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TRANSFER LEARNING FOR
STRUCTURAL HEALTH MONITORING

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STRUCTURAL HEALTH MONITORING**

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To my parents and my wife.

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*Nothing in life is to be feared, it is only to be understood.
Now is the time to understand more, so that we may fear less*
Marie Curie (☆ 1867 - † 1934).

*Quando eu nasci, as frases que hão-de salvar a humanidade
já estavam todas escritas, só faltava uma coisa - salvar a humanidade.*
José de Almada Negreiros (☆ 1893 - † 1970).

ABSTRACT

Structural Health Monitoring (SHM) proposes the continuous assessment of the structural integrity to ensure the safety operation and increase the lifespan of structures from several areas. This traditional methodology still have generalization difficulties among structures, even when structures are nominally and topologically similar. The data sets present divergences between their underlying distributions that do not allow the generalization of the model estimated to different situations. In the last years, transfer learning has gained relevance due to extending the SHM concept to investigate different structures, while minimizing costs with monitoring systems and time associated with data acquisition. This methodology can change how SHM is currently proposed by leveraging knowledge gained from a well-monitored structure to improve the integrity assessment of other structures under unknown conditions. The main idea is to reuse the relevant knowledge from a labeled structure (source domain) to investigate another one (target domain) with limited data. This thesis intends to lay down the foundations of transfer learning for SHM by describing the motivations that led to its application in the analysis of structures. At first, transfer learning is applied to overcome difficulties inherent in the complexity of estimating an accurate finite element model, and unsupervised damage detection of a real bridge is performed using knowledge of its model. Then, transfer learning is combined with a stochastic model for damage detection in an experimental application and its underestimated numerical model, and the quantification of damage levels in the structure is carried out based on a requirement imposed by the transfer learning methodology. Finally, a comprehensive analysis using transfer learning is proposed to investigate three real bridges subjected to environmental and operational conditions, and the importance of the quality of knowledge transferred across different bridges for damage detection is highlighted. The transfer learning methodology indicated satisfactory results in all investigated cases and demonstrates the attractive benefits of its application, which can result in significant progress in the damage identification process considering different structures.

Keywords: Transfer learning. Domain adaptation. Transfer component analysis. Joint distribution adaptation. Maximum independence domain adaptation. Structural health monitoring. Damage identification.

RESUMO

O Monitoramento de integridade estrutural (SHM) propõe a avaliação contínua da condição estrutural para garantir a operação segura e aumentar a vida útil de estruturas de diversas áreas. Esta metodologia tradicional ainda apresenta dificuldades de generalização entre estruturas, mesmo quando as estruturas são nominalmente e topologicamente semelhantes. Os conjuntos de dados apresentam divergências entre suas distribuições subjacentes que não permitem a generalização do modelo estimado para diferentes situações. Nos últimos anos, a transferência de aprendizado ganhou relevância devido à extensão do conceito SHM para investigar diferentes estruturas, minimizando custos com sistemas de monitoramento e tempo associado à aquisição de dados. Essa metodologia pode mudar a forma como SHM é proposto atualmente, aproveitando o conhecimento adquirido de uma estrutura conhecida para a avaliação de outras estruturas sob condições desconhecidas. A ideia principal é reutilizar o conhecimento relevante de uma estrutura conhecida (domínio fonte) para investigar outra (domínio alvo) com dados limitados. Esta tese pretende estabelecer as bases de transferência de aprendizado para SHM. Primeiramente, a transferência de aprendizado é aplicado para superar as dificuldades inerentes à complexidade de estimar um modelo de elementos finitos preciso, e a detecção de dano não-supervisionada de uma ponte real é realizada usando o conhecimento de seu modelo. Então, a transferência de aprendizado é combinado com um modelo estocástico para detecção de dano em uma aplicação experimental e seu modelo numérico subestimado, e a quantificação dos níveis de dano na estrutura é realizada através de um requisito imposto pela metodologia de aprendizagem por transferência. Por fim, uma análise abrangente de três pontes reais submetidas a condições ambientais e operacionais é proposta, e destaca-se a importância da qualidade do conhecimento transferido para detecção de dano. A metodologia de transferência de aprendizado indicou resultados satisfatórios em todos os casos investigados e demonstra os atrativos benefícios de sua aplicação, podendo resultar em avanços significativos no processo de identificação de dano considerando diferentes estruturas.

Palavras-Chave: Aprendizagem por transferência. Adaptação de domínio. Análise de componentes de transferência. Adaptação de distribuição conjunta. Adaptação de domínio de independência máxima. Monitoramento de integridade estrutural. Identificação de dano.

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LIST OF ACRONYMS

ARTL	-	Adaptation Regularization based Transfer Learning
EM	-	Expectation-Maximization Algorithm
BIC	-	Bayesian Information Criterion
DI	-	Damage Index
FE	-	Finite Element
FRF	-	Frequency Response Function
F1	-	F1-score
HSIC	-	Hilbert-Schmidt Independence Criterion
GMM	-	Gaussian Mixture Model
GPR	-	Gaussian Process Regression
JDA	-	Joint Distribution Adaptation
LANL	-	Los Alamos National Laboratory
MIDA	-	Maximum Independence Domain Adaptation
ML	-	Maximum Likelihood
MSD	-	Mahalanobis Squared Distance
PDF	-	Probability Density Function
RBF	-	Radial Basis Function
SHM	-	Structural Health Monitoring
SVM	-	Support Vector Machine
TCA	-	Transfer Component Analysis

LIST OF SYMBOLS

c	- Class
c	- Threshold
d	- Degrees of Freedom
$\mathcal{D}$	- Domain
$f(\cdot)$	- Objective Predictive Function
$\mathbf{f}$	- Prior Distribution
$\mathcal{F}$	- Latent Features Matrix
fn	- False Negative
fp	- False Positive
H	- Centering Matrix
H_0	- Null Hypothesis
H_1	- Alternative Hypothesis
$\mathcal{H}$	- Reproducing kernel Hilbert space
$\mathbf{I}$	- Identity Matrix
$\mathbf{K}$	- Stiffness Matrix
$\mathcal{K}$	- Kernel (Covariance Function)
$\tilde{\mathcal{K}}$	- Empirical Kernel
$\mathcal{L}_0$	- Maximum Mean Discrepancy Matrix
m	- Number of Dimension of Latent Space
$\mathcal{M}$	- Maximum Mean Discrepancy
n	- Number of Observations
N	- Number of Rounds
$P(\mathbf{X})$	- Marginal Probability Distribution
$P(\mathbf{Y} \mathbf{X})$	- Conditional Probability Distribution
Q	- Principal Component
tn	- True Negative
tp	- True Positive
$\mathcal{T}$	- Task
$\mathcal{X}$	- Feature Space
$\mathbf{x}$	- Feature Vector
$\bar{x}$	- Mean Operator

$\mathcal{W}$ - Transformation Matrix

y - True Label

$\hat{y}$ - Pseudo-Label

$\mathcal{Y}$ - Label Space

GREEK LETTERS

α	-	Level of significance
η	-	Mixture Weight
λ	-	Lagrange Multipliers
μ	-	Trade-off parameter
$\phi(\cdot)$	-	Nonlinear Mapping Function
σ	-	Standard Deviation
σ_n	-	Noise Variance
σ_l	-	Length Scale
Σ	-	Covariance Matrix
τ	-	Parametric Distribution Family
θ	-	Component Parameters

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1 INTRODUCTION

This Chapter introduces the main subject discussed throughout this thesis by presenting the interests of applying transfer learning in Structural Health Monitoring (SHM). Initially, Section 1.1 presents the main motivations that led to the development of this thesis by describing the potential benefits that transfer learning can bring to the analysis of populations of structures. Next, Section 1.2 highlights the objectives of carrying out this work. Section 1.3 and Section 1.4 list the main contributions and outline of this thesis.

1.1 MOTIVATION

The importance of infrastructure management represents a significant factor for the growth and development of any society, as it ensures a proper operation of the transportation services and meets the population needs on a daily basis. Structures such as roads, bridges, railway lines, airports, and power generation systems represent some examples of infrastructure that provide essential services around the world.

The proper functioning of a structure can have a significant economic and social impact, since its failure affects the operation of several services and catastrophic events can also occur due to a lack of operational safety. Therefore, monitoring the structural condition becomes necessary, as structures are subject to deterioration that may be related to their aging over time and the external effects to which they were subjected, and the effects related to the presence of damage should be investigated to prevent possible issues that could affect the structural behavior.

An investment strategy and the development of a plan for continuous monitoring are important to prevent possible eventualities from occurring. In 2022, Brazil invested around \$33 billion to meet the costs related to national infrastructure, although an amount of \$85 billion should have been invested per year to address the maintenance costs (RODRIGUES; PINTO, 2022). It is estimated that around \$600 billion should be invested in the infrastructure area over the next 10 years but a value of \$200 billion was applied in the last 20 years, highlighting a significant discrepancy in the amounts invested in the area and increasing the population's concern with the lack of security

(VASCONCELOS, 2023). The American Society of Civil Engineer presented a report referring to this decade that also indicated a significant increase of the deficit related to the infrastructure investment in the United States, which has paid about half of the amount required for infrastructure needs (ASCE, 2021). Thus, a robust and efficient continuous monitoring should be proposed to simultaneously deal with challenging financial situations and ensure the structure's operational safety.

In the last decades, SHM has been proposed to assess the integrity of different structures based on a damage identification strategy (FARRAR; DOEBLING; NIX, 2001). This methodology is often applied assuming a statistical pattern recognition paradigm divided into four stages: operational evaluation, data acquisition, feature extraction and generation, and statistical modeling for feature classification (FARRAR; WORDEN, 2012). In the five-level hierarchy of damage identification (detection, localization, definition of damage type, severity analysis, and prognosis), the first level has been the priority of the scientific community to trigger inspections and avoid the collapses of structures (RYTTER, 1993; WORDEN; DULIEU-BARTON, 2004).

In the SHM context, machine learning is traditionally applied for structural analysis due to the significant technological developments that have allowed its successful application in different circumstances. The purpose of this methodology is to define how machines should think based on the knowledge extracted from data sets measured in different structures. Nonetheless, one important question arises: can machines think and properly assess the structures under different situations?

The assessment of structural condition currently presents a significant limitation when the analysis moves from a single structure to a population-based analysis, which can be homogeneous and heterogeneous structures. This is a consequence of the assumption that machine learning follows, where the training data and testing data belong to the same underlying distributions (YAO; DORETTO, 2010). This assumption may not be ensured in practical situations because of the divergences between data distributions, leading to a poor performance of the estimated model as a consequence (YE; DAI, 2018). Hence, the model updating using newly collected data could be regularly necessary to solve possible setbacks in the analysis but this procedure is often infeasible, expensive, or even impossible to perform

Transfer learning (or knowledge transfer) has recently been proposed as an important methodology in SHM as it provides a solution to reduce the need for new data acquisitions for the learning phase when a previous database is available or when a similar

structure without historical data needs to be monitored (FIGUEIREDO; BROWNJOHN, 2022). This compelling methodology addresses new problems through straightforward and efficient methods, generalizing the information from similar situations (ZHUANG *et al.*, 2021). Instead of estimating new models for each structure, transfer learning allows the knowledge transfer across different domains to improve the learner performance (WEISS; KHOSHGOFTAAR; WANG, 2016).

The concept of transfer learning was first introduced in the 1980s but it has attracted considerable attention in several research areas recently (QUATTONI; COLLINS; DARRELL, 2008; CIREŞAN; MEIER; SCHMIDHUBER, 2012; GAO *et al.*, 2014; OPBROEK *et al.*, 2015; HUYNH; LI; GIGER, 2016; ZOPH *et al.*, 2016; CHOI *et al.*, 2017). For this reason, this methodology is the main subject covered in this thesis as it is still a recent topic in SHM that can have a significant impact on investigating populations of structures, while overcoming the limitations of machine learning.

To address the differences between these methodologies, it is possible to outline an example frequently investigated in real-world situations. There are roughly 10,000 in Portugal, 600,000 bridges in the United States, and an estimated 137,000 bridges in Brazil requiring immediate maintenance, according to a study conducted by the Brazilian Concrete Institute (IBRACON, 2023). With so many bridges, it is financially and technically challenging for the authorities to install an SHM system or collect large quantities of data sets from every single bridge.

A more specific example is the Golden Gate Bridge in San Francisco and the 25 de Abril Bridge in Lisbon. They share the same structural system, the same material, and the same operational and environmental conditions. They were even built by the same construction company that optimized the design of the 25 de Abril Bridge by transposing knowledge gained three decades before with the construction of the Golden Gate Bridge.

Machine learning is not recommended for this analysis, as it would be necessary to estimate a model for each structure. Thus, the estimated models would only present the knowledge contained in the data sets used during their identification. Meanwhile, the concept of transfer learning resembles the human learning that generalizes knowledge to perform related tasks. The knowledge present in the estimated model of a bridge could be reused to evaluate other bridges even under different conditions. Therefore, transfer learning methodology can change how SHM is currently proposed by leveraging knowledge gained from a well-monitored structure to improve the integrity assessment of other structures under unknown conditions.

1.2 OBJECTIVES

To address the main topics discussed in the motivation of this work, the main objective of this thesis is to define the foundations of transfer learning in the context of SHM to allow the generalization of knowledge extracted from different structures for the assessment of their structural integrity. A brief state-of-art on the transfer learning methodology is presented for a better understanding of its theoretical background and a correlation of how this methodology can be proposed in the SHM context is outlined. In addition, a damage identification strategy is performed on different case studies often found in real situations involving SHM to validate the purpose of using knowledge transfer.

1.3 MAIN CONTRIBUTIONS OF THE THESIS

The main contributions of the present thesis are:

- A description of the foundations of transfer learning and how it can be applied in the SHM context, leveraging the relevant knowledge from a known structure to investigate the structural integrity of other structures under unknown conditions;
- Transfer learning is applied to overcome some of the limitations imposed by the calibration process of Finite Element (FE) models. This proposal may increase the use of numerical modeling for long-term monitoring to perform damage detection on real bridges, using a simplified version of their FE models (FIGUEIREDO *et al.*, 2023);
- Development of a novel methodology for damage quantification using a requirement imposed by transfer learning methods is proposed. The progression of the damage extension can be represented by a stochastic regression model that allows describing the uncertainties involved in the process. Hence, a combination of transfer learning and the regression model can be applied for damage quantification assuming the presence of uncertainties (YANO *et al.*, 2021);
- The first transfer learning application for damage detection using long-term monitoring data sets from three real-world bridges under realistic operational and environmental conditions. A series of feature-based methods are proposed to highlight the importance of labeling and the quality of the knowledge for a successful knowledge transfer (YANO *et al.*, 2023).

1.4 OUTLINE OF THE THESIS

This work is organized as follows:

- **Chapter 1 - INTRODUCTION** - The motivation that originated the investigation of the transfer learning methodology is discussed, the main objectives and contributions of this thesis are presented;
- **Chapter 2 - A BRIEF STATE-OF-ART ON TRANSFER LEARNING** - A brief history of the development of transfer learning is discussed and a context of its similarities to human learning is discussed to provide a comprehensive overview. Additionally, the definition of the main terms and transfer learning approaches frequently proposed in different research areas are outlined;
- **Chapter 3 -TRANSFER LEARNING FOR STRUCTURAL HEALTH MONITORING** - The main reasons that led to the application of the transfer learning methodology for SHM are discussed and a brief list of recent works in the field addresses new possible ideas for damage identification. In addition, a detailed description of the feature-based methods proposed in this work is presented;
- **Chapter 4 - ON THE APPLICATION OF TRANSFER LEARNING USING NUMERICAL MODELS TO ENHANCE THE DAMAGE IDENTIFICATION PERFORMANCE** - A numerical-to-experimental transfer learning is addressed as an interesting alternative to overcome the issues related to the calibration of numerical models. The proposed methodology suggests using an unsupervised feature-based transfer learning approach for bridges that applies classifiers trained using only labeled data generated from FE models to evaluate unlabeled monitoring data of a real bridge. At first, this chapter introduce a detailed description of the long-term monitoring of the bridge and the process of the estimation of its FE model. Next, a case study involving a numerical-to-experimental situation highlights the benefits of the application of the proposed methodology. Finally, a comprehensive discussion of the results and main conclusions are discussed.
- **Chapter 5 - ON THE APPLICATION OF TRANSFER LEARNING FOR DAMAGE QUANTIFICATION** - A brief context of how knowledge transfer can be used for the purpose of determining damage levels in different structures is described and the problem statement with the hypotheses and assumptions considered in the chapter is outlined. To address the damage progression behavior,

a detailed formulation of Gaussian process regression (GPR) model is defined. Then, an overview of the proposed methodology for damage detection and quantification based on a combination of transfer learning and a stochastic regression model is demonstrated in a well-known three-story building structure from the Los Alamos National Laboratory (LANL). Finally, final remarks highlighting the benefits and limitations of the proposed methodology are discussed;

- **Chapter 6 - ON THE APPLICATION OF POPULATION-BASED TRANSFER LEARNING** - An introduction underlines the significant benefits of using knowledge transfer for investigating a population of structures, which different types of bridges are investigated. A detailed description of the long-term monitoring data sets of two different bridges located in France is presented, and a similarity analysis based on the dynamic behavior of the bridges is discussed as one possible reason for a succesful knowledge transfer, while preventing a negative transfer. Then, transfer learning is applied in different classification scenarios to highlight the relevance and the quality of the knowledge. Finally, a brief discussion and conclusions of the chapter are presented;
- **Chapter 7 - FINAL REMARKS** - This chapter covers a general discussion and conclusions about the benefits and limitations of transfer learning in the SHM context, and possible ideas for future works.

2 A BRIEF STATE-OF-ART ON TRANSFER LEARNING

Transfer learning can change how SHM analysis are currently proposed due to the significant benefits of the application of this methodology. Hence, it is necessary to understand its theoretical background to ensure an effective implementation. This chapter outlines a brief state-of-art on transfer learning that describes the foundations of this methodology.

Section 2.1 highlights a correlation between the concepts of human learning, machine learning, and transfer learning to understand how the concepts of learning to learn can represent an important alternative for an analysis. In Section 2.2, the necessary requirements for carrying out knowledge transfer are briefly addressed to outline the knowledge to be leveraged and the defined approach used in the process, assessing whether the transfer learning should be achieved. Section 2.3 presents the definition of the main terms that describe the particularities of transfer learning compared to traditional learning methods. Section 2.4 provides a description of the different approaches used for knowledge transfer defined according to the type of knowledge contained in the data sets. Finally, Section 2.5 discusses the main conclusions of this chapter.

2.1 LEARNING TO LEARN

Humans constantly develop and improve their skills to solve several types of activities on daily basis, ranging from the most trivial to the most complex ones, by leveraging the experience acquired throughout their lives. The main idea is based on the inherent characteristic of human beings of learning to learn, which allows adapting and generalizing prior knowledge to find possible solutions to apply in new situations.

It is well known that machine learning focuses on describing how machines "think" and "learn" using a context similar to human learning. The application of these methods in the society has significantly increased in the last decade due to its attractive capabilities. In the medical field, the health condition of patients can be investigated using image processing methods, including heart disease and cancer diagnosis for instance (ARDILA *et al.*, 2019; ATTIA *et al.*, 2019; MCKINNEY *et al.*, 2020). The pattern of financial market involving stock prices can be also monitored by regression methods (KIM, 2003;

TSANTEKIDIS *et al.*, 2017). Additionally, engineering can benefit from the application of these data-driven methods, including civil structures (BROWNJOHN, 2007; MAES *et al.*, 2022), aeronautics (RÉBILLAT; MECHBAL, 2020; PAIXÃO *et al.*, 2021), railways (BARKE; CHIU, 2005; VAGNOLI; REMENYTE-PRESCOTT; ANDREWS, 2018), etc.

The machine learning methodology proposes to make a prediction or decision through the estimated models using the knowledge present in the measured data sets. Nonetheless, the performance of these methods is usually limited to a specific situation, as it relies on the quality and quantity of the data sets used during the learning phase. This can result in an important reduction in the performance of estimated models when applied in new analysis, requiring a new model identification or its updating becomes necessary.

Transfer learning follows the same concept of the human intelligence by intelligently applying previous knowledge to provide potential better solutions, and assist in the future decision-making consequently. There are several examples where the transfer of skill sets and knowledge can be noticed regularly in people's habits. For instance, a person is able to learn how to ride a motorcycle more easily if they already have previous experience of riding a bicycle, the musical concepts of playing a guitar can be useful for learning how to play a new musical instrument, the vocabulary and grammar of one language can be helpful to learn a new language, and so on. Hence, the model is prevented from memorizing how to perform a specific task and its learning ability to generalize is effectively achieved.

It is evident that machine learning and transfer learning share similarities with human learning, as they represent a part of artificial intelligence that involves using the knowledge present in data sets to learn. Nevertheless, the application of transfer learning can possibly present a better performance using less data, as it emulates the generalization capacity of human learning by reusing knowledge accumulated in different domains. Thus, the necessity to identify a new model from the scratch for further analyzes is minimized and consequent computational costs are reduced.

2.2 MAIN QUESTIONS TO PERFORM TRANSFER LEARNING

There are some requirements that need to be addressed before deciding whether transfer learning can be proposed for different situations. This often involves the knowledge to be transferred and the discussion about the necessity for its realization (ZHUANG *et al.*, 2021). Therefore, three important questions mainly deals with:

- **What to transfer?** Definition of the knowledge present in the data sets that

can be transferred across domains. For instance, if we want to transfer knowledge related to temperature dependency in structures, we should investigate them under similar environmental conditions and find common knowledge that can be shared. To address the dynamic behavior of different structures, the modal parameters (e.g. natural frequencies) represent a potential relevant knowledge.

- **How to transfer?** The choice of the type of transfer learning approach is mainly decided based on the previous question, i.e., the definition of the knowledge present in the data sets that can be transferred across domains. Thus, it is possible to select a suitable method to perform transfer learning.
- **When to transfer?** When knowledge transfer is necessary, it is expected that the source knowledge would significantly benefit the analysis of the target domain. However, there is a possibility of poor model performance after the knowledge transfer, representing the occurrence of negative transfer (ROSENSTEIN *et al.*, 2005). This is a result of difficulties in correctly answering the previous questions, i.e., what knowledge that can be shared and how the proposed method will use it to improve the performance of the model. Thus, further analysis about transferability and similarity is necessary to evaluate whether transfer learning should be carried out according to the accuracy of the model.

There are several definitions about the phenomenon of negative transfer, but there is not a formal definition that is a common sense in the transfer learning community. This topic has not been widely investigated in the literature, even though there are examples that faced the consequent challenges associated with the occurrence of negative transference during an analysis (GE *et al.*, 2014; GUI *et al.*, 2018; WANG *et al.*, 2019).

There are some aspects that can contribute to the occurrence of negative transfer. If the divergences between the source and target domains are significant, it is not feasible to set a suitable relationship that allows the transfer to be properly performed. The theoretical background of the proposed method should secure that source knowledge is leveraged to the target task, improving the performance of the classifier as a result. Still, data quality and quantity are important due to the possibility of existing noisy data, the presence of irrelevant knowledge present in the data sets, and class imbalance that can significantly hurt transfer (ZHANG *et al.*, 2023).

2.3 DEFINITION OF TRANSFER LEARNING

Pan and Yang (2010) presented a detailed overview of transfer learning that outlines the notations and definitions of the terms used, the methods categorization, and some examples that highlighted the benefits of applying this methodology. The description of domain and task is necessary to understand the particularities of transfer learning and domain adaptation, defining the context to compare them with the traditional machine learning methods.

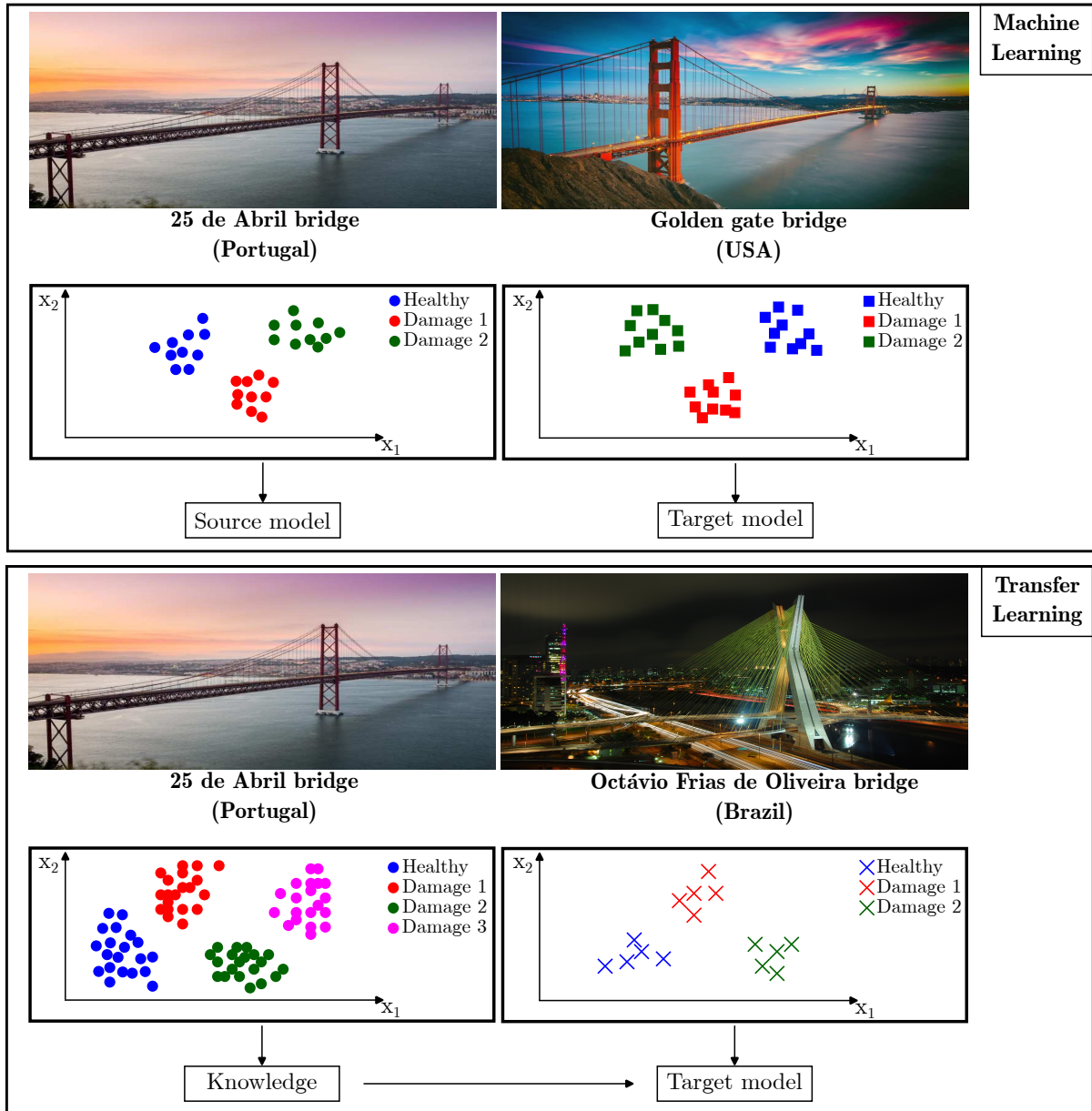
A domain $\mathcal{D}$ is defined by a feature space $\mathcal{X}$ that contains the feature vectors $\mathbf{x}$ and their marginal probability distribution $P(\mathbf{x})$. Meanwhile, a task $\mathcal{T}$ is represented by the label space $\mathcal{Y}$, which in most SHM cases is assumed as binary labels (healthy and damaged), and an objective predictive function $f(\cdot)$ that can be determined based on the training data.

Figure 1 illustrates the relationship between traditional and transfer learning methodologies. Machine learning demands the equivalence between the source and target domains ($\mathcal{D}_s = \mathcal{D}_t$) and their tasks ($\mathcal{T}_s = \mathcal{T}_t$). This condition limits the application of the model only to the circumstances in which it was estimated. In contrast, transfer learning is not limited to such requirement as it allows the analysis even if there are inconsistencies in the domains ($\mathcal{D}_s \neq \mathcal{D}_t$) and tasks ($\mathcal{T}_s \neq \mathcal{T}_t$). The relevant knowledge previously acquired from the source domain is reused to improve the performance of the target task (COOK; FEUZ; KRISHNAN, 2013).

