and generalization of the model is confirmed. Figure 3.11a shows the time series obtained with the predictive model for the target ε_A . The blue points represent the values obtained with the prediction model, and the black points are the observed measurements. From the plot, it is possible to confirm the good fitting of the model outcome regarding the observed values.

In Figure 3.11a, the residuals corresponding to the same target ε_A are represented in grey. In red, overlapping the residuals, the evolution of the moving average (*m.a.r.*) for a time period

of 7 days is represented, whose maximum absolute values are equal to $27.33 \mu\epsilon$ and $4.09 \mu\epsilon$ for the training and prediction sets, respectively. The plot also shows the evolution of the *m.a.r.* standard deviation ($sd_{m.a.r.}$) in blue, whose maximum values are equal to $27.33 \mu\epsilon$ and $16.71 \mu\epsilon$ for the training and prediction sets, respectively. By comparing the predicted *m.a.r.* and $sd_{m.a.r.}$ with the observed values from the learning set, it is possible to notice a considerable reduction on both metrics. This could be an indication that the model is capturing the existing patterns and performing accurately.

As proposed in the methodology, a sensitivity analysis is also carried out to test the robustness of the models and characterize the effects of the inputs (temperatures) on the predicted output (response) of the models (Figure 3.11b). For the proposed models, the correlation of the output was analysed with each input of the NN. The sensitivity analysis for ϵ_A through Model 1 was carried out for temperatures measured in T_d along each month of the period under study in order to understand the differences among the different temperature seasons, as presented in Figure 3.11b. The correlation between ϵ_A and T_d can be seen to be high, confirming the reliability of the prediction.

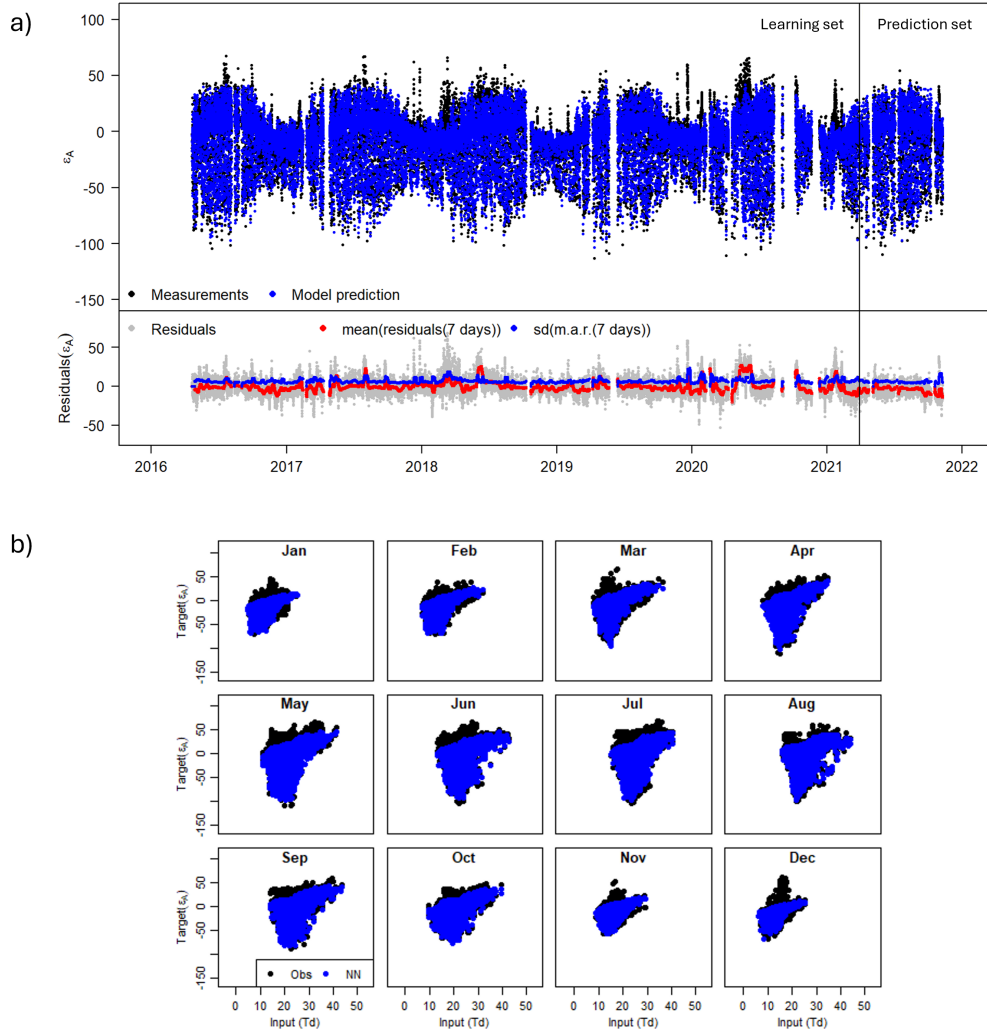


Figure 3.11: Model 1. a) Measurements, predicted values, $m.a.r.$ and $sd_{m.a.r.}$ of strains measured in ϵ_A . b) Sensitivity analysis at target ϵ_A for temperatures at T_d .

3.5.2 Model 2: $(\epsilon_A, \epsilon_B, \epsilon_C, \epsilon_D) = f(T_a, T_b, T_c, T_d)$

This model used the environmental loads (temperatures T_a , T_b , T_c and T_d) as input values, and all the responses (strains ϵ_A , ϵ_B , ϵ_C , ϵ_D) of the section under study as output, where ϵ_A is the reference in this case. The resulting NN model is a four inputs and four outputs model. For this model, the NN with the best performance, i.e. involving the lowest error for the cross-validation set, was a 4-7-4 MLP.

The RMSE values for the training, cross-validation, and testing sets were $10.18 \mu\epsilon$, $10.24 \mu\epsilon$, and $10.17 \mu\epsilon$, respectively. As for the previous model, Figure 3.12a shows the resulting time series for the target ϵ_A where the blue points correspond to the prediction model results, and the

black points correspond to the observed measurements. These results confirmed that a model with a good generalization quality is also obtained.

The bottom plot of Figure 3.12a shows the residuals corresponding to the same target in grey. In red, overlapping the representation of the residuals, it is possible to see an expected *m.a.r.* close to zero for a time period of 7 days whose maximum absolute value for the learning set is $28.38 \mu\epsilon$ and for the prediction set $14.47 \mu\epsilon$. In the same plot, the standard deviation of the *m.a.r.* is also represented (in blue) with a maximum value for the learning set of $24.09 \mu\epsilon$ and the prediction set of $15.14 \mu\epsilon$. By comparing the *m.a.r.* and the $sd_{m.a.r.}$, it is possible to notice, as with Model 1, a reduction of the *m.a.r.* and $sd_{m.a.r.}$ from the learning to the prediction set as evidence of the model accuracy.

The sensitivity analysis for target ϵ_A based on the variations observed in T_d per month are presented in Figure 3.12b. These results also confirm the good correlation of the predicted response with the input.

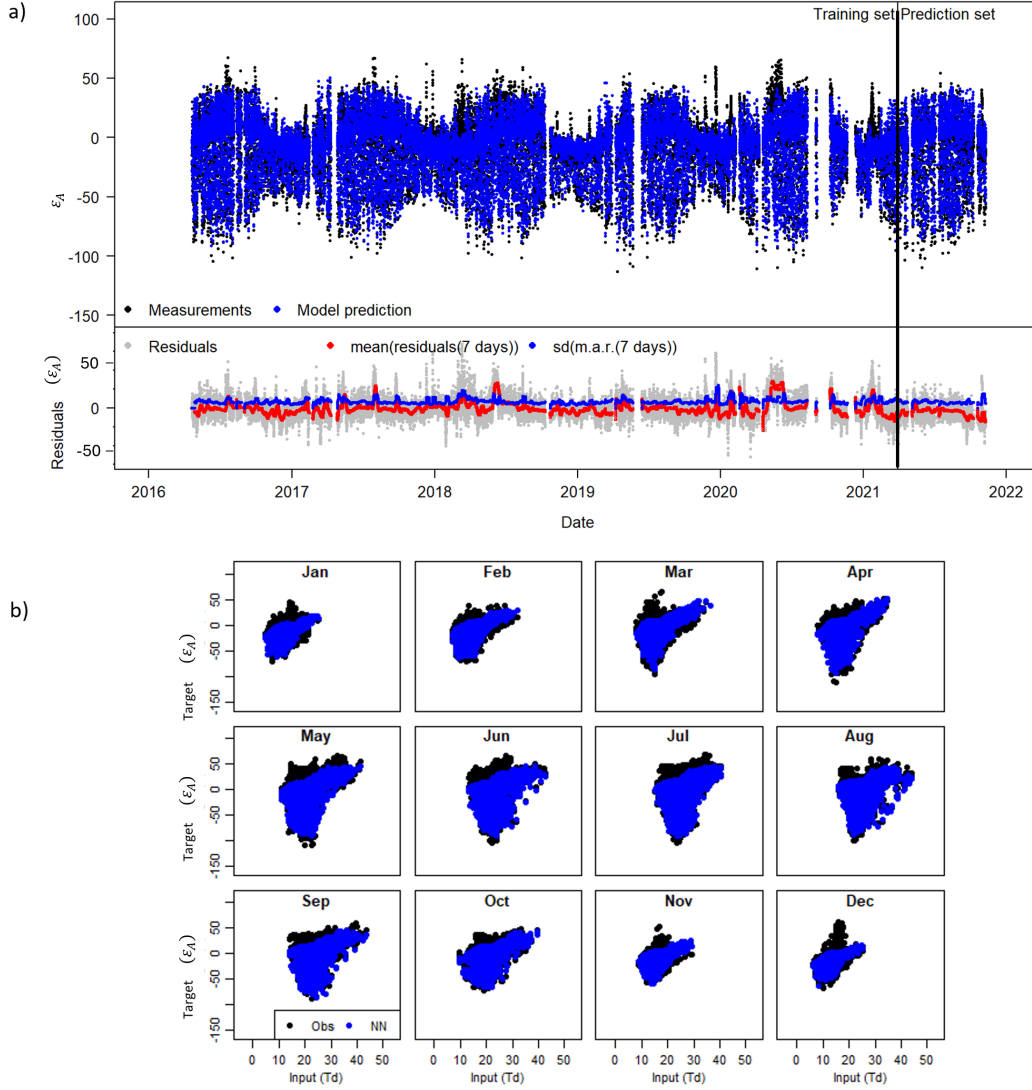


Figure 3.12: Model 2. a) Measurements, predicted values, $m.a.r.$ and $sd_{m.a.r.}$ of strains measured in ϵ_A . b) Sensitivity analysis at target ϵ_A for temperatures at T_d .

3.5.3 Model 3: $\epsilon_A = f(\epsilon_B, \epsilon_C, \epsilon_D)$

This model uses as input and output values the responses (strains) of the section under study, resulting in a NN of three inputs (ϵ_B , ϵ_C and ϵ_D) with one output (ϵ_A). For this model, the network with the best performance, i.e. involving the lowest error for the cross-validation set, was a 3-5-1 MLP. For the chosen model, the RMSE values obtained were $5.79 \mu\epsilon$ for the training set, $5.81 \mu\epsilon$ for the cross-validation set, and the same value, $5.81 \mu\epsilon$, for the testing set. Since the values are in the same range, the good generalization of the model is confirmed. RMSE values of Model 3

are lower than those obtained with Models 1 and 2, showing the best performance among the three models. This can be related to the greater correlation between the variables under study.

Figure 3.13 shows, in the top plot, the time series of the predictive model corresponding to target ε_A . The same plot also represents the points obtained by the prediction model (in blue), overlapping the points corresponding to the observed measurements (in black). From the graph, it is possible to confirm the good fitting of the model.

In Figure 3.13a, the residuals corresponding to the target ε_A are also represented in grey. An expected *m.a.r.* for a time window of 7 days is represented in red overlapping the residuals, and the evolution of $sd_{m.a.r.}$ is shown in blue. The maximum absolute value of *m.a.r.* registered for the learning set is $21.14 \mu\varepsilon$ with a reduction, in the prediction set, to $3.62 \mu\varepsilon$. In the case of $sd_{m.a.r.}$, the maximum value for the learning set is $11.62 \mu\varepsilon$ decreasing to $9.62 \mu\varepsilon$ in the prediction set.

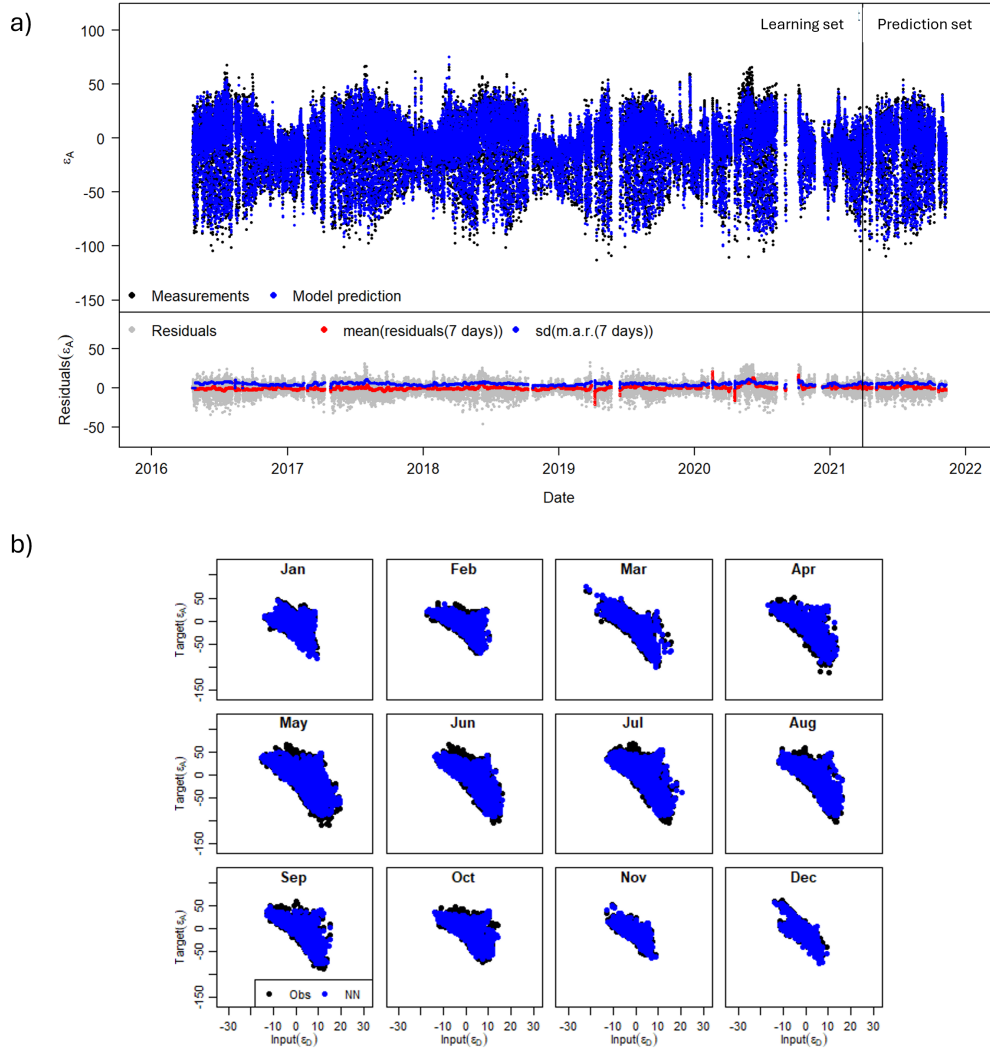


Figure 3.13: Model 3. a) Measurements, predicted values, $m.a.r.$ and $sd_{m.a.r.}$ of strains measured in ϵ_A . b) Sensitivity analysis at target ϵ_A

The plots shown in Figure 3.13b correspond to the variation of ϵ_A based on the variation of ϵ_D , for each month. A good correlation between the two quantities is verified for the cold and warm seasons.

3.5.4 Comparative analysis

From the comparison of the model results, it was possible to confirm that the three models exhibited a good fitting between the observed values and the predicted ones. Table 3.3 shows the performance parameters for the learning and the prediction sets per model by means of the RMSE values, maximum values of the residuals ($|r|_{Max}$), the average value of the residuals across the whole dataset ($E(|r|)$), and the maximum $m.a.r.$ values for the three models proposed.

Given that Model 1 and Model 2 considered the influence of the environmental loads to predict the structural responses, it is possible to compare their performance through the parameters shown in Table 3.3. Given that Model 3 does not consider directly the influence of the environmental loads, since the model was built considering sensors only related to the measurements of the response, the difference in the results, when compared to the other models, can be related to a higher correlation among the considered quantities.

A comparative analysis between the RMSE values results of Models 1 and 2 for the prediction and the learning sets confirms their good generalization since these values are in the same range. On the other hand, the maximum value of the residuals $|r|_{Max}$ shows a decrease from the learning to the prediction set in Model 1 and Model 2, which confirms the adequacy of the prediction. The results of the residual analysis of Model 1, show no significant error or unknown effect at the response point of ϵ_A or in any of the environmental loads. Regarding Model 2, the extra uncertainty added by using more sensor measurements for the prediction could explain the higher residual values when compared with Model 1. When analysing the $m.a.r.$ and $sd_{m.a.r.}$ values in both models, the difference in results between the learning and the predicted sets are in the same range, confirming the model accuracy of prediction at target ϵ_A .

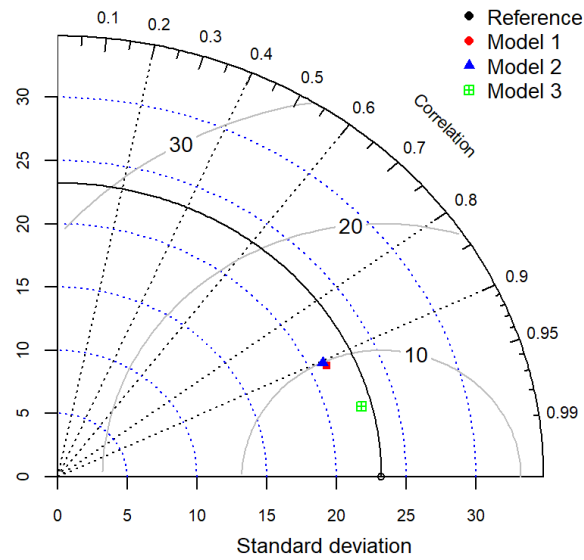
As referred before, Model 3 has a different condition, since it uses different information (only structural responses) compared with the other models. However, it shows a good generalization as suggested by the RMSE results. When considering only response measurements for the prediction model, the predictors were seen to be more stable due to the greater correlation among the quantities. When analysing the residuals, it is possible to see the maximum values of $m.a.r.$ and $sd_{m.a.r.}$ decreasing from the learning to the prediction sets, confirming the good performance of this model.

To evaluate the performance of the models more comprehensively and comparatively, a Taylor diagram is presented in Figure 3.14. The horizontal and vertical axes of the diagram represent the values of the standard deviation, which are connected to each other by circular dotted lines. The radial lines from the origin show the value of the correlation coefficient between the observed values and the model results and the grey circular continuous lines show the RMSE. Consequently, each model is plotted by means of its standard deviation, RMSE and correlation coefficient that are the result of the linear relationship between the model results, for the three proposed cases, and the observed values (described as the reference value) for the strain measured at ϵ_A . The closest model to the reference value is identified as the most accurate model.

Table 3.3: Performance parameters for models 1, 2 and 3.

	Learning set ($\mu\epsilon$)	Prediction set ($\mu\epsilon$)
Model 1	$RMSE$	9.76
	$ r _{Max}$	54.47
	$E(r)$	5.61
	$Max(m.a.r.)$	27.33
Model 2	$RMSE$	10
	$ r _{Max}$	68.42
	$E(r)$	6.80
	$Max(m.a.r.)$	28.38
Model 3	$RMSE$	5.80
	$ r _{Max}$	36.42
	$E(r)$	3.33
	$Max(m.a.r.)$	21.14

* All the values correspond to the strain measured at ϵ_A .

Figure 3.14: Taylor diagram comparing the three model results at target ϵ_A .

From Figure 3.14 it is possible to notice that the three models registered a standard deviation value close to the reference ratio, indicating that all the models accurately captured the variability and trends of the observed values. It is worth noticing that Model 3 (in green) is closer to the reference curve, indicating that the model reproduces the variability of the reference dataset better than the other models. Regarding the correlation coefficient, Model 3 also shows greater correlation compared with the other models. Those differences can be explained by the fact that Model

3 considers just the structural responses and does not include the influence of the temperature in the prediction as Models 1 and 2. Since the correlation of these models was calculated using the temperatures as inputs, the proximity of the models' performance in the Taylor diagram reflects this issue. As such, there is no relevant difference between the performance of Models 1 and 2. The three models are also located near the lowest RMSE circle, confirming the good fitting of the models and in agreement with the performance parameters presented in Table 3.3.

In order to interpret the pattern behaviour during the seasonal temperature changes, polar coordinate plots were created. In Figure 3.15a, it is possible to see the evolution of the values of $m.a.r.$ (calculated for a time window of 7 days and time steps of an hour) in blue and $sd_{m.a.r.}$ in red obtained with Model 1 for the prediction and the learning sets, with separate plots for $m.a.r. > 0$ and $m.a.r. < 0$. For $m.a.r. < 0$ the higher values are seen mostly for the winter season, around $15 \mu\epsilon$ to $20 \mu\epsilon$. Since there is a low dispersion of the values in that period of time (as seen from the values of $sd_{m.a.r.}$), it is possible to relate those high values and the content of error showed by the residuals with the temperatures, considered as the input of the prediction model. Still, for the case of $m.a.r. > 0$, the maximum $m.a.r.$ value is registered in December, around $25 \mu\epsilon$, while $sd_{m.a.r.}$ shows extreme values in May and June. Regarding the values shown in the prediction set, for $m.a.r. < 0$, the highest $m.a.r.$ and $sd_{m.a.r.}$ values were registered in the month of November.

When analysing the results obtained with Model 2, the same pattern can be seen in both the learning and the predicted sets (Figure 3.16) which confirms that the extreme values are time located and due to the recorded temperatures or strains measured at point ϵ_A . In the case of Model 3, the polar plots in Figure 3.17, show high dispersion in the months of February, April and October for the learning set. However, all values are concentrated in the central zone, as expected for the prediction set, thus showing that Model 3, which uses structural strain as input and output, performs as well as the other two while having the advantage of not needing to measure temperatures. Literature and practice review indicates the need to perform temperature measurements for understanding, compensating and controlling strain and other structural responses. Nevertheless, these results suggest that for carefully chosen measurements, such as strains within the same transversal cross-section, structural responses can only be used for building the models and detecting damage, resulting in more precise, more straightforward and less expensive SHM practices.

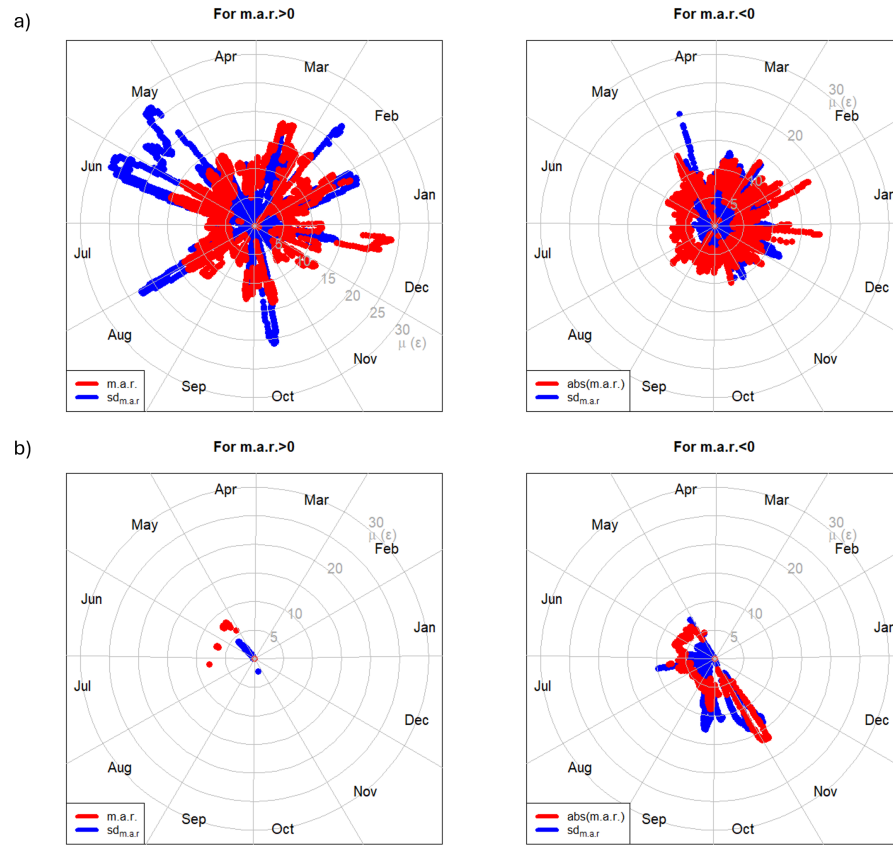


Figure 3.15: a) $sd_{m.a.r.}$ and $m.a.r.$ for the learning set of Model 1, and b) $m.a.r.$ and $sd_{m.a.r.}$ for the prediction set of Model 1, in a polar coordinate system, by month.

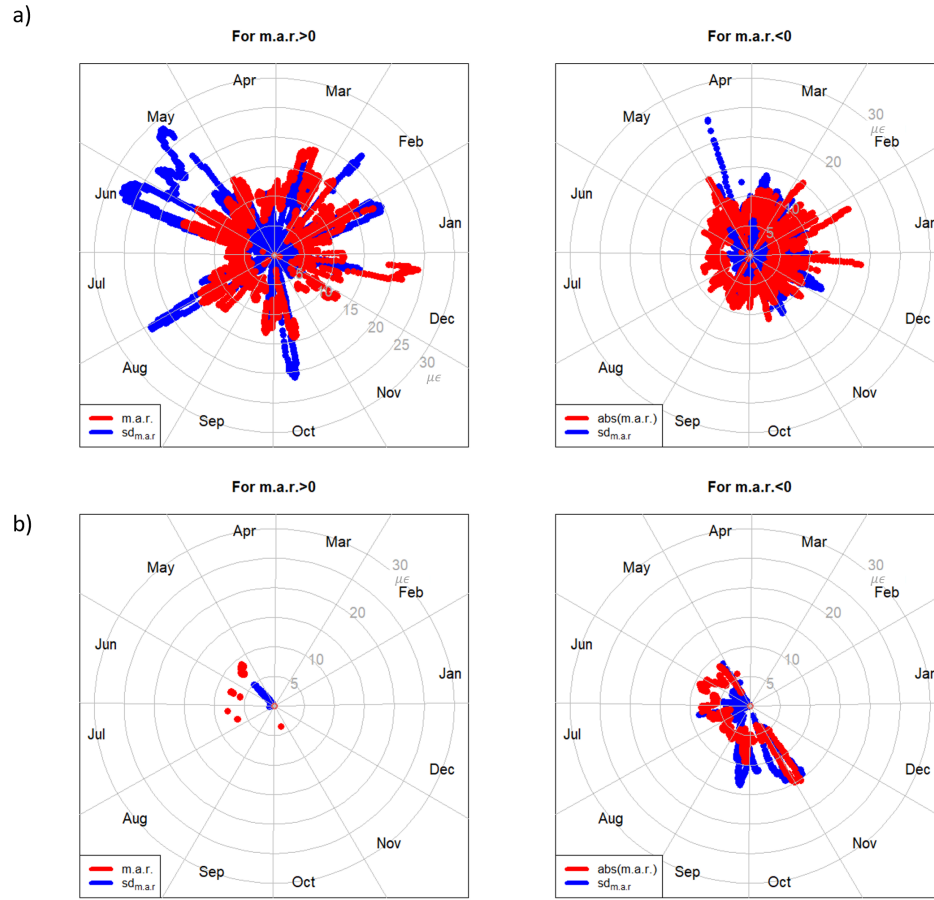


Figure 3.16: a) $sd_{m.a.r.}$ and $m.a.r.$ for the learning set of Model 2, and b) $m.a.r.$ and $sd_{m.a.r.}$ for the prediction set of Model 2, in a polar coordinate system, by month.

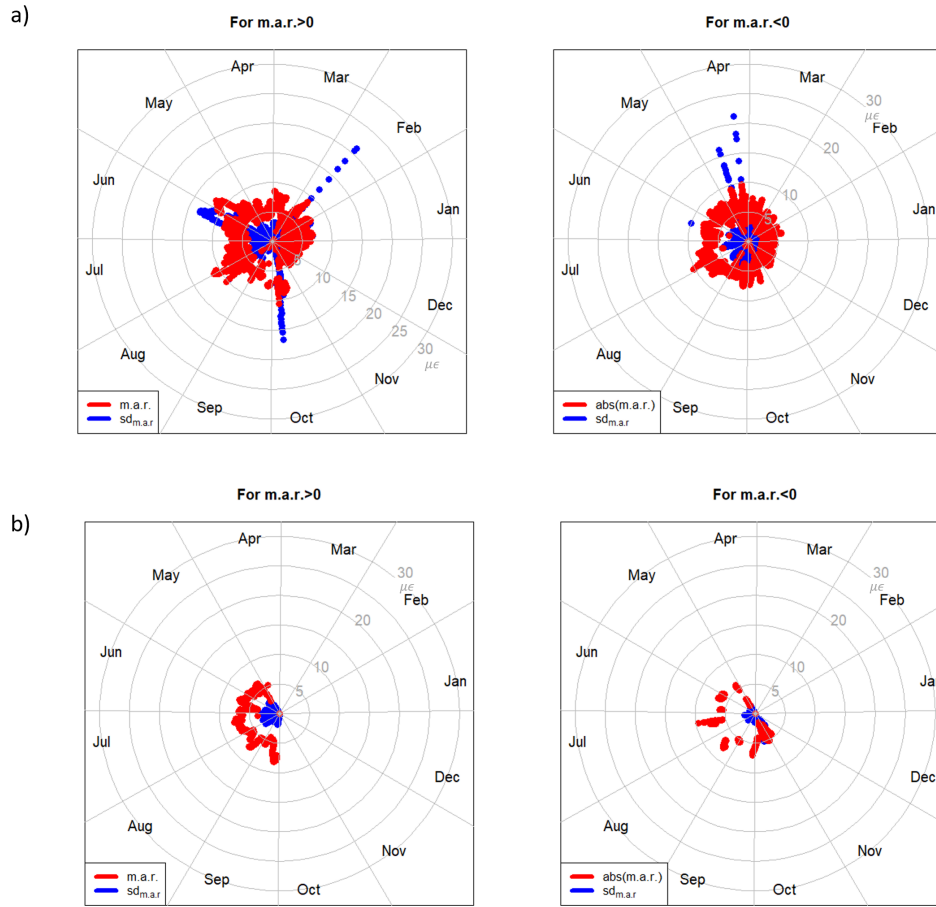


Figure 3.17: a) $sd_{m.a.r.}$ and $m.a.r.$ for the learning set of Model 3, and b) $m.a.r.$ and $sd_{m.a.r.}$ for the prediction set of Model 3, in a polar coordinate system, by month.

3.5.5 Threshold proposal

Plots of $sd_{m.a.r.}$ and the $m.a.r.$ for Models 1 and 2 are shown in Figures 3.18 and 3.19, respectively, to confirm the presence or not of a novelty related with the extreme values showed in Figures 3.16 and 3.17. For this purpose and to enhance interpretability, each correlation plot was discretized by zones based on the percentiles of the $m.a.r.$ and $sd_{m.a.r.}$. In this sense, the 0.1% and the 99.9% percentile of the data set have been calculated and used as internal zone limits in three axis. The three zones proposed are located at the borders of the plots and contain the results with the more significant dispersion. Zone 1 contains residual values with lower $sd_{m.a.r.}$ and the highest $m.a.r.$ values, which can be related to extreme observed values or to the quality of $sd_{m.a.r.}$ prediction at points with extreme temperature values. Zone 2 contains residual values of above 99.9% percentiles, but

with $m.a.r.$ values between the 0.1% and the 99.9% percentile and are related to a significant variation of the residuals based on the time window considered. Finally, Zones 3 contains the residual values with high $sd_{m.a.r.}$ and $m.a.r.$, and are the zones with the highest probability of containing a novelty.

By comparing Model 1 and Model 2 it is possible to notice that no values are located in Zone 3. Instead, as defined by the proposed thresholds, most values are located in the central zone for both sets.

In the results obtained for the prediction set, most values are concentrated in the central zone of the plots, showing the absence of structural novelties. Furthermore, it provides an accurate baseline of the structural behaviour of the bridge that could be used as a reference for future studies.

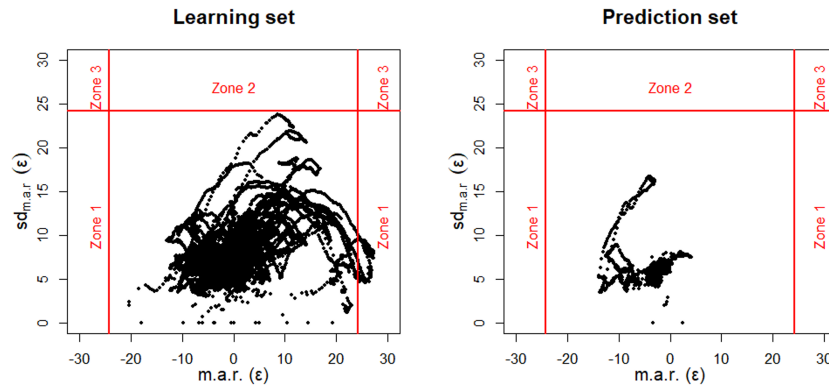


Figure 3.18: $sd_{m.a.r.}$ vs $m.a.r.$ plots of Model 1, for the learning and prediction set.

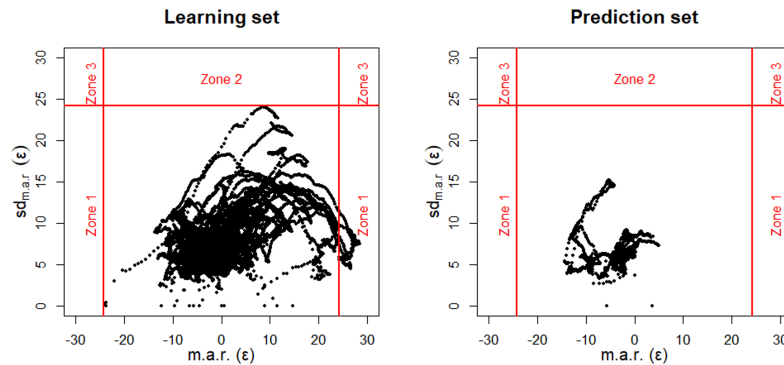


Figure 3.19: $sd_{m.a.r.}$ vs $m.a.r.$ plots of Model 2, for the learning and prediction set.

In the case of Model 3, the same criteria was adopted for threshold definition. As can be

observed in Figure 3.20, some of the values are located in Zone 1 and 2 for the learning set, and only a single value in Zone 3. Related to the prediction set, all values are concentrated in the central zone, as expected.

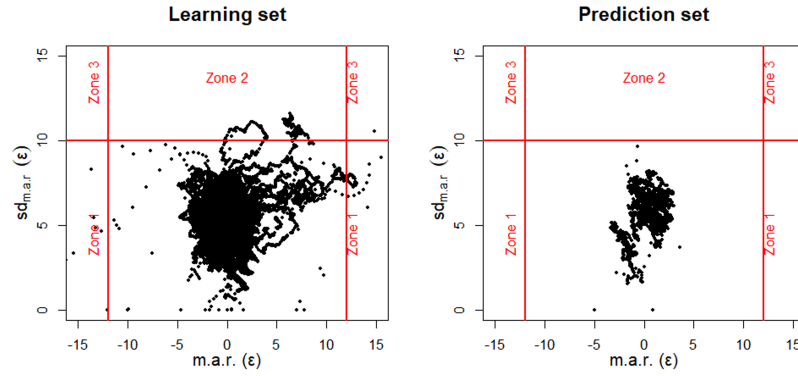


Figure 3.20: $sd_{m.a.r.}$ vs $m.a.r.$ plots of Model 3, for the learning and prediction set.

3.6 Concluding remarks

The methodology proposed in this chapter is based on the development of models that take advantage of the correlation between the structural responses and the main loads, or, in other words, the relation among the structural responses observed in several physical quantities, which allows the identification of patterns and novelties in the structural behaviour. The approach consists of the integral analysis of the proposed models, including i) the revision of the model's performance, i.e. validating the quality of the model to represent the relation between the inputs (environmental loads or structural responses) and the outputs (observed structural response), and ii) the definition of a baseline for the characterization of the residuals, based on the adoption of moving average charts of the residuals ($m.a.r.$) and the m.a.r. standard deviation ($sd_{m.a.r.}$). Novelties in structural behaviour can be identified through this approach for future observations.

Following a supervised learning approach (MLP NN models) for the establishment of an accurate baseline capable of representing the structural behaviour of the 25 de Abril bridge, located in Lisbon, Portugal, five years of hourly measurements gathered from the SHM system installed at the mid-span section bridge were analysed. Three prediction models that combine the environmental loads and the structural responses under study in different ways were proposed to predict, more accurately, the general structural behaviour and assess with more detail all the quantities considered in the study. Model 1 considered environmental loads (temperatures) as input and the

stress measures in one point of the bridge as the output. Model 2 considered the same inputs as Model 1, and the strain measured in four points of the bridge as outputs. Model 3 allows performing a response-response analysis, where the inputs are the strains measured in three points, and the output is the remaining strain (from the set of four strains measured in the section of the bridge under study).

Results showed the good performance of the learning algorithm in the three cases. After confirming the fitting of the models with the observed measurements, a residual analysis was carried out. A moving average analysis with a time window of 7 days and time steps of one hour was performed for all the models. The corresponding standard deviation values were also calculated in all the cases to assess the dispersion in the evolution of the weekly moving average of the residuals. An analysis of the results allows comparing the performance parameters of the first two models that considered the influence of the environmental loads as an input.

Regarding the quality of representation, both models showed good results, pointing to the good performance of the neural network. The residual analysis results also showed a low dispersion in the mean weekly evolution of the residuals with no signs of unusual values. The performance of Model 3 was also adequate, given the good correlation among its quantities. In order to test the robustness of the prediction models and characterise the influence of the inputs on the outputs of the three models, a sensitivity analysis that correlates each output with each input was performed. In order to adopt a baseline for future analyses, limits based on the percentiles obtained from each set were proposed. Three zones were defined based on those limits (0.1% and 99.9% percentiles), establishing internal thresholds related to operational performance indicators suitable for identifying potential novelties for expert consideration and verification.

Based on the defined thresholds, any novelty was identified when analysing the results of Models 1 and 2 in the prediction set. This conclusion is supported by the good results obtained in Model 3, where no possible novelties were identified.

Chapter 4

Enhancing pattern recognition in structural health monitoring using a deep learning approach

This chapter covers the improvement of the pattern recognition for novelty identification, addressing one of the dissertation's four focus topics (see Figure 4.1).

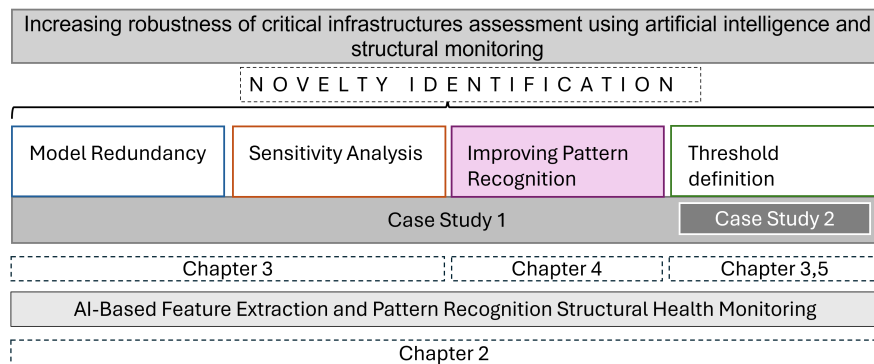


Figure 4.1: Flowchart of the dissertation's structure with the one topics addressed in the present chapter in color.

The challenge of efficient structural safety strategies of large operational structures with high dimensional features is a determinant factor for SHM. The current technological advances contribute to the optimization of data analysis, making the process less demanding in terms of time and computational demand. Regression analysis has been used for the assessment of SHM data since its beginnings due to its theoretical simplicity, and Multiple Linear Regression (MLR) is

currently used to interpret SHM data of operational structures, such as bridges worldwide. The capacity of this approach to explain the conditional distributions of responses and predictors makes it a suitable strategy, to explain, in several cases, most of the observed variability. However, MLR has limitations to explain the non-linearity and the time dependency of the structural relationships. To address this issues, the proposed research improves this current approach by adding a complementary step based on Deep Learning (DL), which is capable of dealing with the referred limitations.

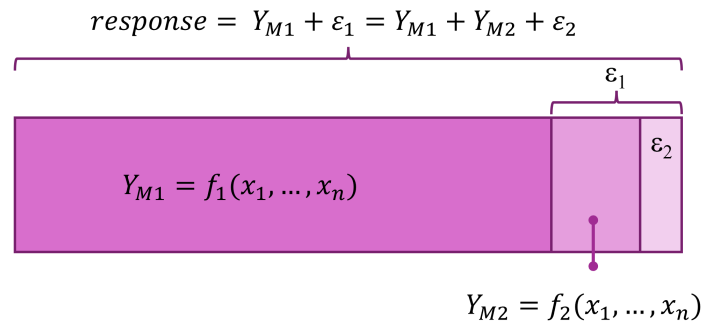


Figure 4.2: Enhancing pattern recognition strategy.

Assuming that improving the decision-making process in the SHM field depends significantly on the quality of the prediction models, the Long Short Term Memory (LSTM) model is proposed to overcome the actual limitations of MLR and improve its performance. To illustrate the benefits of this new approach, the methodology is applied to data gathered from a large-span suspension bridge, the 25 de Abril's bridge, in Lisbon, Portugal. The application quantifies the benefits of the LSTM with respect to the MLR in terms of performance, thus showing the added value of the proposed methodology for interpreting the observed behaviour of the bridge.

4.1 Context and motivation

Infrastructures like bridges or dams are subjected to various daily environmental and operational loads and, as with any structure, to natural hazards during their life cycle. In the case of operational bridges, their damage would imply significant disruption in transportation systems and substantial economic loss to society. In this sense, ensuring their safety and functionality is essential. In the long term, the cumulative influence of external loads can accelerate structural damage and compromise the safety of these infrastructure. Therefore, the safety assessment of operational

bridges raises the attention of researchers, policymakers and investors regarding the importance of assessing the performance over time, recovery capability and long-term loss of bridges under operational loads. In this sense, SHM systems, composed of different types of sensors, provide critical information for experts to analyse and detect any anomalous behaviour.

The interpretation of the massive data that are collected during a long-term monitoring process from the perspective of structural safety becomes a priority of SHM research. The analysis and interpretation of those data are fundamental to assess the structural safety and behaviour of the monitored structure, and are focused on damage or novelty detection and condition assessment. However, formulating reliable and efficient data analysis and signal processing methodologies is still challenging for SHM (Azimi and Pekcan, 2020). Structural response analysis of the structures has been practised qualitatively for decades, from tap testing for fault detection (e.g., on train wheels), and in 1980 it started being addressed by the research communities. Quantitative SHM methods have recently been developed to reduce costs, using digital computing hardware and sensing systems (Sohn et al., 2002). Over time advances have been made in various branches of technology, such as sensing instrumentation, signal acquisition and transmission, data processing and analysis, numerical simulation and modelling. New strategies that benefit from these technological advancements for accurately evaluating the structural health of civil structures using real-time monitored data (Chen and Ni, 2018) have been explored more and more since then.

Data-driven methods establish models based on statistical representations of the gathered data. They explore the data patterns of structural condition changes without any prior knowledge. Traditionally, data-driven strategies were derived from multivariate statistics, and damage detection or condition assessment were solved as statistical pattern recognition problems. Although these methods have been applied in many cases, they have limitations in their ability to deal with large and complex datasets, which reduces the accuracy of their predictions. More recently, several improvements in computational power, chip and sensor technology have enabled the use of Machine Learning (ML) techniques in engineering applications. According to Avci et al. (Avci et al., 2021), those techniques focus on developing intelligent algorithms capable of automatically acquiring knowledge from the available data to provide machines with a human-like ability to learn. Different authors have proposed data-driven ML techniques as an efficient way to assess the global health condition of host infrastructures (Avci et al., 2021; Bao et al., 2019; Santos et al., 2015; Liang et al., 2016; Mishra, 2020).

Data-driven SHM approaches do not require the development of numerical or analytical models to be fitted with in situ data. Instead, those techniques aim at extracting sensitive information from the measured time series, using statistical learning methods (Sohn et al., 2002) for posterior analysis. Consequently, data-driven SHM methodologies are more flexible, less computationally demanding and inexpensive when compared with model-based approaches, which is why these techniques are the most reported in recent SHM literature. Since data-based algorithms can reproduce more easily the relationship between variables under analysis, their application to structures subjected to operational and environmental effects is more comprehensive than numerical or analytical models.

The powerful capabilities of ML techniques to extract information and develop predictive models from extensive data became predominant approaches for SHM. Furthermore, ML algorithms can learn the complex interrelation among influencing factors, thus performing predictions without the need for empirical models. Using those methods can also result in significant time and cost savings and increase computational efficiency in many structural engineering tasks (Salehi and Burgueño, 2018). In the last decade, a preference for ML algorithms and, in particular, for Neural Networks (NN) for learning, recognition, and prediction processes over time is evident in structural engineering branches.