Domain adaptation is a subfield of transfer learning associated with the reduction of the distribution mismatch between different domains as its main aspect (LONG *et al.*, 2016). Likewise, the case of transfer learning, domain adaptation was extensively applied in the literature in several other research areas (GLOROT; BORDES; BENGIO, 2011; Gopalan; Ruonan Li; Chellappa, 2011; GANIN; LEMPITSKY, 2014; GHIFARY *et al.*, 2016). However, there are differences between transfer learning and domain adaptation that do not allow their applications to be reciprocal. For the SHM problems, domain adaptation methods reduce divergences between the features (e.g., modal parameters) under the same structural conditions extracted from different structures. Transfer learning allows the analysis of several structures using different data sets and models regardless of their labels. Formally, domain adaptation focuses on minimizing the distributions distances while preserving the consistency of features and tasks. In this case, the feature space and tasks are similar $\mathcal{X}_s = \mathcal{X}_t$ and $\mathcal{T}_s = \mathcal{T}_t$, but the probability distributions are different $P(\mathbf{X}_s) \neq P(\mathbf{X}_t)$. Meanwhile, transfer learning applies the knowledge regardless

of the correspondence between domains and tasks (PATRICIA; CAPUTO, 2014).

Figure 1 – Comparison between traditional machine learning and transfer learning methodologies in the SHM context.



Source: Prepared by the author.

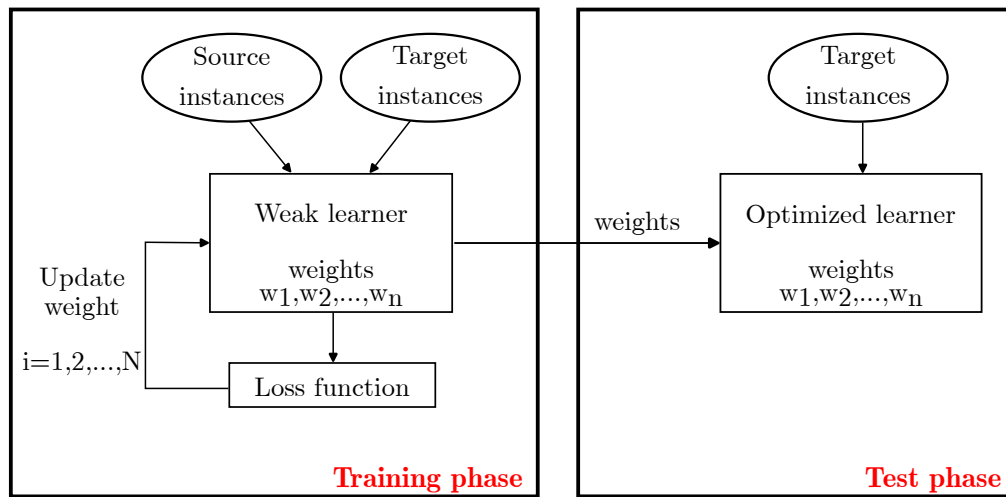
2.4 TRANSFER LEARNING APPROACHES

It is important to define the common knowledge to be shared between different domains, as it defines the transfer learning approach to be applied. According to the knowledge type to be transferred, there are four main approaches (WEISS; KHOSHGOFTAAR; WANG, 2016):

2.4.1 Instance-based transfer learning

This approach proposes reweighting the labeled source data according to their similarities with the target data as a solution to aid learning of the target domain. Figure 2 illustrates a general overview of methods that propose an instance-based transfer learning approach. The source and training target instances are used to estimate a weak learner, which has its weights values initially determined. A loss function is estimated according to the learner's performance, and larger weights are assigned to the useful source data while their values are decreased in contrast. This process is performed iteratively for the optimization of the weak learner and the validation target data is used in the test phase to highlight the efficiency of the estimated model.

Figure 2 – Outline of instance-based transfer learning.



Source: Prepared by the author.

A well-known instance-based transfer learning method, called TrAdaBoost, was proposed by Dai *et al.* (2007) to reuse outdated data sets to solve the data scarcity in the training phase often addressed in real situations. Despite the divergences between the probability distributions of the old and new data sets, it is assumed that there is useful knowledge in outdated data that can be leveraged for further analysis. Thus, the method proposes to adjust the weights of the training instances iteratively according to the performance of a weak learner that assigns larger weights when a correct evaluation is achieved.

A weighting strategy based on the mutual information of different feature representations was proposed by Zhao, Liu and Yang (2018) to improve the recognition of human facial expressions. The similarities between the features of the source and target domains

were highlighted by larger weights of mutual information, which results in a larger amount of training data sets for the target model of each feature representation. Then, weighting parameter learning combines the individual models of each feature representation and improves model performance accordingly.

Wang, Huan and Zhu (2019) proposed a pre-trained model to estimate the influence of source data on the target domain based on the minimization of the loss function that evaluates the performance of the model in image classification. The samples with a negative influence were removed and the remaining data could be used in fine-tuning or estimating an optimized neural network model to evaluate the test data of target domain.

2.4.2 Model-based transfer learning

This approach is mainly applied in methods based on deep learning methods due to the existence of several pre-trained neural networks models that can be adjusted for different analysis. The model parameters and hyperparameters can be transferred across domains to estimate a robust model with accurate predictions, while the computational cost associated to the training phase is reduced

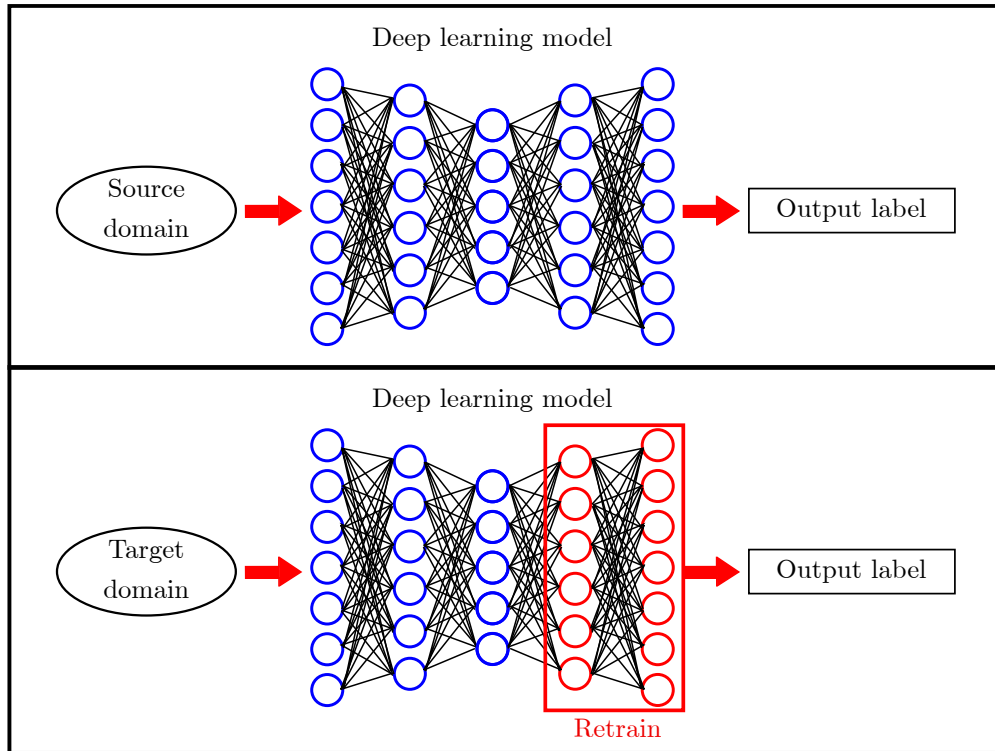
The industry of renewable energy production from wind farms can leverage the application of deep learning models due to the complexity of representing the uncertainties involved in the dynamic behavior of wind turbines. Hu, Zhang and Zhou (2016) investigated a newly built wind farms through a neural network model trained with historical data from other wind farms. The hidden layers of the deep neural network model were trained and fine-tune was performed through backpropagation with the labeled data to determine the model parameters. Then, a fine-tuning using data sets from each new wind farm was carried out, resulting in a model capable of generalizing and predicting the wind speed applied to the wind turbines.

In medical diagnosis, the performance of deep learning models is often affected by the availability of quality images and concerns about the privacy of several patients. Shin *et al.* (2016) proposed the layer adjustment of pre-trained convolutional neural network models to overcome these limitations, and to provide reliable tomography image diagnosis of lymph node detection and lung disease. The proposed model-based transfer learning approach indicated a better classification accuracy when compared to traditional methods, proving the benefits of reusing the knowledge present in pre-trained models to perform a task related to its initial purpose.

Jang, Kim and An (2019) suggested the application of a hybrid image scanning embedded an unmanned aerial vehicle to detect cracks in large structures using a pre-trained deep learning model. The last two layers of a pre-trained convolutional neural network model were retrained using a combination of raw vision and infrared images of a laboratory structure under different conditions. Thus, the proposed approach induces an improvement in model performance and results in a robust model capable of reducing possible false alarms.

Figure 3 demonstrates the application of a deep learning model for a model-based transfer learning approach. It is assumed that there is a significant amount of label data in the domain to estimate a well-trained neural network model, which is capable of correctly evaluating the input data. For knowledge transfer, the structure of the estimated model is preserved and the target data is used to retrain the last layers of the neural network model to perform its task.

Figure 3 – Outline of model-based transfer learning.



Source: Prepared by the author.

2.4.3 Relation-based transfer learning

The application of this transfer learning approach is a topic that has not yet been extensively investigated and further analysis is necessary to understand its extension to several situations. This approach focuses on establishing a relationship between the data sets collected from different domains and using this relationship as the knowledge that can be shared to improve the model and classifier performance.

To address the relationship between the source and target domains, Markov logic networks represent an interesting alternative that can be used to determine the probabilities of the relations between first-order logic, taking into account the existence of uncertainties during the process. However, the definition of this relationship may not be trivial and it can often be computationally expensive, which justifies conducting knowledge transfer. For instance, Mihalkova, Huynh and Mooney (2007) prevented setting the relationship between domains from the scratch through the transfer via automatic mapping and revision method. At first, the source instances and their labels established the structures of the Markov networks and their transfer to the target domain was performed afterwards, which might be necessary reweighting the model using the target instances. The proposed methodology resulted in a robust model that had its effectiveness evidenced in benchmarks with different types of data sets, presenting an improvement of its accuracy while ensuring faster predictions.

In the area of natural language processing, there are examples of data instances that share similarities in text structures, although they belong to different domains. For example, Li *et al.* (2012) suggested using the Relational Adaptive bootstrapping method to perform sentiment and topic analysis on different but related benchmarks that evaluate film and product reviews. It is defined a correlation between words contained in a text instead of the information in documents that indicate the common sentiment between the investigated domains. Then, the evaluation of the text structures of the target domain were evaluated through an indirect connection between the patterns found in the source domain.

2.4.4 Feature-based transfer learning

Figure 4 shows an example of feature-based transfer learning approach. A new representation of the structural behavior is described by damage-sensitive features, which are estimated from raw data sets measured from distinct structures. In this approach, features

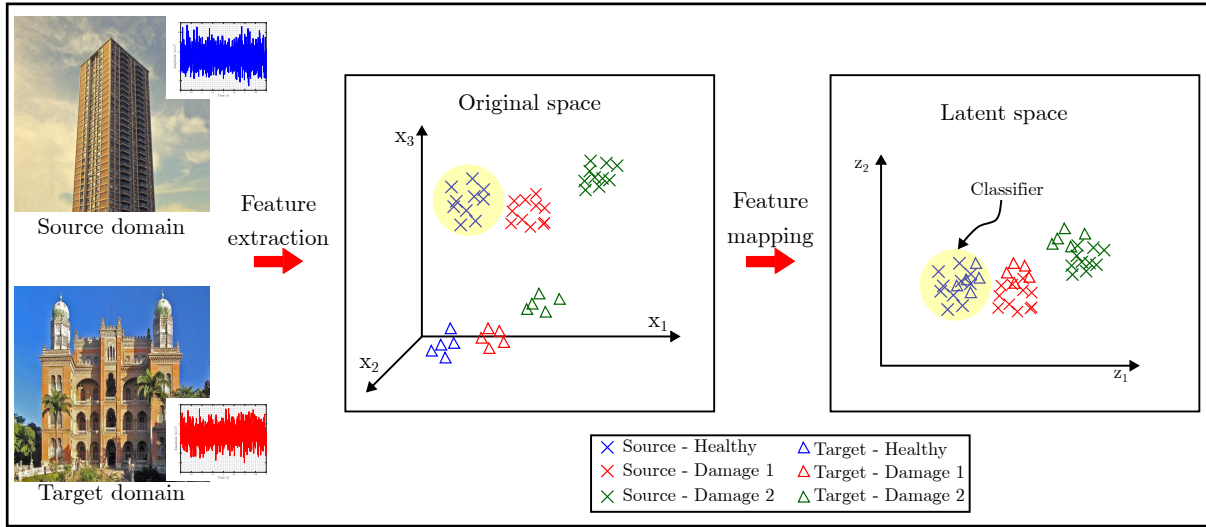
extracted from source and target domains can be mapped into a shared latent space, where their divergences are mitigated. Therefore, the knowledge present in the source features is assigned to the definition of a model or classifier to evaluate the unlabeled target features.

The geodesic flow kernel method proposed by Gong *et al.* (2012) is an example that follows a feature-based transfer learning approach that performs object recognition on benchmarks with different types of images. This method deals with the domain shift by integrating an infinite number of subspaces between source and target domains, and domain-invariant features are determined to indicate which of them are useful for transfer learning. The benefits of knowledge transfer application were evidenced by comparing its performance with other methods that do not transfer, showing an improvement in the performance of the classifier according to the increase of a defined adaptability metric.

The work of Wang *et al.* (2017) suggested the application of two feature-based transfer learning methods, called Balanced Domain Adaptation and Weighted Balanced Domain Adaptation, to evaluate images from different benchmark data sets. The alignment of the conditional and marginal distributions of features extracted from images was carried out through their mapping into a shared latent space, assuming the respective importance of the probability distributions during analysis. Additionally, the Weighted Balanced Domain Adaptation represents a potential solution to the class imbalance problem often addressed in real situation by adjusting weights for the investigated classes.

Working conditions that perform drilling operations also represent an interesting application of transfer learning in engineering cases. Ritto *et al.* (2022) proposed a set of feature-based transfer learning methods to investigate drilling components under different configurations that were subjected to friction effects during their operation. As the drilling operation proceeds, the localization of torsional friction effects changes according to the variation of the length or diameters of drill strings. Therefore, knowledge transfer enables the alignment the features from different configurations through their projection into a latent space, and knowledge transfer can be performed using a robust classifier trained using a known condition

Figure 4 – Outline of feature-based transfer learning.



Source: Prepared by the author.

2.5 CONCLUSIONS

This chapter presented a brief description of the state-of-art of transfer learning methodology, providing an overview of the main topics, definitions, and approaches that involve the process of leveraging the knowledge in different domains. It is widely known that the machine learning has its roots based on the context of human learning, as its main idea is to extract information and patterns present in data sets. However, this methodology has restrictions related to its application being assigned to individual cases. Thus, transfer learning emerges as a potential solution to overcome such limitations as it allows the generalization of models and classifiers for several analysis.

The adaptability of this methodology can cover a wide range of different areas, including natural language processing, sentiment analysis, medical field, engineering, image classification, etc. In addition, a more formal discussion based on the main terms related to the learning concept was evidenced by comparing the similarities and differences between the source and target domains and their respective tasks.

Despite the potential benefits resulting from the transfer process, there are certain requirements that need to be met for the transfer to occur properly in real situations. It is necessary to correctly define the type of knowledge to be used across domains in order to select an adequate learning transfer approach, which can be based on features. Otherwise, there is a possibility of negative transfer, which damages the performance of the estimated model.

3 TRANSFER LEARNING FOR STRUCTURAL HEALTH MONITORING

In the SHM context, a common situation handled in long-term monitoring of several structures deals with situations where there is a significant amount of labeled data from one structure ("expensive" data) and a lack of labeled data from other structures ("cheap" data) due to difficulties mainly related to data acquisition. Therefore, transfer learning represents an attractive solution, whereas the application of machine learning methods may be limited.

This chapter addresses the main motivations that led to the development of the transfer learning methodology to assess the integrity of different structures and how the application of these methods implies in the analysis of real-world situations. First, Section 3.1 introduces the reasons that corroborate the need to implement transfer learning methods in a SHM context. Then, section 3.2 presents an overview of recent works that generally mainly propose the application of feature-based and model-based transfer learning approaches during SHM analysis. Section 3.3 formally describes three methods based on well-known features that are often applied in different cases to reduce divergences between source and target domains. Finally, Section 3.4 presents partial considerations regarding the application of the proposed methods for SHM cases.

3.1 REASONS TO DEVELOP A TRANSFER LEARNING METHODOLOGY FOR SHM

Transfer learning is a subfield of machine learning that can be understood from different perspectives. Here, we summarize four reasons to develop a transfer learning methodology for SHM analysis (YANG *et al.*, 2020):

- Transfer learning discusses how machine learning models can be adapted to new situations (structures), purposes (levels of damage identification), and different environments (operational and environmental conditions). The idea is to determine relevant structural knowledge from a structure or a set of structures to be reused in the damage identification process of new structures. If knowledge comes from a set of structures, some authors also called it population-based transfer learning

(GARDNER *et al.*, 2021). The benchmark data can be from laboratory models, numerical models, or similar bridge structures.

- The ability to learn how to deal with new situations is associated with the human brain’s ability to adjust previous experiences (monitoring or numerical data) to help solve new problems (damage identification levels). Adaptation is an innate ability of intelligent beings, and SHM of bridges should also be endowed with transfer learning ability.
- We observe that the authorities manage similar structures; collecting long-term monitoring data from every structure is not possible due to financial and technical limitations. Additionally, knowledge transfer can overcome the limitation on knowledge about the presence of structural damage, as it is not feasible to introduce real damage to a structure. Therefore, transfer learning can reuse the experience gained in the past monitoring data, for instance, from a set of structures to help make more effective decisions in new situations and environments.
- Transfer learning can make machine learning models for specific structures more reliable and robust. It is not possible to measure data sets from all operational and environmental conditions in the training phase. Thus, transfer learning has the potential to allow the model generalization while also being discriminant when data changes occur.
- Numerical models (like FE models) are digital replicas of bridges that can simulate the structural response. Even when well-calibrated, these models are not exact and do not fit all experimental information. Thus, the probability distribution of some of its generated features is expected to differ compared to the features extracted from experimental measurements. As long as the numerical models share the physics of real bridges, they do not need to be precise and make that knowledge transferable for real bridges.

3.2 A ROADMAP OF TRANSFER LEARNING FOR STRUCTURAL HEALTH MONITORING

Transfer learning is an emerging topic in SHM that has been investigated recently, but it is possible to find some papers that deals with structural analysis in other study fields. Early research papers were mainly focused on rotating machinery components to

perform fault diagnosis before the transfer learning methodology was effectively applied in the SHM field (WANG *et al.*, 2016; LU *et al.*, 2017; LI *et al.*, 2020).

As it represents a new methodology in SHM analysis, there was a need to define how knowledge transfer could be proposed in different types of structure populations and avoid identifying new models for the analysis of individual cases consequently. Then, the foundations of population-based SHM for mechanical systems have been laid down in the papers of Bull *et al.* (2021b), Gosliga *et al.* (2021), and Gardner *et al.* (2021). Although these papers only describe a brief overview of transfer learning and investigate laboratory structures, it is possible to have a better understanding of how transfer learning can be proposed in real situations and how to deal with the possible drawbacks addressed during an extensive analysis.

The first paper described homogeneous populations (e.g., a population of wind turbines in a wind farm) as a set of nominally-identical structures that present equivalent behavior, framework, and boundary conditions. Nevertheless, these structures may present differences associated with the properties of material and manufacturing process, even though they are assumed to be identical. In this case, transfer learning can be facilitated due to the analogy of structures and a generalized model can be shared between these types of structures to assess their integrity.

Another important topic addressed by these papers was the similarity of populations of structures to carry out a suitable transfer. The attributed graph was an alternative suggested to represent the structures in an abstract context of their main components to allow their comparison in a population set. The theoretical background of this type of representation was outlined to describe its formal definition and terminology to set the similarities between different structures, and provide a successful knowledge transfer consequently when a satisfactory similarity index is achieved.

There are some authors who investigated the effects of similarities between different structures on knowledge transfer analysis. For instance, Delo *et al.* (2022) proposed a similarity analysis between different types of structures to evaluate the feasibility of transfer learning. A graph-matching method investigated the similarities between bridges and airplanes, showing their disagreement through a similarity index that does not allow knowledge transfer. The similarity index highlighted the differences between the structures according to their framework, while the similar ones indicate the possibility of transferring data. In contrast, higher indices levels were achieved when structures of the same type were compared, indicating the algorithm's ability to assign the types

of systems correctly. Meanwhile, Gosliga *et al.* (2022) suggested the application of an irreducible element representation to assess the correspondences between various types of bridges and estimate their similarity before the application of knowledge transfer.

The last paper in the series on foundations of population-based SHM investigated heterogeneous populations by mapping their modal parameters extracted from distinct structures to another shared subspace. A categorization of population types based on the material that composes the structures, topology, and geometry was proposed to address the similarities among different structures. Thus, it is possible to determine the existence of similarities even between heterogeneous structures and avoid the possibility of resulting in a negative transfer.

Recent advancements in the application of transfer learning endorse using the model-based approach. For instance, a vision-based method to detect bridge defects using transfer learning with convolutional neural networks was proposed by Zhu *et al.* (2020). A pre-trained convolutional neural network model, denominated Inception v3, was applied to extract the relevant information from images of defects typically found in bridge elements. Then, this knowledge was used as input data of a neural network to determine the presence of damage and indicate its type. The comparative studies indicated a better performance of the methodology based on transfer learning for image processing, which provides an intelligent management assessment and reduces the need for manual visual inspections.

Tronci *et al.* (2022) proposed transfer learning for bridge SHM by leveraging the knowledge from speech recording data sets to enrich the training phase of a classifier applied to assess the structural condition of a real bridge. The knowledge from source domain was reused in the target domain through a pre-trained deep learning model using audio data sets to extract features from experimental data collected from the bridge. Then, the Mel-frequency cepstral coefficients were assumed as the investigated damage-sensitive features in a binary classification of the structural damage assessment of the bridge.

Pan, Bao and Li (2023) proposed a data anomaly detection based on a model-based transfer learning approach that uses the similarity of the anomalous patterns across different bridges and shares the knowledge incorporated in a deep neural network. The proposed methodology converted vibration and environmental data sets from a source bridge into an image format to train convolutional neural networks for data anomaly classification.

An interesting approach that has become noteworthy is feature-based transfer learning due to the use of damage-sensitive features extracted from data sets of different structures,

representing how SHM is traditionally proposed. The importance of this approach is related to the possibility of using modal parameters that represent a valuable information about the structural dynamic behavior, incorporating the physical phenomena involved and providing a better insight from an engineering perspective.

Recently, Transfer Component Analysis (TCA) and Joint Distribution Adaptation (JDA) represent some of the main feature-based methods used in SHM analysis as it reduces the divergences between the distributions while preserving the data information (NAM; PAN; KIM, 2013). In 2020, Liu and Worden (2020) presented one of the first papers that introduced the concept of transfer learning involving the SHM analysis. Their work extended the concept of traditional methodologies often applied in structural analysis and presented new inspiring alternatives for further analysis in the hierarchy of damage identification. The results of a simple numerical example were encouraging due to the ability of generalizing a classifier to different cantilever beams.

A more comprehensive analysis was presented by Gardner, Liu and Worden (2020) to define a case study that is effectively based on transfer learning for damage detection. Three different feature-based methods, namely TCA, JDA, and Adaptation Regularization based Transfer Learning (ARTL) were applied on data sets from several laboratory structures to underline their significant benefits in terms of classification performance when compared with traditional machine learning methods.

Han *et al.* (2020) presented the advantages of using the JDA method with deep learning models to evaluate the integrity of wind turbines, gearboxes, and bearings. In each case analyzed, statistical features were extracted from the source domain's labeled data and used to train convolutional neural networks to investigate similar structures' behavior. The JDA application reduced the mismatch of the joint probability distributions of features to provide more suitable models, which may be used for practical cases of structural diagnosis even when the structure is under different operational conditions. Meanwhile, Ozdagli and Koutsoukos (2020) compared prediction accuracy of the unlabeled target data with and without domain adaptation in two laboratory case studies, namely from a gearbox and a three-story frame structure. The results demonstrated the effectiveness of TCA where the access to labeled experimental data is limited.

The benefits of using TCA compared with other methods, such as principal component analysis and kernel principal component analysis, were presented by Bull *et al.* (2021a). The data collected from different aircraft tailplanes were used to determine a nonlinear function that generalized the features in the healthy condition. In contrast, features in

the damaged condition were classified as outliers.

It is well-known that the effects of environmental and operational conditions can affect the performance of machine learning methods usually applied in structural integrity analysis. Silva, Yano and Gonsalez-Bueno (2021) applied TCA to minimize the variations in the features caused by temperature effects using an experimental testbench under different scenarios. At first, a feature extraction was performed based on the real and imaginary parts of the electromechanical impedance signals that represented different structural conditions. Then, the divergences between the features due to temperature effects were compensated after their mapping to a latent space, where the knowledge comprised in the features under reference temperature could be transferred to evaluate the features at other temperatures.

A comprehensive study about a population-based of bolted joint structures was proposed by Silva *et al.* (2023) to detect a loss of tightening torque using a classifier with the ability to extend its knowledge within the population of structures. This important type of configuration is extensively used in several structures to provide appropriate structural robustness and stiffness, while damping the effects of vibrations during its operation. However, it is complex to perform direct measurements of their behavior and knowledge transfer using TCA was proposed as a solution to overcome this limitation. A set of particular beams, namely the Orion beam, with different dimensions and contact interface was investigated using a classifier trained in a safe torque condition to indicate when the progressive loosening of the bolts were noticed.

3.3 METHODS TO PERFORM FEATURE-BASED TRANSFER LEARNING

In this work, a feature-based approach is considered in the analysis, as SHM is traditionally defined in the context of a statistical pattern recognition paradigm that performs feature extraction on the measured raw data (FIGUEIREDO; BROWNJOHN, 2022). This approach requires an adequate representation (feature) that contains information about the structural behavior as knowledge to be transferred (PAN; YANG, 2010; YANG *et al.*, 2020). Thus, natural frequencies are attractive damage indicators often used to characterize the structural condition due to the simplicity of their estimation and also because they can properly represent the integrity of structures due to their dependency on stiffness and mass.

Herein, the main idea is to perform transfer learning based on the perspective of

domain adaptation for a structure-to-structure analysis, assuming a labeled source domain and an unlabeled target domain. Thus, the domains and tasks of the source and target are equivalent, but their probability distributions present statistical differences (DAY; KHOSHGOFTAAR, 2017).

3.3.1 Transfer Component Analysis (TCA)

The TCA method (PAN *et al.*, 2011) represents a feature-based transfer learning method that uses a nonlinear mapping function $\phi(\cdot)$ to infer the features from source ($\mathbf{X}_s$) and target domains ($\mathbf{X}_t$) into a latent space, named reproducing kernel Hilbert space ($\mathcal{H}$). In this subspace, the divergences between marginal distributions are mitigated ($P(\phi(\mathbf{X}_s)) \approx P(\phi(\mathbf{X}_t))$). In contrast, their conditional distributions are equivalent ($P(\mathbf{Y}_s|\phi(\mathbf{X}_s)) = P(\mathbf{Y}_T|\phi(\mathbf{X}_t))$).