Regression analysis is a technique used for forecasting and prediction, and its application significantly overlaps with the areas of ML and DL. Regression analysis allows understanding the conditional distributions that relate the response parameters and the predictors in a structure, which is why it is widely used in the SHM field. However, the significant increase of monitoring data and the reduction of computation costs popularised the use of ML to analyse and interpret SHM data. Nowadays, DL, a paradigm of ML that allows computational models composed of multiple processing layers to learn representations of data with several levels of abstraction has been gaining significant attention. DL algorithms can learn to correlate the features to the desired output and run the entire feature extraction process. Therefore, DL models can find a direct mapping between the raw inputs and the final outputs, allowing the system to perform complex tasks by breaking them into smaller and simple parts (Avci et al., 2021). According to LeCun et al. (LeCun et al., 2015), Recurrent Neural Networks (RNNs) are one of the major groups in which DL architectures can be categorized. RNNs are considered the deepest of all neural networks, and they are capable of generating and addressing memories of arbitrary-length sequences of input patterns. Furthermore, they can overcome the time dependency limitation of regression models or simpler neural networks

that do not consider the sequential structure of data for any observation (Caterini and Chang, 2018). This is achieved by mapping the entire history of previous inputs that are saved as memory in the network's internal state and used after to predict the desired output.

The authors in Dang et al. (Dang et al., 2020) state that RNNs are suitable for feature learning of sensor measurements due to their ability to capture time-dependent characteristics. However, the sensor data usually consists of long sequential samples; which means that RNNs suffers from a problem known as exploding or vanishing gradients. To address these long-range dependency issues, a branch of RNN architectures called LSTM is proposed herein. The explanation of the relationship between variables and the structural behaviour defined by the MLR is improved by the LSTM, given its capacity to process time-dependent sequential data. The benefits of this approach, over traditional MLR, are that the added value can be quantified and easily understood by those responsible for the structural safety assessment.

In the present work, the performance of the proposed approach is going to be tested by the analysis of daily temperature time-series obtained from the 25 de Abril bridge in Lisbon, Portugal, in order to predict displacements at the central span of the bridge. Structural displacement measurement is an essential area of safety assessment; it can directly reflect whether the deformation of a structure exceeds its safety limit and provide effective parameters for structural damage identification and health monitoring (Wang and Li, 2020). Displacement monitoring has several applications in civil structures, such as dams (Mata, 2011; Rico et al., 2019a) or bridges (Akiyama et al., 2020; Le and Nishio, 2019; Yang et al., 2018; dos Santos et al., 2019). The analysis of the observed patterns in the time-series will aim to determine whether the structure is within the safety limits.

Long-term time-series corresponding to environmental and operational effects were adopted in previous studies for the the prediction of structural responses and structural condition assessment (Shi et al., 2019; Le and Nishio, 2019; Dang et al., 2020; Santos et al., 2017). Based on those references, the daily temperature change, regarded as one of the environmental effects, is treated as a load that gives the response (displacements) for pattern recognition.

4.2 Theoretical background

Multivariate linear regression and long short term memory models are going to be explained in this section.

4.2.1 Multivariate linear regression

Regression-based models are widely used in structural monitoring because of their ability to represent the conditional distribution of the response variables given a set of predictors. Statistical learning applications focused on this type of dependent relationship have been considered by many supervised models. To illustrate the performance of this type of approach, two supervised regression models will be explored and explained in this research: the multivariate linear regression and the long short term memory neural network.

Linear regression is a simple model of regression that minimises the sum of the square errors of a linear combinations of inputs to obtain the best estimate of an output (dependent variable). MLR is an extension of simple linear regression since it considers multiple explanatory variables to forecast the values for the dependent variable. It can be generally defined by (Kromanis and Kripakaran, 2014):

$$\delta_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_s X_{ni} \quad (4.1)$$

where δ_i is the predicted value of the dependent variable δ for the i^{th} step, n is the number of explanatory variables, $x_{1i}; x_{2i}; \cdots; x_{ni}$ are the values for the explanatory variables $x_1; x_2; \cdots; x_n$ at the i^{th} time step, β_0 is the intercept and $\beta_1; \beta_2; \cdots; \beta_n$ are regression coefficients. The values for β_n are computed to minimise an error function based on least-squares estimates.

MLR is widely used in SHM due to its theoretical and computational simplicity. Furthermore, considering that most physical relations between environmental or operational actions and structural responses have a linear nature (Santos, 2014; Cury and Cremona, 2010), the application of regression models is a common practice in SHM data analysis.

4.2.2 Long short term memory neural networks

Deep RNN, like all neural architectures, are inherently designed for multi-dimensional data in which the attributes are independent. However, specific data types, such as time series, contain sequential dependencies among the features. Following Aggarwal (Aggarwal, 2018) in a time series data set, a value at time t is closely related to its values at the previous time window. When the values at individual time positions in the sequence are treated independently of each another, this information is lost. In RNNs, there is a one-to-one correspondence between the layers in the network and the specific positions in the sequence.

In contrast to feed-forward neural networks, RNNs create connections from posterior layer(s) to anterior layer(s) or connections among neurons in the same layer, resulting in networks with dynamic systems (Caterini and Chang, 2018). Typical neural network architectures do not consider the sequential structure in data for any observation; their corresponding hidden states are independent. Therefore, instead of a variable number of inputs in a single input layer, the network contains a variable number of layers. Each layer has a single input corresponding to that time position in the sequence.

RNNs are proposed for feature learning of sensor measurements because they capture time-dependent characteristics. However, the sensor data usually consist of long sequential samples. Therefore, RNNs suffer either from issues known as gradient exploding or vanishing (Dang et al., 2020; Ribeiro et al., 2024). To cope with the long-term dependencies, advanced RNN variants such as LSTMs introduce gates to avoid the problem and enable each recurrent unit to capture dependencies of different time scales adaptively.

The LSTM consist of an advanced RNN architecture that can learn long-range dependencies due to its memory cells composed by a chain of recurrent nodes (Ding et al., 2018) that enhance the time series prediction. These memory cells help the network to control the information by adopting the input gate, forget gate, and output gate (Gulgec et al., 2020). According to da Costa et al. (da Costa et al., 2020), previous data-driven methods assume that training (source) and testing (target) condition monitoring data have similar distributions. The truth is that there is a distribution and feature shift across other domains besides different operating conditions, fault modes and noise.

4.3 Proposed methodology

For a day-to-day approach, the assessment of the structural behaviour and the identification of possible novelties is addressed by data-driven models in a period when the structural behaviour is considered consistent with standard conditions. By following this approach, one can learn about the relationship between the structural response and the main loads in the section of the structure under study. However, noisy and incomplete data signals are a common problem in long-term, continuous and autonomous monitoring. Thus, the interpretation of low-quality datasets is a daily challenge in the SHM field.

In this sense, ML techniques applications in both real and study cases are more common, since they allow to learn from such low-quality datasets that contains incomplete/missing signals and,

despite the limitations, produce accurate enough predictions (Salehi and Burgueño, 2018; Bull et al., 2020; Santos et al., 2013; Lin et al., 2017). As mentioned before, DL as a paradigm of ML allows the computational models composed of multiple processing layers to learn representations of data with several levels of abstraction, showing much accurate results than the ones obtained with ML models. For this study, the proposed approach combines the DL advantages, through an LSTM model, with the computational simplicity of the MLR model, the current approach used for SHM analysis of infrastructures, in order to improve its predictive capacity. According to Rico et al. (Rico et al., 2019a), using LSTM models to model the residuals obtained from traditional regression models, in their case applied to concrete dam monitoring, is an innovative strategy to improve the current approach based just on MLR analysis, since the time-dependent analysis of the non-explained part of the models can provide information on the evolution or cyclic repetition of information related to errors (measurements and model) and other unknown effects.

Following a similar approach, the residuals of the MLR model applied to the SHM measurements of an instrumented suspended bridge will be used to train the LSTM model, thus adding value to the interpretation of SHM data through a DL strategy. The results of the combined prediction can provide a more reliable understanding of the structural behaviour (see Figure 4.3). Each step of the proposed strategy is described in the following.

- **Step 1: Current approach applied to SHM analysis**

As referred before, an MLR model-based strategy, currently used for SHM data analysis of suspended bridges, was adopted to estimate structural response parameters, such as displacements (δ), as a function of the selected main loads, such as temperatures. The MLR model is described by,

$$\delta = \delta_{MLR} + \varepsilon_{MLR} \quad (4.2)$$

A reference data set is adopted to determine the regression coefficients based on an optimization process that minimizes the mean squared error. Once the model δ_{MLR} is obtained, it can estimate a new data set, namely the prediction set. However, there is still a portion of data that are not explained by the model itself, i.e. the residuals of the model:

$$\varepsilon_{MLR} = \delta - \delta_{MLR} \quad (4.3)$$

- **Step 2: Reducing uncertainty using a Deep Learning model**

The unexplained pattern of the structural behaviour obtained from the MLR model, Eq. 4.3 will be explained by the following LSTM model,

$$\delta - \delta_{MLR} = \delta_{LSTM|MLR} + \epsilon_{LSTM|MLR} \quad (4.4)$$

In the case of LSTM models, the dataset is divided into three disjoint sets: training, validation and test set. The hyperparameters (size of LSTM cell, number of time-steps of each input sequence, loss function, optimisation method and batch size) of the LSTM model are chosen through the training set. Holding out the test set, the LSTM model is trained on the training set, optimising the loss function for different combinations of the hyperparameters, which are then confirmed through the validation set (Rico et al., 2019a).

- **Step 3: Final model**

The predicted value for the structural behaviour is then obtained by adding both model predictions, i.e. δ_{MLR} and $\delta_{LSTM|MLR}$ as:

$$\delta - \delta_{MLR} = \delta_{MLR} + \delta_{LSTM|MLR} + \epsilon_{LSTM|MLR} \quad (4.5)$$

To assess the quality of the models' representation, several performance parameters were adopted for all of the cases, namely, the Mean Squared Error (*MSE*), the Mean Absolute Error (*MAE*) and the Standard Deviation (*SD*). The gain in percentage (%) between the two models in the different error metrics is then calculated as presented in Table 4.1 the higher is the percentage of gain means that the performance of the model is better. Consequently, it is possible to confirm if there is an improvement in the accuracy of the predictions.

Table 4.1: Percentage of gain (%) per performance parameter.

$\delta_{MLR} / \delta_{LSTM MLR}$	Gain %
$MSE[mm^2]$	$(1 - MSE_{LSTM MLR} / MSE_{MLR} \times 100)$
$MAE[mm]$	$(1 - MAE_{LSTM MLR} / MAE_{MLR} \times 100)$
$SD[mm]$	$(1 - SD_{LSTM MLR} / SD_{MLR} \times 100)$

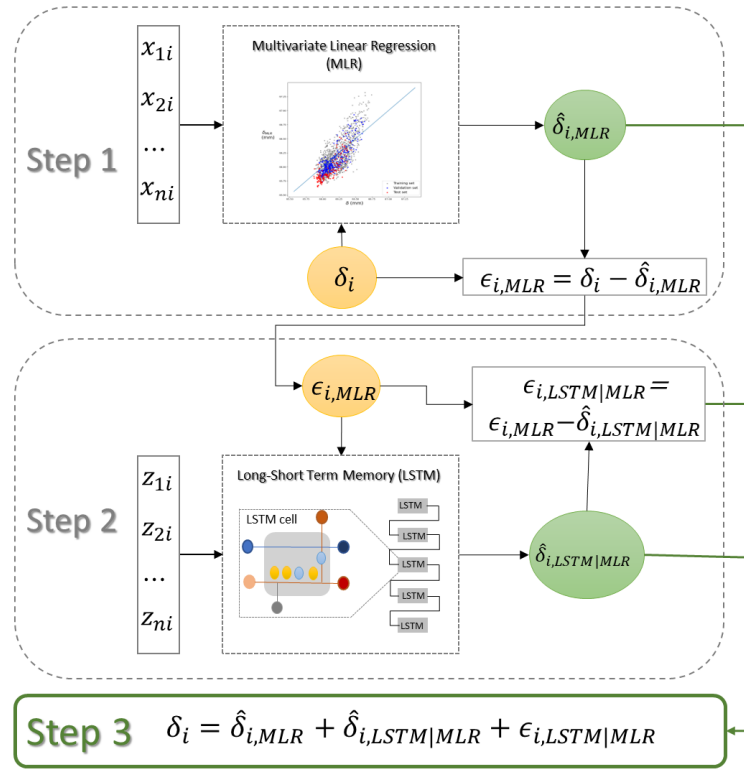


Figure 4.3: Proposed methodology, composed by step 1: Current approach applied to SHM analysis, step 2: Reducing uncertainty using a Deep Learning model and step 3: The final model.

4.4 Case study: The 25 de Abril bridge

The suspended 25 de Abril bridge, located in the river Tejo, Portugal, is the case study selected to apply the proposed methodology. The bridge deck consists of a suspended stiffening truss with 1344 vertical hangers that, at the same time, are suspended by four principal cables supported at piers P2 and P5 and at pylons P3 and P4 (Figure 4.4). The deck's stiffening truss cross-section supports six car lanes at the upper chord level and a double electrified track railway at the lower chord level.

The statistical features obtained from all the quantities measured at the bridge involve hourly maximum and minimum values, hourly medians, and hourly quartiles. The median values are fundamental since they are expected to be free of the influence of extreme values related to traffic and other fast effects, thus reflecting only slow effects that can be analysed with higher precision. The data acquired continuously on the 25 de Abril bridge reflects numerous effects generated by simultaneous actions imposed on the structure.

The data for this study are from an approximate four-year monitoring period, from 07/03/2017

to 31/12/2020, with hourly measurements of the parameters (21304 data points per parameter). It is essential to mention that vehicular traffic and train loads are not measured directly. However, they are indirectly included in the residual analysis.

For this study, displacements and temperatures measured in the central span of the stiffening truss are considered. Displacements are measured by twenty magnetostrictive displacement sensors, twelve located in the stiffening truss's central span and eight on the piers P1, P2, P5 and P7. Temperature is measured at Section 0 using electrical resistance thermometers. Considering that there are two thermometers in each of the chords of Section 0 (Figure 4.4), the mean value of each temperature pair was considered as the representative temperature value for the corresponding chord section to simplify the analysis. The corresponding mean value are $T_a = (T_1 + T_2)/2$, $T_b = (T_5 + T_6)/2$, $T_c = (T_7 + T_8)/2$ and $T_d = (T_3 + T_4)/2$ (in $^{\circ}\text{C}$). Displacement sensors in the stiffening truss are located in the girders of the deck, measuring north and south displacements at sections 22N and 22S (Figure 4.4).

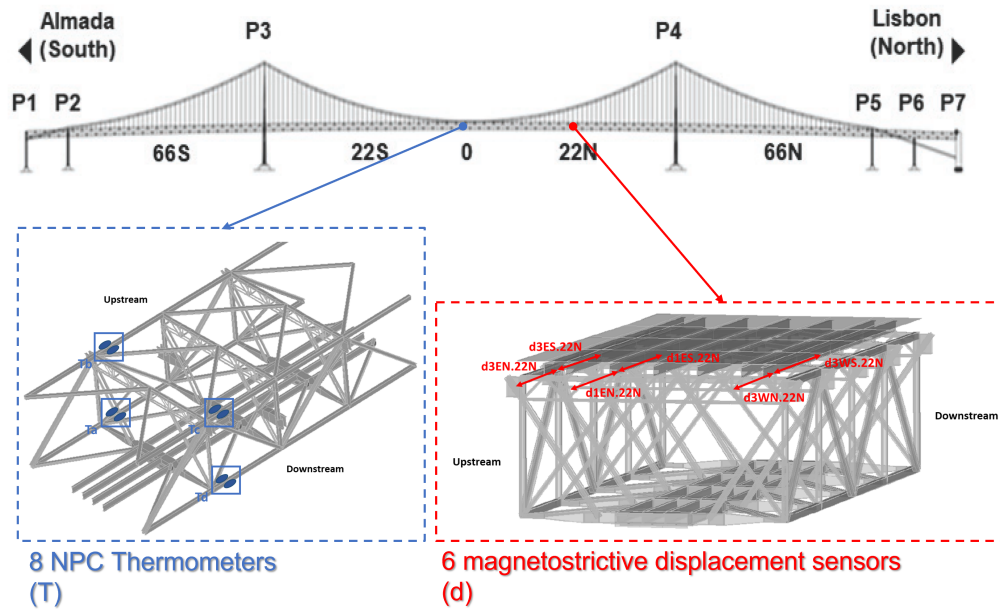


Figure 4.4: Schematic representation of the 25 de Abril bridge monitoring sensors located in the section under study.

Figure 4.5 shows the daily evolution of the displacement measurements and temperatures at the selected section in each month of the year. The changes in the temperatures during the day and in the other months are more evident compared with the displacements that seem to remain stable. However, displacement changes have a smaller range.

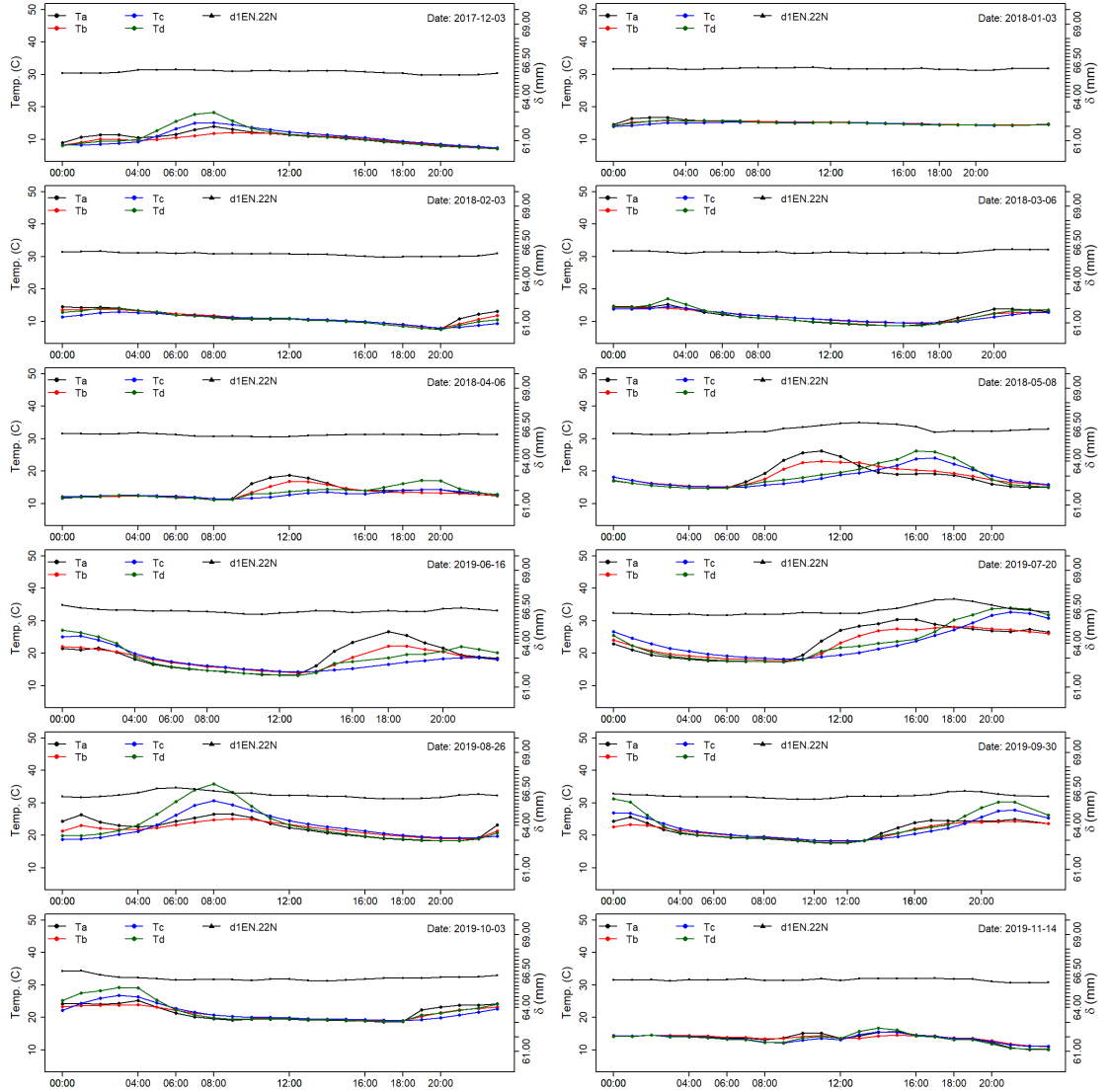


Figure 4.5: Example of daily measurements per month of a year. Temperatures at Section 0 (T) and displacement (δ) measured by sensor d1EN.22N at Section 22N.

4.5 Application and evaluation of the results

As referred before, temperatures and displacement measurements were chosen as the inputs and outputs to be analysed, respectively.

4.5.1 Application of the MLR approach

MLR models were developed considering the temperatures (T_a, T_b, T_c, T_d) as predictors or inputs and the six displacements ($\delta^{d1EN.22N}, \delta^{d1ES.22N}, \delta^{d3EN.22N}, \delta^{d3ES.22N}, \delta^{d3WN.22N}, \delta^{d3WS.22N}$) as

the predictions or outputs. The dataset was split into two disjoint sets for all the cases: a reference set, from March 2017 to May 2020, and a prediction set, from May 2020 to December 2020. For this study, the results corresponding to displacement $\delta^{d1EN.22N}$ will be presented as a reference for all cases.

The observed displacement measurements and the MLR results of $\delta^{d1EN.22N}$, considered to present the advantages of the proposed methodology in this study, are shown in Figure 4.6. However, it is possible to notice the missing data in both the training and prediction set.

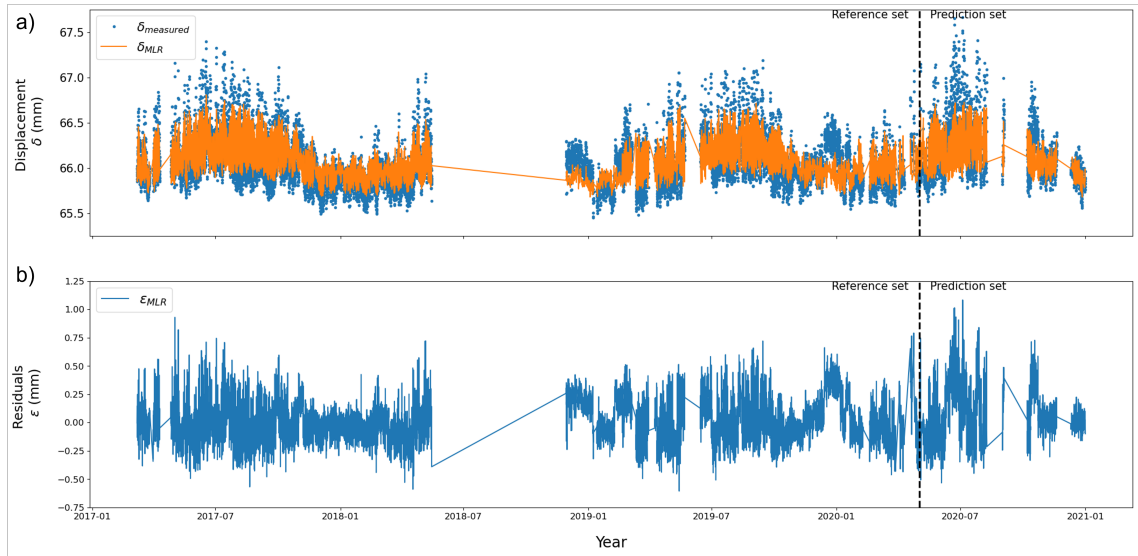


Figure 4.6: (a) Measured displacements ($\delta^{d1EN.22N}$) and MLR model estimate (δ_{MLR}). (b) MLR residuals (ϵ_{MLR}).

The difference between the observed data and the MLR results ($\delta - \delta_{MLR}$), called the residuals of the model, is then calculated and represented in Figure 4.6b. By the performance parameters (Table 4.2), it is possible to confirm that the model has a good performance. Regarding the residuals, all the values are close to zero, and no unusual behaviour is registered. Figure 4.7a shows in a cloud of points the measurements and the predicted displacement δ_{MLR} corresponding to displacement $\delta^{d1EN.22N}$.

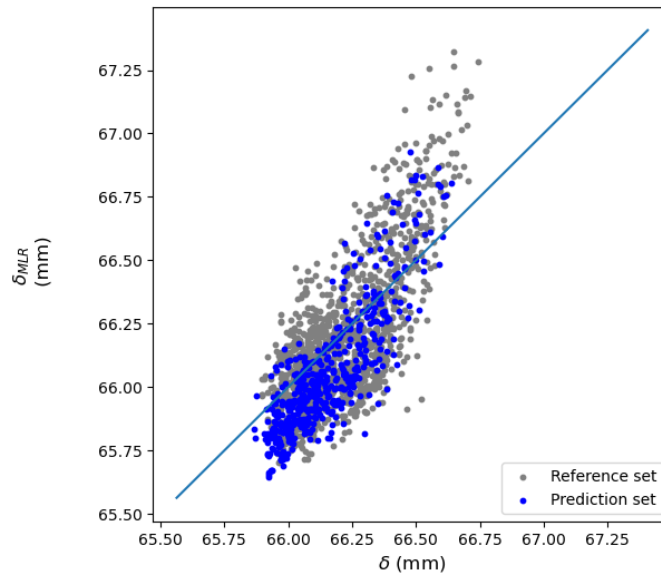


Figure 4.7: Predicted values δ_{MLR} versus measured displacements $\delta^{d1EN.22N}$ for the period March 2017 to December 2020.

Table 4.2: Performance parameters obtained from the MLR model to predict the displacements (δ) at the d1EN.22N, for the period between March 2017 to December 2020.

	MSE (mm^2)	MAE (mm)	SD (mm)
Reference set (March 2017 to May 2020)	0.033	0.138	0.118
Predicted set (May 2020 to December 2020)	0.038	0.141	0.137

4.5.2 Reducing uncertainty through deep learning

In this study, LSTM models were presented as a complement to overcome the limitations of MLR and improve the current approach. SHM data often present missing data due to the missing signals. Since the LSTM approach follows sequential learning based on long and short memory, missing data would be difficult to train properly due to the empty periods that do not provide the needed information to explain the time dependency of variables under analysis. Instead of using observed displacements to train the model, the information contained in the residuals of the MLR model was adopted instead. To overcome the limitation of empty data, two shorter periods with complete data were chosen to be analysed by the LSTM models. Periods of three months, one from the reference set (June 2017 to September 2017) and another from the prediction set (May 2020 to August 2020), were chosen to be explored (see Figure 4.8).

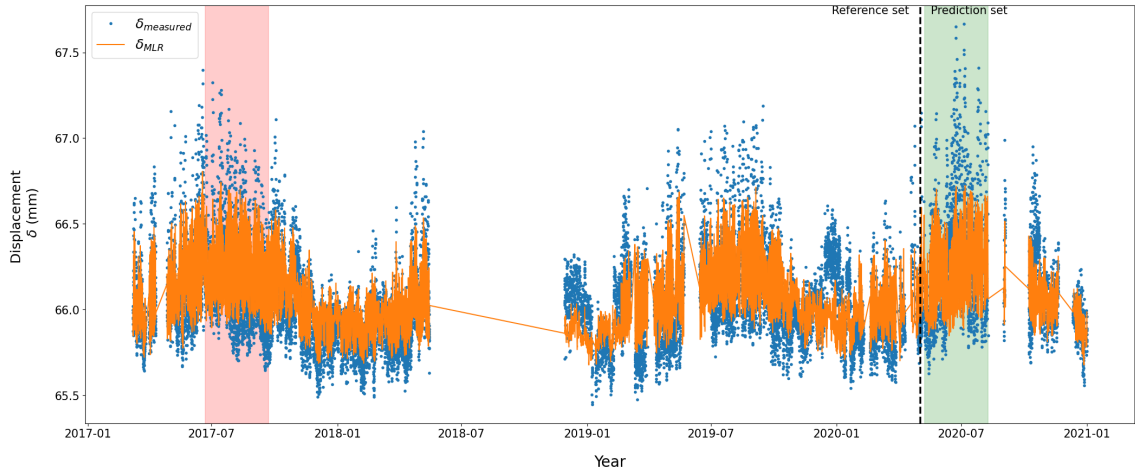


Figure 4.8: Portion selected from the reference set in red and in green the portion selected from the prediction set.

For each LSTM models, the dataset was split into training, validation and test sets. The hyperparameters (size of LSTM cell, number of time-steps of each input sequence, loss function, optimisation method and batch size) were chosen through the training set and the performance was confirmed with the validation set.

Accordingly, each model consisted of an LSTM cell of dimension 32. The training was carried out using the Python deep learning library Keras (Chollet et al., 2015) with Tensorflow (Abadi et al., 2015) as a back-end, a batch size of 4, 'Rmsprop' (Dauphin et al., 2015), as an optimiser and the Mean Squared Error (MSE) as a loss function. The models receive a sequence of 168 time-steps of the inputs (corresponding to 7 weeks of data).

Considering that the residuals ($\epsilon_{MLR}^{d1EN.22N}$) had the temperature effect already removed, for the LSTM model, the MLR residuals of the other displacements ($\epsilon_{MLR}^{d1ES.22N}$, $\epsilon_{MLR}^{d3EN.22N}$, $\epsilon_{MLR}^{d3ES.22N}$, $\epsilon_{MLR}^{d3WN.22N}$, $\epsilon_{MLR}^{d3WS.22N}$) in the study section were adopted as predictors of the model, and the residuals of the MLR model ($\epsilon_{MLR}^{d1EN.22N}$) applied at the referential displacement ($\delta^{d1EN.22N}$), was considered the outcome.

Figures 4.9 and 4.10 show the fit of the LSTM|MLR model with the residuals of the MLR model ($\delta - \delta_{MLR}$): a) for the chosen period of three months between June 2017 and September 2017, belonging to the training set of the MLR residuals, and in b) for the chosen period of three months between May 2020 and August 2020, belonging to the prediction set of the MLR residuals. Figure 4.10 shows the MLR residuals corresponding to the prediction set, and sudden spikes can be observed compared to the residuals belonging to the training set (Figure 4.9). However, in addition to those disturbances in the trend, all the values remain in the same range and close to

zero.

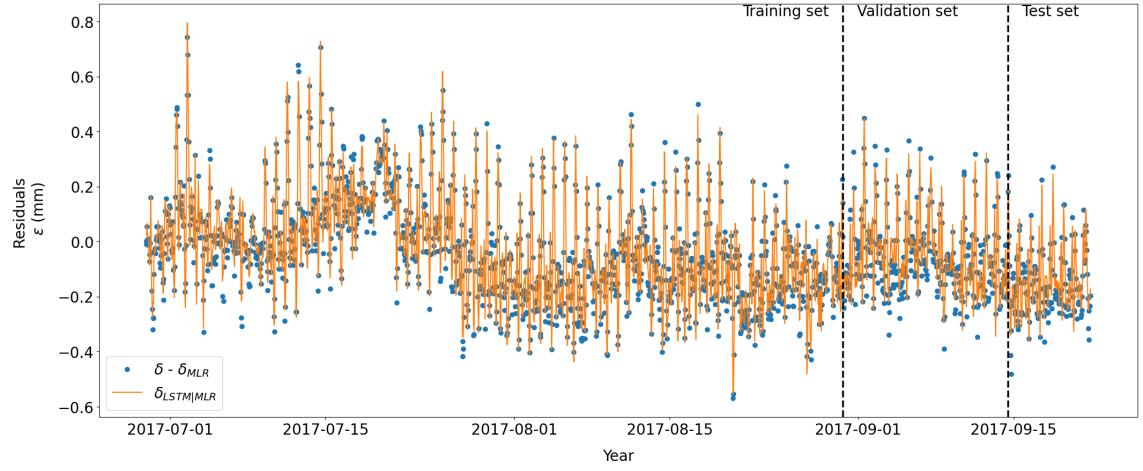


Figure 4.9: Differences between MLR residuals ($\delta - \delta_{MLR}$) and LSTM|MLR ($\delta_{LSTM|MLR}$) model fit from June 2017 to September 2017 (training set).

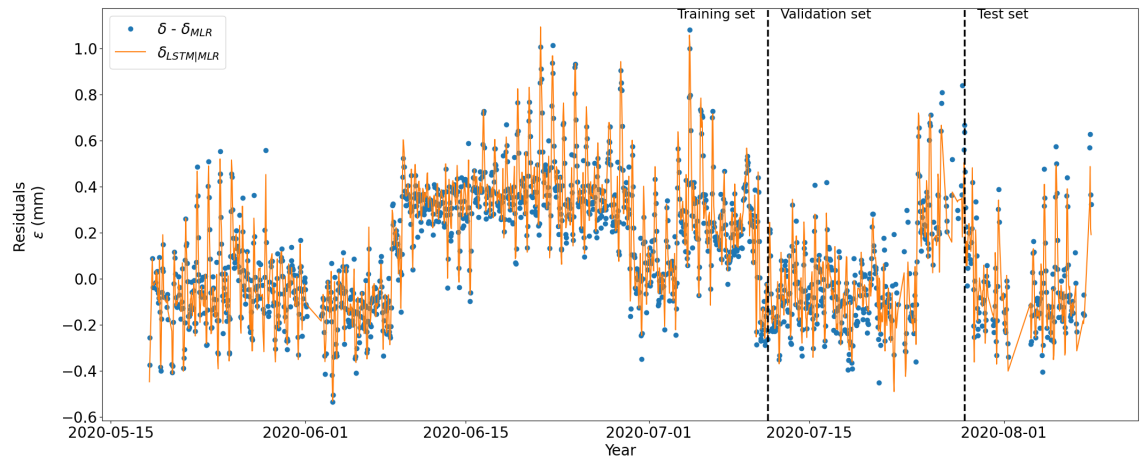


Figure 4.10: Differences between MLR residuals ($\delta - \delta_{MLR}$) and LSTM|MLR ($\delta_{LSTM|MLR}$) model fit from May 2020 to August 2020 (prediction set.)

It can be seen that the LSTM|MLR model can learn the pattern of the structural behaviour described by the residuals of the MLR model and provide, as the proposed methodology suggests Eq. (4.4), better predictions of the displacements, than using the baseline MLR model only Figure 4.11 shows the observed values against the predicted values of the MLR model and the MLR + LSTM|MLR. Comparing the results clearly shows that the MLR + LSTM|MLR model presents better results than the MLR model.

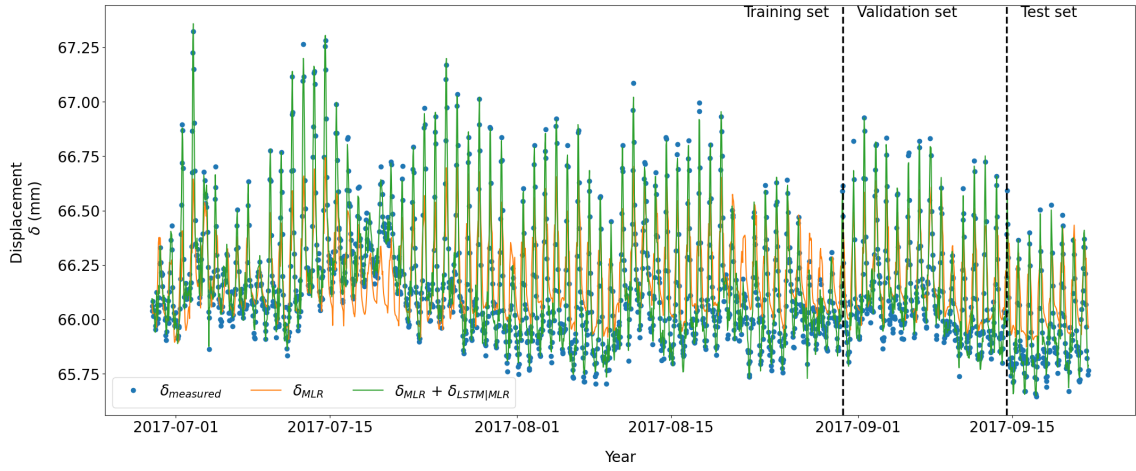


Figure 4.11: Measured displacements, MLR model predictions and MLR + LSTM|MLR model predictions for period (a) June 2017 to September 2017 (training set) and (b) May 2020 to August 2020 (prediction set).

To better understand the quality of the predictions obtained by the proposed approach, Figures 4.12 and 4.13 show the cloud of points between the measured displacements δ against the predicted values from the LSTM|MLR for both periods (training and predicted set of the MLR residuals). The improvement of the LSTM|MLR predicted values (see Figures 4.12, 4.13) for both periods is considerable when compared with the predictions of the MLR model (Figure 4.8), in which the cloud spreads far from the identity line.

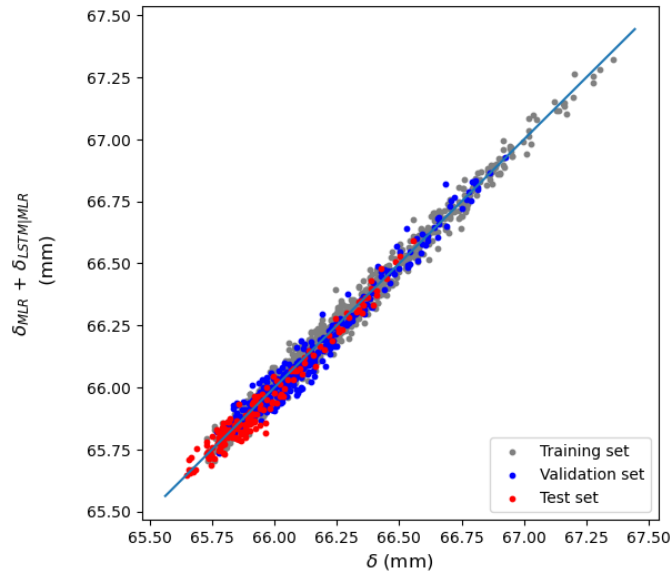


Figure 4.12: Predicted values $\delta_{MLR} + \delta_{LSTM|MLR}$ versus measured displacements δ for the period June 2017 to September 2017 (training set).

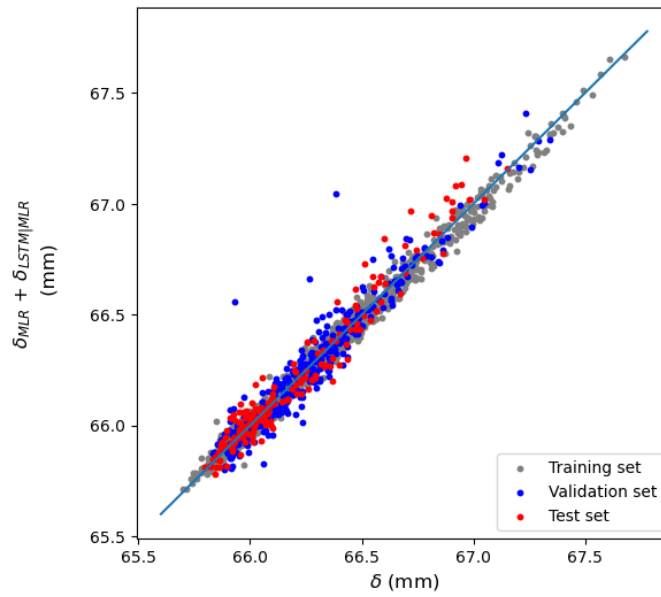


Figure 4.13: Predicted values $\delta_{MLR} + \delta_{LSTM|MLR}$ versus measured displacements δ for the period May 2020 to August 2020 (prediction set).

4.5.3 Performance comparison

Table 4.3 presents the results of the performance parameters MSE , MAE and SD for the training, validation and test datasets for the period between June 2017 to September 2017 corresponding to the training set of the MLR residuals. The last row of each section of the table shows the gain between the two models in the different error metrics.

Table 4.3: Performance parameters obtained from the MLR model and from the new MLR+*LSTM*|MLR model for the period between June 2017 to September 2017.

	Model	MSE (mm^2)	MAE (mm)	SD (mm)
Training set	δ_{MLR}	0.036	0.151	0.116
	$\delta_{MLR} + \delta_{LSTM MLR}$	0.001	0.03	0.02
	<i>Gain</i>	96.62%	81.60%	81.69%
Validation set	δ_{MLR}	0.022	0.123	0.086
	$\delta_{MLR} + \delta_{LSTM MLR}$	0.001	0.034	0.027
	<i>Gain</i>	91.43%	72.20%	67.93%
Test set	δ_{MLR}	0.038	0.175	0.090
	$\delta_{MLR} + \delta_{LSTM MLR}$	0.002	0.037	0.026
	<i>Gain</i>	94.58%	78.61%	70.77%

* All the values correspond to the displacement measured at $d1EN.22N$.

Table 4.4 presents the results of the performance parameters *MSE*, *MAE* and *SD* for the training, validation and test datasets for the period between May 2020 to August 2020 corresponding to the prediction set of the MLR residuals. The last row of the table shows the gain between the two models in the different error metrics.

Table 4.4: Performance parameters obtained from the MLR model and the new MLR+ *LSTM*|MLR model for the period between May 2020 to August 2020

	Model	MSE (mm^2)	MAE (mm)	SD (mm)
Training set	δ_{MLR}	0.094	0.249	0.178
	$\delta_{MLR} + \delta_{LSTM MLR}$	0.001	0.031	0.023
	<i>Gain</i>	98.35%	87.46%	86.59%
Validation set	δ_{MLR}	0.050	0.175	0.139
	$\delta_{MLR} + \delta_{LSTM MLR}$	0.008	0.062	0.066
	<i>Gain</i>	83.30%	64.25%	52.15%
Test set	δ_{MLR}	0.048	0.177	0.131
	$\delta_{MLR} + \delta_{LSTM MLR}$	0.005	0.054	0.049
	<i>Gain</i>	88.94%	69.42%	62.38%

* All the values correspond to the displacement measured at $d1EN.22N$.

As can be seen, the gain between the MLR model and the MLR + $LSTM|MLR$ is significant for each error metric in both evaluation periods. In the case of the evaluation period corresponding to the training set, the results of the MLR + $LSTM|MLR$ model shows a gain in every metric ranging from 67.93% (for the SD of validation set) to 96.62% (for the MSE of the training set). In the case of the evaluation period corresponding to the prediction set, the results of the MLR + $LSTM|MLR$ model shows a gain in every metric, ranging from 52.15% (for the SD of the validation set) to 98.35% (for the MSE of the training set). These results demonstrate the capacity of the proposed strategy to reduce the uncertainty contained in the MLR residuals corresponding to the actual monitoring strategy of the bridge by enhancing the performance of the predictions, as confirmed by the percentage of gain in each of the error metrics. Moreover, the proposed MLR+ $LSTM|MLR$ model can learn the pattern of residuals obtained from the MLR model by capturing the sequential time-dependency of the variables. The remaining error of the model corresponds to a more accurate explanation of the residual pattern focused on its sequential structure. Therefore, the obtained results confirm that the proposed strategy is better at capturing the non-linearities and long-term dependencies of the monitored data.

4.6 Concluding remarks

This study proposes a methodology that improves the actual strategy of interpretation of SHM data based on MLR models. Monitoring operational structures is particularly complex due to the influence of different external loads related to natural hazards and operational issues that can accelerate structural damage and compromise its safety. In addition, missing and incomplete datasets due to sensing system interruptions or signal reading complications are a common challenge in SHM.

The theoretical and computational simplicity of the MLR approach for interpreting the information gathered by the SHM system makes it the preferred strategy for the SHM analysis of many operational structures, such as bridges. However, MLR models present limitations since they cannot explain the inherent non-linearity and time dependency of the variables in the system. The proposed methodology overcomes those limitations and enhances the predictive capacity of the strategy, ultimately leading to better and more reliable decision-making processes that can ensure the structural safety of the monitored structures.

The proposed methodology showed the capacity of the LSTM model to reduce the uncertainty contained in the results of the MLR model by capturing the sequential structure still present in the residuals of the MLR model. By combining both methods, the sensitivity to early novelty detection

increases since it describes more accurately any change or error not registered by the MLR model, considering the time-dependency of the variables. The unexplained pattern obtained from the MLR model was used to train the LSTM model taking advantage of the knowledge generated by the MLR model. The LSTM model explained that pattern, considering the sequential structure of the residuals and, given the results that were obtained, reduced the uncertainty present in the first step of the analysis. Based on those results, it is possible to see the benefit of the deep learning model for complementing the current approach of SHM analysis, namely to improve the accuracy for the novelty detection and interpretation of structural bridge behaviour.

The added value of the proposed strategy focuses on complementing the MLR based methodology to overcome its limitations. It is essential to highlight that the dataset used for this study comes from an operational structure with continuous and autonomous monitoring. Therefore, the available dataset is not ideal and presents missing values in the sequence, which can affect the data-driven methods. Still, the improved results after the application of the proposed methodology showed that the complementary approach of the LSTM model on the analysis is able to deal with imperfect datasets by taking advantage of the information generated by the MLR model and the ability to explain the sequential structure of the residuals considering the time dependencies and non-linearity of the variables.

When pattern recognition is performed during a period that corresponds to a situation where the structure behaved normally, it is possible to identify behaviour patterns that are different from the expected ones (if they exist). In the context of SHM, one can identify as a novelty or a case of damage a given measurement vector from the structure or system of interest representing a different behaviour. The improved results obtained in the present study promise to motivate detailed exploitation of this approach, namely using different target predictions or additional inputs, and considering a more extended period of observation, to create better predictive models capable of enhancing early damage detection in civil operational structures.

Chapter 5

Integrating supervised and unsupervised learning to improve novelty detection thresholds in structural health monitoring

This chapter covers the threshold definition for novelty identification, addressing one of the dissertation's four focus topics (see Figure 5.1). In this chapter, a concrete dam is selected as the representative structural system for demonstrating the proposed methodology for threshold definition, developed within the framework of both supervised and unsupervised learning approaches.