Several well-known methods can be used to calculate distances between the feature distributions, such as Kernel Mean Matching (YU; SZEPEŠVARI, 2012) and Kullback-Leibler Divergence (HARMOUCHE; DELPHA; DIALLO, 2014). The Maximum Mean Discrepancy is applied to evaluate the average squared distance between the domains in the reproducing kernel Hilbert space (GRETTON *et al.*, 2006). However, the determination of the nonlinear mapping function is complex. One possible solution is to implicitly determine the mapping function through a kernel (covariance) matrix $\mathcal{K}(x, x') = [\phi(x)^T \phi(x')]$ (SCHÖLKOPF, 2001). Then, the Maximum Mean Discrepancy ($\mathcal{M}$) can be described as:

$$\mathcal{M}(P(\phi(\mathbf{X}_s)), P(\phi(\mathbf{X}_t))) = \left\| \frac{1}{n_s} \sum_{i=1}^{n_s} \phi(x_{s_i}) - \frac{1}{n_t} \sum_{j=1}^{n_t} \phi(x_{t_j}) \right\|_{\mathcal{H}}^2 = \text{tr}(\mathcal{K}\mathcal{L}_0) \quad (1)$$

where $\mathcal{K} \in \mathbb{R}^{(n_s+n_t) \times (n_s+n_t)}$ is kernel matrix defined by the source $\{x_{s_i}\}_{i=1}^{n_s}$ and target $\{x_{t_j}\}_{j=1}^{n_t}$ features, and the $\mathcal{L}_0$ matrix can be written as:

$$(\mathcal{L}_0)_{ij} = \begin{cases} \frac{1}{n_s^2}, & x_i, x_j \in \mathcal{D}_s \\ \frac{1}{n_t^2}, & x_i, x_j \in \mathcal{D}_t \\ -\frac{1}{n_s n_t}, & \text{otherwise.} \end{cases} \quad (2)$$

An empirical kernel ($\tilde{\mathcal{K}}$) is associated with a transformation matrix ($\mathcal{W}$) to enable the features mapping to a m -dimensional space ($m \ll n_s + n_t$), being defined as $\tilde{\mathcal{K}} = \mathcal{K}\mathcal{W}\mathcal{W}^T\mathcal{K}$. So, the equation 1 can be rewritten as:

$$\mathcal{M}(P(\phi(\mathbf{X}_s)), P(\phi(\mathbf{X}_t))) = \text{tr}(\mathcal{W}^T\mathcal{K}\mathcal{L}_0\mathcal{K}\mathcal{W}) \quad (3)$$

A requirement that must be ensured after the feature mapping is to preserve the data properties. Thus, the determination of the weights of the mapping matrix results in an optimization problem defined as the minimization of the probability distribution distance while keeping the data variance as a constraint. Formally, this optimization problem can be defined as:

$$\begin{aligned} \min_{\mathcal{W}} \quad & tr(\mathcal{W}^T \mathcal{K} \mathcal{L}_0 \mathcal{K} \mathcal{W}) + \mu tr(\mathcal{W}^T \mathcal{W}) \\ \text{subjected to} \quad & \mathcal{W}^T \mathcal{K} H \mathcal{K} \mathcal{W} = \mathbf{I} \end{aligned} \quad (4)$$

where $\mathbf{I}$ is the identity matrix, $H = \mathbf{I} - (\frac{1}{n_s + n_t})\mathbf{1}$ is the centering matrix, $\mathbf{1}$ is a matrix of ones, and $\mu > 0$ is the trade-off parameter. One possible solution to determine the weights of $\mathcal{W}$ is to use the Lagrange multipliers (GARDNER; LIU; WORDEN, 2020), leading to an eigenvalue problem defined by:

$$[(\mathcal{K} \mathcal{L}_0 \mathcal{K} + \mu \mathbf{I})^{-1} \mathcal{K} H \mathcal{K}] \mathcal{W} = \lambda \mathcal{W} \quad (5)$$

where the m leading eigenvectors define the transformation matrix $\mathcal{W}$, and the resulting features embedding into the latent space are determined by $\mathcal{F} = \mathcal{K} \mathcal{W}$.

3.3.2 Joint Distribution Adaptation (JDA)

The JDA method (LONG *et al.*, 2013) is a feature-based transfer method that minimizes the divergences between the joint distributions by reducing the differences between marginal distributions $P(\phi(\mathbf{X}_s)) \approx P(\phi(\mathbf{X}_t))$ and conditional distributions $P(\mathbf{Y}_s | \phi(\mathbf{X}_s)) \approx P(\mathbf{Y}_T | \phi(\mathbf{X}_t))$.

The definition of joint distributions is nontrivial due to the missing labels of target data. It leads to assuming the class-conditional distributions, $P(\phi(\mathbf{X}_s) | \mathbf{Y}_s = c)$ and $P(\phi(\mathbf{X}_t) | \mathbf{Y}_t = c)$ with class $c = \{0, 1, \dots, C\}$, instead of conditional distributions as one suitable solution. A base classifier uses the source knowledge to assess the target domain, and it is applied iteratively to estimate the target pseudo-labels at each round (GARDNER *et al.*, 2021). Thus, it is possible to perform an optimization of the mapping function until the convergence of the target pseudo-labels for the determination of class-conditional distributions.

Again, the distance metric used for the analysis of the probability distributions mismatch is determined through the kernel-based maximum average discrepancy, which can

be defined as:

$$\mathcal{M}(P(\phi(\mathbf{X}_s)), P(\phi(\mathbf{X}_t))) + \mathcal{M}((\phi(\mathbf{X}_s)|\mathbf{Y}_s), (\phi(\mathbf{X}_t)|\mathbf{Y}_t)) = \text{tr}(\mathcal{W}^T \mathcal{K} \mathcal{L}_c \mathcal{K} \mathcal{W}) \quad (6)$$

where $\mathcal{K}$ is the kernel matrix and $\mathcal{W}$ is the transformation matrix. Unlike the TCA method, the $\mathcal{L}_c$ matrix is defined based on the number of samples from the source and target domains according to the labels estimated by the base classifier. So, the $\mathcal{L}_c$ matrix can be written as:

$$(\mathcal{L}_c)_{ij} = \begin{cases} \frac{1}{n_s^{(c)} n_s^{(c)}}, & x_i, x_j \in \mathcal{D}_s^{(c)} \\ \frac{1}{n_t^{(c)} n_t^{(c)}}, & x_i, x_j \in \mathcal{D}_t^{(c)} \\ \frac{-1}{n_s^{(c)} n_t^{(c)}}, & \begin{cases} x_i \in \mathcal{D}_s^{(c)}, x_j \in \mathcal{D}_t^{(c)} \\ x_j \in \mathcal{D}_s^{(c)}, x_i \in \mathcal{D}_t^{(c)} \end{cases} \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

where $\mathcal{D}_s^{(c)} = \{x_i : x_i \in \mathcal{D}_s \wedge y(x_i) = c\}$ represent the source features and their true labels $y(x_i)$ and $\mathcal{D}_t^{(c)} = \{x_j : x_j \in \mathcal{D}_t \wedge \hat{y}(x_j) = c\}$ represent the target features with their target pseudo-labels $\hat{y}(x_j)$.

Following the optimization problem that proposes to reduce the distances between probability distributions while the data properties are preserved, the minimization can be described as follows:

$$\min_{\mathcal{W}^T \mathcal{K} H \mathcal{K} \mathcal{W} = \mathbf{I}} \sum_{c=0}^C \text{tr}(\mathcal{W}^T \mathcal{K} \mathcal{L}_c \mathcal{K} \mathcal{W}) + \mu \text{tr}(\mathcal{W}^T \mathcal{W}) \quad (8)$$

where H is the centering matrix, $\mathbf{I}$ is the identity matrix, and μ is the trade-off parameter of the regularization term. Note that the minimization of equation 8 when $c = 0$ demonstrates that TCA is a particular case of the JDA method, indicating that the first iteration results in the reduction of the marginal distributions as an initial estimate. So, the Lagrange multipliers are applied again as a solution to this problem, resulting in an eigenproblem defined as:

$$\left(\mathcal{K} \sum_{c=0}^C \mathcal{L}_c \mathcal{K} + \mu \mathbf{I} \right) \mathcal{W} = \mathcal{K} H \mathcal{K} \mathcal{W} \lambda \quad (9)$$

where the m smallest eigenvectors represent the optimal weights of transformation matrix $\mathcal{W}$, and the transfer features into the latent space are determined through $\mathcal{F} = \mathcal{K} \mathcal{W}$.

3.3.3 Maximum Independence Domain Adaptation (MIDA)

The MIDA method (YAN; KOU; ZHANG, 2018) is a feature-based transfer method that aims to project features and domain features extracted from the source and target domains to a latent space where their independence is maximized. This implies the minimization of divergences between the probability distributions as the differences across different domains become less significant.

In contrast to the other methods, the domain features provide the ability to outline prior knowledge about the domains investigated. Thus, the assessment of a single or several domains using discrete or continuous labels becomes possible. A traditional assumption for domain features is to use a one-hot coding scheme to indicate each observation associated with a given domain.

A feature augmentation is performed by embedding the features and domain features in a matrix $\hat{\mathbf{X}} = [\mathbf{X}; \mathbf{D}]$ before projecting them into a high-dimensional space using a kernel matrix. Then, a feature mapping to a m -dimensional latent space is performed through a transformation matrix estimated after solving a maximization problem related to an independence metric.

The proposed interdomain independence criterion is determined by the Hilbert-Schmidt Independence Criterion (HSIC) (GRETTON *et al.*, 2005). By definition, this dependence metric estimates the quadratic Hilbert-Schmidt norm of the cross-variance, which can be written in terms of the kernel matrix as:

$$\text{HSIC} = \text{tr}(\mathcal{K} \mathcal{W} \mathcal{W}^T \mathcal{K} H \mathcal{K}_D H) \quad (10)$$

where $\mathcal{K}$ is the kernel matrix, $\mathcal{W}$ is the transformation matrix, H is the centering slatematrix, and $\mathcal{K}_D$ is the kernel matrix of domain features often estimated as a linear kernel (LIU *et al.*, 2020). The data variance must be preserved after performing feature mapping to the latent space to address data properties. Therefore, the maximization problem can be rewritten as:

$$\begin{aligned} \max_{\mathcal{W}} & -\text{tr}(\mathcal{W}^T \mathcal{K} H \mathcal{K}_D H \mathcal{K} \mathcal{W}) + \mu \text{tr}(\mathcal{W}^T \mathcal{K} H \mathcal{K} \mathcal{W}) \\ \text{subject to } & \mathcal{W}^T \mathcal{W} = \mathbf{I} \end{aligned} \quad (11)$$

where $\mathbf{I}$ is the identity matrix and μ is the trade-off parameter of the regularization term. By employing Lagrange multipliers as a solution, the maximization problem can be estimated as an eigenproblem that can be described as $\mathcal{K}(-H \mathcal{K}_D H + \mu H) \mathcal{K}$, where the m leading eigenvectors represent the transformation matrix $\mathcal{W}$.

3.4 CONCLUSIONS

This chapter presented a description of transfer learning by discussing the main reasons that led to the application of this methodology in SHM analysis. There are similarities between structures that justify the reuse of relevant knowledge for damage identification even in different structures. Furthermore, the problems related to data acquisition, environmental and operational effects that can affect structural analysis, and the difficulty of calibrating FE models can be overcome through knowledge transfer.

A roadmap of transfer learning for SHM was outlined with the first papers in the research area to investigate numerical models and laboratory structures, which represented the cornerstones for more complex analysis such as population-based transfer learning of homogeneous and heterogeneous structures. Additionally, the importance of investigating the similarities between different structures was discussed as it represents a relevant topic for the success of knowledge transfer.

A brief overview of recent work that proposed transfer learning using different approaches were cited to highlight several possibilities that knowledge transfer can provide. Model-based and feature-based represent the main approaches for the integrity assessment of different structures, as the latter one being frequently applied to SHM cases because the analysis is traditionally carried out using features extracted from data sets (e.g., modal parameters of structures).

In this work, the proposed methodology is based on three different methods that apply transfer learning via domain adaptation, which are called TCA, JDA, and MIDA. Therefore, a detailed description of these methods was presented with the formulations and particularities of each method for a better understanding of the reader.

4 ON THE APPLICATION OF TRANSFER LEARNING USING NUMERICAL MODELS TO ENHANCE THE DAMAGE IDENTIFICATION PERFORMANCE

This chapter proposes an unsupervised feature-based transfer learning approach for bridges with a domain adaptation method, where classifiers are trained only with labeled data generated from FE models (source domain). Then, unlabeled monitoring data (target domain) is used to test the classification performance. The ability to adapt a classifier built on a well-known labeled data sets to a new scenario with unlabeled data sets is an interesting opportunity to transit bridge SHM from research to practice.

As numerical and monitoring data are related to the same bridge, both domains are assumed to have similar statistical distributions, with slight differences caused by the uncertainties inherent to the FE models. The transfer learning via domain adaptation is performed using TCA, which transforms damage-sensitive features from the original space to a new shared latent space, where the differences between feature distributions are reduced. This methodology may increase the usage of numerical modeling for long-term monitoring, as it overcomes some of the limitations imposed by the calibration process of FE models. The effectiveness of this unsupervised approach is illustrated through the classification performance of classifiers built on source data with and without domain adaptation, and using the benchmark data sets from the Z-24 Bridge as the target data. The results of this chapter can be found in Figueiredo *et al.* (2023).

The organization of this chapter is as follows. Section 4.1 poses the transfer learning as a solution to generalize SHM for almost every bridge. Section 4.2 lays down the basic assumptions behind the proposed SHM approach. Then, Section 4.3 explains the unsupervised damage detection approach based on transfer learning from numerical models to experimental data, where TCA is proposed as a domain adaptation technique; two machine learning algorithms are introduced for data normalization and feature classification. Then, Section 4.4 is provided to give an overview about the case study and its data sets; in particular, it provides a summary about the data acquisition and monitoring plan as well as the probabilistic finite element modeling used to generate numerical data. Section 4.5 provides the main analysis carried out using two classifiers with different modeling assumptions. Section 4.6 intends to compare and discuss the classification performance with and without domain adaptation. Finally, Section 4.7 provides the main conclusions

of this chapter and gives some indications of future works.

4.1 NUMERICAL-TO-EXPERIMENTAL TRANSFER LEARNING

With increasing changes in the operational and environmental conditions where our bridges are built, mainly caused by increased traffic, climate change, and extreme natural events (NASR *et al.*, 2020), SHM plays an important role to evaluate the structural degradation of our bridges and to increase their resilience against such conditions.

Even though new technologies have opened alternative perspectives to observe and analyze the bridge responses, it is widely recognized that SHM based on full-field monitoring is still not capable of producing reliable information on the presence of damage (FIGUEIREDO; BROWNJOHN, 2022). This limitation has been attributed to low signal-to-noise ratios by the sensing technology or to the inability of data analysis methods to unveil information about damage hidden in the data.

Unsupervised machine learning algorithms for statistical modeling and feature classification stage have been integrated in classifiers when both training and test data are rooted in the same underlying distribution (FIGUEIREDO *et al.*, 2011). Such assumption challenges the generalization of machine learning and make them application-specific to situations where bridges are built in the same operational and environmental conditions. As bridges are one-of-a-kind structures, every time authorities need to set up an SHM system for a certain bridge, new training data must be measured on that bridge to train a robust model for classification, which can be significantly costly for the authorities. Thorough critical reviews on the limitations and challenges of machine learning were given recently in several publications (FLAH *et al.*, 2021; MALEKLOO *et al.*, 2021).

The concept of transfer learning can be applied on labeled data sets generated from a FE model to unlabeled experimental bridge data, providing significant benefits in applying SHM to most of the bridges. The use of FE models to generate source labeled data is of particular interest, as those models are already used in bridge engineering for damage identification, but also to perform data augmentation from numerical models and build hybrid data sets along with monitoring data for the training of machine learning algorithms (FIGUEIREDO *et al.*, 2019; BUD *et al.*, 2022). Actually, the domain adaptation may be a solution in situations where FE models have not been calibrated or contain deviations but capture the underlying changes in the features due to damage. Some authors have already tested it on laboratory applications (GARDNER; LIU; WORDEN, 2020; BULL *et al.*, 2021a), but few applications have been tested on experimental bridge data.

In bridges, transfer learning is particularly promising as authorities can measure long-term data from a small group of bridges not nominally identical but with structural similarities or develop numerical models to get enough samples to build machine learning algorithms to detect damage in bridges without long-term monitoring data. This fact may change the way we perform SHM, as we may move to population-based SHM with the associated savings in investment and operation costs of permanent SHM systems.

Some review papers have already posed transfer learning as a solution to deal with the lack of monitoring data (MALEKLOO *et al.*, 2021; FIGUEIREDO; BROWNJOHN, 2022). However, most publications in the SHM field are still based on (i) simplified numerical models, (ii) simplified laboratory structures, and (iii) classifiers trained with supervised strategies. Knowledge transfer using real data sets from long-term monitoring systems of bridges or from numerical models can truly be beneficial, and the authors are not aware of any similar application of TCA in bridges.

Therefore, this chapter proposes a data-driven unsupervised damage detection approach for bridges, where TCA is used to create a new feature space, by reducing the divergences between distributions from different domains and to enable the outlier detection of target data using knowledge from numerical models as source data, which do not need to be accurately estimated. Numerical modeling is just used to generate damage-sensitive features from a given bridge in the source domain. The target domain is composed of experimental features of the same bridge estimated from long-term monitoring data. The effectiveness of the approach is shown by evaluating the classification performance of unlabeled target data with and without domain adaptation, using real-world experimental data sets from the Z-24 Bridge in Switzerland.

4.2 PROBLEM STATEMENT

Some assumptions are taken to support the implementation of the proposed SHM approach for bridges based on transfer learning and domain adaptation:

1. numerical modeling (parents and offspring FE models) of the Z-24 Bridge is available to generate training data. It intends to cover those real cases where there are not representative historical measurements to allow the training of a classifier;
2. the numerical modeling is not required to be exact and to fit all experimental information. It is only a kind of digital replica to simulate the structural response

and generate numerical data. Thus, the probability distribution of some of the FE-based features is expected to differ when compared with the features extracted from experimental measurements, which can degenerate the achievement of the damage detection;

3. a data set with experimental observations (natural frequencies) from a range of several operational and environmental conditions as well as the damaged condition is assumed from a real-world bridge for validation of a given classifier. The goal is to verify the binary classification performance of a classifier trained with data from numerical modeling only;
4. natural frequencies are used as damage-sensitive features; natural frequencies derived from FE models were assumed as source data; and natural frequencies estimated in the experimental campaign as unlabeled target data;
5. TCA is implemented to reduce the probability distribution distance between the source (numerical) and the target (experimental). Some plots of histograms are illustrated before and after domain adaptation to prove the similarities and the existence of a common feature space after the normalization process;
6. a quantitative comparison is made regarding the false-positive (Type I) and false-negative (Type II) errors, using two traditional classifiers based on the Mahalanobis squared distance (MSD) and the Gaussian Mixture Model (GMM).

4.3 STATISTICAL MODELING FOR FEATURE CLASSIFICATION

4.3.1 Mahalanobis Squared Distance

The MSD is a distance metric for multivariate statistics outlier detection (WORDEN; MANSON; FIELLER, 2000). When one considers the training matrix ($\mathcal{X}$) with multivariate mean vector ($\bar{x}$) and covariance matrix (Σ), the MSD (or DI in the context of SHM) between feature vectors from $\mathcal{X}_s$ and any new feature vector (or observation) from the test matrix ($\mathcal{X}_t$) is determined as

$$\text{DI}(x_t) = (x_t - \bar{x}) \Sigma^{-1} (x_t - \bar{x})^\top \quad (12)$$

The assumption is that if a new observation is obtained from data collected on the damaged condition, which might include operational and environmental variability sources, the observation is further from the mean of the normal condition. In contrast,

if an observation is obtained from a system within its undamaged condition, even with operational and environmental variability, this feature vector is closer to the normal condition's mean.

For an outlier damage detection, a hypothesis test can be defined assuming the null hypothesis (H_0) as the undamaged condition and the alternative hypothesis (H_1) as presumably the damaged condition. A single-dimensional separation between a new feature vector and an existing distribution is established to determine whether a feature vector is from a structure within the undamaged condition. For instance, in equation 12, if a multivariate feature vector $\mathbf{x}_s$ is extracted from the undamaged condition that corresponds to a multivariate Gaussian random distribution, then the DI will be Chi-square distributed with d degrees of freedom, $DI \sim \chi_d^2$ (FIGUEIREDO; CROSS, 2013).

When d increases, the probability density function (PDF) can be approximated by a Gaussian distribution, as predicted by the central limit theorem. Therefore, multivariate outliers can be defined as observations having DIs above a certain level.

The assumption of a Chi-square distribution is important for the outlier detection because it permits one to define a cut-off value or threshold, c , for a level of significance, α , in the form of $c = invF_{\chi_d^2}(1 - \alpha)$, where $F_{\chi_d^2}$ is the cumulative distribution function of the central Chi-square distribution. Thus, a feature vector is considered a multivariate outlier (the null hypothesis is rejected) when its DI is equal to or greater than c .

The selection of α carries a trade-off between the Type I error (a false-positive indication of damage) and the Type II error (a false-negative indication of damage). It has to be carefully chosen because a relatively high value would lead to an excessive number of outliers and false alarms, whereas too low value could leave some outliers undetected (OMENZETTER; BROWNJOHN; MOYO, 2003).

The empirical rule, also referred to as the three-sigma rule or 68-95-99.7 rule, is a statistical rule stating that for a normal distribution, almost all observations will fall within three standard deviations (denoted by σ) of the mean. Therefore, under this rule, 68% of the data falls within 1σ , 95% percent within 2σ , and 99.7% within 3σ from the mean. In this case, we assume a level of significance equal to 5% as it is normally acceptable, which corresponds to have 95% of undamaged observations correctly classified and 5% of false alarms.

4.3.2 Gaussian Mixture Model

The GMM is a cluster-based model that uses multivariate finite mixture models to capture the main clusters/components of features corresponding to the normal (undamaged) condition of a bridge, even when there is the influence of operational and environmental conditions. Then, an outlier detection strategy is performed using the distance to the clusters that represent the structural conditions (FIGUEIREDO; CROSS, 2013). Basically, the damage detection is carried out based on multiples MSD-based algorithms, where the covariance matrices and mean vectors are functions of the main components.

Suppose that the data sets of a training matrix $(\mathcal{X}_s)$ represents a mixture of Q distributions (MCLACHLAN; PEEL, 2000):

$$f_{\text{mix}}(x_s) = \sum_{q=1}^Q \eta_q f_q(x_s|\theta_q), \quad (13)$$

where $f_q(x_s|\theta_q)$ is the density of a distribution from a known parametric distribution family $\tau(\theta)$. The data sets are used to estimate the component parameters $\theta = (\theta_1, \dots, \theta_q)$ and the mixture weights $\eta = (\eta_1, \dots, \eta_q)$ of the underlying mixture distributions. In this case, multivariate Gaussian mixture distributions represent each component density in the form of (MCLACHLAN; PEEL, 2000)

$$f(x_s|\bar{x}_q, \Sigma_q) = \frac{\exp\left\{-\frac{1}{2}(x_s - \bar{x}_q)^\top \Sigma_q^{-1}(x_s - \bar{x}_q)\right\}}{(2\pi)^{d/2} \sqrt{\det(\Sigma_q)}}, \quad (14)$$

with unknown parameters $\theta_q = \{\bar{x}_q, \Sigma_q\}$ defined by the mean vectors $\bar{x}_q$ and covariance matrices Σ_q , while the sum of mixture weights are constrained to be equal to one ($\sum_{q=1}^Q \eta_q = 1$).

The estimation of the parameters uses the classical maximum likelihood (ML) based on the expectation-maximization (EM) algorithm (DEMPSTER; LAIRD; RUBIN, 1977). In addition, the Bayesian information criterion (BIC) can be applied to define the appropriate number of components, which introduces a penalty term for the number of parameters in the model.

For the outlier detection strategy, each observation x_t is determined based on the MSD from the clusters estimated. Formally, for each main component q of the data, the MSD (or DIs) can be defined as:

$$\text{DI}_q(x_t) = (x_t - \bar{x}_q)^\top \Sigma_q^{-1} (x_t - \bar{x}_q), \quad (15)$$

Finally, the DI for each observation is given by the minimization of the DI estimated on each component,

$$\text{DI}(x_t) = \min [\text{DI}_q(x_t)]. \quad (16)$$

4.4 CASE STUDY: Z-24 BRIDGE

4.4.1 Structural description

The Z-24 Bridge (Fig. 5) was a post-tensioned concrete box girder bridge with a total length of approximately 54m, presenting a main span of 30m and two side spans of 14m, as illustrated in (Fig. 6). A monitoring system was installed on the bridge and several testing was extensively carried out to provide a comprehensive "feasible tool" for vibration-based SHM analysis in civil engineering before its demolition (PEETERS; ROECK, 2001). For further information about the description of the Z-24 Bridge, the reader is referred to the following papers (PEETERS; ROECK, 2001; PEETERS; MAECK; ROECK, 2001; MAECK; ROECK, 2003; REYNDERS; ROECK, 2009).

4.4.2 Data acquisition and monitoring plan

A long-term monitoring program was carried out from November 11, 1997, until September 10, 1998, to quantify the operational and environmental variability present on the bridge and to detect damage artificially introduced in the last month of operation. Every hour, eight accelerometers captured the bridge's vibrations and an array of sensors measured environmental parameters, such as the temperature at several locations.

Progressive damage tests were performed from August 10 to September 10, 1998, before the demolition of the bridge to prove that realistic damage has a measurable influence on the bridge dynamics (PEETERS; MAECK; ROECK, 2001). Note that the period corresponding to the installation of hydraulic jacks in one of the piers is considered as "undamaged" in this study. The continuous monitoring system was still running during the progressive damage tests, which permits one to validate the SHM system to detect cumulative damage on long-term monitoring.

In this case, the natural frequencies of the Z-24 Bridge are used as damage-sensitive features (LUSCHER; BORWNJOHN, 2000). They were estimated using a reference-based stochastic subspace identification method on time series from the accelerometers (PEETERS; ROECK, 1999). The first three natural frequencies estimated hourly from

November 11, 1997, to September 10, 1998, with a total of 5012 observations, are plotted in Fig. 7.

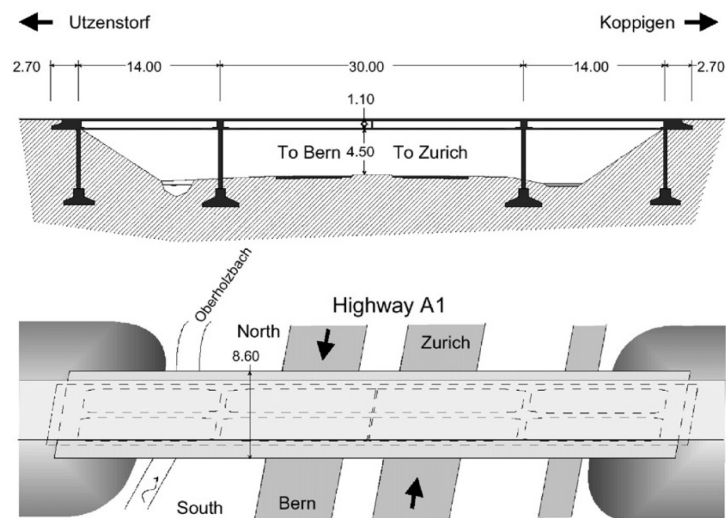
It is assumed that the bridge operates within its undamaged condition (healthy condition), under operational and environmental variability, from November 11, 1997, to August 10, 1998 (1-4410 observations). On the other hand, the bridge is considered damaged from August 10 to September 10, 1998 (4411-5012 observations). For the healthy condition period, the observed jumps in the natural frequencies are associated with the asphalt layer in freezing periods, contributing significantly to increase the bridge's stiffness (PEETERS; MAECK; ROECK, 2001). Note that the damage scenarios are carried out in a sequential manner, which causes a cumulative degradation of the bridge.

Figure 5 – View of the Z-24 Bridge.