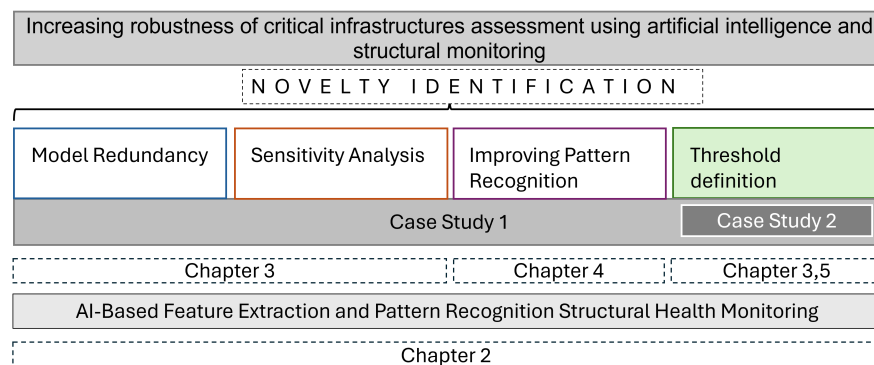


Figure 5.1: Flowchart of the dissertation's structure with the one topics addressed in the present chapter in color.

Dam surveillance activities are based on the observation of the structural behaviour and the

interpretation of the past behaviour supported by the knowledge of the main loads. For day-to-day activities, data-driven models are usually adopted. Most of the applications are related to the adoption of regression models for the analysis of horizontal displacements recorded in pendulums. In recent years, new approaches based on machine learning methods, such as artificial neural networks, have been used. The traditional regression models assume that the effects of the inputs (mainly related to the hydrostatic pressure and temperature changes) can be studied separately. This principle is well accepted in the analysis of horizontal displacements. However, for the analysis of the relative movements between blocks, this assumption may not be valid because it depends on the stress state in the dam body.

Multilayer Perceptron (MLP) models can be adequate to predict the relative movement between blocks once they can represent the non-linearities related to simultaneous hydrostatic and thermal effects. In this chapter, a MLP model is developed for the interpretation of the relative movements between blocks observed in a concrete dam in operation. Methodologies for the threshold definition related to novelty identification are proposed, to take into account the evolution of the records over time and to take advantage of the simultaneous measurements of several quantities that represent the structural response.

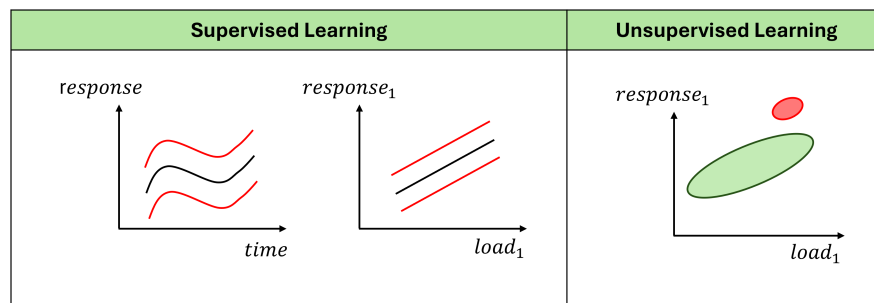


Figure 5.2: Illustration of threshold definition methodologies: regression-based approach (left) and clustering-based approach (right).

5.1 Context and motivation

Structural monitoring involves observing a phenomenon or event and its impact on the structure. The purpose of the analysis and interpretation of the measurements gathered during an inspection is to enhance the conceptual understanding of the dam's behaviour and aims to define, based on better parameters, eventual models. Once a model is built, the dam's condition assessment is based on test hypotheses and scenario simulations supported by the monitoring data and the prediction

of the structural behaviour across space and time. The procedure of providing information for assessing the dam's structural condition is a form of critical analysis capable of reducing the intrinsic uncertainty related to the dam's behaviour.

The assessment of the dam's condition based on the information provided by the monitoring system is possible if the information is updated. Any abnormal behaviour can be readily identified, allowing for the implementation of an appropriate intervention or prevention measures. The assessment of the structural behaviour of the dam and its condition must be performed for each dam independently, even for dams of the same type, since they are influenced by several aspects, such as the heterogeneities in the dam's foundation and the surrounding areas of the dam or the different loads (as a consequence of environmental or operational conditions) that the structure is exposed to. For each concrete dam, different models can be used according to each purpose, to the existing knowledge about the actual structural behaviour, and the quality of information available for the characterization of the structure's behaviour. The selection of the conceptual model to be used for dam surveillance activities must take into account: (i) the purpose of the analysis (safety assessment, prediction of deformations, interpretation of the recorded data from the monitoring system, or analysis of an accident or abnormal behaviour), (ii) the identification of the key factors of the physical problem, and (iii) the available geological and geotechnical information.

During a dam's life, the performance and safety conditions are under continuous assessment due to the potential failure scenarios identified during the design phase and due to the other scenarios "suggested" by the observed behaviour through the analysis of relevant parameters (such as water level and temperature variations, among other things), as seen in Figure 5.3. Typically, these parameters will describe the loads or operating conditions to which the system is subjected, the materials of the structure, the materials of the structure's foundations, and the structural response of the dam (ICOLD, 2009). Thus, visual inspections and measurements collected by the structural monitoring system are fundamental for safety control activities. The main physical quantities measured through the monitoring system are seepage and leakage, uplift pressure, horizontal displacements, vertical displacements, relative displacements between blocks (contraction joint movements), and relative displacements in the rock mass foundation. The interpretation of the observed values is usually based on knowledge related to the physical and chemical phenomena that govern the structure and, whenever possible, is based on deterministic or data-based models. For decision-making, deterministic models are preferred, while in day-to-day activities, data-based models are the most commonly used.

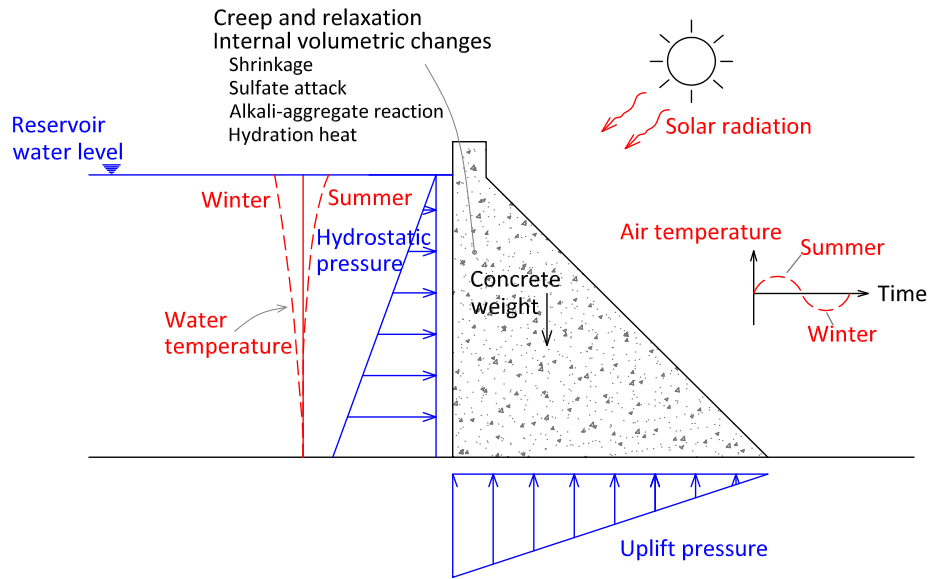


Figure 5.3: Some of the parameters analysed for the assessment of dam safety and performance.

The most common approaches for data-based models are the HST (hydrostatic, seasonal, time) and the HTT (hydrostatic, thermal, time) models, in which the effects of hydrostatic pressure, temperature, and time are considered as additive effects, and their separation is valid (ICOLD, 2003; Lombardi, 2004; Léger and Leclerc, 2007; ICOLD, 2009; Mata, 2011). The hydrostatic pressure is usually considered as a polynomial function of the water height. However, in addition to the pressure from the water, dams in cold regions may be exposed to loads from an ice sheet (Hellgren et al., 2022). The time effect is represented by polynomial functions or by functions of another type (exponential or s-shaped). The thermal effect is considered differently in each approach. In the HST approach, the temperature effect is represented by sinusoidal functions with a one-year period, which are a function of the day of the year only. In the HTT approach, the temperature effect is a function of the measured temperatures. A large number of publications about HST and HTT models can be consulted in the literature (ICOLD, 2003; Lombardi, 2004; Léger and Leclerc, 2007; ICOLD, 2009; Mata, 2011; Hellgren et al., 2022; Simon et al., 2013; Mata et al., 2013; Ranković et al., 2014; Salazar et al., 2015, 2017; de Granrut et al., 2019; Li and Wang, 2019; Rico et al., 2019b; Mata et al., 2021; Nogara and Bolzon, 2023; Bolzon et al., 2025).

MLR is one of the most commonly used data-based models (ICOLD, 2003), showing good performance, mainly for case studies related to the prediction of horizontal and vertical displacements observed on a dam body. On the other hand, new models based on machine learning have been studied and published for about a decade with positive results; these are proposed mainly for

the analysis of displacements. Proposed machine learning models could differ in their approach and advantages; such is the case of NN models, which principally allow the identification of non-linear relationships between the input quantities, if any. One main aspect to take into account in the case of NN models is that suitable generalization criteria, such as cross-validation criteria, must be adopted to avoid overfitting (Mata, 2011).

There are quantities, such as seepage, uplift pressure, and relative movements between blocks, in which regression models could be used with special care since the separation of effects may not be valid. The variation observed differs for "open" or "closed" joints. Joint opening and closure are governed by normal stress criteria. The non-linear behaviour presented by the contraction joints can be explained by the non-resistance of the contraction joints to tension. As referred to by Hariri and Kianoush (Hariri-Ardebili and Kianoush, 2014), modelling the joints (contraction, peripheral and lift joints) has an important role in both the static and the seismic analysis of concrete arch dams (Hariri-Ardebili and Kianoush, 2014). Some authors developed a non-linear joint element to represent the behaviour of vertical contraction joints in concrete dams (Hariri-Ardebili and Kianoush, 2014; Ahmadi et al., 2001; Azmi and Paultre, 2002; Du and Tu, 2007; Wang et al., 2012; Hariri-Ardebili et al., 2013). The current knowledge in the field of machine learning allows the proper interpretation and prediction of these quantities, including anomaly detection (Hellgren et al., 2021; Salazar et al., 2021), and this knowledge that is expected to grow in the following years.

The definition of thresholds for novelty identification related to movements in contraction joints is a natural step in the safety control activities of dams. For the identification of damage or gross measurement errors, the limits can be based on deterministic models or even on the maximum values observed in the dam life history affected by a multiplicative factor. However, in the past, identifying novelties earlier could be based on narrower limits resulting from data-based models. Nowadays, the definition of thresholds has been mainly based on considering a multiplicative factor associated with the standard deviation of residuals (the part not explained by the model that is adopted). This analysis allows the point-to-point identification of values that exceed established limits without any temporal or multidimensional context. Thus, two methodologies for threshold definition are presented in this work. One complementary to the traditional approach that can be used for the identification of novelties in a temporal context through the consideration of moving averages and the moving standard deviation of the residuals, and the other considers, in a multidimensional context, through the use of the density-based spatial clustering of applications

with noise (DBSCAN) method (Ester et al., 1996).

5.2 Proposed methodology

The priority for any threshold definition process is an adequate model with a proper approach. The HTT approach was chosen in this study because of the daily variation observed in the quantity under study (relative movement between blocks), when temperature values from thermometers with daily variation records are taken into account, HTT approach is more accurate compared with the HST approach, since the stationary sinusoidal function do not describe well the daily variations of air temperature. Enough information was obtained from the dam body's thermometer and water level measurement devices. Regarding the machine learning method that was adopted, the authors selected the MLP method. The methodology for the definitions of thresholds based on the residuals of the data-based models developed from the past history of the records (relative movements between blocks in the case study) is detailed ahead:

- The adoption of the HTT formulation for the development of the prediction model requires the selection of the main physical quantities to be used. The water height and the concrete dam body temperature variations are the selected main inputs in the proposed model.
- The separation of effects in the analysis of the relative movements between blocks may not be verified, so a model capable of mapping the interaction between the inputs is recommended. In this sense, an MLP model was found to be suitable. Once the MLP model is obtained, the influence of the main loads on the responses, as well as the analysis of the residuals, r , can be analysed.
- The definition of thresholds for novelty identification based on the residuals can be defined according to three possible approaches: (i) based on one record at a time, (ii) based on a time window of records, (iii) and based on the simultaneity of the responses measured, as shown in the following.
- A threshold definition based on one record at a time is the most used type of threshold in dam engineering and consists of the adoption of a multiplier n applied to the standard deviation of the residuals, $sd.r$, as follows: $n \times sd.r$. Values of n equal to 3 and 4 correspond to a confidence level of 99.73 % and 99.99 %, respectively, since residuals are assumed to follow a Gaussian distribution.

- A threshold definition based on a time window of records of one physical quantity is based on the moving average of the residuals, $m.a.r.$, and the moving standard deviation of the residuals, $m.sd.r.$, adopting a time window of records over time. The size of the time window may depend on the case under study.
- A threshold definition based on the measurement of simultaneous responses measured allows the identification of novelties related to a cluster of data (with m features) related to the m quantities considered in the analysis. *DBSCAN* is a method suitable for this approach, in which it is necessary to adopt, as an initial step, suitable values for the Epsilon distance, ϵ and the MinPoints, $MinP$. Hence, the residuals related to several physical quantities $(r^1, \dots, r^m)$, with m being the number of features measured simultaneously, are assessed to define clusters of the ones that present a behaviour far from that of the remaining data.

The proposed flowchart for the interpretation of the relative movements between blocks and for the operational threshold definition is presented in Figure 5.4.

The theoretical background related to the MLP algorithm, the moving average, the moving standard deviation of the residuals, and the *DBSCAN* method are presented in the following sub-sections.

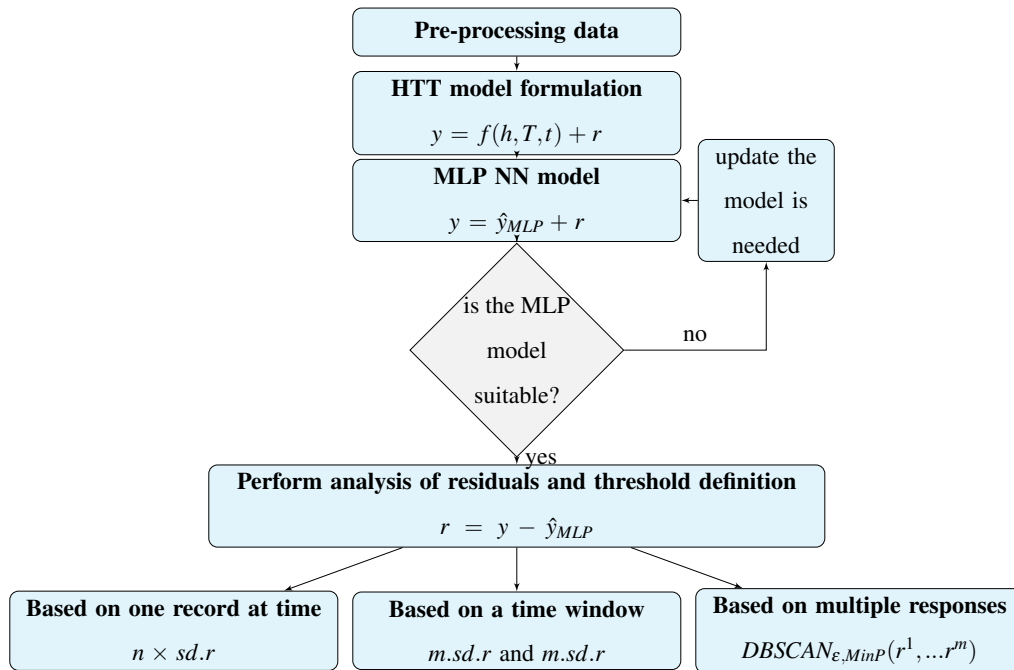


Figure 5.4: Proposed flowchart for the definition of thresholds for novelty identification.

5.2.1 Multilayer perceptron neural network algorithm

NN models have caught the attention of the scientific community since the 1990s (Housner et al., 1997) due to their ability to learn the pattern of structural behaviour in large infrastructures with a good capacity for generalization (Mata, 2011; Mata et al., 2021; Shokri and Tavakoli, 2019; Fallahian et al., 2018; Aggarwal, 2018; Sun et al., 2020b; Salehi and Burgueño, 2018; Liu et al., 2018b). A NN computes a function of the inputs by propagating the computed values from the input neurons to the output neurons using different weights as an intermediate parameter (Aggarwal, 2018). A MLP is a feed-forward algorithm with neurons arranged in layers. It is the most widely used model for cognitive tasks such as pattern recognition and function approximation (Mata, 2011). The specific architecture of feed-forward networks assumes that all nodes in one layer are connected to those of the next layer. The input layer transmits the data to the output layer going through a set of hidden layers that perform computations that include refining the weights between neurons over many input-output pairs to provide more accurate predictions.

The MLP learns by an iterative weight adjustment process that enables the correct learning using the training data so that, in a testing phase, it predicts the unknown data. Those weights w are located in each connection between the input layer x with N neurons and the hidden layer l with Q . The first layer receives the inputs, and the last layer produces the outputs. The middle layer is called the hidden layer. Within it, the information is constantly feed-forwarded from one layer to the next one having two associated values: the input value and the weight. In mathematics and programming, weights are shown in a matrix format W , where the number of columns contains the input dimensions (input values and weights), and the number of rows contains the output dimensions (hidden layer neurons Q). Another weight associated with the network is the bias b . Bias is attached to every layer in the network except for the input layer and carries neurons that try to account for unforeseen or non-observable factors. Activation functions are applied to each of the neurons in the hidden layer. The activation function will map the linear combinations of the inputs and weights to the following layer, in the case presented in Figure 5.5 from the input layer to the hidden layer and, in a further step, to the output layer of network L .

For regression problems, such as those found in the framework of SHM, the activation functions must be differentiable so that any non-linear models built from them can be derived with respect to their weights (Bishop, 1995). In this case, the activation function from the input layer to the hidden layer f can be the logistic sigmoid or the hyperbolic tangent function. The activation function from the hidden layer to the output layer g is a linear function.

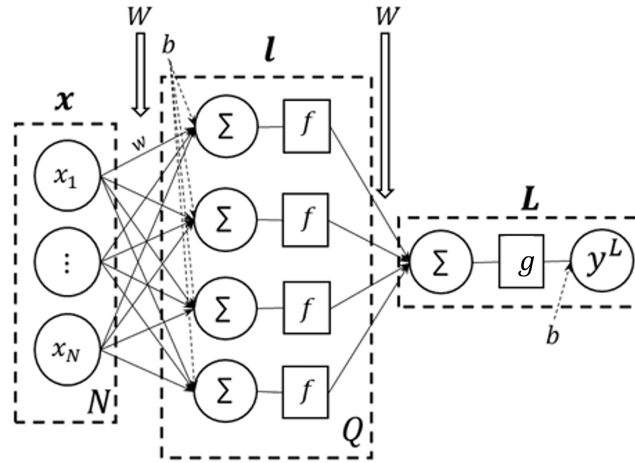


Figure 5.5: MLP architecture where x represents the input layer, l represents the hidden layer, L represents the output layer, b represents the bias and w represents the weights. Adapted from (Mata, 2011).

5.2.2 Time-window threshold definition based on the moving average and moving standard deviation of the residuals

The detection of any deviation not identified by the prediction model between the observed and predicted data, is one of the main objectives of the residual analysis. A moving average control chart of the residuals ($m.a.r.$) is a type of memory control chart based on an unweighted moving average, and it is defined as

$$m.a.r._i = \frac{m.sum.r._i}{w} = \frac{\sum_{j=i-w+1}^i r_j}{w}, i \geq w \quad (5.1)$$

where w is the width of the moving average at time i .

In order to describe the dispersion of residuals, the $m.sd.r.$ is also presented in order to know how much the residuals vary or how spread they are along time, being defined as

$$m.sd.r._i = \sqrt{\frac{1}{w-1} \sum_{j=i-w+1}^i (x_j - \bar{x}_{jtoi})^2} \quad (5.2)$$

For these periods, the average of all observations within a time window of w size up to time i defines the moving average. Four different $m.a.r.$, related to 6, 12, 24, and 168 records, correspondent to a quarter, a half, an entire day, and a week, are potential options to be considered in this

type of study. However, only the results of a *m.a.r.* and *m.sd.r.* with a time window of one day and a time step of one hour are presented in this work.

Once the *m.a.r.* and the *m.sd.r.* are established, the definition of a baseline of the structural behaviour under normal conditions is possible. The *m.a.r.*, in this sense, allows the identification of extreme values and trends along a time period. The *m.sd.r.* allows the identification of any increment of variability and/or randomness along the same time period. Those changes might suggest novelty.

5.2.3 Multivariate threshold definition based on DBSCAN algorithm

Density-based spatial clustering of applications with noise is a clustering algorithm proposed by Ester et al., 1996 (Ester et al., 1996). It searches for “core objects”, points that contain a minimum of observations (MinPoints) within its neighbourhood (defined by an epsilon radius), including the core point itself. If a point is found outside of any of the core object’s neighborhood, it is considered noise (Han et al., 2011). Border points are points within reach of a core object without the minimum points in their neighbourhood to be considered core objects themselves (Figure 5.6). DBSCAN is known to be able to discover clusters with shapes other than linear and be robust enough to handle outliers and noise.

The clusters are created as follows: after uncovering a core object (i.e., a point with a high density of neighbours according to the parameters), DBSCAN starts a cluster with it and all its neighbours. All points within the Epsilon distance of the neighbours are then added to the cluster. This process continues until there are no more points within the distance. All the points that do not belong to a neighbourhood (i.e., to a cluster) are considered noise or outliers.

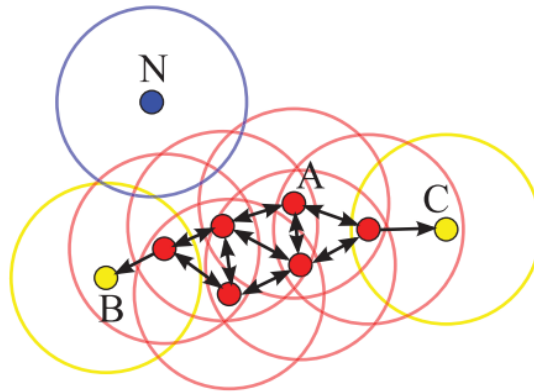


Figure 5.6: DBSCAN illustration with MinPoints = 4 and epsilon distance represented by circles. Core points, such as A, are represented in red, B and C, in yellow, are border points, and N is a noise point, represented in blue. From (Schubert et al., 2017).