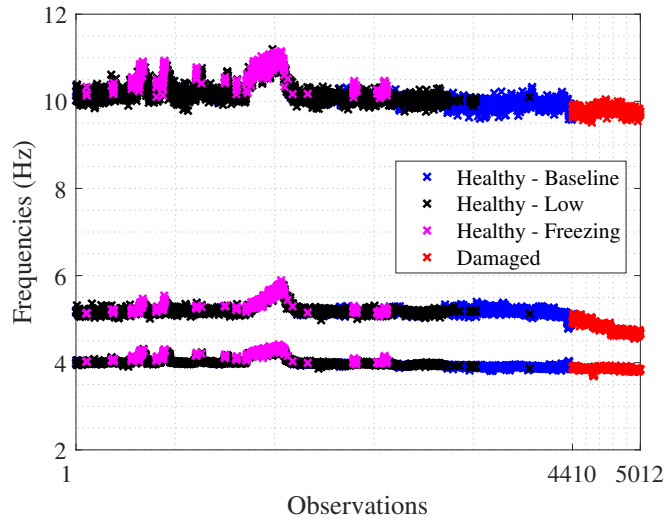
Source: Silva *et al.* (2019).

Figure 6 – Front view (top) and top view (bottom) of the Z-24 Bridge (units in meters).



Source: Reprinted with permission from Maeck and Roeck (2003).

Figure 7 – First three experimental natural frequencies of the Z-24 Bridge estimated hourly.



Source: Prepared by the author.

4.4.3 Numerical modeling and data sets

A reference model was used to generate three parent FE models to represent the healthy structural condition with variations due to operational and environmental effects. Then, a Latin Hypercube simulation was conducted to investigate the probability distributions of the model parameters and estimate the offspring FE models consequently. The numerical modeling and its calibration process are comprehensively described in Bud *et al.* (2022).

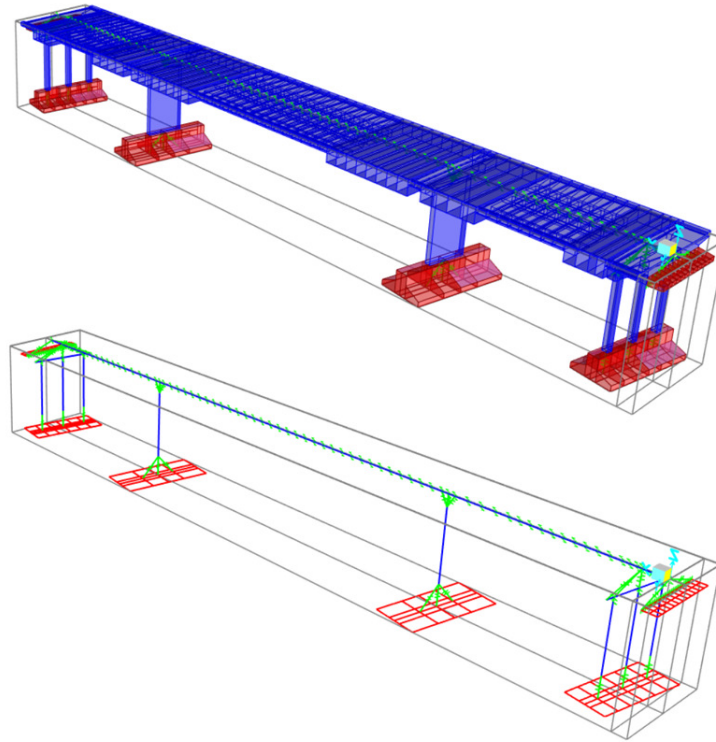
4.4.4 Reference FE model

An initial FE model of the Z-24 Bridge is constructed based on the design project (Fig. 8). The model is simple enough to run tens of thousands of analyses in a reasonable time frame. Beam finite elements are used to model the piers, the lateral columns, and the girder. Our experience has shown that the variability of the cross-sectional dimensions of the girder is instrumental for the correct recovery of the dynamic bridge features, so the girder dimensions in the blueprints are strictly respected. Conversely, the use of the shell finite elements to model the girder seems to bring little precision increment to the model and comes at a much higher computational cost, so the beam elements are considered the best option. Shell elements are restricted to the modeling of area elements, as the abutment slabs and foundation blocks. This strategy secures a computational time for

running one FE model of roughly 14 seconds on an average computer, as opposed to 90 seconds for models composed of shell elements only. The soil-structure interaction is modeled using spring elements with initial stiffnesses established based on the bridge design project. The asphalt layer is explicitly included in the model to consider the global stiffness increment registered when the ambient temperature drops below 0°C . The asphalt is modeled with beam elements connected to the girder using rigid links.

The initial FE model is subsequently calibrated to form the reference model, by recovering the experimental natural frequencies and mode shapes, when the temperature is above 10°C (healthy-baseline), by iteratively jiggling a set of calibration parameters, chosen between the model features based on their epistemic uncertainty level.

Figure 8 – FE model of the Z-24 Bridge: rendered view (top) and finite elements (bottom).



Source: Figueiredo *et al.* (2023)

The uncertainty regarding the environmental conditions adds to that regarding the material parameters and structural integrity, typically resulting in having more calibration (unknown structural) parameters than objective functions (e.g., natural frequencies) to be used for model updating. However, additional constraints need to be enforced on the calibration parameters, such as physically plausible bounds and expected correlations between the parameters, which actually lead to an over-constrained problem. To solve it, a procedure is encoded as an iterative constrained minimization. In each calibration

step, the calibration parameters are tuned to minimize the difference between the average values of the first natural frequencies measured on the structure and those predicted by the numerical model, while ensuring that the values of the calibration parameters remain within the limits of what is physically plausible. The calibration parameters include the spring elastic stiffness that models the soil-structure interaction, the modulus of elasticity of the concrete, the resilient modulus of the asphalt, and the asphalt layer's thickness.

The procedure is described in full detail in reference Bud *et al.* (2022) and is not restated here. Instead, the full list of calibration parameters, their initial (project) values, limits of variation, and final values after model calibration are presented in Table 1. Note that the limits of variation reflect the epistemic uncertainty corresponding to each calibration parameter. Indeed, wider limits of variation correspond to parameters related to soil-structure interaction, while the limits of variation of the mechanical stiffness of concrete and asphalt are tighter. Table 2 lists the first four natural frequencies before and after the calibration process, along with the target (i.e. average measured) frequencies.

Since we are using only the first four natural frequencies to identify the calibration parameters, the model is not fully identifiable, in the sense that there could exist more than one parameterizations that are observationally equivalent. However, since we enforce physically plausible limits on the variability of the uncertain parameters, we argue that other observationally equivalent parameterizations would be close to the one we chose as a reference. Therefore, the distance between equivalent parameterizations should be well covered by the probabilistic distribution used in the offspring generation, as presented in the next section.

Table 1 – Calibration parameters.

Parameter	Initial	Limits of variation	Final
Normal soil stiffness under pier footings	180 MPa/m	$\pm 60\%$	202 MPa/m
Transversal soil stiffness under pier footings	210 MPa/m	$\pm 60\%$	270 MPa/m
Normal soil stiffness under abutment columns footings	100 MPa/m	$\pm 60\%$	139 MPa/m
Transversal soil stiffness under abutment columns footings	100 MPa/m	$\pm 60\%$	126 MPa/m
Normal soil stiffness under abutment plates	180 MPa/m	$\pm 60\%$	250 MPa/m
Transversal soil stiffness under abutment plates	200 MPa/m	$\pm 60\%$	278 MPa/m
Normal soil stiffness around abutment columns	100 MPa/m	$\pm 60\%$	125 MPa/m
Transversal soil stiffness around abutment columns	100 MPa/m	$\pm 60\%$	139 MPa/m
Elasticity modulus of concrete	37.5 GPa	$\pm 10\%$	35.5 GPa
Resilient modulus of asphalt	6 GPa	$\pm 25\%$	4.5 GPa
Asphalt thickness	12 cm	$\pm 40\%$	8 cm
Column elastic hinge rotational stiffness	14 kNm/rad	$\pm 300\%$	50 kNm/rad

Table 2 – Natural frequencies before and after calibration.

	f_1 (Hz)	f_2 (Hz)	f_3 (Hz)	f_4 (Hz)
Target	3.912	5.184	9.980	10.632
Initial	3.917	4.982	9.768	10.709
After calibration	3.914	5.178	9.872	10.777

4.4.5 Parent and offspring FE models

In this study, the FE observations are generated using a probabilistic paradigm based on the following steps:

1. as the structure's stiffness is strongly dependent on the ambient temperature, three parent models are defined to characterize the healthy condition for baseline (or normal), low, and freezing temperatures;
2. in this context, temperatures above 10°C are defined as baseline temperatures; temperatures ranging between -2°C and 10°C are defined as low temperatures; temperatures below -2°C are defined as freezing temperatures. The distinction is necessary as low temperatures increase the resilient modulus of asphalt, but are not enough to freeze the soil. Freezing temperatures stiffen both the asphalt and the foundation soil;
3. for the baseline temperatures, it is defined a parent FE model equal to the reference model; for the low temperatures, a parent FE model is derived from the reference model, with changes only in the asphalt layer; for the freezing temperatures, a parent FE model is defined from the reference model with changes in the asphalt layer and in the foundation soil;
4. for each parent FE model, offspring FE models are generated by perturbing the model, using Gaussian probabilistic distributions of the uncertain parameters. The uncertain parameters are selected from the calibration parameters (see Table 1), namely those found to influence considerably the damage-sensitive features of the structure. The standard deviation is defined as one sixth of the plausible interval of variation for each variable, to ensure that 99.7% of the values generated by the Gaussian distribution fall within the plausible ranges defined in Table 1. The uncertain parameters, their reference values, and standard deviations are listed in Table 3;
5. the generation of models, analysis, and post-processing are automated using a API linking Matlab, where the values of the uncertain parameters are generated, to

CSIBridge, where the finite element model is run. A total of 12.000 models are run, i.e., 4.000 for each of the parent models. The combinations of the uncertain parameters were generated using the Latin Hypercube method (BUD *et al.*, 2022);

6. damage-sensitive features are extracted from the FE models and used along with features extracted from the monitoring data.

Table 3 – Probabilistic variation of uncertain parameters.

Parameter	Reference	Std. deviation
Normal soil stiffness under pier footings	202 MPa/m	26.7 MPa/m
Transversal soil stiffness under pier footings	270 MPa/m	36.7 MPa/m
Normal soil stiffness under abutment columns footings	139 MPa/m	13.35 MPa/m
Normal soil stiffness under abutment plates	250 MPa/m	33.35 MPa/m
Transversal soil stiffness under abutment plates	278 MPa/m	35 MPa/m
Transversal soil stiffness around abutment columns	139 MPa/m	20 MPa/m
Elasticity modulus of concrete	35.5 GPa	0.7 GPa
Resilient modulus of asphalt	4.5 GPa	0.5 GPa
Asphalt thickness	8 cm	1 cm
Column elastic hinge rotational stiffness	50 kNm/rad	10 kNm/rad

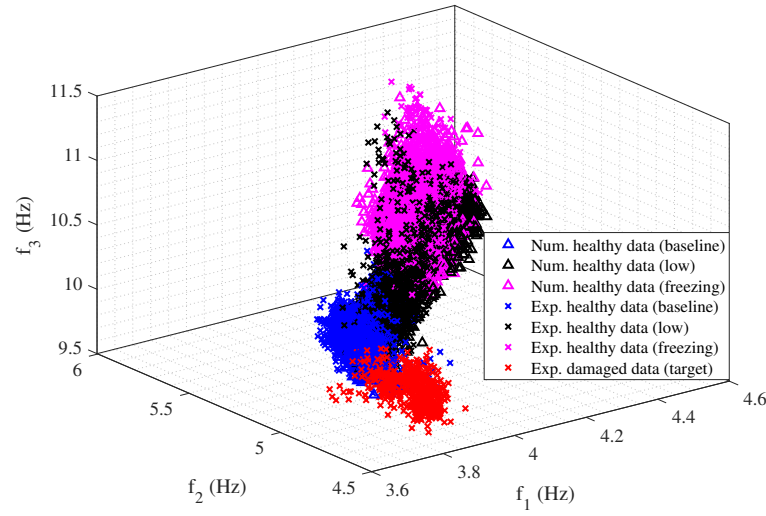
4.5 RESULTS

FE models can generate high-quality data for the training of machine learning algorithms for damage detection (FIGUEIREDO *et al.*, 2019). Bud *et al.* (2022) have shown that the first two natural frequencies obtained from probabilistic FE models can be used to train the algorithms to the same specificity and sensitivity levels as the one-year worth of experimental data from the real structure. However, how can we use the numerical data for the training of machine learning algorithms when the calibration process fails to derive numerical features close to the experimental ones?

Figure 9 shows the first three numerical and experimental natural frequencies on the three-dimensional original feature space. The numerical data are only composed of observations in the healthy condition; on the other hand, the experimental data are composed of observations in the healthy and damaged conditions. For a more comprehensive interpretation of the feature distribution, Fig. 10 shows the first two natural frequencies in the two-dimensional feature space for both data sets in an overlapping format. It is possible to observe: (i) for the healthy condition with operational and environmental variations, the first two natural frequencies from the FE models overlap the experimental

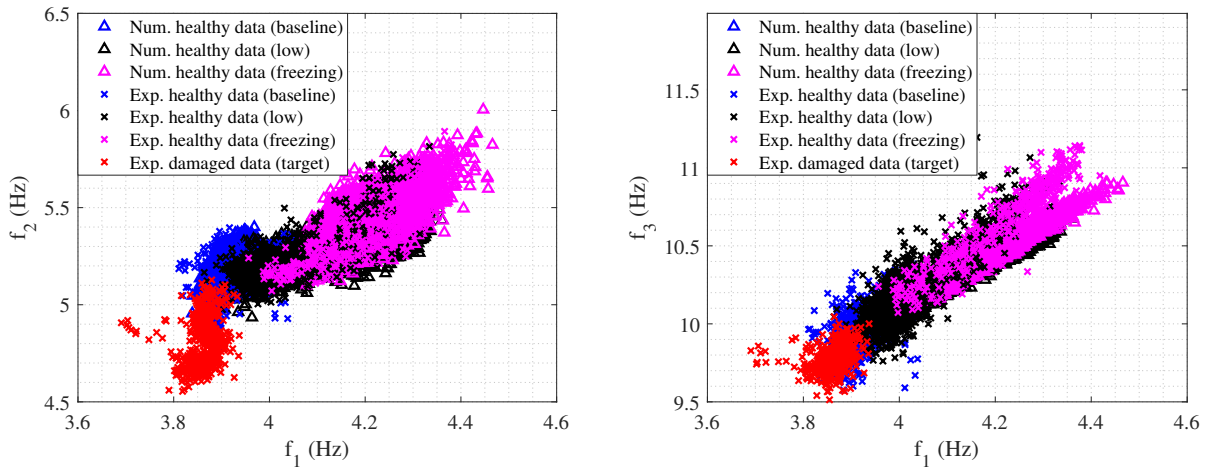
ones; however, the third natural frequency seems to occupy a different region from the experimental one; (ii) for the damaged condition, the natural frequencies tend to occupy a distinct region, as suggested by the move to the lower-left corner of the feature space caused by the stiffness reduction. In the form of histograms, Fig. 11 plots the marginal distributions of the three natural frequencies, where one can observe similarities in shape but significant shifts in the mean of all distributions.

Figure 9 – Three-dimensional feature distribution in the original feature space (numerical and experimental).



Source: Prepared by the author.

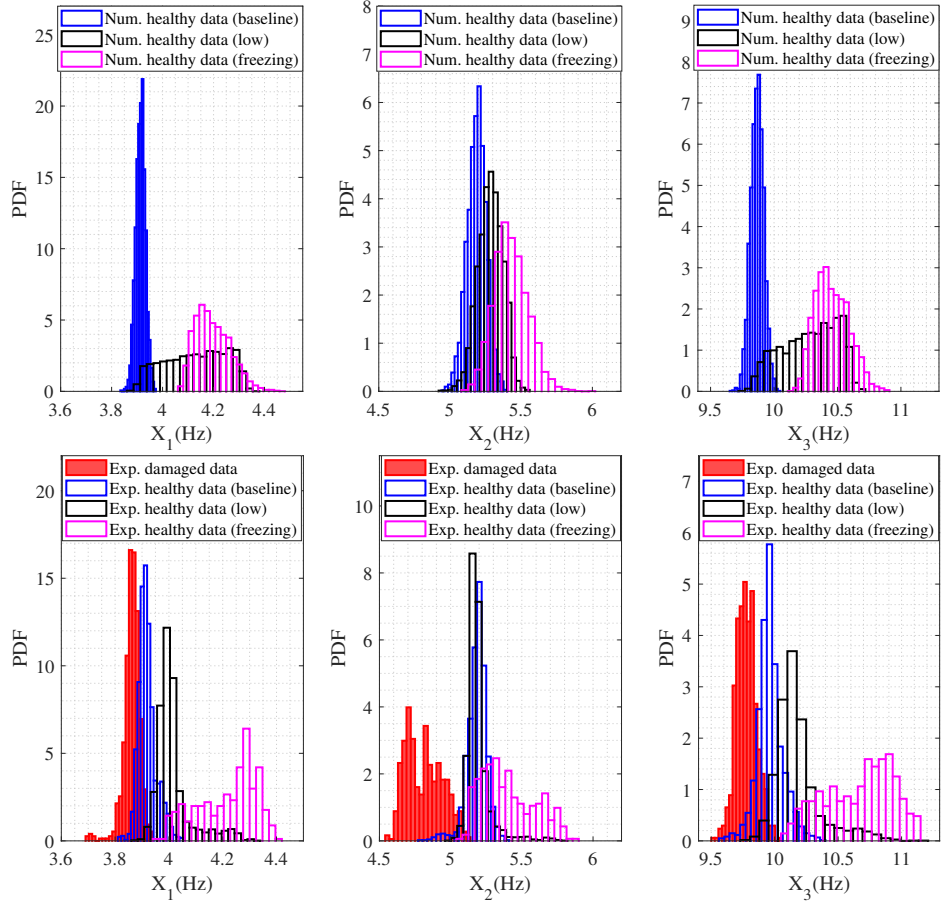
Figure 10 – Two-dimensional feature distribution in the original feature space.



Source: Prepared by the author.

Now, TCA is applied for domain adaptation in both the source and target domains to extract features by mitigating domain differences while being discriminant for damage

Figure 11 – Marginal distributions of the numerical (top) and experimental (bottom) data in the original feature space.



Source: Prepared by the author.

detection. There are different types of kernels that can be applied in TCA, making it possible to use any proper kernel during the analysis (XIE *et al.*, 2016). Different types of kernels could be employed, such as a radial basis function (RBF), exponential kernel, polynomial kernel, and the linear kernel (SCHOLKOPF; SMOLA; MULLER, 1998). Here, a combination of a linear kernel $\mathcal{K}_{lin}$ and exponential kernel $\mathcal{K}_{exp}$ is applied. These kernels are given by (RASMUSSEN; WILLIAMS, 2006):

$$\mathcal{K}_{lin}(x, x') = [\phi(x)^T \phi(x')] \quad (17)$$

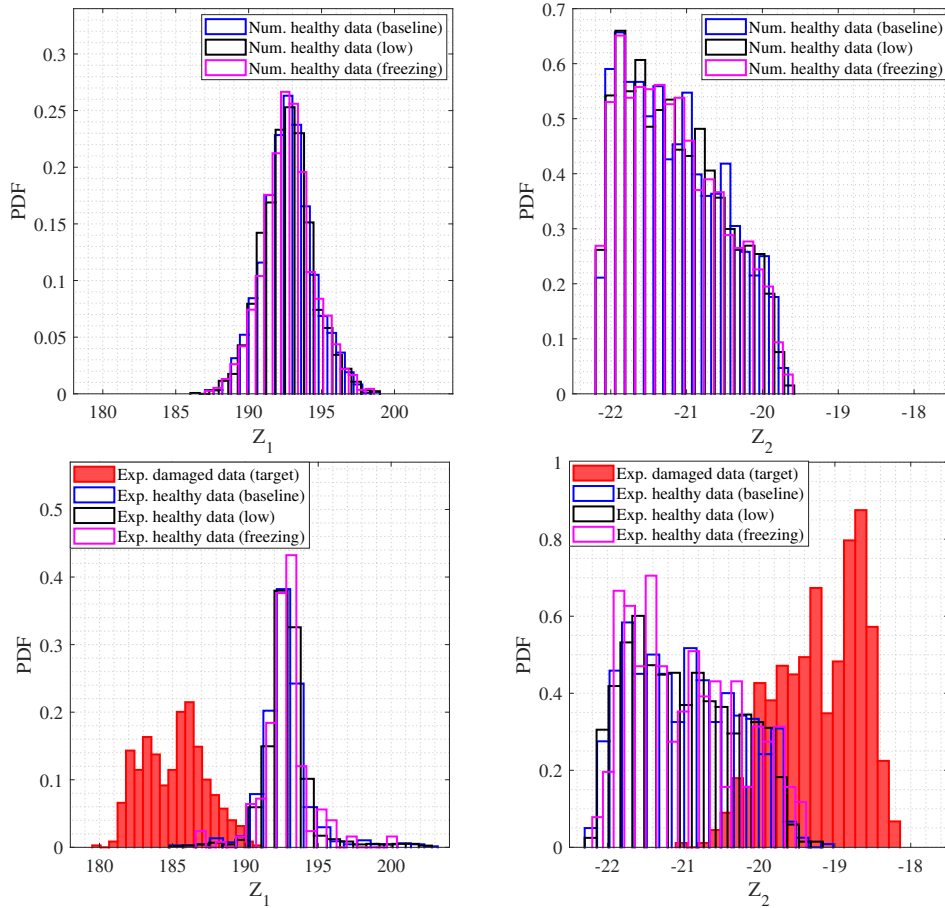
$$\mathcal{K}_{exp}(x, x') = \exp\left(-\frac{|x - x'|}{\sigma_l}\right) \quad (18)$$

$$\mathcal{K} = \mathcal{K}_{lin} + \mathcal{K}_{exp} \quad (19)$$

where σ_l is the lengthscale. After some sensitive analysis, a combination of a linear and an exponential kernels was applied in this case, assuming the trade-off parameter is set to $\mu = 0.1$ and the lengthscale is $\sigma_l = 5$ due to the minimization of the misclassification described by the total error.

In the latent feature space (also known as transformed feature space), Fig.12 presents the marginal distributions for the first two components, which can consistently map both the source and target domains. As the primary goal of TCA is to approximate the source and target domain marginal distributions, one can infer that the mapping is adequate for the undamaged condition. Additionally, Fig. 13 is the visualization of the learned mapping in the latent two-dimensional feature space.

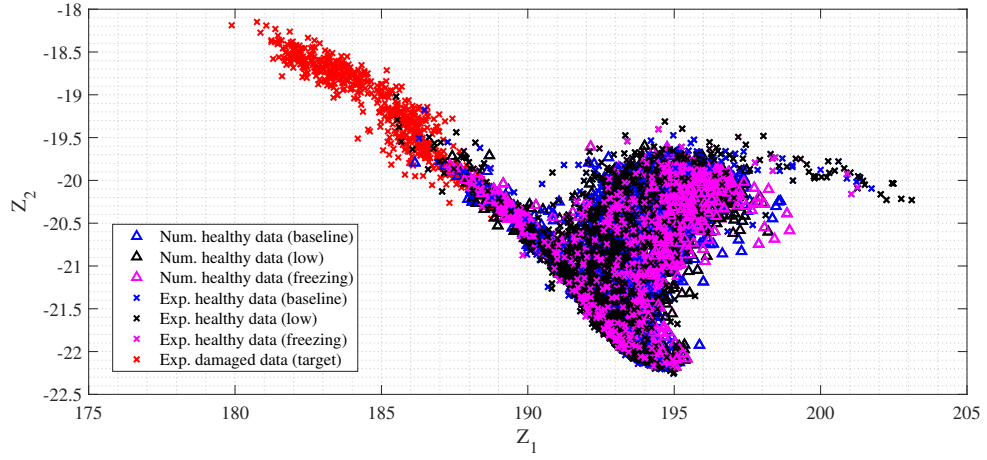
Figure 12 – Marginal distributions of the numerical (top) and experimental (bottom) test data on the first two TCA-transformed components (latent feature space).



Source: Prepared by the author.

Two classifiers based on an unsupervised learning strategy and on numerical data only are used, namely the MSD-based and the GMM-based algorithms to take into account the existence of multimodal distributions. The GMM assumes two principal components ($Q = 2$), as already suggested in Figueiredo *et al.* (2014) based on the BIC. The training

Figure 13 – Visualisation of the TCA-transformed components.



Source: Prepared by the author.

matrices for both classifiers comprise (i) the first three natural frequencies in the original feature space and (ii) the first two transfer components in the latent feature space. In each feature space, the test data comprise the entire experimental data sets (1-5012), where the first 4410 observations correspond to the healthy condition.

The training step to determine the transformation matrix ($\mathcal{W}$) is performed by randomly dividing half of the numerical data sets and half of the undamaged experimental data. The test data use the rest of the numerical and experimental healthy data set and the damaged target experimental data. The behavior of the healthy numerical and experimental data is similar and, consequently, show similar patterns after mapping to the latent space. Meanwhile, damaged data can be identified as outliers as it does not show consistency with the labels used to determine the mapping matrix.

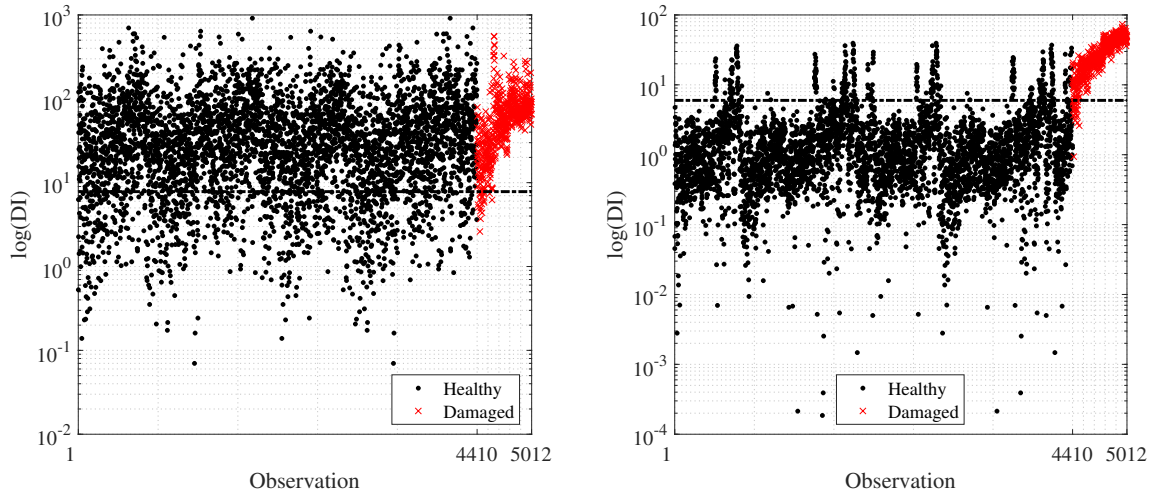
Figure 14 and Figure 15 present the binary classification (healthy and damaged conditions) in both feature spaces (original and latent), where a DI is assigned to each observation. The threshold is established for a level of significance of 5%, as it is conventionally regarded as the critical level of significance in civil engineering. A summary of the classification performance is given in Tables 4 and 5 in terms of Type I and Type II errors and for both classifiers. Overall, the transformation shows an improvement of the classification in terms of minimizing the Type I error to values close to the level of significance assumed (5%), i.e., from 80.22% to 8.25% for the MSD classifier and from 82.36% to 4.31% for GMM classifier. However, one can observe a trade-off between the Type I and Type II errors, which have different consequences to the bridge's safety and the SHM system's reliability. Nevertheless, the bridge's safety improvement is significant in terms

of the total number of misclassifications (from 70.97% to 7.68% for MSD classifier and from 72.72% to 4.07% for GMM classifier). The improvement of those results is related to the adjustment of the mean of the distributions caused by the domain adaptation, as suggested by the thresholds in the figures.

Note that as we are dealing with real data under temperature effects, the undamaged data sets are not drawn from a pure multivariate Gaussian distribution, and so a relative high number of false alarms are expected for the MSD-based classifier as demonstrated in the latent feature space, with a Type I error (8.25%) higher than the level of significance of 5%. These effects can also be unveiled in Fig. 14 and Fig. 15, especially at those spikes observed in the latent feature space for the undamaged condition (FIGUEIREDO; CROSS, 2013).

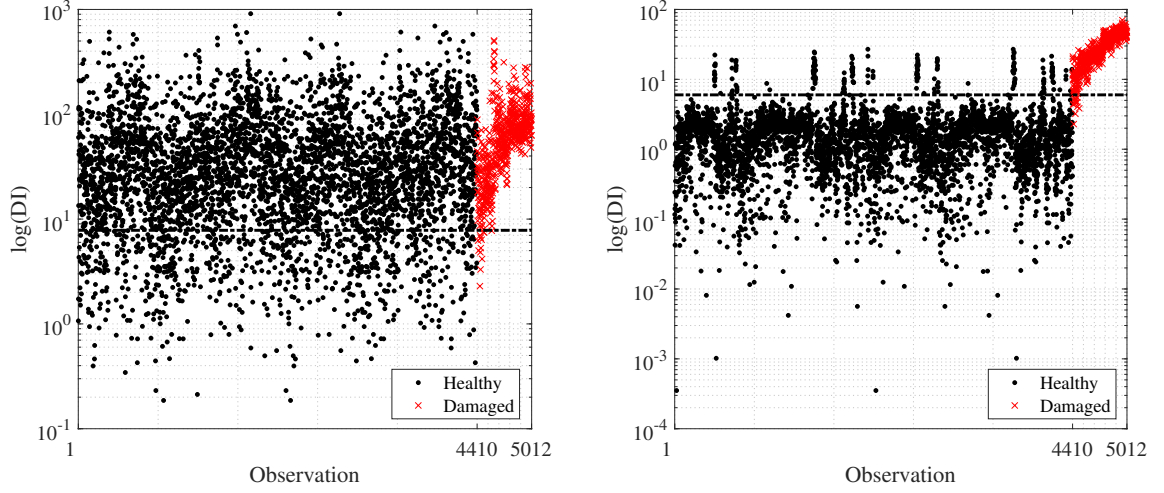
In conclusion, TCA reveals good generalization abilities when two components are retained, creating a much more appropriate subspace for the target data. It properly reduces the domain differences attaining exceptional accuracy levels ($>90\%$) when predicting the target experimental data.

Figure 14 – Classification performance in the original (left) and latent (right) feature spaces for the MSD-based classifier.



Source: Prepared by the author.

Figure 15 – Classification performance in the original (left) and latent (right) feature spaces for the GMM-based classifier.



Source: Prepared by the author.

Table 4 – MSD Classification performance for damage detection in terms of Type I and Type II errors for two training strategies (calibrated FE models).

Training strategy	Type I error	Type II error	Total
Original feature space	3538 (80.22%)	19 (3.15%)	3557 (70.97%)
Latent feature space	364 (8.25%)	21 (3.48%)	385 (7.68%)

Source: Prepared by the author.

Table 5 – GMM Classification performance for damage detection in terms of Type I and Type II errors for two training strategies (calibrated FE models).

Training strategy	Type I error	Type II error	Total
Original feature space	3632 (82.36%)	13 (2.16%)	3645 (72.72%)
Latent feature space	190 (4.31%)	14 (2.32%)	204 (4.07%)

Source: Prepared by the author.

4.6 DISCUSSION

The probability distribution of the observations were separated according to three temperature ranges to demonstrate the non-Gaussian behavior of the investigated features.

Two unsupervised classifiers that only use healthy data for the training were introduced, to deal with the multimodality of the features. As the data do not follow a fully multivariate Gaussian behavior due to the effects of different temperature ranges in the data sets, it may prevent the successful use of the MSD-based classifier, as it assumes

the existence of a multivariate Gaussian distribution. The results in the latent feature space support this statement, as the error Type I from the GMM-based classifier (4.31%) is close to 5%, in contrast with the MSD-based one (8.25%). Note that the GMM-based has more flexibility to model the data, as it fits a model with two Gaussian components ($Q = 2$).

The features in the latent space shown in Fig. 13 do not have an ideal separation of classes yet. However, the results show an improvement in the classification performed in the latent space created by TCA.

The kernel selection is not trivial and is problem specific. An independent analysis is normally necessary to investigate which kernel is more appropriate. In this case, a combination of linear and exponential kernels was proposed, as the classification results showed a significant improvement in the TCA performance compared to linear and nonlinear kernels, using both classifiers (MSD and GMM).

4.7 CONCLUSIONS

This chapter presented the performance gain from transfer learning via domain adaptation using the well-known TCA in a bridge for SHM analysis. TCA was applied as a feature-based transfer learning approach to mitigate the divergences between the first three natural frequencies from FE models and a long-term monitoring system.

The effectiveness of the domain adaptation was shown through two classifiers with access to labeled training data (source) from numerical models and unlabeled test experimental data (target), in situations where both domains are from similar but statistically different distributions. The comparison was done by computing the classification performance of unlabeled target data with (latent feature space) and without (original feature space) domain adaptation.

Two classifiers based on an unsupervised learning strategy were proposed. The MSD-based and the GMM-based machine learning algorithms were implemented for statistical modeling and feature classification on real-world data sets from the Z-24 Bridge in Switzerland. The model for the target classification is exclusively built using undamaged numerical data from the source domain. Even after calibration, it was shown that the numerical model could not fit well the third natural frequency, which compromises the classification performance. This strategy proved to reduce the distribution change between source and target domains. TCA revealed generalization abilities when two components are retained

by properly reducing the domain differences attaining exceptional accuracy levels ($>90\%$) when predicting the target experimental data.

5 ON THE APPLICATION OF TRANSFER LEARNING FOR DAMAGE QUANTIFICATION

A novel methodology for damage quantification based on the TCA application is proposed in this chapter. In this case, the requirement of domain adaptation methods in combination with a Gaussian process regression (GPR) model is considered for the determination of the damage levels of a building structure. The regression model is trained using the latent data sets of the numerical model (source) to evaluate the unlabeled structure (target). The effectiveness of the proposed methodology in the representation of the feature patterns tends to improve when the consistency of labels between the domains is achieved, indicating the current damage level present on the structure when the regression model achieves its best performance (lowest error). The results of this chapter can be found in Yano *et al.* (2021)

The work is organized as follows. First, a brief discussion about the application of knowledge transfer for damage quantification is presented in Section 5.1. Section 5.2 presents a problem statement that describes the work assumptions and main contributions. The proposed methodology is then described, and the damage detection and quantification steps are highlighted in Section 5.3. Next, the details of the experimental setup and the numerical model are outlined in Section 5.4. Section 5.5 presents the TCA application to assist the damage detection and the identification of a GPR model to determine the damage levels in the target structure. An example of negative transfer due to the problem of label inconsistency is presented in Section 5.6. Finally, the final remarks are addressed in Section 5.7 to explain the benefits and drawbacks dealt with while applying the proposed methodology.

5.1 KNOWLEDGE TRANSFER FOR DAMAGE QUANTIFICATION

A topic that has not been investigated in the literature is the knowledge transfer of damage levels between different structures. The main problem with directly applying classical TCA for damage quantification is the requirement of labels consistency, assuming the same damage types and extension of the actual damage and the simulated ones. To overcome this issue, the idea is to use the knowledge from the labeled source data to estimate a GPR model in the latent space and evaluate the target data. The application

of this regression model has been extensively investigated in SHM as it determines a robust model capable of describing the uncertainties involved in the process (TELOLI *et al.*, 2021).

Teimouri *et al.* (2017) highlighted the benefits of the GPR model by comparing its performance with neural network models to determine the extension and location of damage in aircraft structures. Different damaged scenarios on a composite airfoil were tested to describe the impact of uncertainties. The results indicated that the GPR model could accurately predict the damage using different kernels. Pavlack *et al.* (2021) combined the GPR model with the polynomial chaos expansion for damage quantification of the debonding size in the blade of wind turbines. The results provided a reasonable estimation of the damage size using the calibrated learning model. Paixão *et al.* (2021) applied GPR models for damage quantification in two case studies carried out on composite structures. Although the variation of temperature in the composite plate and fatigue loads used in coupons, the GPR models could determine the extent of damage on both structures under the uncertainties introduced by these effects.

The GPR is a stochastic model that can be used, in this case, to determine a correlation between latent features and damage labels. Once a GPR model is specified, its information about the mean and variance can be applied to estimate the damage levels in the target domain. However, the differences of features' behavior do not allow the use of the estimated GPR model for a different setup, requiring a new learning procedure. TCA is applied to provide the same estimated model for both domains to avoid this limitation.

This chapter proposes a methodology with an important contribution due to the possibility of evaluating the integrity of structures. The requirement of equivalence between labels imposed on domain adaptation methods, which often limit their implementation, is applied for damage quantification of a structure through the knowledge transfer from its numerical model.

The benchmark data of the Los Alamos National Laboratory (LANL) is investigated to demonstrate the effectiveness of the proposed method. The natural frequencies extracted from a three-story building structure (target domain) and its numerical model (source domain) are analyzed for damage detection and, mainly, for quantification of damage levels. It is reasonable to assume that the numerical model fails to accurately represent the structural dynamics due to the assumptions made in the model estimation and complexity of the structure. The divergences between the features extracted are reduced by TCA, allowing the application of a distance-based classifier in the latent

space that assesses the structural conditions of the target data. Then, a GPR model trained using the latent features of the labeled source domain is applied to investigate the damage levels of the experimental setup.

5.2 PROBLEM STATEMENT

The current chapter proposes a new methodology for damage detection and quantification using a numerical model data sets to assess the LANL benchmark through the TCA application. Some assumptions are considered in this work:

1. The definition of the numerical model follows the assumptions described by the report available on the LANL website (FIGUEIREDO *et al.*, 2009);
2. The column thickness of the building structure is changed in the numerical model to describe the damage progression. Several rounds of the numerical model are performed assuming a range of column thickness values, resulting in two damage levels in each round due to the number of columns changed per floor. In this work, only the damage detection and quantification are determined, and its location in the structure is not investigated;
3. The features analyzed to detect and quantify damage are the natural frequencies of the numerical model (source) and the experimental data (target);
4. TCA projects the source and target data sets into the latent space where their divergences are minimized. The knowledge transfer from the source domain benefits the damage detection of the unlabeled target data, which the performance of the classifier can demonstrate;
5. In the hierarchical structure of damage identification (detection, location, type, quantification, and prognosis), damage detection and quantification refer to the 1st and 4th levels (FIGUEIREDO; BROWNJOHN, 2022);
6. The GPR model is applied for the damage quantification. It is estimated using the source data and its labels' knowledge to assess the unlabeled target data. In the latent space, the features of the source and target domains present similar patterns and allow sharing the information from the source domain to assess other structures;
7. As novelty contribution, this work performs transfer learning via domain adaptation through TCA and leverages the labels' consistency in both domains, allowing the

assessment of the damage levels of the target domain. In the latent space, the estimated GPR model is expected to present its best performance when this consistency is achieved, enabling the determination of the damage levels in the structure.

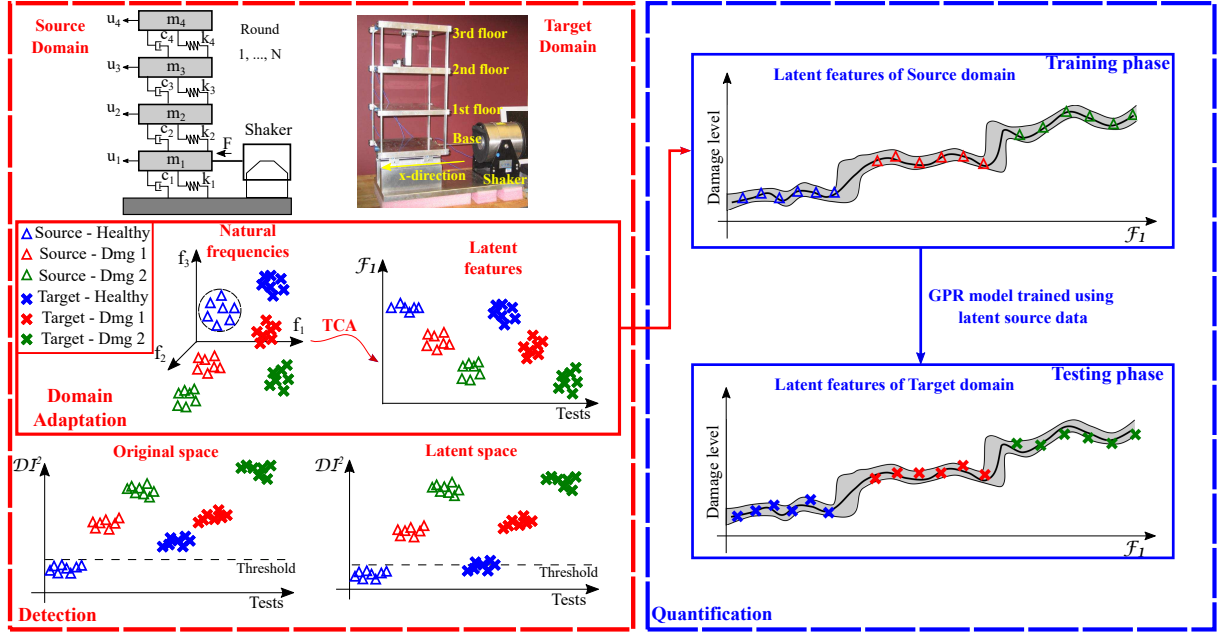
5.3 PROPOSED METHODOLOGY

Figure 16 illustrates an overview of the two main steps of the proposed methodology. In this work, the damage identification is performed using the first three natural frequencies extracted from the Frequency Response Functions (FRFs) of the data sets under different structural conditions. Although the features represent the same structural conditions; the resulting mismatch undermines the application of the numerical model to describe the structure's behavior. TCA is applied to minimize the effects of the distribution discrepancies, and damage detection is performed using the MSD in the latent space. The latent source data is applied to train the classifier, and the latent target data is evaluated in a binary classification (healthy and damaged conditions). Once the presence of damage is detected, damage quantification can be performed.

The second part of the proposed methodology applies the GPR models to describe the features patterns. The training phase is performed using the latent features of the source domain and their labels of damage levels. Once the labels of the source data correspond to the target data and indicate the labels equivalence between domains, the GPR model can correctly assess the damage levels of the building structure due to the similarities between the feature's behavior.

The proposed methodology is highlighted in algorithm 1. The numerical model is simulated N rounds reducing the original column thickness, resulting in N possible damage scenarios. In this analysis, the data sets from each round of the numerical model are analyzed individually with the target data. The performance of the GPR model is investigated in each round by the root-mean-square error (RMSE) (KANG; LIU; LI, 2020). This metric compares the values determined by the regression model and the expected damage levels. For instance, the numerical model's first round ($N = 1$) introduces damage, and the features are extracted from its data sets. TCA is applied and damage detection is performed, evaluating the performance of the classifier. A GPR model is estimated using the latent features of the source domain and their labels, allowing the determination of the structural damage levels of the laboratory building. Thus, the performance of the regression model is determined based on the RMSE value. The numerical model assumes thickness values with smaller dimensions for the next rounds, and the main steps are

Figure 16 – Overview of the proposed methodology.



Source: Prepared by the author.

performed again.

Algorithm 1 Proposed methodology

Input: First three natural frequencies of numerical model (labeled source data) $\{(\mathbf{X}_s^i, \mathbf{y}_s^i)\}_{i=1}^N$ and three-story building structure (unlabeled target data) $\mathbf{X}_t$

for $i = 1, \dots, N$ **rounds do**

Domain adaptation

Construct the kernel matrix $\mathcal{K}$ using the source $\mathbf{X}_s$ and target $\mathbf{X}_t$ data sets

Implement TCA considering the regularization term μ and #dimension m

Damage detection in the latent space

Train classifier using the features of source domain

Binary classification of the target domain through an outlier detection approach

Evaluate the classifier performance

Damage quantification in the latent space

(Training phase) Estimate GPR model using the source data and their labels

(Testing phase) Determine damage levels of target data

Calculate of the RMSE value

end for

Output: Damage levels of target data and RMSE error

In addition, an analysis considering all data sets from the numerical model and experimental data is proposed to highlight the harmful effects when the equivalence between domain labels is not maintained. In the following subsections, an overview is outlined to describe the damage detection methodology and a brief description of the GPR models.

5.3.1 Damage Detection Methodology

A classifier based on MSD is trained using the source data in the healthy condition. The testing data are the remaining features of the source data in damaged conditions and the target data. In this case, an outlier detection approach is applied for damage detection. The MSD (or DI in the SHM context) in the N rounds can be described as (SARMADI; KARAMODIN, 2020):

$$\text{DI}_N = (x_N - \bar{x})^T \Sigma^{-1} (x_N - \bar{x}) \quad (20)$$

where x_N is the test data in the current round, $\bar{x}$ and Σ are the mean and covariance matrix of the source data in the healthy condition, respectively. A threshold is defined based on the maximum distance of the source data in the healthy state for classification.

The classifier's performance is measured by the macro-average F1-score (Macro F1). This metric is often applied in machine learning as it ensures the same weights for all labels (GARLA; TAYLOR; BRANDT, 2013). The definition of the Macro F1 is based on the average of the F1-scores ($F1$) of each condition described by the confusion matrix, i.e., the numbers of true positive (tp), false negative (fn), false positive (fp), and true negative (tn) determined in the classification step (LIPTON; ELKAN; NARYANASWAMY, 2014). The F1-score and Macro-F1 can be defined as:

$$F1 = \frac{2tp}{2tp + fn + fp} \quad (21)$$

$$\text{Macro F1} = \frac{1}{n} \sum_{i=1}^n F1_i \quad (22)$$

5.3.2 DAMAGE QUANTIFICATION USING GPR MODEL

As previously described, the proposed methodology uses a regression model to evaluate the condition of the experimental setup. This model is estimated using the features of the numerical model ($\mathcal{F}_s$) projected onto the latent space. It is possible to generate N possible damage conditions, train N regression models, and then compare the accuracy of each estimated model in describing the behavior of the experimental features ($\mathcal{F}_t$) also projected into the latent space. It is expected that the smallest error (between regression model and experimental data) will be obtained when the numerical model (source domain) simulates a condition closer to the current state of the structure (target domain). Thus,

a regression model is necessary for describing the tendency of damage propagation based on the features investigated. It is also interesting for such a model being non-parametric so that different scenarios of possible damage can be simulated.

The GPR model is a powerful non-parametric model that follows the Bayesian framework that allows the prediction of the data sets while presenting the uncertainties involved in the analysis (RANGANATHAN; YANG; HO, 2011). The set of nonlinear functions are considered to be random variables that follow a Gaussian process, in which any finite subset of the functions presents a joint (multivariate) Gaussian distribution that can be described by a mean function and kernel (covariance) function (HE; SIU, 2011).

Following the Bayesian framework, the definition of the prior distribution $\mathbf{f}$ often assumes that the mean function is zero, which it does not impact the posterior distribution as it is not restricted to be zero (SCHULZ; SPEEKENBRINK; KRAUSE, 2018). Formally, the prior distribution $\mathbf{f}$ can be written as $\mathbf{f} = f(\mathcal{F}_s) \sim \mathcal{N}(\mathbf{f}|0, \mathcal{K})$, where $\mathcal{K}$ is the kernel matrix. In real situations, the prior distribution presents noisy data sets and it is necessary the addition of a noise term ϵ with zero mean and variance σ_n^2 , i.e., $\mathbf{y} = f(\mathcal{F}_s) + \epsilon$ with $\epsilon \sim \mathcal{N}(0, \sigma_n^2)$.

The prior distribution describes the properties of the functions sampled based on a Gaussian process. This distribution can be adjusted according to the training data sets, resulting in the training outputs $\mathbf{y}$. The knowledge of the prior distribution can be applied to determine the function values at the test data sets $\mathbf{f}_*$ through the definition of a joint (multivariate) Gaussian distribution, which can be described as:

$$\begin{pmatrix} \mathbf{y} \\ \mathbf{f}_* \end{pmatrix} \sim \mathcal{N}\left(0, \begin{bmatrix} \mathcal{K}(\mathcal{F}_s, \mathcal{F}_s) + \sigma_n^2 \mathbf{I} & \mathcal{K}(\mathcal{F}_s, \mathcal{F}_t) \\ \mathcal{K}(\mathcal{F}_t, \mathcal{F}_s) & \mathcal{K}(\mathcal{F}_t, \mathcal{F}_t) \end{bmatrix}\right) \quad (23)$$

where $\mathcal{K}(\mathcal{F}_s, \mathcal{F}_s)$ is the covariance matrix between the latent features of the source domain, $\mathcal{K}(\mathcal{F}_t, \mathcal{F}_t)$ is the covariance matrix between the latent features of the target domain, $\mathcal{K}(\mathcal{F}_s, \mathcal{F}_t)$ and $\mathcal{K}(\mathcal{F}_t, \mathcal{F}_s)$ is the covariance matrix between the latent features of the source and target domains.

Given the training data and test inputs, the predictive distribution can be determined by conditioning the joint Gaussian prior distribution to establish only the functions that include the data sets (RASMUSSEN; WILLIAMS, 2006). The resulting predictive distribution also follows a multivariate Gaussian distribution $p(\mathbf{f}_*|\mathcal{F}_s, \mathbf{y}, \mathcal{F}_t) \sim \mathcal{N}(\bar{\mathbf{f}}_*, \Sigma_*)$, such that:

$$\bar{\mathbf{f}}_* = \mathcal{K}(\mathcal{F}_t, \mathcal{F}_s)[\mathcal{K}(\mathcal{F}_s, \mathcal{F}_s) + \sigma_n^2 \mathbf{I}]^{-1} \mathbf{y} \quad (24)$$

$$\Sigma_* = \mathcal{K}(\mathcal{F}_t, \mathcal{F}_t) - \mathcal{K}(\mathcal{F}_t, \mathcal{F}_s)[\mathcal{K}(\mathcal{F}_s, \mathcal{F}_s) + \sigma_n^2 \mathbf{I}]^{-1} \mathcal{K}(\mathcal{F}_s, \mathcal{F}_t) \quad (25)$$

Likewise to TCA, the GPR model is sensitive to the kernel selection due to the underlying assumptions about the patterns of the features that led to its selection (LI *et al.*, 2019). Several kernels could be used in this analysis, and the same type of kernel applied in TCA would be an alternative. However, the features in latent space do not behave like the original features, and another kernel would be more appropriate. Thus, the exponential kernel is applied in this work to correlate latent features patterns due to its properties that result in the best performance of the estimated GPR model. The exponential kernel can be described as (WILSON; ADAMS, 2013):

$$k(\mathcal{F}, \mathcal{F}') = \sigma_f^2 \exp\left(-\frac{\|\mathcal{F} - \mathcal{F}'\|}{\sigma_l}\right) \quad (26)$$

where σ_f^2 is the signal variance and σ_l is the length-scale. The estimation of the hyperparameters $\theta = [\sigma_f^2, \sigma_l]$ was performed considering the maximization of the log-likelihood based on the training data (CHALUPKA; WILLIAMS; MURRAY, 2013). The log-likelihood is defined based on the covariance matrix of the process, that depends on the kernel hyperparameters θ and noise variance σ_n^2 , with known derivatives. This expression can be described as (KANG; LI, 2020):

$$\log p(\mathbf{y}|\mathcal{F}) = -\frac{1}{2} \mathbf{y}^T (\mathcal{K} + \sigma_n^2 \mathbf{I})^{-1} \mathbf{y} - \frac{1}{2} |\mathcal{K} + \sigma_n^2 \mathbf{I}| - \frac{n}{2} \log 2\pi \quad (27)$$

where a gradient based optimization procedure was implemented to find the optimal values.

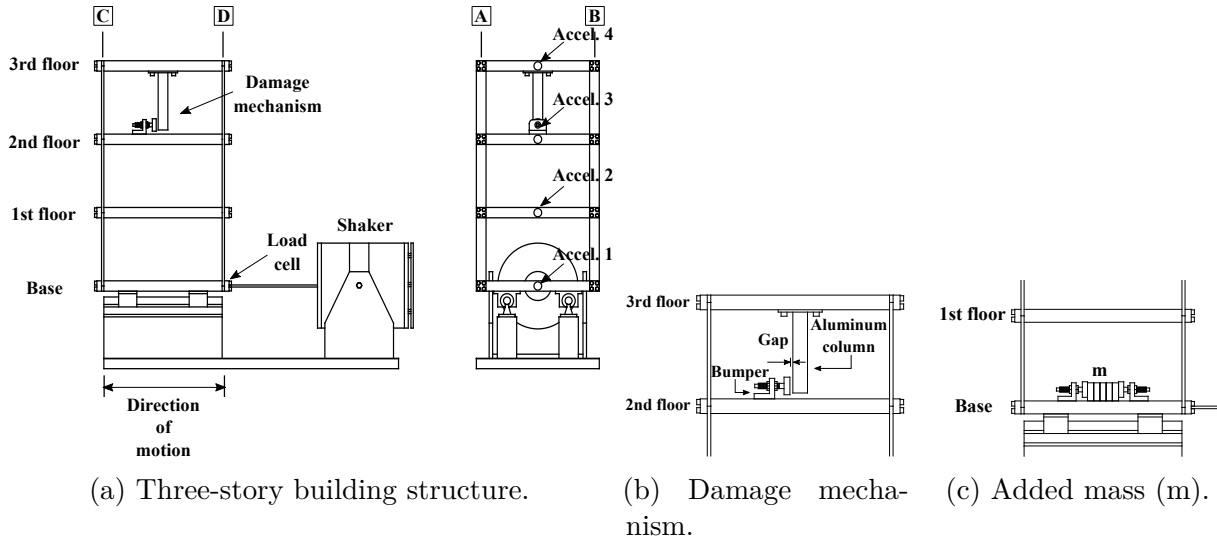
5.4 CASE STUDY - THREE-STORY BUILDING STRUCTURE

5.4.1 Experimental setup

The three-story building structure analyzed is well-known in the SHM field. The variety of different scenarios applied to the structure is the main reason that induced several researchers to investigate its dynamical behavior (BANDARA; CHAN; THAMBIRATNAM, 2014; NGUYEN; CHAN; THAMBIRATNAM, 2014; CHAMPNEYS *et al.*, 2020; YANO *et al.*, 2021). Figure 17a shows the structure's layout, where aluminum plates and four aluminum columns were assembled using bolted joints to compose each floor. Figure 17b shows the damage mechanism located at the center of the structure's top floor.

This mechanism introduces nonlinear effects due to the intermittent impacts between the aluminum column, and bumper (ENTEZAMI; SHARIATMADAR; KARAMODIN, 2019). Also, the rails that supported the structure restricted its displacement in the direction of the shaker.

Figure 17 – Modified schematic drawing of the building (FIGUEIREDO *et al.*, 2009).



Source: Prepared by the author.

The data acquisition is performed using an electromagnetic shaker to excite the base floor with random input signals assuming a band-limited range of 20-150 Hz. On the opposite side of the shaker, four accelerometers are placed in each floor's center to measure the system's response separately. The collected data consists of fifty tests in each of the structural conditions, where the time-series present 8192 samples, assuming a sampling frequency of 320 Hz.

Table 6 summarizes all structural conditions investigated in this work, assuming that the structure operates only under the linear regime and not considering the nonlinear effects introduced by the damage mechanism. The gap between the aluminum column and bumper is insufficient to allow the interaction between these components, but the masses of these components are considered in the analysis. The damage scenario is represented in this work by the stiffness reduction in some columns when replacing them with others with half of the original thickness value, being represented by conditions 4 to 9. For instance, condition 4 represents replacing one aluminum column on the first floor with another one presenting 50% the original thickness. Meanwhile, condition 9 describes replacing two columns on the third floor for two other aluminum columns with 50% of the original dimension.

On the other hand, the mass added to the floors represented by conditions 2 and

3 does not represent a damaged state. The achieved effect is an operational variation. Figure 17c illustrates the mass of 1.2 kg introduced at the base level, describing condition 2. For more details, the benchmark data and all information about the structure can be found at the LANL website (FIGUEIREDO *et al.*, 2009).

Table 6 – Description of the structural condition investigated.