5.3 Case study: The Feiticeiro dam

The hydroelectric development of Baixo Sabor is composed of two schemes. The upstream scheme (termed the Baixo Sabor dam) is 12.6 km away from the Sabor river mouth. The downstream scheme (termed the Feiticeiro dam, Figure 5.7 is about 3.3 km far from the mouth of the Sabor river (Cunha and Vieira Soares, 2012). The Feiticeiro dam comprises a concrete gravity dam with an overflow-controlled spillway and a downstream stilling basin. The dam is 45 m high and has a crest length of 315 m, which is divided into twenty-two blocks. The total concrete volume is equal to 130,000 m³.



Figure 5.7: Overall view of the Feiticeiro dam.

In accordance with the best technical practices, the monitoring system of the Feiticeiro dam aims at the evaluation of the loads, the characterisation of the rheological, thermal and hydraulic properties of the materials, and the evaluation of the dam's structural response. The monitoring system of the Feiticeiro dam consists of several devices that make it possible to measure quantities such as the concrete and air temperatures, reservoir water level, seepage and leakage, displacements in the dam and in its foundation, joint movements, strains and stresses in the concrete, and pressures, among others (LNEC, 2013b,a, 2020).

The system used for the measurement of the reservoir water level comprised a high-precision pressure meter, which provides a record of the water height over time, and a level scale. The air temperature and humidity were measured in an automated weather station placed on the right-side bank approximately 100 m apart from the dam crest.

The concrete temperature was measured by 76 electrical resistance thermometers distributed across a dam thickness of several blocks. The location of the thermometers was defined taking into account the set of other electrical resistance devices (strain gauges, embedded jointmeters and strain gauges) that also allowed for the measurement of the concrete's temperature.

Displacements were measured using an integrated system that included 3 pendulums, 8 rod extensometers, and geodetic observations. The relative movements between blocks were measured by superficial and embedded jointmeters.

The deformation of the concrete was measured with electrical strain gauges arranged in groups and distributed in radial sections, allowing the determination of the stress state through the knowledge of the deformation state and of the deformation law of the concrete. The quantities of drained and infiltrated water were measured individually in drains of the drainage system installed in the dam foundation and in weirs that differentiated the total quantity of water that flows in the drainage gallery in several zones of the dam. The drainage system comprised a set of 57 drains distributed over the drainage gallery with 3 drains per block. All the water extracted from drains and leakages was collected in 4 weirs.

The measurement of the uplift pressure at the foundation was performed by a piezometric network that comprised 26 piezometers. A real-time data acquisition system for the auscultation instrumentation (ADAS) was installed at Feiticeiro dam, allowing the measurement of the following physical quantities (Cunha et al., 2017):

- Horizontal movements based on the pendulum method through the use of optical telecoordinometers (4–20 mA signal);

- Vertical movements through rod strain meters with a position transducer of the vibrating wire type;
- Discharges through level gauges with ultrasonic sensors (4–20 mA signal);
- Pressures through piezometers with pressure transducers of the vibrating wire type;
- Relative movements between blocks through 3D jointmeters with a position transducer of the vibrating wire type, located in the inspection galleries;
- Relative movements between blocks through 1D jointmeters with a resistance transducer of the Carlson type, embedded in the concrete dam body;
- Concrete strain through strain meters with resistance strain meter transducers of the Carlson type, embedded in the concrete dam body;
- Concrete temperature through thermometers with resistance thermometer transducers of the Carlson type.

The responses under study are variations of the relative movements between blocks (at the higher level) measured by 7 automated jointmeters. The water level and the concrete temperature are measured by several thermometers located in the dam body, and they represent the main environmental loads studied in this case.

The mathematical calculations and the graphic representations presented ahead were supported by the R project software (Team, 2021; Posit team, 2019; Venables and Ripley, 2002b; Peters et al., 2002).

In this case study, the daily variation of the opening-closing movements between blocks measured at the 134.2 m level and through 3D jointmeters were analysed (jointmeter designed by BT3, BT5, BT7, BT8, BT10, BT12, and BT13).

The location of the jointmeter part of the automated monitoring system is shown in Figure 5.8. The data analysed correspond to a period between April 2017 and June 2022, with more than 38,660 records per variable. Measurements from the automated monitoring system are taken every hour. In the case of gaps in records, the values were estimated by interpolation between consecutive records.

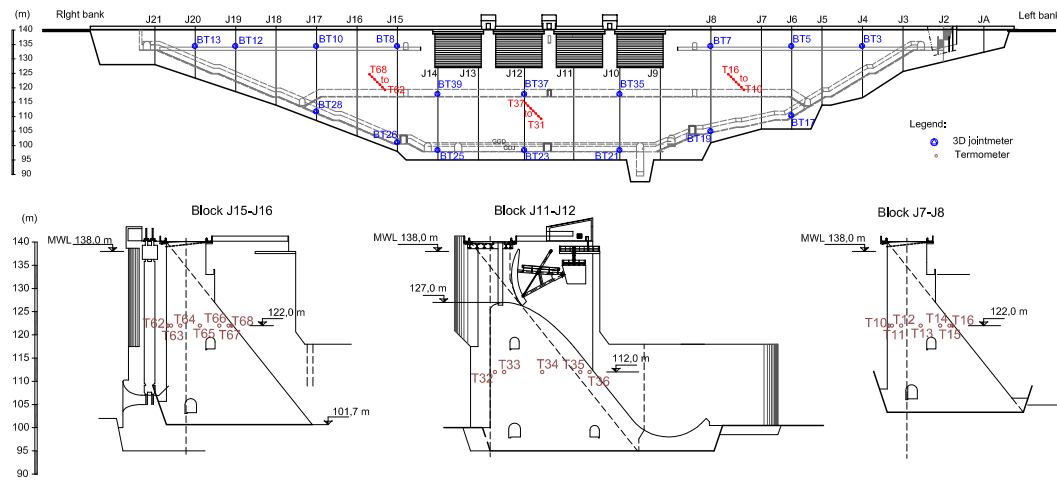


Figure 5.8: Feiticeiro dam—thermometers and 3D jointmeters included in the automated monitoring system. (MWL—Maximum reservoir water level).

The samples regarding the relative movements between blocks were collected every two weeks for manual measurements and every hour for automated measurements, as seen in Figure 5.9. A value raise indicate opening movements, and a decrease indicate closing movements.

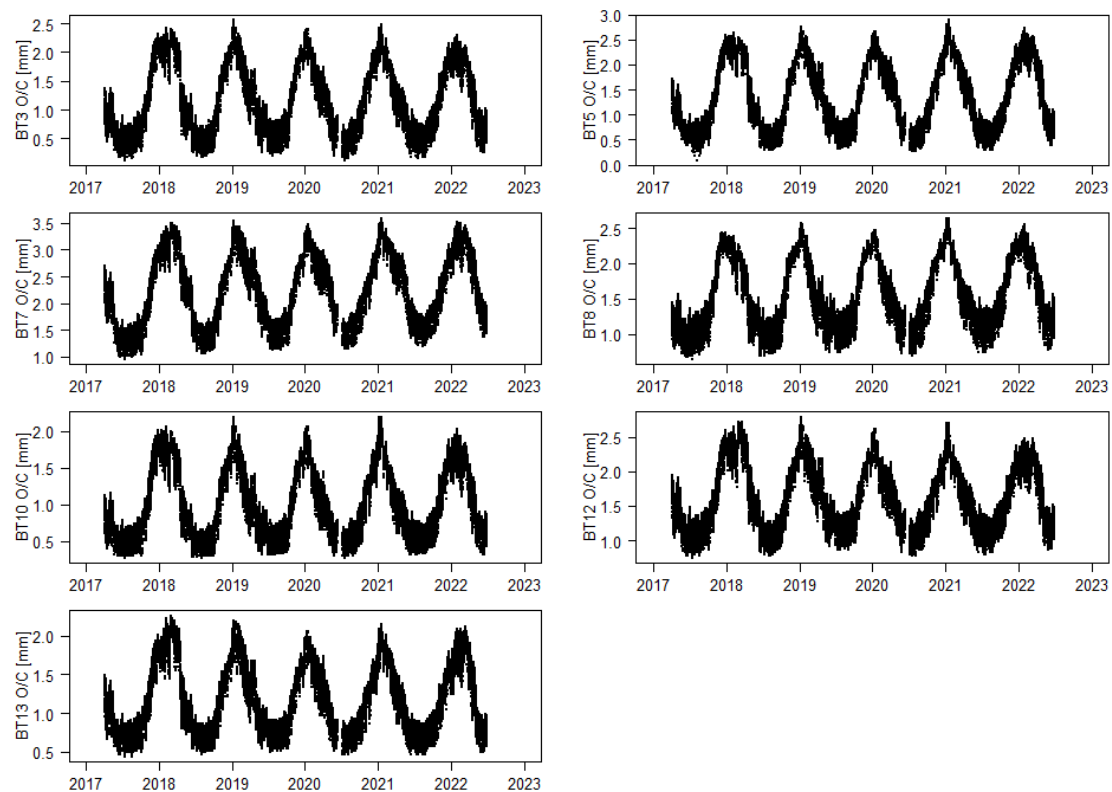


Figure 5.9: Time series of the relative movements between blocks measured between April 2017 and June 2022.

Once the measuring devices to be studied in this work were installed in the downstream face of the dam body (a visiting gallery at the level of 134 m is non existent), they measured the relative movements between blocks in a zone that is strongly influenced by the daily variations of the temperatures, as shown in Figure 5.10, regarding the measurements between the 1st and the 8th of August 2018.

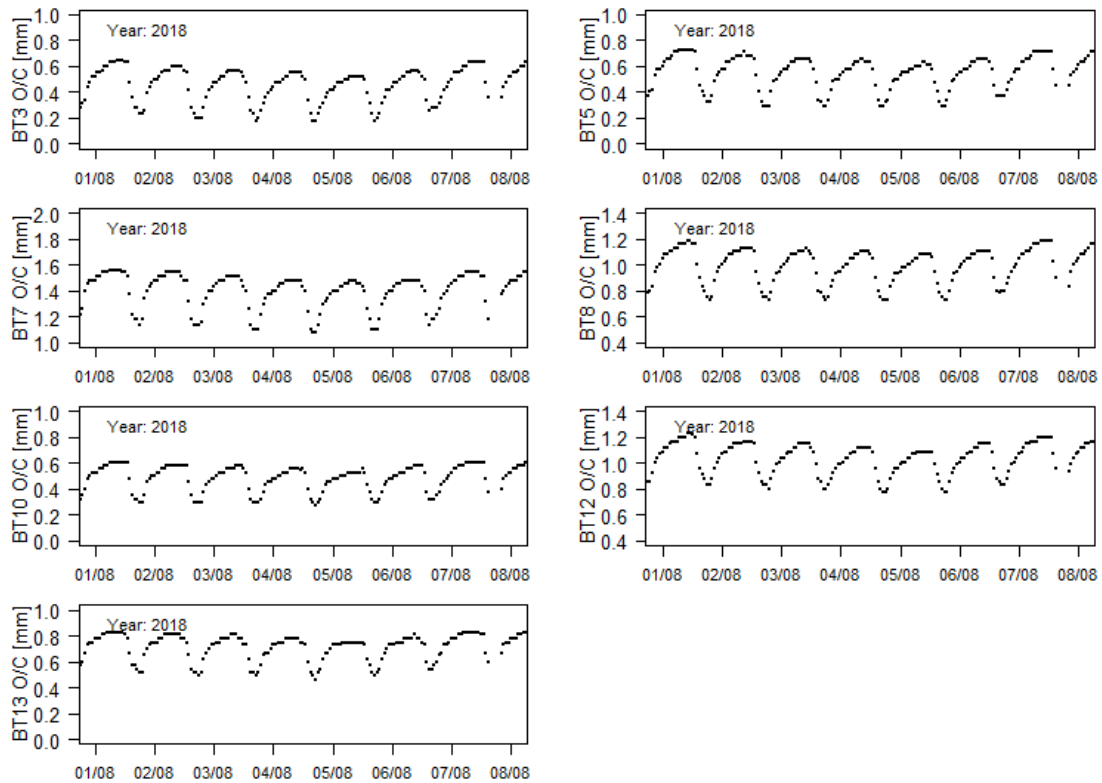


Figure 5.10: Time series of the relative movements between blocks measured between the 1st and the 8th of August 2018.

Among the different loads acting on concrete dams, it is typical to distinguish, as the most important loads for structures in normal operations, the hydrostatic pressure and the temperature variation. The time evolution of the reservoir water level is presented in Figure 5.11.

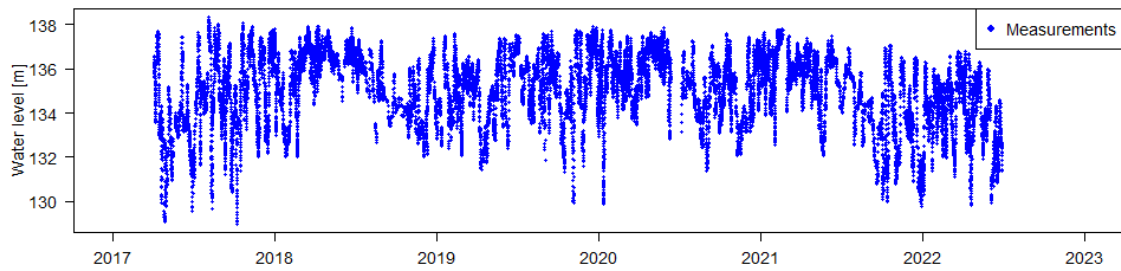


Figure 5.11: Time series of the reservoir water level measurements between April 2017 and June 2022.

The temperature variations observed in the dam body were recorded through thermometers embedded in the dam body (blocks J7–J8, J11–J12, and J15–J16). The relative position of the thermometers are presented in Figure 5.8 and Table 5.1, and their records are those shown in Figure 5.12.

Table 5.1: Relative location of the thermometers in the dam body.

Thermometer	Block	Level (m)	Position
T10	J7–J8	122.1	u.f.
T11	J7–J8	122.1	1 m u.f.
T15	J7–J8	122.1	1 m d.f.
T16	J7–J8	122.1	d.f.
T31	J11–J12	112.0	u.f.
T32	J11–J12	112.0	1 m u.f.
T33	J11–J12	112.0	oth
T35	J11–J12	112.0	oth
T62	J15–J16	122.1	u.f.
T64	J15–J16	122.2	oth
T65	J15–J16	122.1	1/2 th.
T66	J15–J16	122.2	oth

Legend: u.f.—upstream face, d.f.—downstream face,
oth—other, th—thickness.

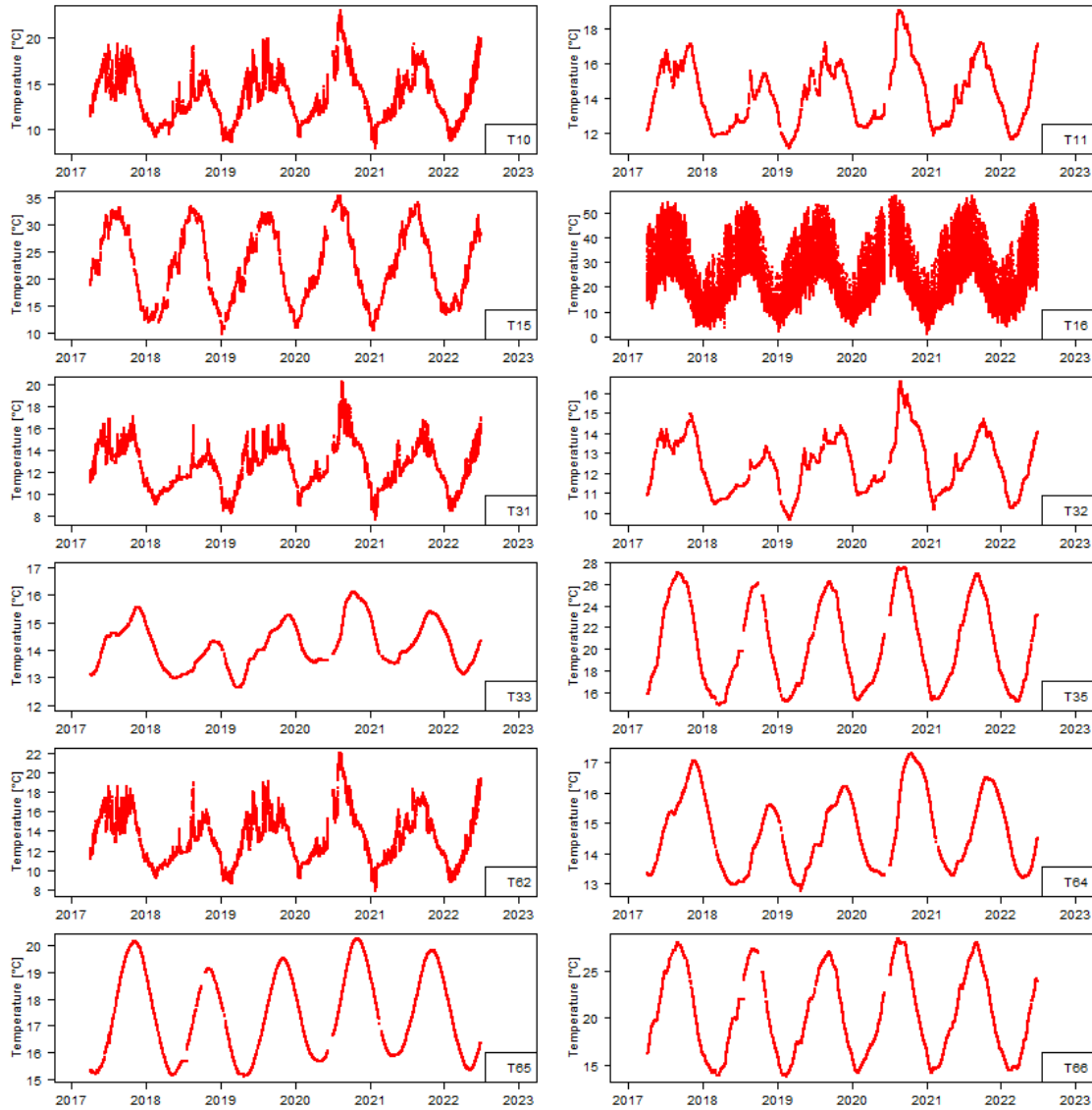


Figure 5.12: Temperatures in the dam body recorded between April 2017 and June 2022.

The observations presented in Figures 5.9–5.12 will be used for the computation of the models presented in this work.

Based on the evolution of the time series of the joint movements, water level, and temperature variations, it is expected that the thermal effect is more significant when compared with the water level effect. Figure 5.13 presents an example of the temperature and the water height in the structural response for the case study. Figure 5.13 (top) shows the evolution of opening-closing movement measures in the jointmeter BT3 vs. the temperature measures in the thermometer T37. As expected, the movement between the blocks is in the closing direction when the temperature increases. Figure 5.13 (bottom) shows the evolution of the opening-closing movement measures

in the jointmeter BT3 and the water height when the temperature measured in the thermometer T37 is 10 °C. The opening movement increases slightly with an increase in the water height.

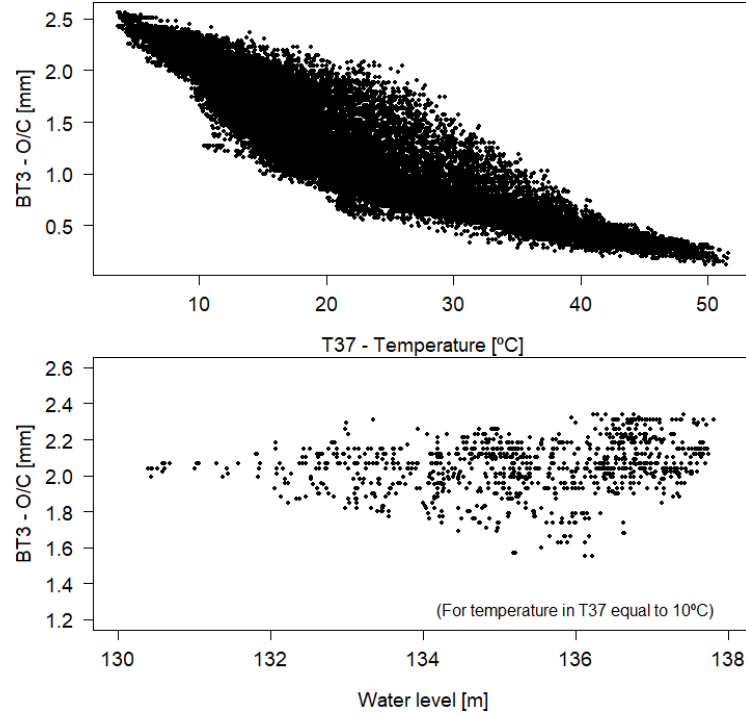


Figure 5.13: Opening-closing mov. measured in BT3 vs. temperature measured in T37 (top). Opening-closing mov. measured in BT3 vs. water level for temperature measured in T37 equal to 10 °C (bottom).

5.4 Results and discussion

5.4.1 Model formulation, construction, and performance

The MLP-NN model based on an HTT approach considered, as an input layer, 15 parameters (representing the hydrostatic pressure (h), squared hydrostatic pressure (h^2), fourth hydrostatic pressure (h^4), where h is the reservoir water height that can vary between 0 and 45 m — and the temperature effects measured at T10, T11, T15, T16, T31, T32, T33, T35, T62, T64, T65 and T66), seven responses at the output layer (representing the opening-closing movements between blocks measured at BT3, BT5, BT7, BT8, BT10, BT12 and BT13), and one hidden layer. Every neuron in the network is fully connected.

A hyperbolic tangent transfer function was chosen as the activation function for the hidden layer, and a linear activation function was chosen for the output layer. The generalized back propagation delta learning rule algorithm was used in the training process. To find the optimum result

(through the minimization of a cost function defined by the mean squared error), 5 initializations of random weights and a maximum of 1500 iterations were performed for each MLP architecture.

A randomization of the learning set was previously carried out, making it possible to define the training set, the cross-validation set and the test set, with a number of samples equal to 65%, 15%, and 20%, respectively. The cross-validation was used as the stopping criteria. In each iteration, the performance for the training set is usually better than before, but if at any time the error for the cross-validation set increases, the MLP model may lose its generalization capacity. The training stops when the error for the cross-validation set begins to increase, with a better generalization thus being ensured (Mata, 2011). The test set was used as an auxiliary element that enabled us to carry out the quality evaluation of the MLP model for the training set. In this case study, the network with the best performance was a 15-25-7 MLP (less error for the cross-validation set). The results are represented in Figures 5.14–5.16 and described in Table 5.2.

Table 5.2: MLP model performance parameters.

	Measurements		Model			
	<i>Min</i>	<i>Max</i>	<i>r_{Min}</i>	<i>r_{Max}</i>	<i>sd</i>	<i>R</i> ²
	[mm]	[mm]	[mm]	[mm]	[mm]	%
BT3 O/C	0.16	2.56	-0.22	0.35	0.060	99.81
BT5 O/C	0.29	2.85	-0.32	0.39	0.072	99.79
BT7 O/C	1.03	3.57	-0.29	0.33	0.068	99.92
BT8 O/C	0.70	2.61	-0.21	0.34	0.063	99.86
BT10 O/C	0.25	2.15	-0.21	0.30	0.056	99.77
BT12 O/C	0.81	2.72	-0.24	0.37	0.067	99.85
BT13 O/C	0.48	2.21	-0.22	0.28	0.048	99.86

Legend: *r* - residuals, *sd* -standard deviation of the residuals, *R*²- coefficient of determination.