Condition	Description
1	Baseline
2	1.2 kg added at the base
3	1.2 kg added on the 1st floor
4	Stiffness reduction in 1BD
5	Stiffness reduction in 2BD
6	Stiffness reduction in 3BD
7	Stiffness reduction in 1AD and 1BD
8	Stiffness reduction in 2AD and 2BD
9	Stiffness reduction in 3AD and 3BD

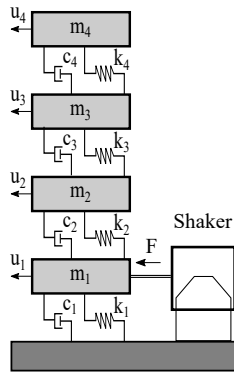
Source: Prepared by the author.

5.4.2 Numerical Model

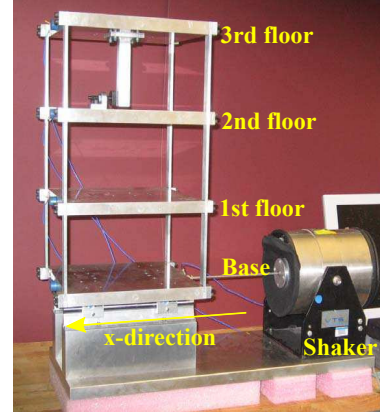
In this section, a physics-based model is proposed to adequately describe the behavior of the building structure, allowing one to extract features from a numerical model that can be adjusted to all the structure’s labels. Figure 18 shows a classical lumped mass model with four degrees-of-freedom under shear effects and the experimental setup. The friction effects resulting from the interaction between the structure and the rails are not neglected in the proposed numerical model by introducing a degree of freedom at this level. In this case, the experimental inputs are used to maintain the consistency of the measured responses and validate the estimated model.

All structural components are composed of the same material as the experimental setup, where the aluminum’s mechanical properties are employed to describe the integrity of the building structure. This work considers the modulus of elasticity as a random variable with a known mean and variance to insert some uncertainties in the numerical model. Following the maximum entropy principle (JAYNES, 1957), a Gamma distribution can approximate this random variable. The modulus of elasticity was considered to be Gamma distributed with a mean equal to 65 GPa and a standard deviation of 0.15 GPa. This procedure ensures some level of data dispersion related to the numerical model. Tables 7 and 8 summarize the dimensions and masses of the columns and plates that compose the building floors and the damage mechanism components embedded in the structure.

Figure 18 – Numerical model and building structure.



(a) Drawing of 4 degrees-of-freedom.

(b) Building structure (FIGUEIREDO *et al.*, 2009).

Source: Prepared by the author.

Table 7 – Dimensions of the structure's components.

Component	Dimension [mm]
Column length, L_c	152.0
Column thickness, h_c	6.0
Column width, b_c	25.0
Plate height, h_f	25.0
Plate width, b_f	305.0

Source: Prepared by the author.

Table 8 – Masses of the structure's components.

Component	Mass [kg]
Aluminum column, m_c	0.06
Aluminum plate, m_f	6.26
Bumper, m_{bm}	0.20
Column screw block, m_{cf}	0.04
Suspended column, m_{sc}	0.26

Source: Prepared by the author.

5.4.3 Description of Damage Progression

The healthy condition of the experimental setup presents aluminum columns with 6.0 mm thickness according to the official report (FIGUEIREDO *et al.*, 2009), and it represents the structural condition to be compared with the damaged conditions. Meanwhile, the thickness dimensions that define the damage progression are within the interval between 4.5 mm to 1.5 mm with a 0.3 mm variation, describing a total of 11 rounds to be investigated ($N = 11$).

The damage levels in the structure are defined by the column dimensions for each structural condition, resulting in different levels of stiffness reductions y according to the number of components replaced. The definition of damage levels can be written as (SUN; BETTI, 2015):

$$y = \left(\frac{K_H - K_D}{K_H} \right) \times 100\% \quad (28)$$

where K_H is the stiffness matrix in the healthy condition and K_D is the stiffness matrix in the damaged conditions to be investigated. Table 9 presents the damage levels according to the column thickness.

Table 9 – Description of the damage level given by the stiffness reduction.

Round, N	h_c [mm]	Conditions	y [%]
1	4.5	1 to 3	0.0
		4 to 6	14.5
		7 to 9	28.9
2	4.2	1 to 3	0.0
		4 to 6	16.4
		7 to 9	32.8
3	3.9	1 to 3	0.0
		4 to 6	18.1
		7 to 9	36.3
4	3.6	1 to 3	0.0
		4 to 6	19.6
		7 to 9	39.2
5	3.3	1 to 3	0.0
		4 to 6	20.8
		7 to 9	41.7
6*	3.0	1 to 3	0.0
		4 to 6	21.9
		7 to 9	43.8
7	2.7	1 to 3	0.0
		4 to 6	22.7
		7 to 9	45.4
8	2.4	1 to 3	0.0
		4 to 6	23.4
		7 to 9	46.8
9	2.1	1 to 3	0.0
		4 to 6	23.9
		7 to 9	47.9
10	1.8	1 to 3	0.0
		4 to 6	24.3
		7 to 9	48.6
11	1.5	1 to 3	0.0
		4 to 6	24.6
		7 to 9	49.2

*Structural damage condition.

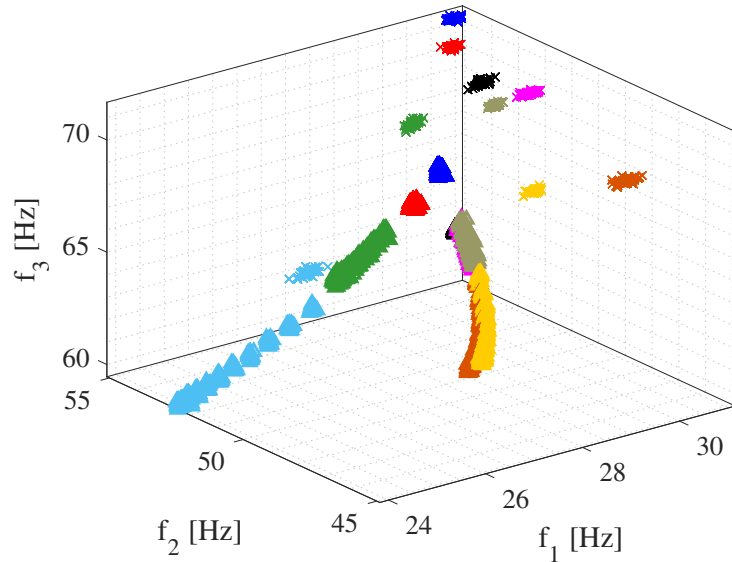
Source: Prepared by the author.

5.5 RESULTS

Figures 19 and 20 illustrate the features (first three natural frequencies of the system) extracted from the numerical model (source) considering its N rounds and from the experimental data (target). The ability of the identified model to represent the structure's behavior can be verified by comparing the feature patterns. However, there are divergences in magnitude between the analyzed domains, which may arise from the assumptions made during the model identification.

Some features of different conditions almost overlapped in the numerical model. For instance, features from conditions 4 and 6 are near to each other, and conditions 7 and 9 also present the same behavior. The proximity of these natural frequencies can be related to the equivalent changes in the stiffness matrix, which occur at different array positions. This behavior can impair the TCA application because the features' separability before the mapping is necessary for a correct classification according to the structural condition they represent.

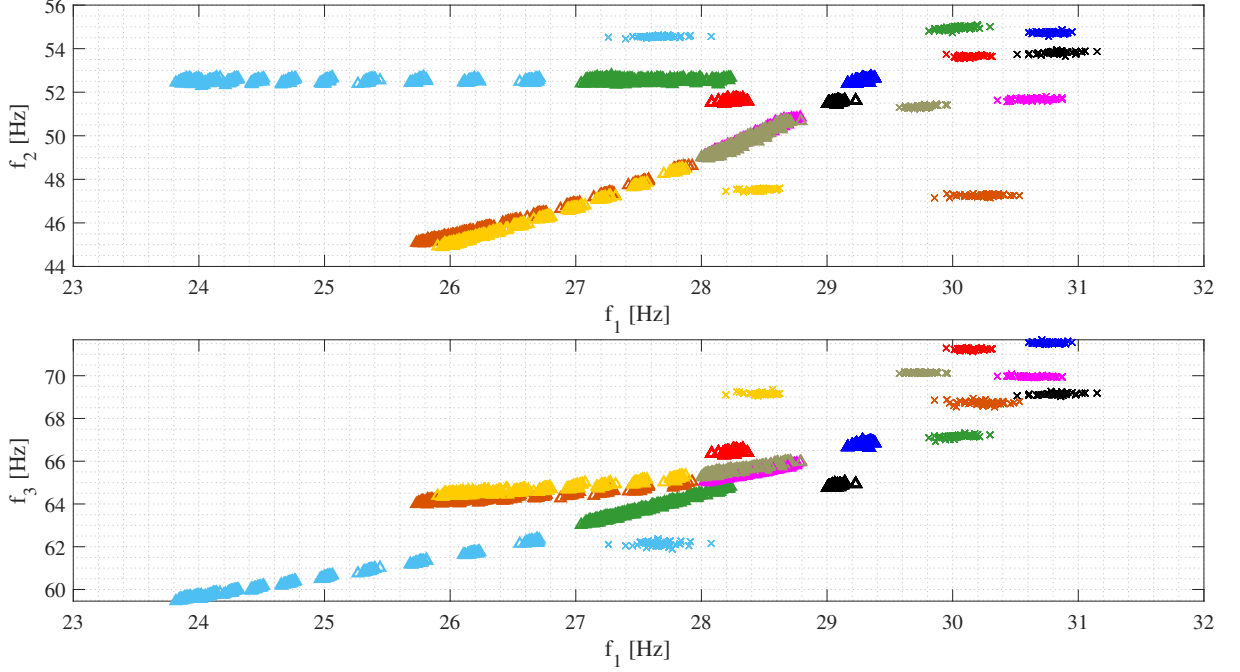
Figure 19 – Features of source domain (Δ) and target domain ($\times$), where colors $\blacksquare$ represents the baseline condition, $\blacksquare$ condition 2, $\blacksquare$ condition 3, $\blacksquare$ condition 4, $\blacksquare$ condition 5, $\blacksquare$ condition 6, $\blacksquare$ condition 7, $\blacksquare$ condition 8, and $\blacksquare$ condition 9.



Source: Prepared by the author.

There are 150 feature vectors in the source domain per condition, resulting in a feature matrix with 1350 samples ($\mathbf{X}_s \in \mathbb{R}^{1350 \times 3}$). Likewise, the target domain has 50 features per condition, presenting a total of 450 feature vectors ($\mathbf{X}_t \in \mathbb{R}^{450 \times 3}$). In this case, only the figures considering the numerical model in the sixth round ($N = 6$) are presented. This

Figure 20 – Two-dimensional features of source domain (Δ) and target domain ($\times$), where colors ■ represents the baseline condition, ■ condition 2, ■ condition 3, ■ condition 4, ■ condition 5, ■ condition 6, ■ condition 7, ■ condition 8, and ■ condition 9.



Source: Prepared by the author.

round corresponds to the situation where the numerical model can represent the structural condition of the building structure, ensuring consistency between the domain labels.

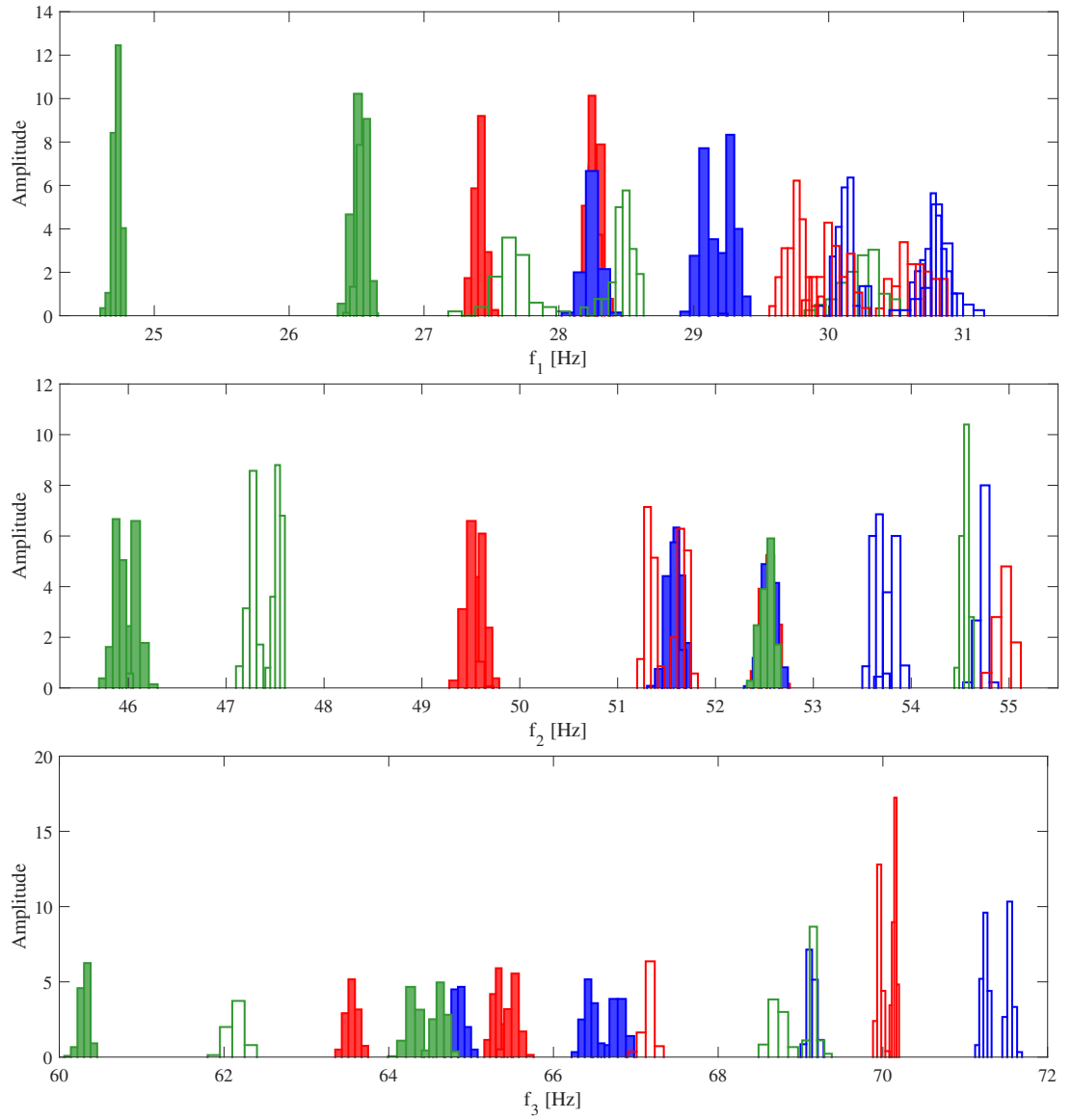
Figure 21 shows histograms of features of both domains considering the healthy and damaged labels due to the classification proposed in this work. The overlapping of some histograms under different structural conditions highlights the difficulties in the classification and proves the need for the TCA application to assist the damage detection step.

The TCA parameters are defined by the optimization of the macro F1 determined through the variation of the number of components (dimension of the latent space) and trade-off parameter, where $m = 1$ and $\mu = 0.1$, respectively. In fact, the trade-off parameter of the regularization term can be determined through a sensitivity analysis.

The TCA method is then applied, and Figure 22 shows the latent features and their histograms. The latent features are correctly grouped in a binary classification, showing the TCA's ability to determine a consistent mapping that approximates data distributions and preserves data properties.

The features from structural conditions 2 and 3 form a group with those from the

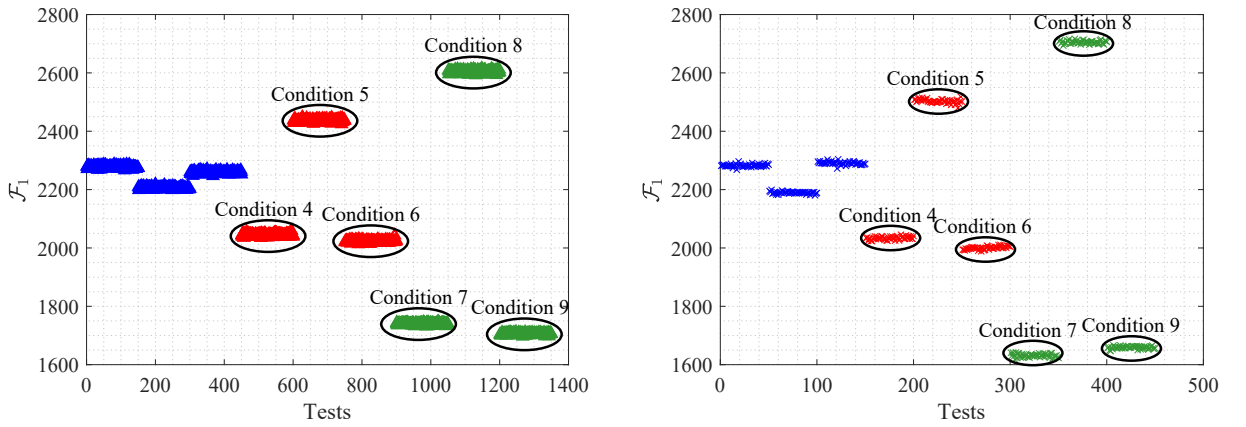
Figure 21 – Histograms of features from the source (filled color) and target domains (empty color) in the original space, where colors ■ represents the healthy condition, ■ first damage level, and ■ second damage level.



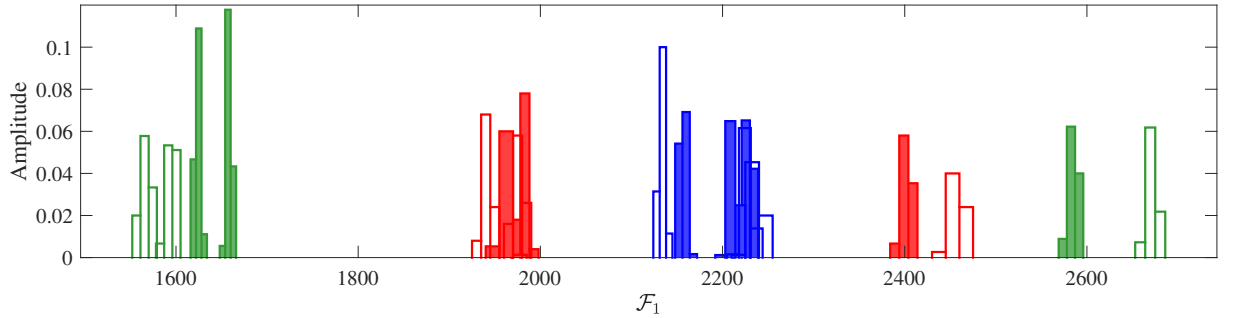
Source: Prepared by the author.

baseline condition features at the center of the latent space, not indicating a large dispersion of the first latent component. Meanwhile, the features related to the damage on the second floor (conditions 5 and 8) are located at the top of the features group in the healthy condition. Meanwhile, the damaged conditions are properly included in the damaged groups, and their arrangement may be associated with the damage levels and locations in the structure. For instance, the features in the most damaged conditions (conditions 7, 8, and 9) are more distant from the undamaged features.

Figure 22 – Latent features and histograms after the TCA application, where colors ■ represents the healthy condition, ■ first damage level, and ■ second damage level.



(a) Latent features of source domain (left) and target domain (right).



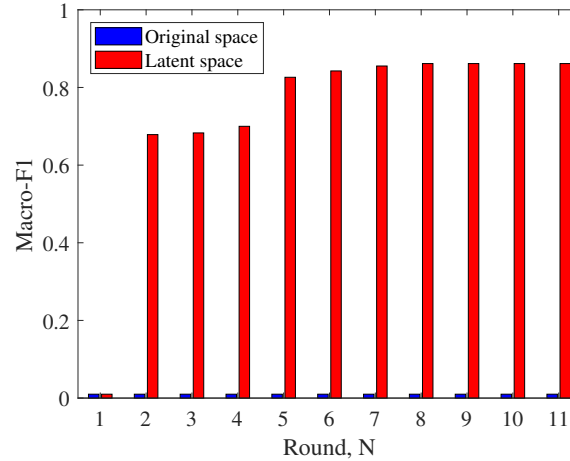
(b) Histograms of source (filled color) and target (empty color) features after the TCA application.

Source: Prepared by the author.

An overview of the classifier performance is highlighted in Figure 23, where all N rounds of the numerical model are individually investigated. The separation problem of features in the original space prevents an adequate classification, and the results prove that the classifier completely fails to fulfill its assignment. In contrast, the TCA increases the classifier performance as the damage level progresses due to the domain labels' agreement. The distance-based classifier suggests the convergence of its performance from the sixth

round. It provides the determination of the presence of damage even though the numerical model presents more severe damage conditions than the actual damage existing in the structure.

Figure 23 – Performance of the classifier in the original and latent spaces.



Source: Prepared by the author.

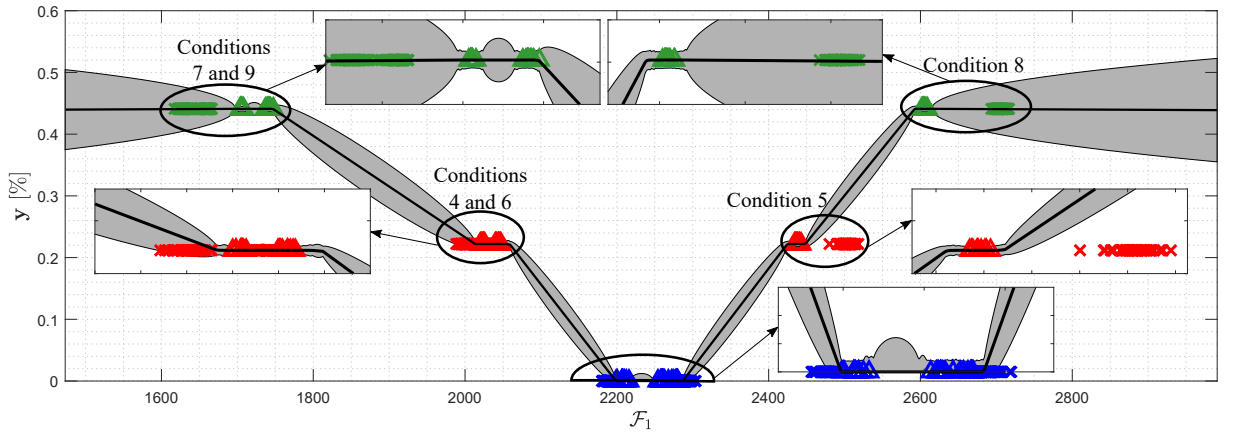
The results presented in the damaged detection step highlighted the difficulties of the classifier in the original space. Thus, the determination of the damage extension with these data sets is not feasible, and the GPR model is not estimated as it would not fulfill its purpose. On the other hand, the features after the TCA application allow the determination of a GPR model capable of generalizing the latent data sets due to their similar behavior, representing an interesting idea that uses numerical models to analyze the real structure.

Figure 24a shows the prediction of damage levels estimated by the GPR model in the sixth round ($N = 6$). The results correctly determine the damage levels of the real structure according to the information from its numerical model, resulting from the consistency between the labels that represent the thickness of the replaced columns in the source and target domains. A slight imprecision of the trending curve can be observed in the classification in the first damage level of the experimental setup due to the proximity of the target data in condition 5 with the source data in condition 8. However, the GPR model correctly evaluates the damage levels as expected and provides a reliable assessment of the building structure using the structural knowledge of the numerical model.

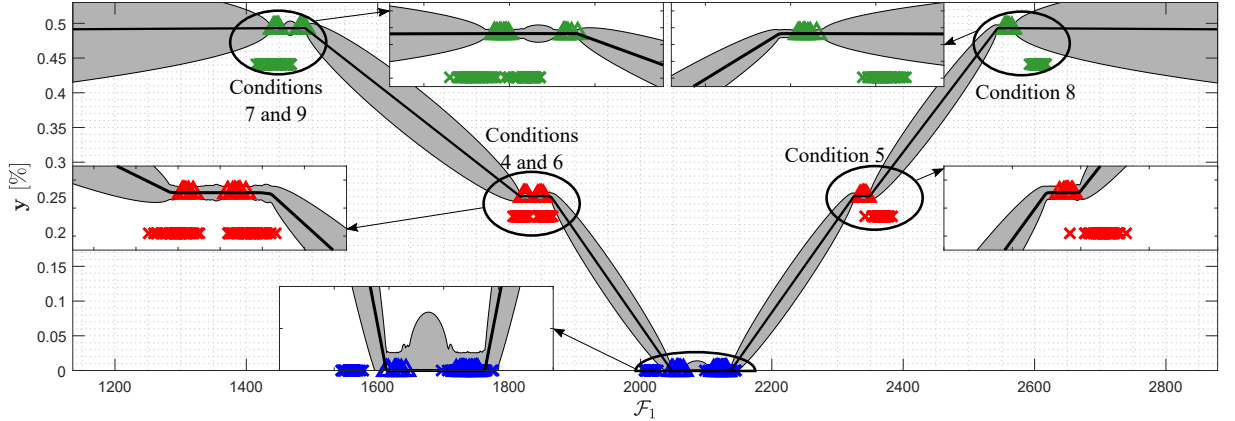
The GPR model estimated in the eleventh round ($N = 11$) of the numerical model is illustrated in Figure 24b. The features present similar values in some conditions to those of the experimental data. It is expected that the GPR model would be able to accurately

determine the damage levels due to this similarity between the values of the features. However, this does not occur due to the label inconsistencies that are used in the GPR model identification, resulting in the wrong classification of the structural condition of the experimental setup. Therefore, the requirement of equivalence between domain labels is important for the quantification of damage levels through knowledge transfer across domains using the combination of TCA and GPR models.

Figure 24 – Prediction of the latent target data ($\times$) based on the GPR model trained using latent source data (Δ), where colors $\blacksquare$ represents the healthy condition, $\blacksquare$ first damage level, $\blacksquare$ second damage level, and $\blacksquare$ is the confidence intervals.



(a) GPR model in the sixth round ($N = 6$).



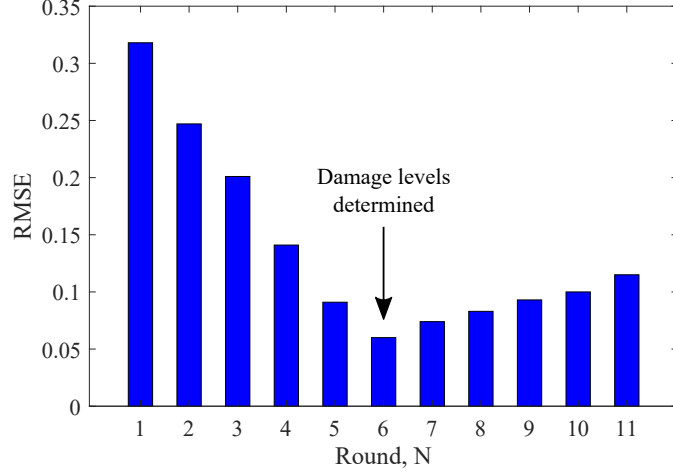
(b) GPR model in the eleventh round ($N = 11$).

Source: Prepared by the author.

The RMSE values determined in the N rounds comparing the expected damage levels and determined by the GPR model are demonstrated in Figure 25. The lowest RMSE value ($\sim 6.1\%$) occurs in the sixth round ($N = 6$) and highlights the moment when the labeling consistency is achieved, presenting a slight imprecision due to the damage located on the second floor of the structure. Furthermore, the low RMSE values also prove the

ability of the GPR model to detect the presence of structural damage in a range of column thickness if the actual value of the structural component is within the assumed interval.

Figure 25 – RMSE value determined based on the GPR model for the N rounds investigated.



Source: Prepared by the author.

5.6 PROBLEMS OF LABELS INCONSISTENCY

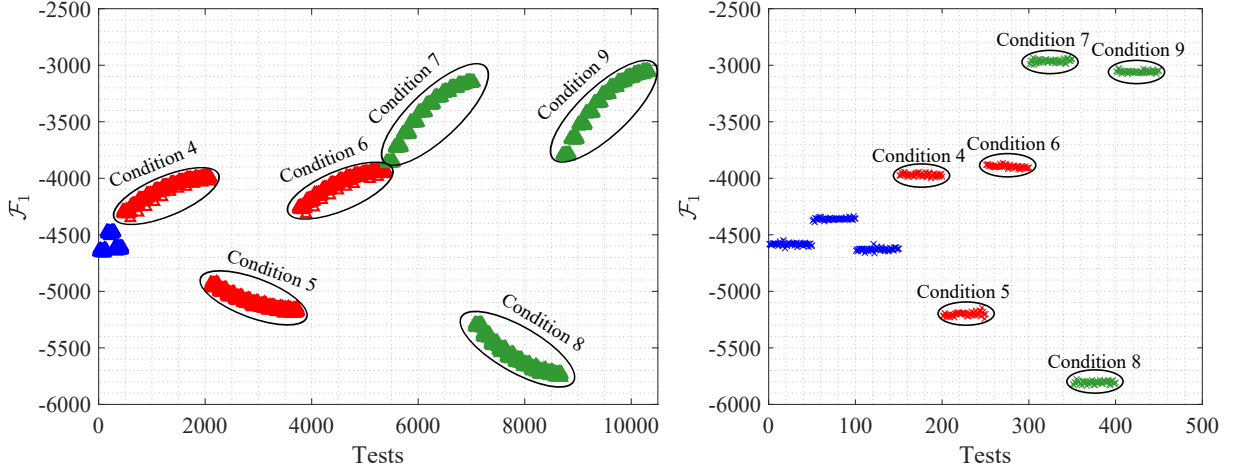
The application of a straightforward approach assuming features under all structural conditions becomes reasonable. Then, a comparison between the performance of the TCA under these circumstances and the original methodology is performed.

In this context, the source data has 10350 samples feature vectors ($\mathbf{X}_s \in \mathbb{R}^{10350 \times 3}$), while the target data has the 450 samples ($\mathbf{X}_t \in \mathbb{R}^{450 \times 3}$). In this analysis, TCA is applied again, assuming the linear kernel with the same trade-off parameter ($\mu = 0.1$) and the number of components ($m = 1$). Meanwhile, the exponential kernel is considered for the GPR model.

Figure 26 shows all features of the source and target domains in the latent space. The separability of latent features according to structural conditions is similar to the previous results, and the damage progression in the numerical model is highlighted in its features patterns. In this case, the distance-based classifier presents an equivalent result to the original proposal after the convergence of the performance metric. This similarity of performance is a result of the TCA method that reduces the average probability distributions of the source and target domains. However, there is an imbalance between the labels domain. For this reason, the latent features extracted from the structure with

the highest damage level coincided with the most severe condition of the source data to reduce the divergences between the averages of the distributions.

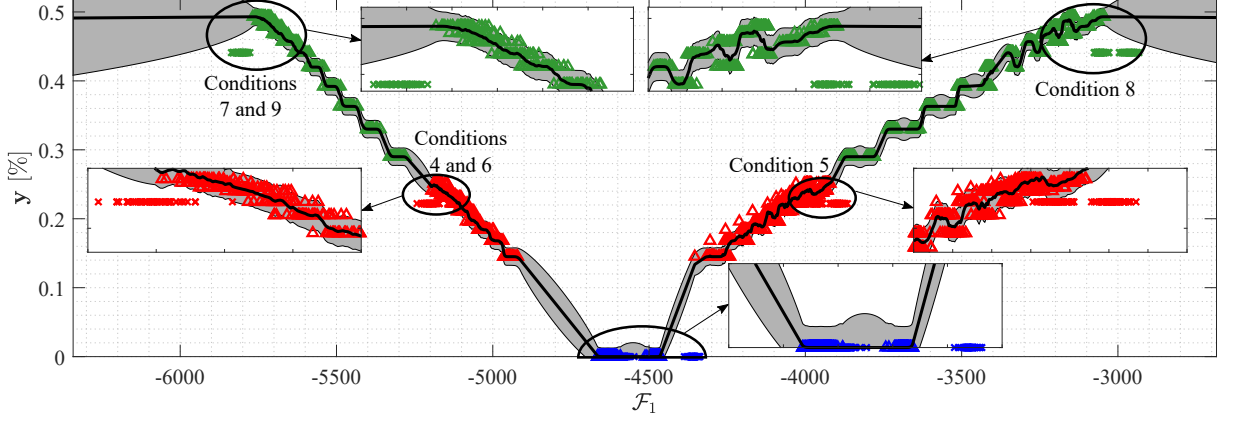
Figure 26 – All features from the source and target data in the latent space, where colors ■ represents the healthy condition, ■ first damage level, and ■ second damage level.



Source: Prepared by the author.

The GPR model using all the features of the source domain for the learning phase is shown in Figure 27. The GPR predictions present inaccuracies that prevent application for the damage quantification step. The behavior presented by the GPR model mainly follows the latent features in the most severe conditions, resulting in an incorrect prediction of the regression model. Therefore, it is not recommended to use all data sets under different conditions in TCA, as the imbalance between the labels affects the minimization of divergences between distributions. Meanwhile, the original methodology proposed in this work does not present this issue due to investigating the behavior of individual features, intending to determine the moment when consistency between labels is achieved.

Figure 27 – GPR model prediction of target data ($\times$) trained using all source data (Δ) in the latent space, where colors $\blacksquare$ represents the healthy condition, $\blacksquare$ first damage level, $\blacksquare$ second damage level, and $\blacksquare$ is the confidence intervals.



Source: Prepared by the author.

5.7 CONCLUSIONS

The LANL benchmark data and its numerical model were investigated to prove the feasibility of applying TCA in a case study that exemplifies general SHM cases. The proposed methodology proved its efficiency for damage detection and, mainly, for damage quantification analysis using knowledge from different structures (numerical model and experimental setup). It is a possible solution to a problem still arising in SHM associated with the damage identification in different structures.

The possibility of adjusting a numerical model to describe real structures' behavior and applying a domain adaptation method to reduce features discrepancies extracted from different systems and models may change how SHM is implemented. The label consistency does not need to be fully respected for damage detection. It allows one to use a simple model that separates the features into two classes (binary classification). However, the similarity between the labels of source and target domains is necessary for higher levels in the damage identification hierarchy.

For damage detection, TCA allowed the analysis of the three-story building structure (target domain) using the knowledge of its numerical model (source domain). The minimization of the divergences between the natural frequencies improved the integrity classification of the laboratory structure, which was not possible to carry out before the TCA application.

The requirement of consistency between structure labels imposed by domain adapta-

tion methods usually limits its application in several cases. This limitation was used to quantify the damage of the structure through a GPR model. The equivalence between latent features is achieved when the regression model presents its best performance, that is, the lowest RMSE value ($\sim 6.1\%$). In contrast, a general strategy considering all structural conditions in the numerical model is not recommended due to the imbalance between the domain labels that harms the damage quantification.

There are some limitations of the proposed methodology that need to be discussed. Identifying a suitable mathematical model is not trivial, even though it may be oversimplified. It is necessary to estimate a simple surrogate model that describes the physics involving the structural behavior for damage quantification. Another topic that needs to be investigated is the proper selection of the kernel and its hyperparameters in the application of TCA and the GPR model. This procedure is not straightforward to be carried out and demands a comprehensive analysis due to the properties of each kernel, and the corresponding impact of its parameters variation.

6 ON THE APPLICATION OF POPULATION-BASED TRANSFER LEARNING

This chapter intends to carry out transfer learning for damage detection using long-term monitoring data sets from three real-world bridges under realistic operational and environmental conditions. Another important topic discussed herein is the importance of labeling and the quality of the knowledge present in the source structure when performing transfer learning. The results of this chapter can be found in Yano *et al.* (2023).

The chapter is structured as follows. Section 6.1 presents a brief description of the PI-57 and PK 075+317 Bridges, highlighting their structural similarities that justify the knowledge transfer from a bridge engineering perspective. In Section 6.2, heuristic similarities between the Z-24 and PI-57 Bridges are discussed, and the proposed methodology is applied. Section 6.3 describes the application of transfer learning from the Z-24 Bridge to the PK 075+317 Bridge to highlight its potential even when the bridges present different frameworks and purposes. Finally, Section 6.4 discusses the proposed methodology's benefits and limitations.

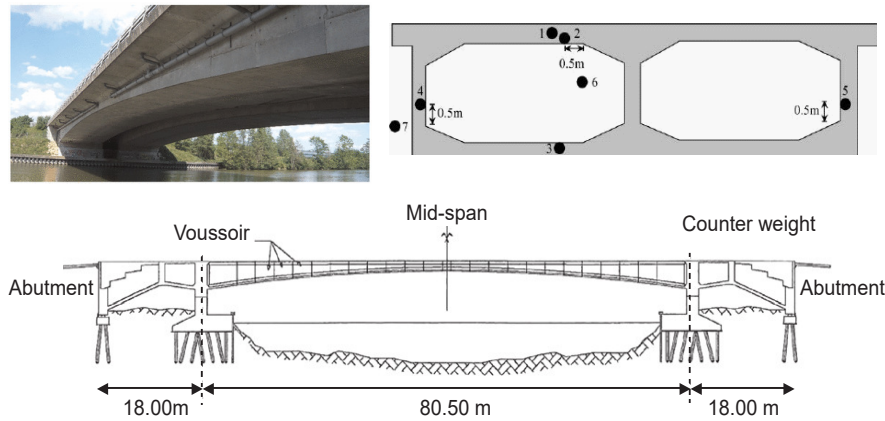
6.1 DESCRIPTION OF THE PI-57 AND PK 075+317 BRIDGES

6.1.1 The PI-57 Bridge

The PI-57 Bridge (Fig. 28) is a post-tensioned segmental bridge in France with two side spans of 18 m and a main span of 80.50 m. Since its construction, this bridge has had several problems with localized cracks and an increase in deflection in the central region. A maintenance plan was necessary to reinforce the decks, and an additional longitudinal prestressing was applied to solve the structural problems (CURY; CREMONA; DUMOULIN, 2012). Then, this bridge did not present significant structural damage that compromised its operation, assuming it works in a healthy condition. For further information about the description of the PI-57 Bridge, the reader is referred to the following papers (ALVES *et al.*, 2015b; ALVES *et al.*, 2015a; CARDOSO; CURY; BARBOSA, 2019).

A monitoring plan was carried out in two parts according to the corrective measures applied on the PI-57 Bridge. Sixteen accelerometers were used to measure vibration data every three hours per day, and an array of sensors to collect the environmental

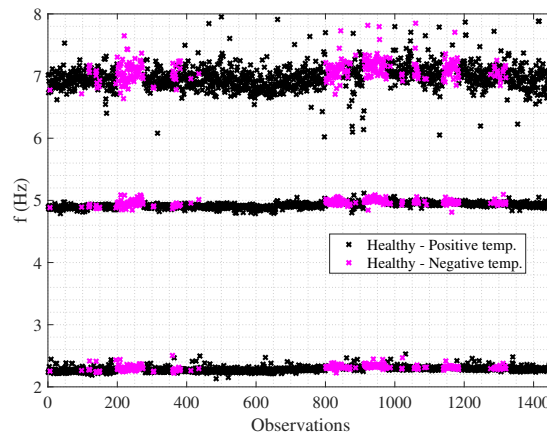
Figure 28 – PI-57 Bridge.



Source: Cury, Cremona and Dumoulin (2012).

parameters, as the bridge is also subject to the effects of positive ($T \geq 0^{\circ}C$) and negative temperatures ($T < 0^{\circ}C$). Fig. 29 illustrates the first three natural frequencies extracted from the vibration data sets under temperature effects, assuming the bridge was in its original configuration (healthy condition) between November 21, 2008, and April 3, 2009 (1-656 observations) and the bridge reinforcement was performed from November 21, 2008, to April 3, 2009 (657-1458 observations).

Figure 29 – Natural frequencies of the PI-57 Bridge.



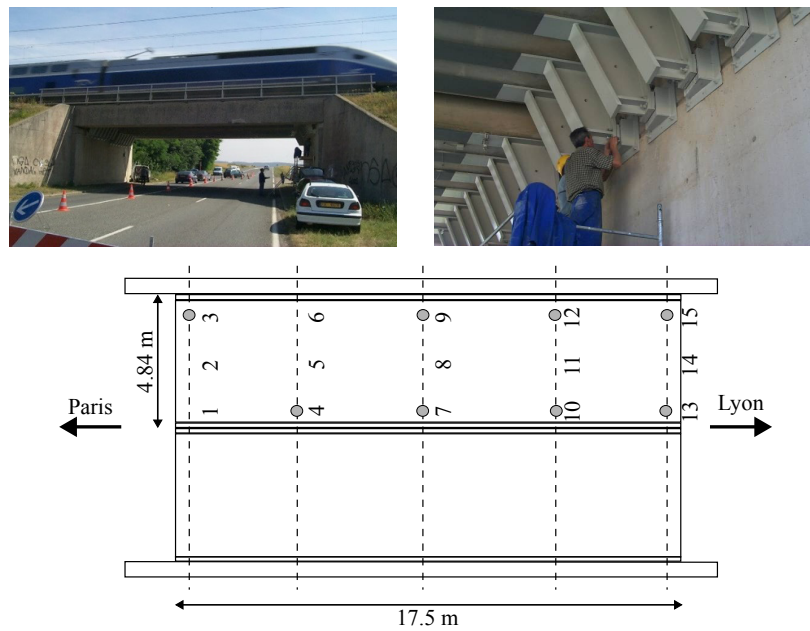
Source: Prepared by the author.

6.1.2 The PK 075+317 Bridge

The PK 075+317 Bridge (Fig. 30) is a reinforced concrete railway bridge that is part of the railway line connecting the cities of Paris and Lyon in France. A retrofit

process was necessary to prevent potential resonance effects induced by high-speed trains crossing the structure. To address the structural reinforcement, a particular system comprising rods and bearings was introduced to increase structural stiffness and shift the first natural frequency of the bridge from the excitation frequency. For further information about the description of the PK 075+317 Bridge, the reader is referred to the following papers (CREMONA, 2004; CURY; DIDAY, 2010; CURY; CREMONA, 2012a; CURY; CREMONA, 2012b).

Figure 30 – PK 075+317 Bridge.



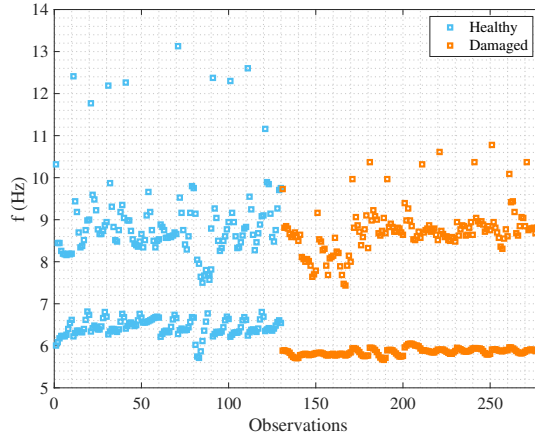
Source: Cury, Cremona and Dumoulin (2012).

A monitoring plan was conducted from June 23 to 26, 2003, to investigate the retrofit's impact on the bridge's dynamical behavior. During this period, eight accelerometers were positioned along the length of the bridge deck to measure its response under different conditions, while an array of sensors measured the temperature during the tests. In contrast to the other two bridges investigated in this paper, the PK 075+317 Bridge is subject only to positive temperatures, and so it is not affected by environmental effects associated with negative temperatures.

Fig. 31 shows the first two natural frequencies estimated upon feature extraction from the measured raw data sets. The variation of the natural frequencies is highlighted only in the first frequency, as proposed by the tightening of the special bearings. In this paper, the structure is considered to be operating in a healthy condition after the retrofit (1-130 observations) and in the damaged condition in its original condition before the retrofit

(131-280 observations), as it is not trivial to introduce real damage to the structure.

Figure 31 – Natural frequencies of the PK 075+317 Bridge.



Source: Prepared by the author.

6.2 TRANSFER LEARNING BETWEEN THREE-SPAN BRIDGES

6.2.1 Why knowledge transfer upon data sets from Z-24 and PI-57 Bridges?

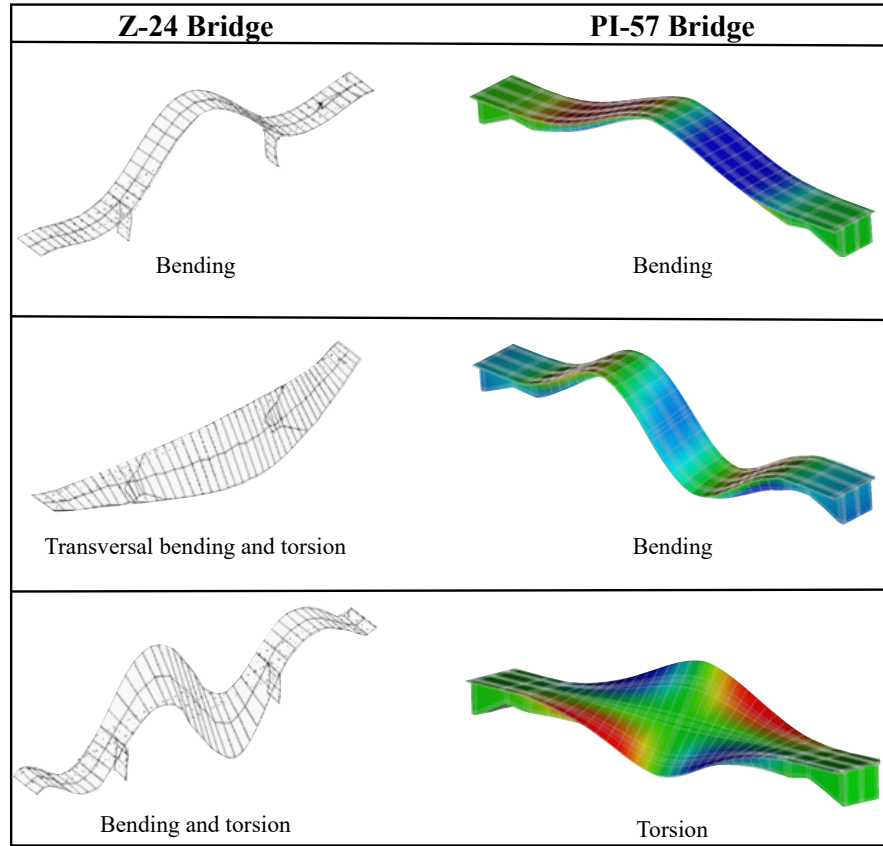
As one-of-a-kind structures, it is difficult to find two equal bridges. However, from a bridge engineering point of view, we believe that knowledge transfer should be performed when structures share similarities. For this study, we tried to find two similar bridge structures where those similarities can be recognized from a heuristic manner, even though assuming the existence of minor differences.

In terms of material and geometry, both Z-24 and PI-57 Bridges are post-tensioned concrete box girders with three spans. This similarity can be even observed in the dynamics through the comparison of the first three mode shapes (Fig. 32). Even though the second and third modes do not assume the same configuration, they interchange signatures of bending and torsion mode shapes.

In terms of operational and environmental conditions, both are road bridges under similar negative and positive ambient temperatures. The higher maximum positive temperature for the Z-24 Bridge may be useful for interpolation by spanning a larger range of temperatures. From Fig. 33 and Fig. 34, one can observe some degree of temperature dependency of the natural frequencies in both bridges, even though the natural frequencies from the Z-24 Bridge are highly dependent on the signal of the temperature due to the asphalt influence as discussed in Section 4.4; this mismatch can be a drawback then

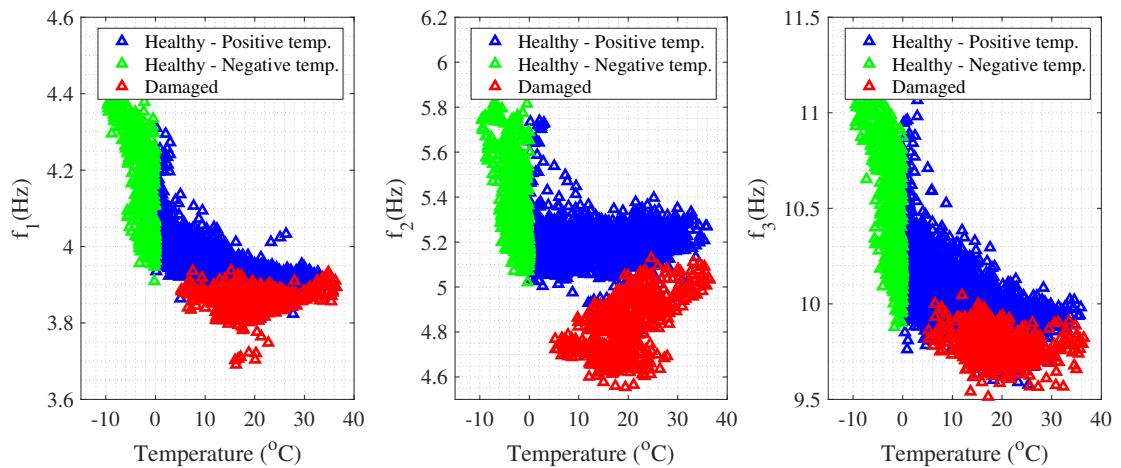
performing transfer learning, as will be shown later.

Figure 32 – Comparison of the configuration of the mode shapes associated with the first three natural frequencies.



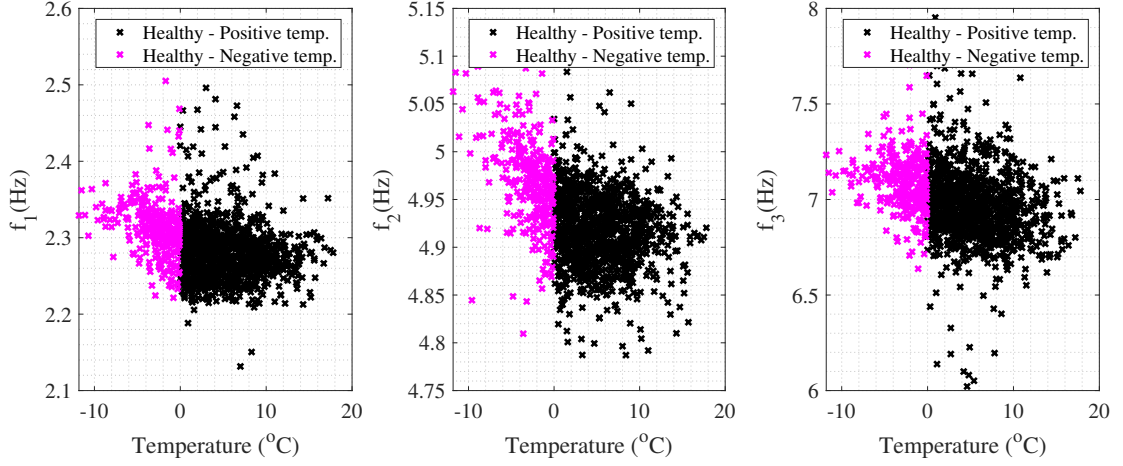
Source: Adapted from Peeters and Roeck (2001) and Cury, Cremona and Dumoulin (2012).

Figure 33 – Natural frequencies in the original feature space (Z-24 Bridge) along with the ambient temperature.



Source: Prepared by the author.

Figure 34 – Natural frequencies in the original feature space (PI-57 Bridge) along with the ambient temperature.



Source: Prepared by the author.

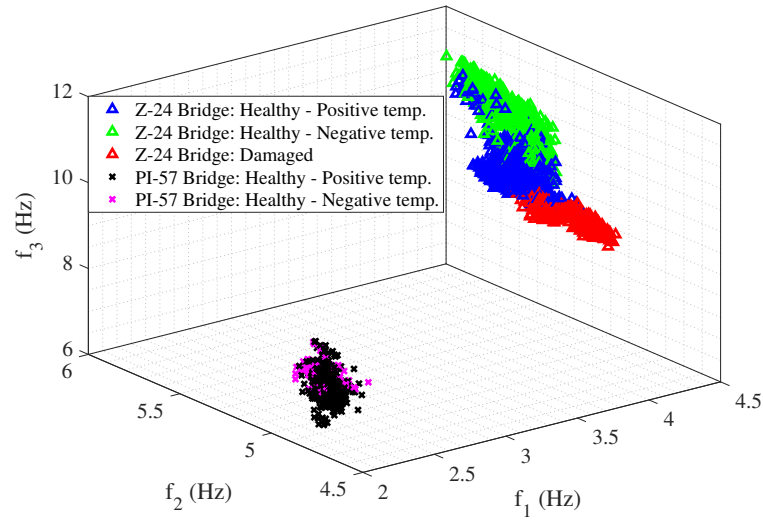
6.2.2 Feature visualization

Fig. 35 illustrates the first three natural frequencies from the Z-24 and PI-57 Bridges as observations in the three-dimensional feature space. Each observation corresponds to a state condition assumed to be a function of ambient temperature and damage. As there is no information about the presence of damage in the PI-57 Bridge, observations from the damaged condition are only highlighted for the Z-24 Bridge. The Z-24 Bridge has 5012 observations, with 4410 and 602 observations in the healthy and damaged conditions, respectively. Meanwhile, the PI-57 Bridge has 1458 observations in healthy condition only. There is an evident separation of the observations from both bridges in the feature space due to differences in the structural stiffness and their environmental and operational conditions.

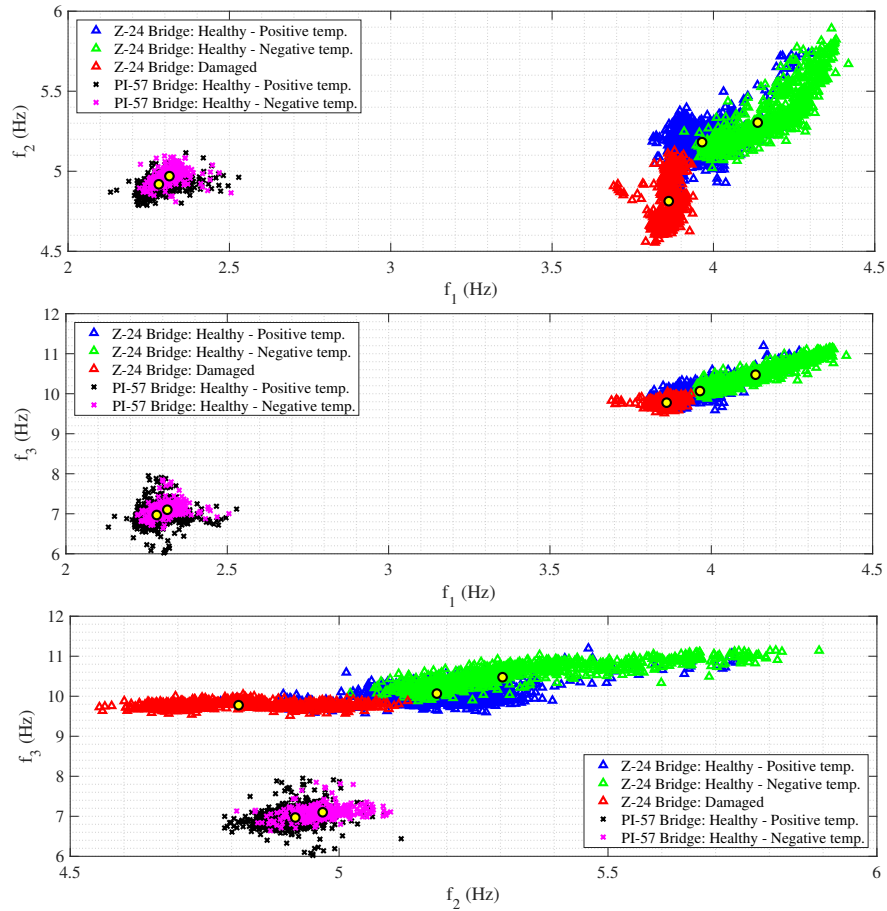
The observations in two-dimensional feature space are also shown in Fig. 36 with pair of frequencies to provide a deeper interpretation of both bridge data sets. It is possible to notice that the natural frequencies of the PI-57 Bridge form clusters not dispersed as the ones from the Z-24 Bridge, as expected due to the higher positive temperature range undergone by the Z-24 Bridge.