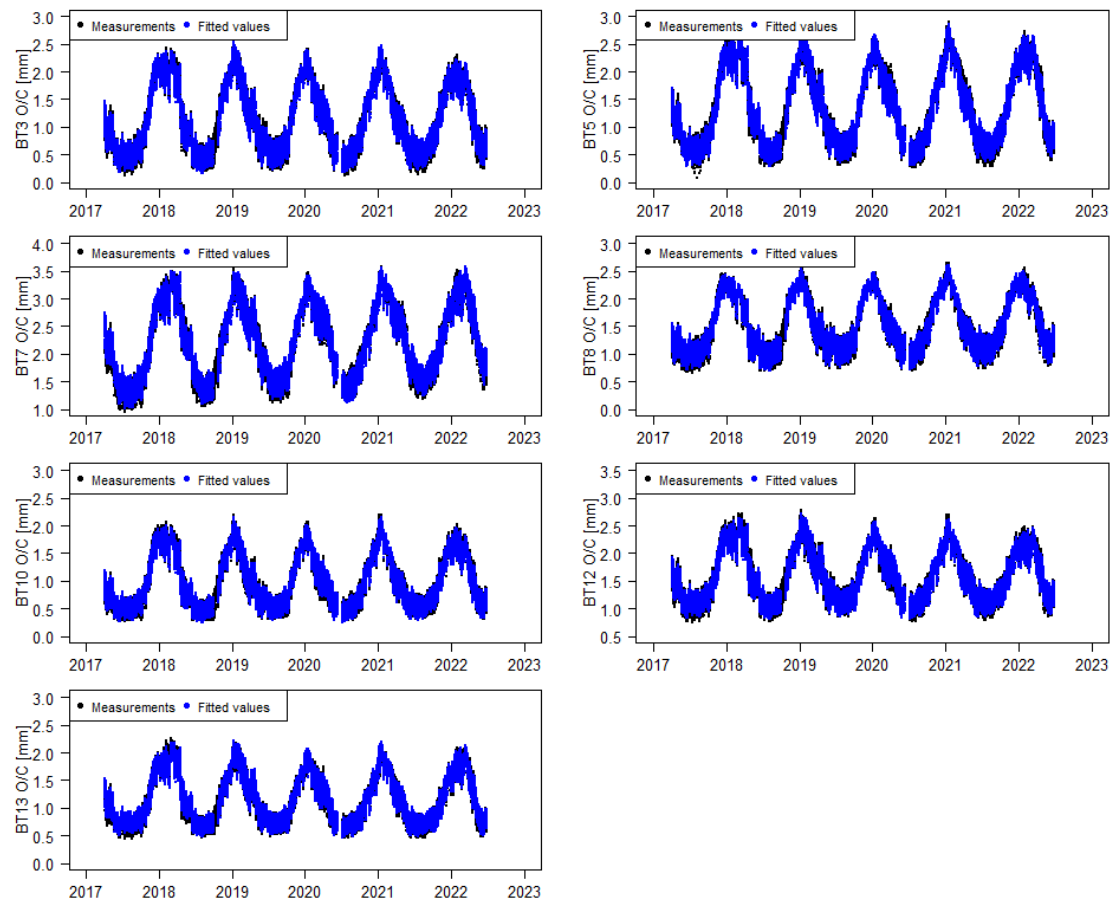


Figure 5.14: Time series of the fitted values and recorded values for the movements measured through 3D jointmeters.

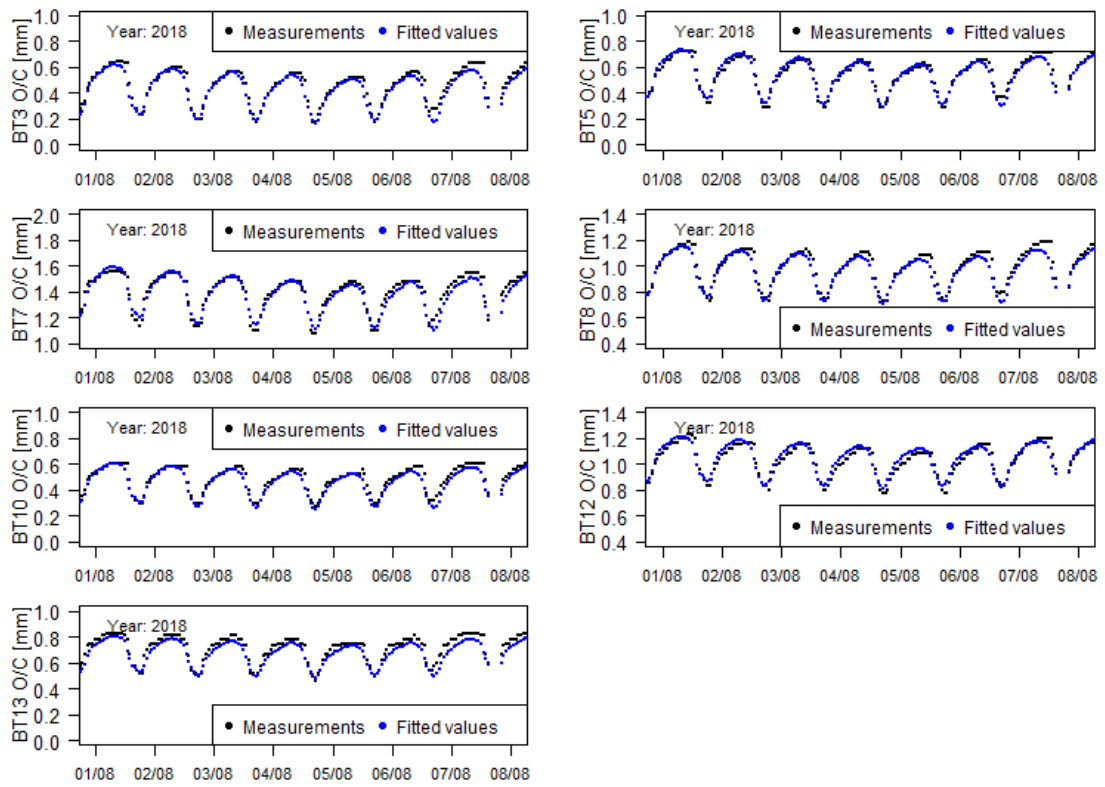


Figure 5.15: Time series of the relative movements between block measurements and fitted values between the 1st and the 8th of August 2018.

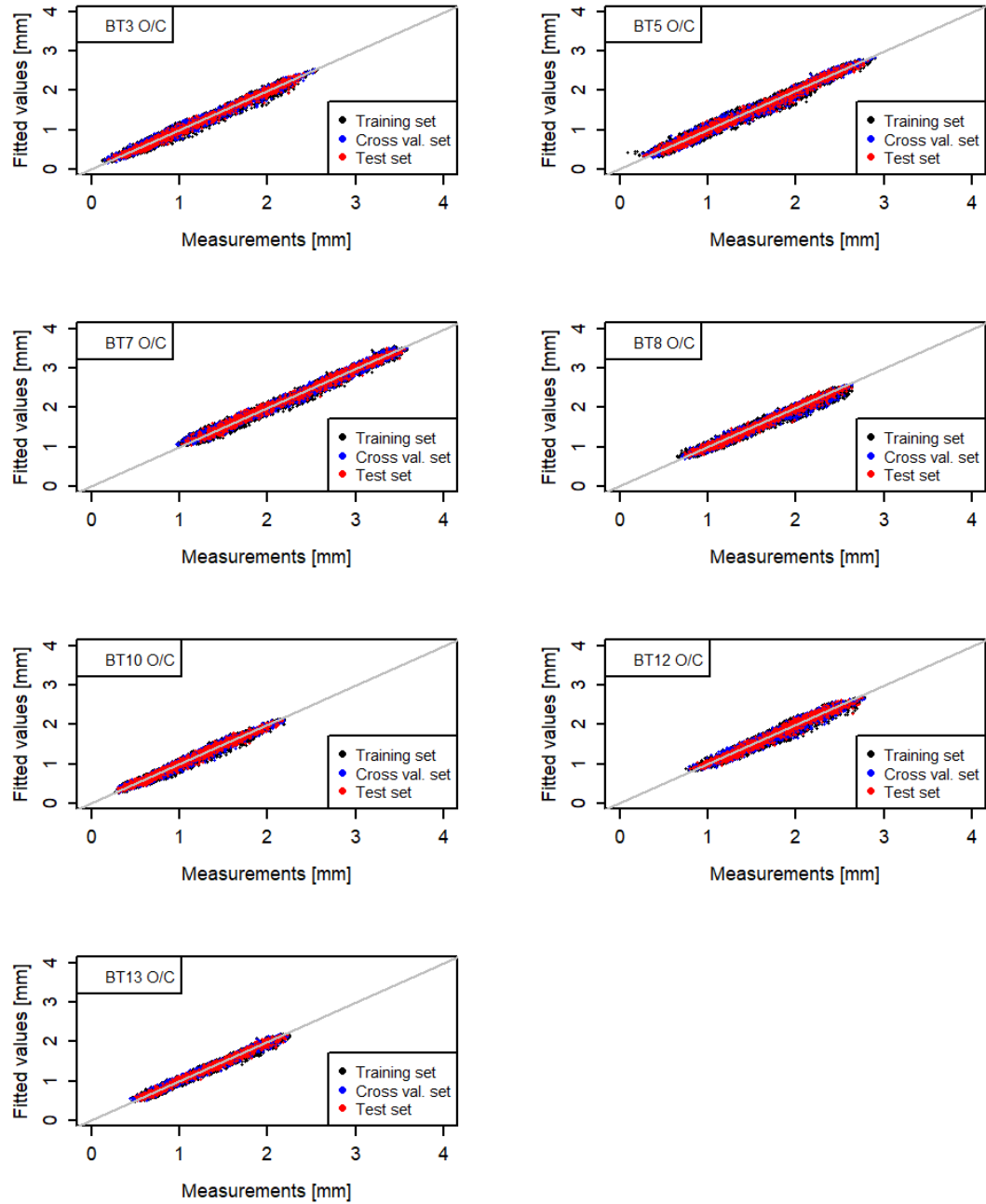


Figure 5.16: Fitted values vs. recorded values for the movements measured through 3D jointmeters.

5.4.2 Threshold definition for a singular record

The traditional approach adopted for threshold definition in regression models consists of adopting a multiplicative factor associated with the standard deviation of the residuals. Usually, multiplicative factors equal to 3 or 4, corresponding to a confidence level of 99.73 % and 99.99 %,

respectively, are adopted. This approach assumes that the residuals follow a normal distribution (an assumption that is often not verified for real cases but that allows a good approximation). The same type of criterion can also be used in the MLR-NN model following the limits shown in Figure 5.17.

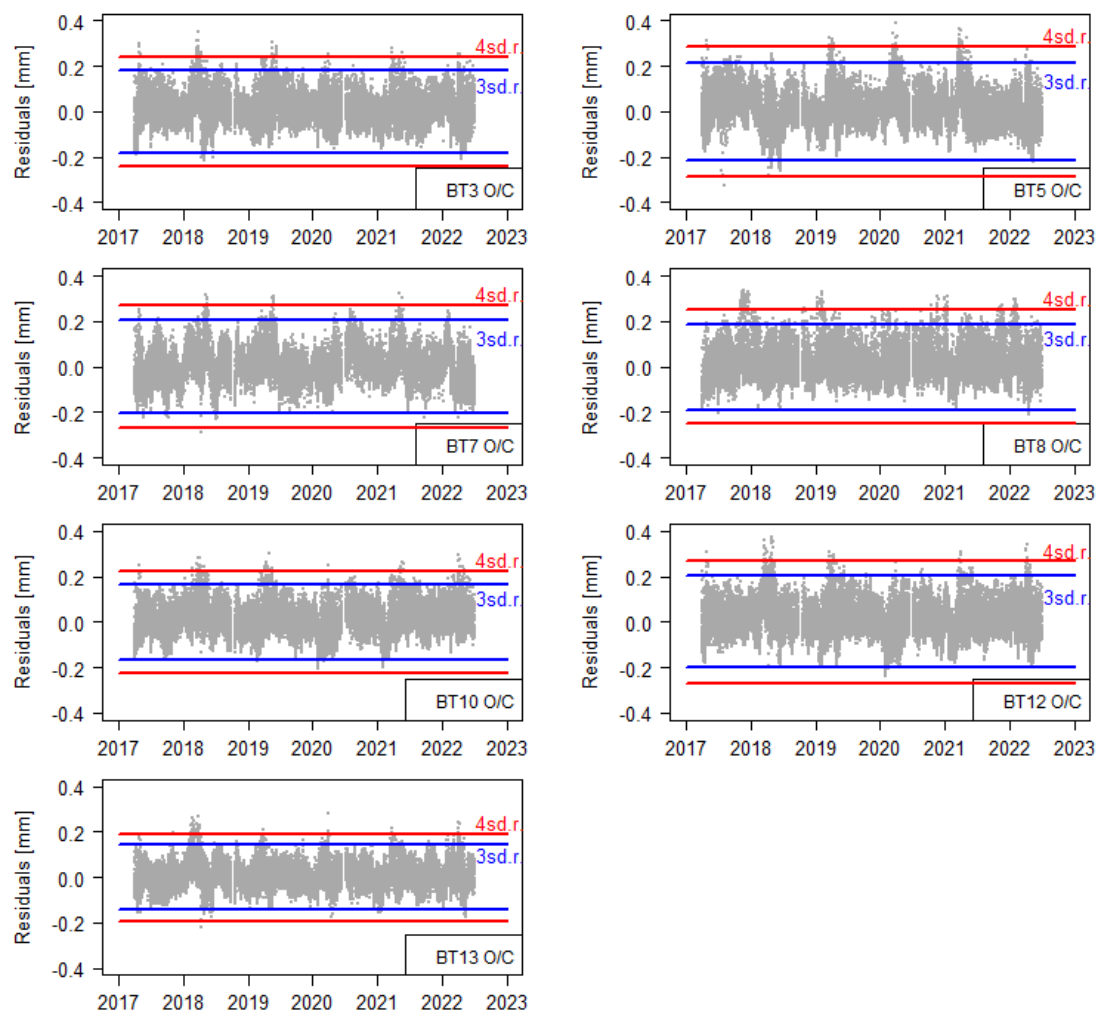


Figure 5.17: Residuals of the movements measured through 3D joint meters, and threshold definition based on a multiple of the standard deviation of the residuals.

5.4.3 Threshold definition for novelty identification based on a time period evolution of the residuals

In case a novelty is identified, verifying if it is an isolated record is relevant in order to avoid the false internal warning since, usually, isolated novelties are associated with measurement errors. A critical aspect of dam safety control activities is the pattern recognition in the observed behaviour, including their expected evolution over time. With the exception of extreme load events and other

time effects (such as the existence of internal expansion reactions in the concrete), the pattern in the observed behaviour is expected to be continuous over time. Thus, one way to identify novelties in the dam's behaviour is to analyse the evolution of this behaviour (through the residuals) in a time window over time. Since daily variations resulting from daily temperature changes are observed, a moving window with 24 hourly records and with a time step equal to the measurement frequency (1 h) was adopted.

Figure 5.18 shows the evolution of the moving average of the residuals ($m.a.r.$) and of the moving standard deviation of the residuals ($m.sd.r.$) in a time window of one day over time.

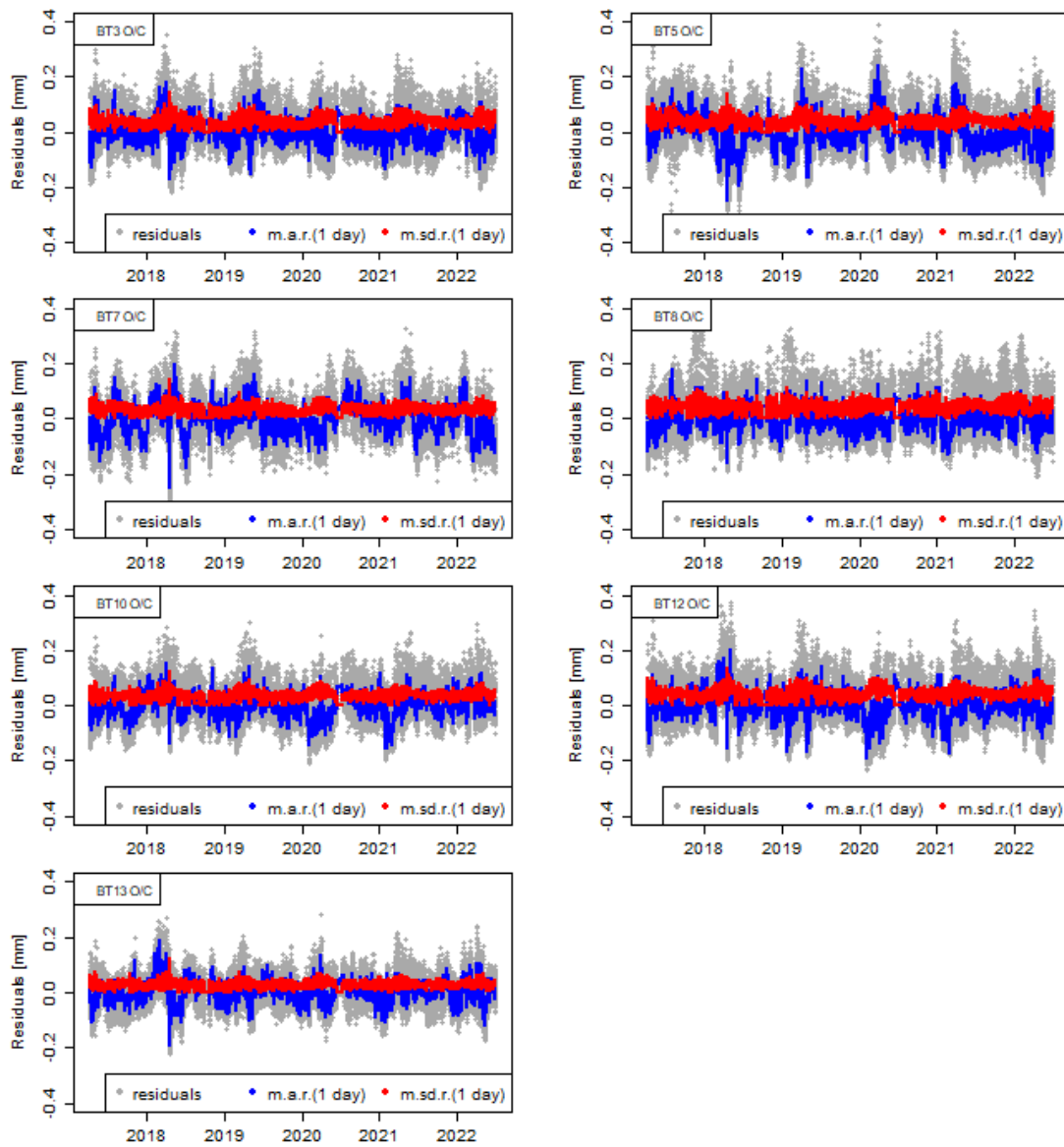


Figure 5.18: Residuals, $m.a.r.$, and $m.sd.r.$ over time.

The simultaneous analysis of the $m.a.r.$ and $m.sd.r.$ allows us to identify if the predicted values

are moving away from the recorded values (i.e., if the residuals are increasing, meaning that the non-explained part of the model is increasing), and if the residuals increase along time, this could suggest a damage evolution. The definition of thresholds based on multiplicative factors associated with the standard deviation of the residuals is also proposed in this analysis. Similar to the single record analysis, thresholds based on multipliers of 3 and 4 for the standard deviation of the residuals are also proposed, although these values can be updated depending on the results, as seen in Figure 5.19. The priority in this kind of analysis is to identify periods in which the residuals and their evolution are higher; consequently, a deeper analysis of the data can be carried out.

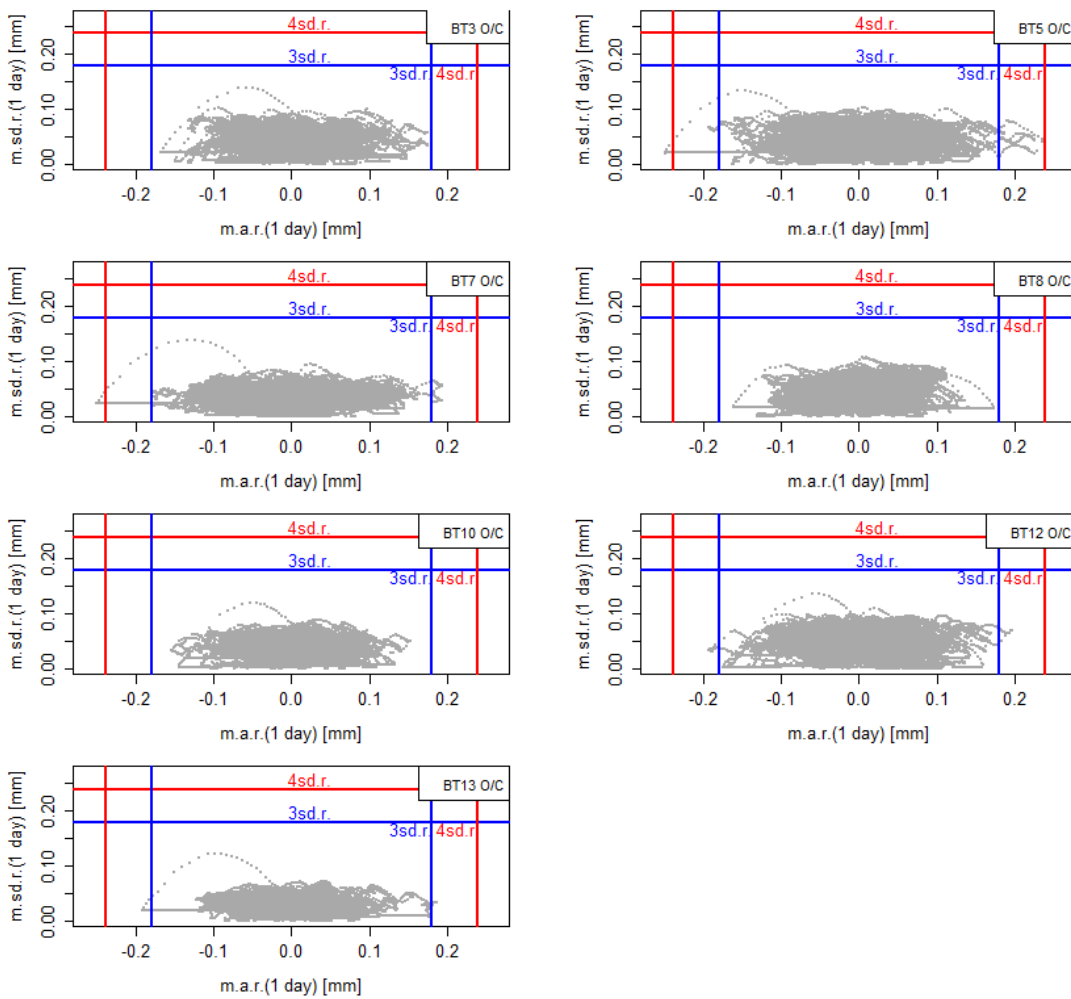


Figure 5.19: $m.sd.r.$ vs $m.a.r.$, and threshold definition based on multiples of the $m.sd.r.$ and $m.a.r.$, for each quantity.

5.4.4 Threshold definition for novelty identification based on multivariate data

Both of the previous analyses consider one physical quantity at a time. However, considering several quantities at the same time is relevant for an integral judgment. To address this consideration, a threshold definition based on the DBSCAN method is used. By definition, the residuals should follow a distribution similar to a normal distribution with a zero mean. Based on this premise, a criterion for the identification of spread records (in the n features dimension—seven in this case study) that are far from most of the records is defined. An analysis of the effect of the parameters Epsilon and MinPoints were performed as presented in table 5.3. Values of Epsilon = 0.12 and MinPoints = 7 were adopted for this case study, as seen in Figure 5.20. These values were defined based on the number of variables and the standard deviation of the residuals.

Table 5.3: Number of potential novelties based on several Epsilon and MinPoints values.

MinPoints	Epsilon				
	0.08	0.10	0.12	0.14	0.16
5	79	9	5	3	0
6	102	12	5	3	1
7	116	14	5	3	1
8	126	22	5	3	1
9	140	22	5	3	1

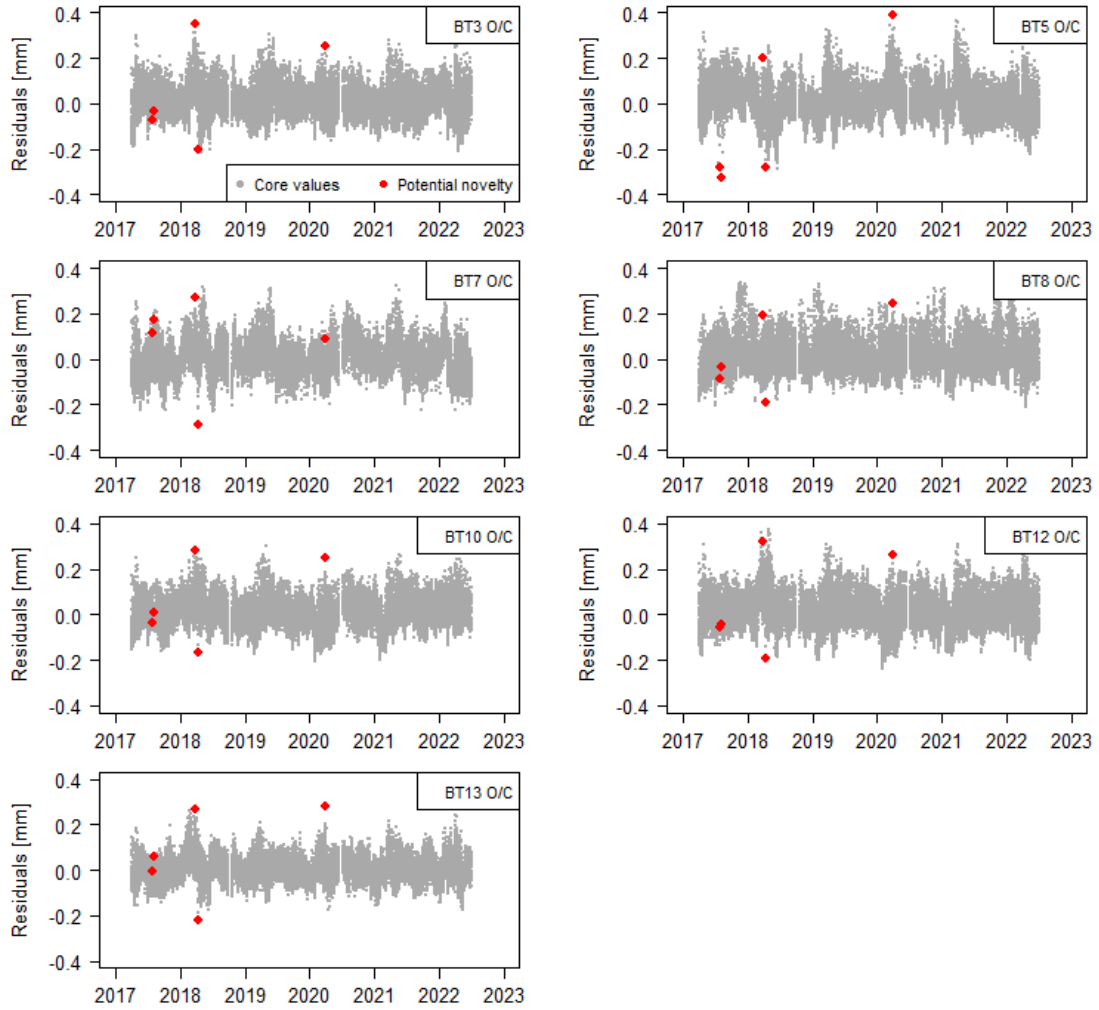


Figure 5.20: Novelty identification based on a multivariate analysis based on the DBSCAN method (adopting Epsilon = 0.12 and MinPoint $s = 7$).

The dam behaviour in the time period under study presents a good performance, and there is no abnormal behaviour. The monitoring system records were used for defining the thresholds based on the three proposed procedures. Based on the thresholds defined and for future measurements, the records above the thresholds are the potential candidates to represent a novelty. They should be assessed in order to identify whether they are related to a measurement error or due to other situations.

5.5 Concluding remarks

This chapter presented procedures for the definition of thresholds regarding the observed structural behaviour in a concrete dam for safety control activities. The explanatory capacity of the residual

analysis allows the definition of a more accurate baseline for the characterization of the structural behaviour.

The analysis of relative movements between blocks through data-based models is unusual due to the nonlinearity of the observed data, which cannot be represented in traditional linear regression models. In this case, an MLP model was developed to interpret the observed relative movements between blocks. The residuals (the part not explained by the model) resulting from the model were used in this work to define thresholds for novelty identification. The explanatory capacity of the residual analysis allows the definition of a more accurate baseline for the characterization of the structural behaviour. In this work, the analysis of the relative movements between blocks was performed based on hourly recorded measurements. The main inputs that were considered are a function of the water level and the temperatures measured in several thermometers spread along the dam body. The proposed procedures allow for the earlier detection of novelties through the analysis of the residuals of the MLP prediction model adopted for the interpretation of the relative movement between blocks, for (i) a singular record, (ii) a moving time period, and (iii) multivariate records. The main issues related to the definition of thresholds can be summarised as follows:

- The definition of univariate thresholds based on the residuals, one for each quantity, is the first recommended step. This approach, through the use of multiplicative factors associated with the standard deviation of the residuals, allows an easy novelty identification that, in some cases, could be related to measurement errors.
- The second type of threshold proposed in this study can be defined by the adoption of a moving window with the moving average and the standard deviation of the residuals. This kind of approach allows the specialist to have immediate information concerning the evolution over time.
- Finally, the third type of threshold proposed can be defined based on multiple factors related to the behaviour of the residuals for all the quantities considered in the model. For this approach, a strategy based on the DBSCAN algorithm, which proved to be suitable for multivariate analysis, was used.

To be effective, dam safety control activities must be considered an ongoing process. In this sense, applying the proposed procedures for operational issues in different dams and considering

different quantities is suggested. It is important to highlight that each procedure has its singularities and challenges. The observed structural behaviour, the performance of the model adopted, and the quality and frequency of the measurement recorded need to be considered for the adoption of an adequate multiplicative factor for univariate thresholds and the adoption of adequate parameters for multivariate thresholds.

The definition of the moving window size for calculating the moving average and the standard deviation depends on the measurement frequency of the records and the reservoir's exploitation regime. Despite these challenges, the implementation of any of the proposed procedures in an automated monitoring system can adequately support dam surveillance activities.

Chapter 6

Conclusions and future developments

6.1 Conclusions

The present dissertation focusses on the use of AI and SHM to increase the assessment of critical infrastructure. This purpose involves research on AI-based strategies, namely ML and DL approaches, that can complement or enhance current SHM methodologies for pattern recognition and novelty detection. To achieve this goal, new methodologies applied to SHM data acquired on site were performed and assessed, in order to find the one that fits better considering the structure, its monitoring system and its structural response. However, the major goal of the present dissertation is to increase the robustness of the structural assessment of critical infrastructures subjected to multi actions using AI-based strategies and monitoring data (see Figure 6.1).

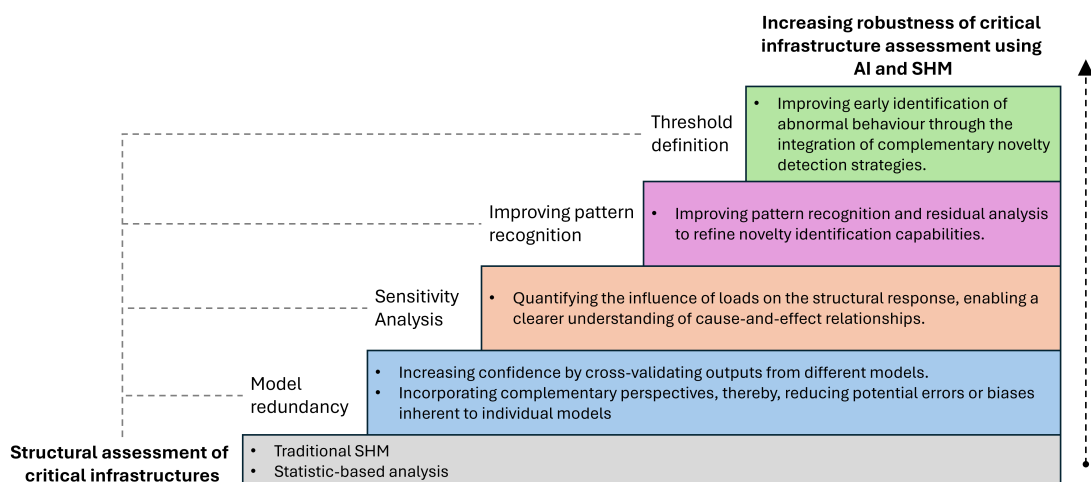


Figure 6.1: Proposed key steps to increase the robustness of structural assessment.

To accomplish the mentioned goal, key steps are considered:

- Model redundancy to increase confidence in the assessments by cross-validating their outputs. Model redundancy is capable of diagnosing abnormal behaviour by offering complementary perspectives that help to expose potential errors or biases in individual models. This approach improves the robustness of the monitoring framework and supports more informed decision making in situations where the models yield conflicting results.
- Sensitivity analysis to understand and quantify the effect that each load has on the structural response. Sensitivity analysis aims to characterise the influence that each input has on the output of the adopted model.
- Continuous improvements in pattern recognition. The identification of patterns in the residuals (the part not explained by the base models), makes it possible to incrementally reduce the uncertainties in the forecasts.
- Definition of thresholds, by adopting strategies that better fit the purpose of the novelty identification.

A roadmap with case studies to illustrate how to perform the proposed key steps is presented in three chapters (Chapters 3 to 5).

In Chapter 3 a methodology supported by ML models is presented for the characterization and prediction of the structural behaviour based on the main loads and the observed structural responses. By comparing the observed values and predicted outcomes from the ML models, it is possible to identify new trends or pattern variations that can help the prediction of future observations.

The results showed a good performance of the chosen learning algorithm, an MLP in the three proposed models:

- Model 1 considered environmental loads (temperatures) as input and the strain measures in one point of the bridge as the output.
- Model 2 considered the same inputs as Model 1, and the strain measured in four points of the suspended 25 de Abril bridge as outputs.
- Model 3 allows performing a response-response analysis, where the inputs are the strains measured in three points, and the output is the remaining strain (from the set of four strains measured in the section of the bridge under study).

After confirming the fitting of the models with the observed measurements, a residual analysis was carried out.

Regarding the quality of the representation, all models showed good results, pointing to the good performance of the neural network. Moreover, the results highlighted the redundancy of the models in terms of the inputs and the outputs that characterize the system under study, which improves the assessment process and decreases the potential for errors or biases that may exist in individual models. The residual analysis results also showed a low dispersion in the mean weekly evolution of the residuals with no signs of unusual values. In order to test the robustness of the prediction models and characterise the influence of the inputs on the outputs of the three models, a sensitivity analysis that correlates each output with each input was performed. A good correlation was found in the results that were obtained and a better understanding of the effect of the inputs on the observed structural response was also achieved.

Finally, thresholds that were defined based on the moving average of the residuals and the moving average of the standard deviation of the residuals allow the novelty identification in terms of patterns that exceed a predefined threshold. In the selected case study, the threshold was defined based on a percentile of the residuals, where these residuals are the part that is not explained by the adopted model.

In Chapter 4 a methodology that improves the actual strategy of interpretation of SHM data based on MLR models is proposed. This methodology overcomes the MLR limitations and enhances the predictive capacity of the strategy, ultimately leading to better and more reliable decision-making processes that can ensure the structural safety of the monitored structures. The key feature of this methodology that improves the overall performance is to define the final model by combining a sequence of models that explain the part not explained by the previous model. At first, simpler models can be adopted and after that, an improvement can be made by new models (sometimes using more complex models) that explain or characterize the pattern not explaining in the previous models, decreasing, as a consequence, the final residuals.

The proposed methodology showed the capacity of the proposed DL algorithm LSTM model to reduce the uncertainty contained in the results of the MLR model by capturing the sequential structure that was still present in the residuals of the MLR model. By combining both methods, the sensitivity to early detection of novelties increases since it describes more accurately any change or error that is not perceptible by the MLR model, considering the time-dependency of the variables. The unexplained pattern obtained from the MLR model was used to train the LSTM model taking

advantage of the knowledge generated by the MLR model. Based on the results, it is possible to confirm the benefit of using a DL approach that complements the current strategy of SHM analysis to improve the accuracy for the novelty detection and interpretation of structural behaviour.

Chapter 5 explores dam surveillance activities based on the observation of the structural behaviour and the interpretation of the past behaviour supported by the knowledge of the main loads. Procedures for the definition of thresholds regarding the observed structural behaviour in a concrete dam for safety control activities were proposed to allow an earlier detection of novelties. These procedures are based on the analysis of the residuals of the MLP prediction model, adopted for the interpretation of the relative movement between blocks, for i) a singular record, ii) a moving time period, and iii) a multivariate records.

The definition of univariate thresholds for novelty identification based on the residuals, one for each quantity, using multiplicative factors associated with the standard deviation of the residual was proposed for the first case. The second type of proposed threshold was defined by adopting a moving window where the moving average and the standard deviation of the residuals were considered as referentials. Finally, the third type of proposed threshold was defined based on multiple factors related to the behaviour of the residuals for all the quantities considered in the model. For this approach, a strategy based on the DBSCAN algorithm, that proved to be suitable for multivariate analysis, was used. Based on the results that were obtained, it was possible to conclude that the implementation of any of the proposed procedures in an automated monitoring system can support, adequately, dam surveillance activities.

To summarise, the present dissertation explored four key strategies for increasing the robustness of critical infrastructure's assessment and novelty detection in SHM: model redundancy, sensitivity analysis, enhanced pattern recognition, and threshold definition. Results confirmed their effectiveness and enabled the evaluation of ML and DL methods for in-situ SHM data.

Overall, the proposed methodologies showed potential for real-time novelty detection when applied to critical infrastructure SHM data. Although limited to novelty identification, these results also represent a step toward full damage identification and indicate the methodologies provide automatic and reliable tools to support safety assessment and decision-making for critical infrastructure stakeholders. Still, it should be emphasized that conclusions related to the structural assessment of any critical infrastructure should be drawn from the analysis of the results of the model in combination with engineering judgement and knowledge on structure history.

6.2 Future developments

This dissertation demonstrated the advantages and potential of the proposed methodologies, using specific, though representative, case studies. However, given the need to scale up dissemination to end users, the application of the proposed methodologies to other case studies is recommended, both in terms of the type of structure and target quantities.

Moreover, in the application of AI-based strategies, a wide range of methods can be explored depending on the specific objectives. Therefore, the performance of other methods should also be addressed in future research, namely:

- novelty identification through clustering approaches, auto-associative neural networks, and particularly autoencoders to categorize the datasets. Autoencoders are especially effective in SHM strategies due to their ability to handle large, variable datasets.
- pattern recognition of structural behaviour, as well as for predicting future behaviour through AI regression models. They can be trained using knowledge obtained from numerical models that simulate structural behaviour that never happened before. For example, this can be useful for the safety control activities of concrete dams during extreme floods (Irazábal et al., 2025).
- classification approaches through ensemble models, support vector machines, discriminant analysis and neural networks are some methods that are suggested to be tested.

As mentioned in the previous section, the present dissertation reaches the point of novelty identification representing a step forward to achieve an automated damage identification strategy. However, for that purpose, it is necessary to work with data sets that may represent damage scenarios and undamaged structural behaviour to promote a reliable orientation to the interpretation of the monitored data, aiding decision making. In this context, numerical models are widely used to simulate different scenarios in the assessment of critical infrastructures, mainly to represent the expected behaviour under normal conditions. Numerical models representing certain damage scenarios are also available for specific studies. In particular, they may allow the generation of synthetic damaged datasets through the simulation of various damage conditions.

As an example, for the 25 de Abril bridge, multiple damage scenarios were simulated based on imposed actions such as traffic, erosion, wind, temperature variations, and earthquakes, as well as stiffness loss in highly demanded structural elements and vulnerable metallic components

(e.g., cables, bearings, or elements exposed to traffic) [SAFESUSPENSE project - Safety control and management of long span suspension bridges POCI-01-0145-FEDER-031054]. Based on the assumption that there are data sets to represent structural damage and that the monitoring system under operation is suitable to record key quantities, it will be possible to identify predefined damage scenarios through a classification process of the pattern defined by a set of measured quantities (see Figure 6.2).

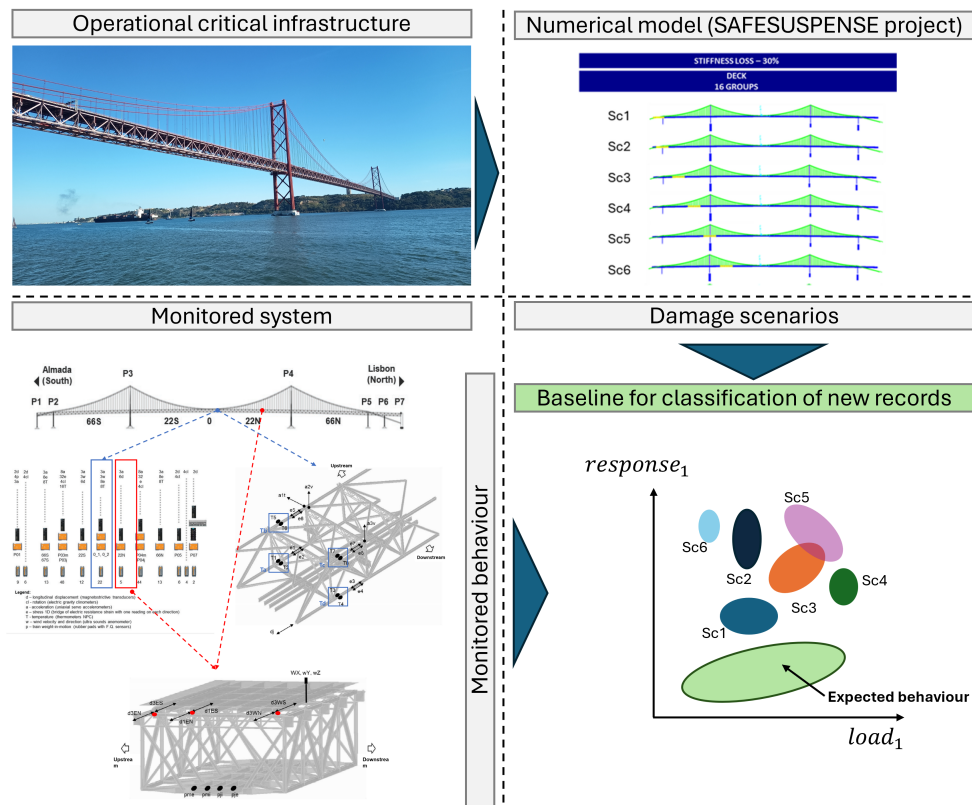


Figure 6.2: Graphical roadmap for classification of the real-time behaviour to identify potential damage scenarios.

Another relevant topic for future research could address the efficiency and robustness of monitoring systems, assessing (see Figure 6.3):

- whether the defined monitoring systems (in the design or in operation phases) allow, with redundancy, the identification of damage scenarios (and identify the level of damage, if possible);
- whether the precise instruments are available and in the right location;

- whether the measurements and the interpretation of the information are adequate to identify novelties; and
- the level of dependence on a sensor for analysing observed behaviour, among other issues.

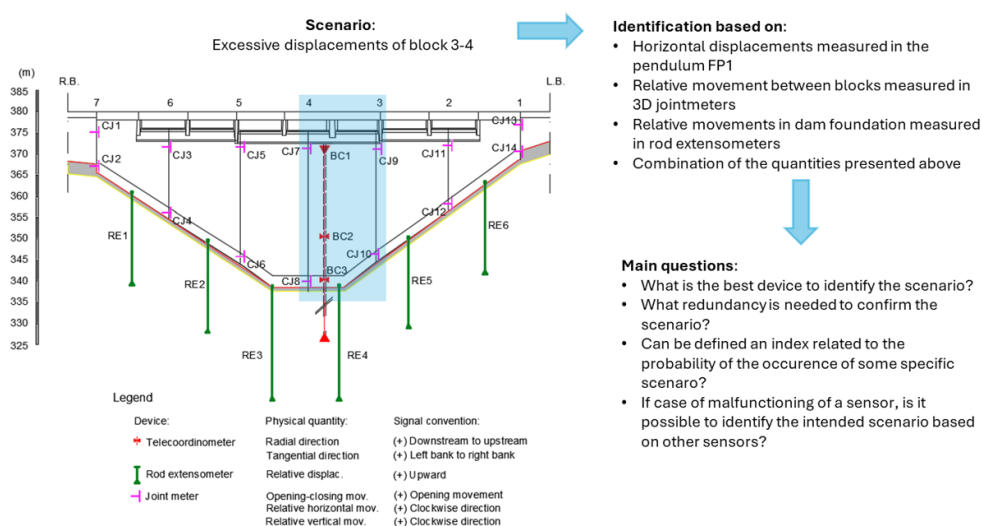


Figure 6.3: Need for assessing the efficiency and robustness of monitoring systems.

Finally, a research able to classify the severity of the damage level for potential damage scenarios is also relevant, therefore, it is highly dependent on the development of adequate numerical models that are "representative" of the potential expected damage scenarios.

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