Fig. 37 and Fig. 38 show the histograms and box plots estimated for each natural frequency to demonstrate its dispersion. The probability distributions overlap despite representing different structural conditions, which may impair the structural integrity assessment. In addition, the box plots indicate an evident variability of the features due

Figure 35 – Three-dimensional original feature space for both Z-24 and PI-57 Bridges.



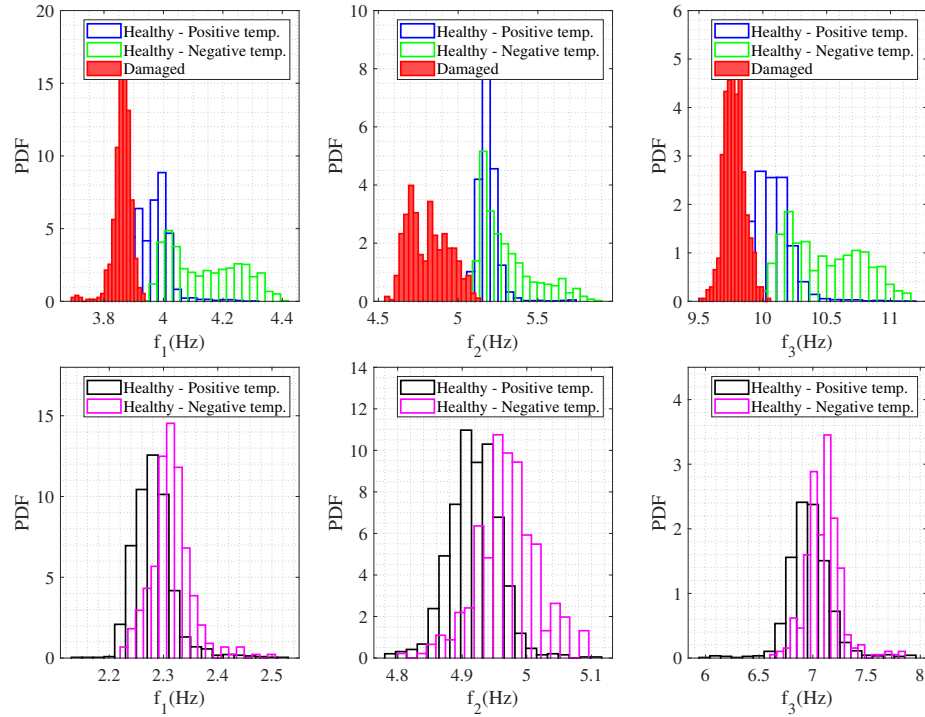
Source: Prepared by the author.

Figure 36 – Two-dimensional representation of the original feature space, where $\bullet$ is the average frequency values of each cluster.

Source: Prepared by the author.

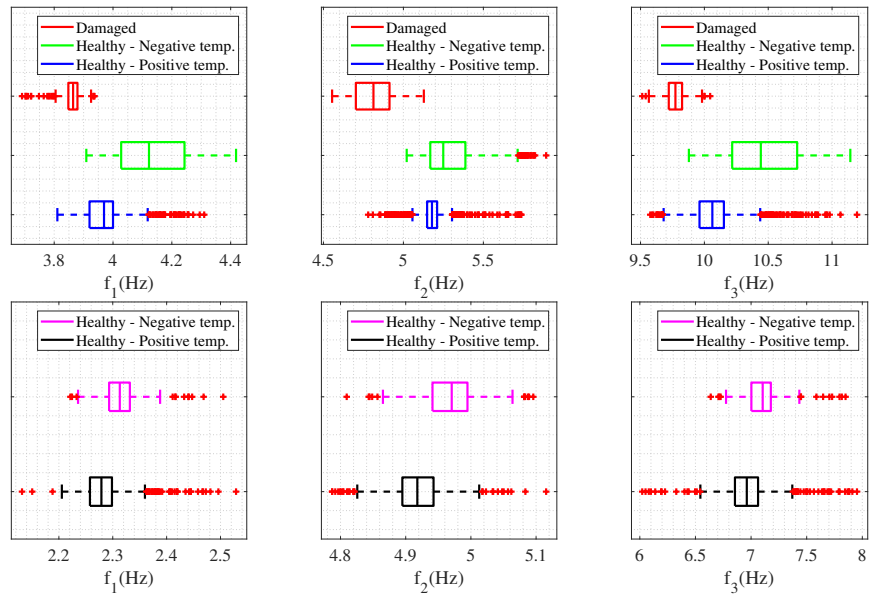
to the environmental and operational conditions, resulting in the presence of some outliers. It is important to note that the histograms of the Z-24 Bridge in the healthy condition do not follow a Gaussian distribution behavior due to the influence of negative temperatures, which changes the bridge's global stiffness.

Figure 37 – Marginal distributions of the Z-24 Bridge (top) and PI-57 Bridge (lower) in the original feature space.



Source: Prepared by the author.

Figure 38 – Box plot of the Z-24 Bridge (top) and PI-57 Bridge (bottom) in the original feature space.



Source: Prepared by the author.

6.2.3 Transfer learning strategies

Two transfer learning strategies are used to show the importance of the source data quality for damage detection. First, an unsupervised classification of the Z-24 Bridge (target) is assumed through an outlier detection using the structural knowledge from the PI-57 Bridge (source). Secondly, transfer learning from the Z-24 Bridge (source) to the PI-57 Bridge (target) is performed, assuming a supervised classification as the labels of the source data are known (healthy and damaged).

A pre-processing normalization is performed based on the source data, using the mean and standard deviation values, i.e., the mean is subtracted from all damage-sensitive features, and their values are divided by the standard deviation. The Gaussian kernel is applied to correlate the damage-sensitive features extracted from the bridges due to its attractive properties (MATASCI *et al.*, 2015). This kernel can be defined as:

$$k(x, x') = \exp\left(-\frac{\|x - x'\|^2}{2\sigma_l^2}\right) \quad (29)$$

where σ_l represents the length scale. The training phase corresponds to the determination of the transformation matrix $\mathcal{W}$ that infers the mapping into a two-dimensional latent space ($m = 2$), using half of the features of the source and target domains. Meanwhile, the remaining data is mapped to the latent space through the given matrix in the test phase.

To evaluate the transfer learning methods, a support vector machine (SVM) classifier (WIDODO; YANG, 2007) is defined with knowledge from the source domain only. The SVM defines a hyperplane as a decision boundary that differentiates two classes. Then, the classification performance is assessed by an accuracy indicator written as:

$$Accuracy = \frac{tp + tn}{tp + fp + tn + fn} \quad (30)$$

where tp is the number of true positives, tn is the number of true negatives, fp is the number of false positives, and fn is the number of false negatives.

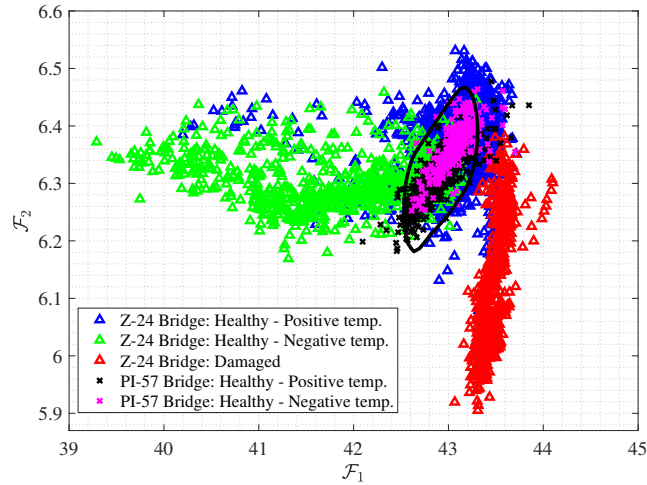
6.2.4 Transfer learning from PI-57 to Z-24 Bridges (unsupervised classification)

The hyperparameters are assumed to be the same for TCA, JDA, and MIDA methods. The determination of the hyperparameters was carried out based on sensitivity analysis to avoid overfitting the transformation matrix. Thus, the trade-off parameter, μ , is set

1×10^{-5} and characteristic lengthscale, σ_l , is equal to 70.

Fig. 39 shows the latent features after applying TCA and the hyperplane estimated by the SVM classifier. Each latent feature corresponds to observations mapped in the latent space. The latent source features (PI-57 Bridge) are clustered close to the latent target features (Z-24 Bridge) under the positive temperature range of operation, while the classifier defines the damaged features as outliers. However, the latent target features under negative temperatures diverge considerably and highlight that temperature effects have an important role in the structural dynamics of the Z-24 Bridge, which are not covered by the data (and knowledge) from the PI-57 Bridge.

Figure 39 – Latent feature space after TCA application (PI-57 to Z-24 Bridges), where — is the hyperplane estimated by the SVM classifier.

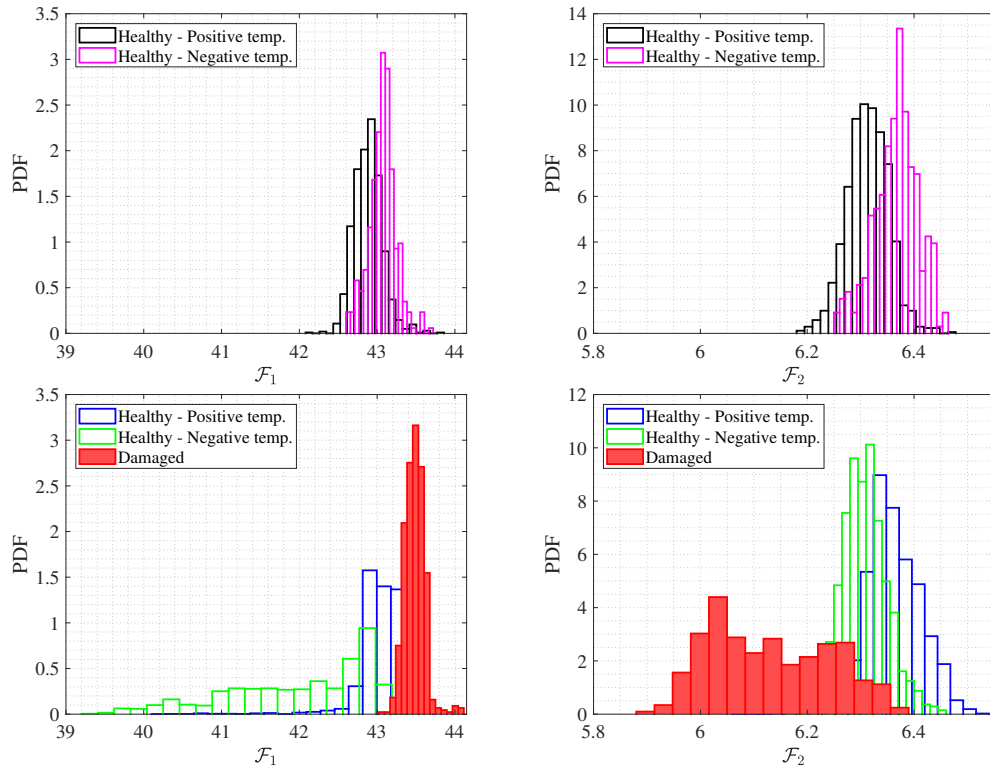


Source: Prepared by the author.

Fig. 40 shows the histograms for each latent feature and demonstrates that TCA correctly aligns the two latent features according to their structural conditions. It is shown that the first latent feature of the target domain is mainly affected by the effects of negative temperature due to presenting a significant variation in their behavior, leading to a reduction in the performance of the SVM classifier.

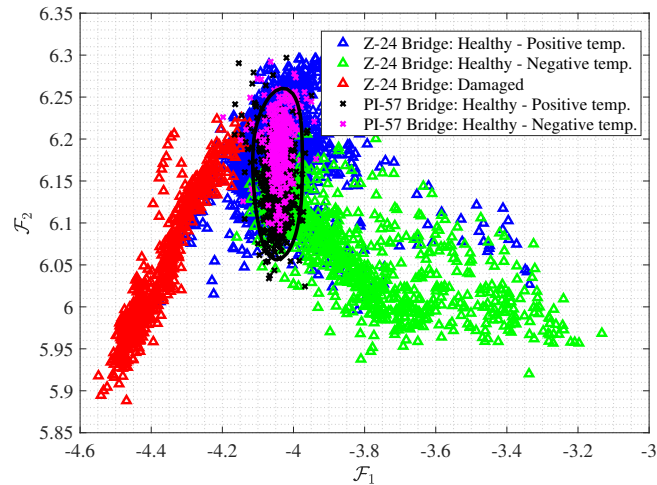
The JDA method considering ten iterations uses the SVM classifier to determine the pseudo-labels. Fig. 41 shows the latent features and the hyperplane estimated using the source (PI-57 Bridge) knowledge. The source latent features are clustered with a part of the latent target features in the positive condition, aiding the correct classification of some features. Note that the temperature effects still influence the patterns of the features from the Z-24 Bridge despite the transformation matrix optimization. Meanwhile, damaged features of the target bridge are correctly reported as outliers.

Figure 40 – Marginal distributions of the PI-57 Bridge (top) and Z-24 Bridge (bottom) after TCA application.



Source: Prepared by the author.

Figure 41 – Latent feature space after JDA application (PI-57 to Z-24 Bridges), where — is the hyperplane estimated by the SVM classifier.

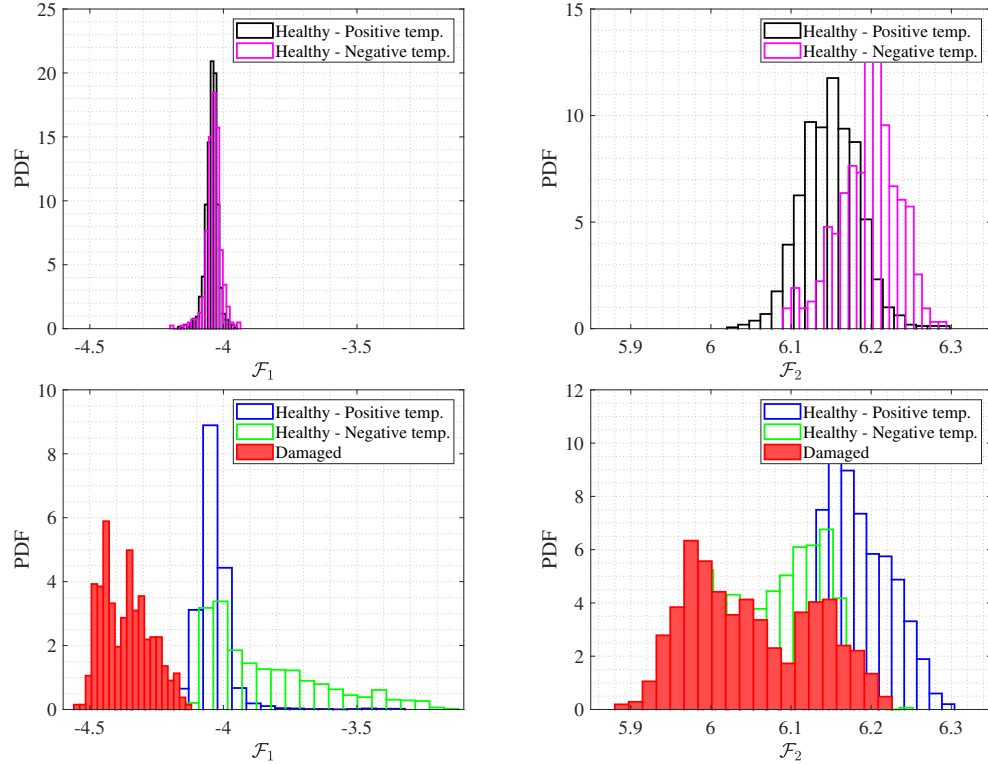


Source: Prepared by the author.

Fig. 42 shows the histogram of the latent features through the JDA method and points out the reduction of divergences between the source and target bridges. Again, there is a significant variation of the first latent feature due to the effects of negative temperatures. In addition, there are overlaps in the histograms of the second latent feature that might

impair the structural condition evaluation.

Figure 42 – Marginal distributions of the latent features of PI-57 Bridge (top) and Z-24 Bridge (bottom) after JDA application.

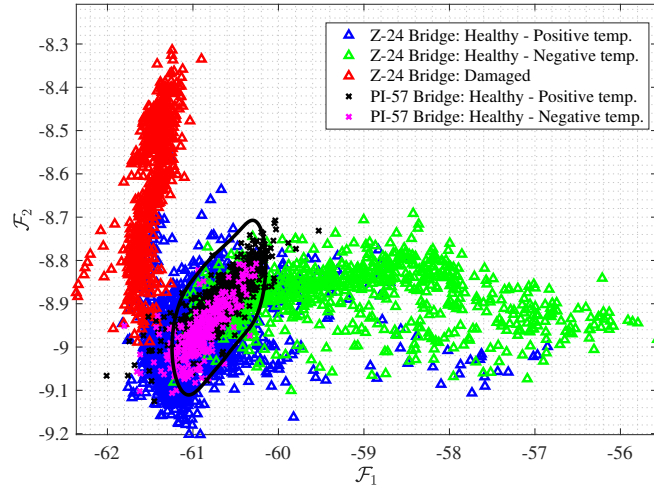


Source: Prepared by the author.

Fig. 43 and Fig. 44 present the latent space features and their histograms after applying the MIDA method. The results highlight an evident reduction of the divergences between the source and target features, resulting from maximizing independence among features and domain features. Thus, the classifier can correctly evaluate the damaged features of the target bridge. However, the MIDA method still has limitations related to the effects of negative temperature on the target bridge that impair an accurate evaluation, showing a significant dispersion indicated by the histograms.

Table 10 highlights the classifier performance for damage detection and provides a suitable comparison of the proposed methods. TCA and MIDA improved the accuracy of the classifier from 12.0% to 69.2% and 69.1%, respectively, over the assessment in the original space due to the proper assignment of most features of the Z-24 Bridge. The optimization of the transformation matrix associated with the alignment of the joint distributions performed by the JDA method aided the features embedding, resulting in the classifier's accuracy of 73.6%. The confusion matrix illustrated in Fig. 45 highlights the main reason for the difference in the performance of knowledge transfer methods. The JDA method reduced the number of false positives compared to the TCA and MIDA

Figure 43 – Latent feature space after MIDA application (PI-57 to Z-24 Bridges), where $\mathcal{H}$ is the hyperplane estimated by the SVM classifier.



Source: Prepared by the author.

methods due to more accurate classification of the features in the healthy condition. This result indicates the importance of aligning the joint distributions of latent features to properly determine the decision boundary by the SVM classifier.

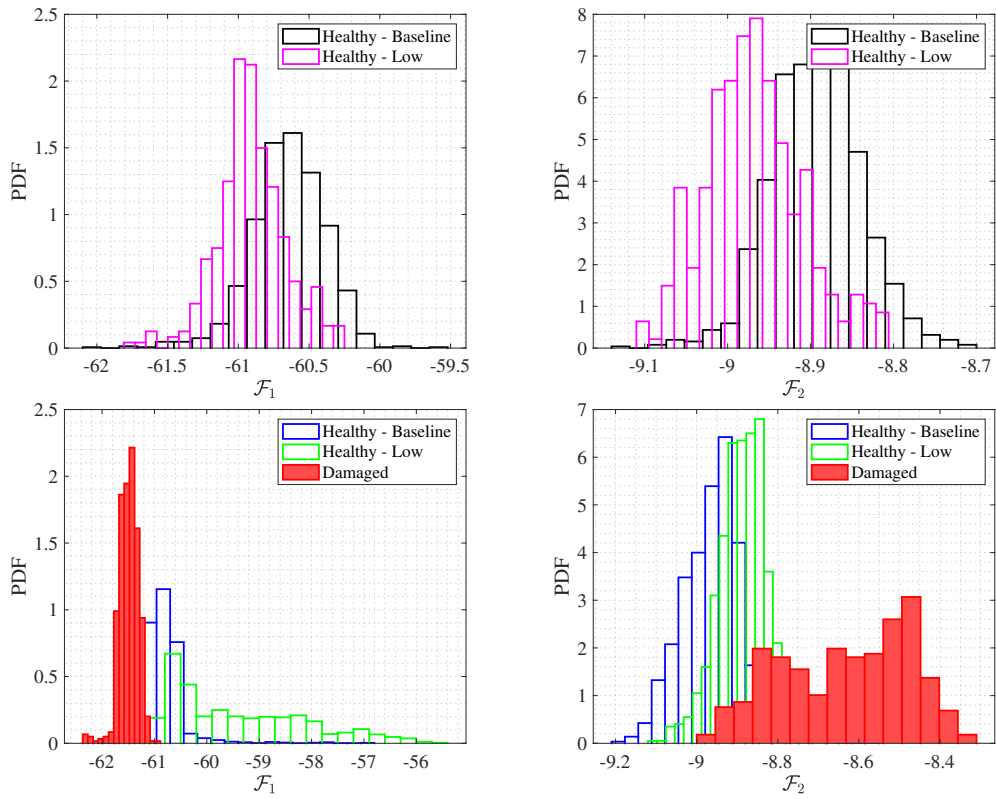
Table 10 – Performance of SVM classifier using TCA and JDA (PI-57 to Z-24 Bridges).

Classifier	Original space	Latent space		
Accuracy [%]	-	TCA	JDA	MIDA
Source domain	95.0	95.0	95.0	95.0
Target domain	12.0	69.2	73.6	69.1

Source: Prepared by the author.

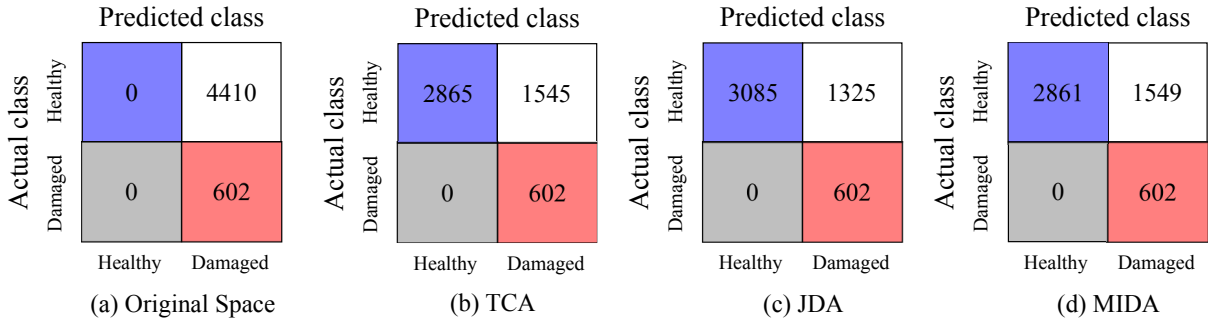
In both cases, negative temperatures effects have a major role in the behavior of the Z-24 Bridge, as evidenced by the classification performance. This results from the proposed methods preserving the significant dispersion of the feature patterns after mapping them into latent space, which is not covered by the hyperplane estimated by the SVM classifier. Nevertheless, the distances between the distributions were minimized after applying the proposed methods, proving their ability to mitigate the divergences between the features investigated.

Figure 44 – Marginal distributions of the latent features of PI-57 Bridge (top) and Z-24 Bridge (bottom) after MIDA application.



Source: Prepared by the author.

Figure 45 – Confusion matrix of SVM classifier using TCA and JDA methods (PI-57 to Z-24 Bridges).



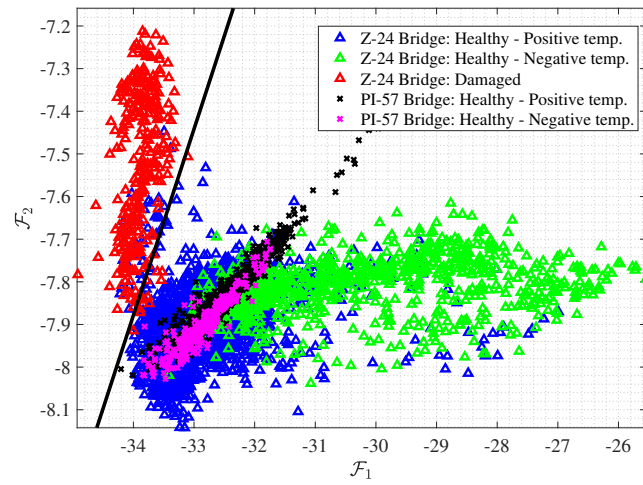
Source: Prepared by the author.

6.2.5 Transfer learning from Z-24 to PI-57 Bridges (supervised classification)

Again, TCA, JDA, and MIDA methods assume the same values for their hyperparameters to maintain the consistency between these methods and compare their performance. Thus, the trade-off parameter, μ , is 1×10^{-5} and the characteristic length-scale, σ_l , is set to be 15.

TCA is applied, and Fig. 46 illustrates the latent features and the hyperplane estimated by the SVM classifier using the source knowledge (Z-24 Bridge). Overall, the source features are adequately evaluated, while the linear hyperplane indicates some misclassifications. In this case, the source labels are known a priori and do not affect the security evaluation of the Z-24 Bridge. Meanwhile, the SVM classifier correctly separates the target features according to their structural conditions.

Figure 46 – Latent feature space after TCA application (Z-24 to PI-57 Bridges), where — is the hyperplane estimated by the SVM classifier.

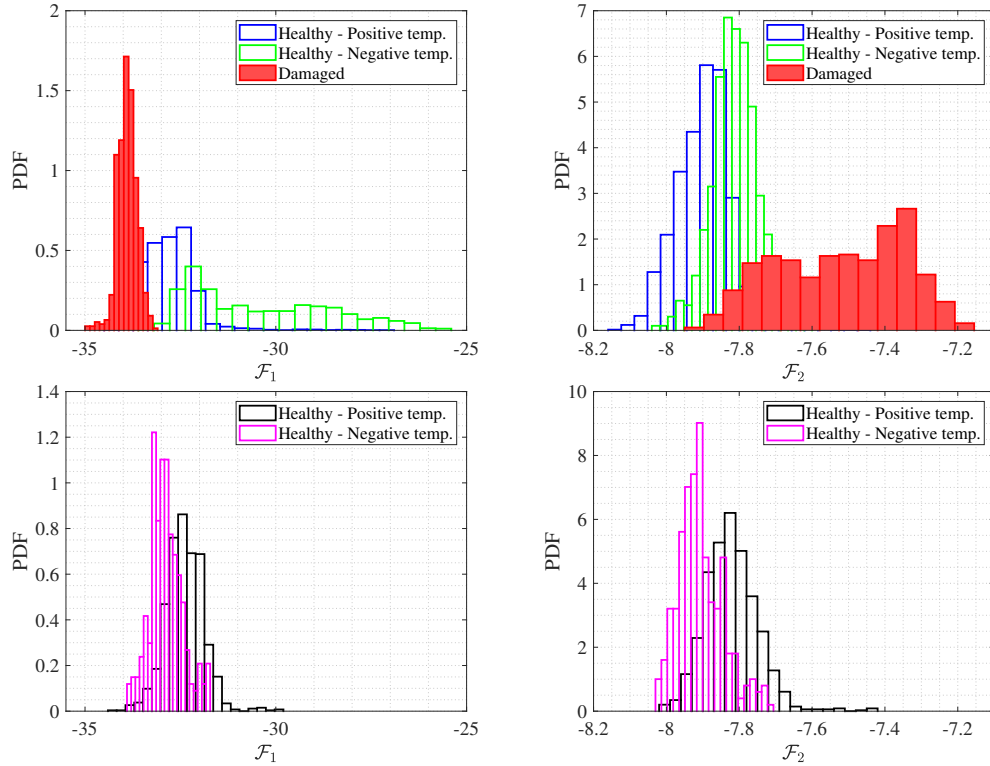


Source: Prepared by the author.

The histograms of the latent features are individually displayed in Fig. 47, indicating the distance reduction between the source and target domains under the same structural conditions. The two latent features in the healthy condition are correctly aligned, but the histograms of the damaged features indicate a different pattern. Again, the effects of negative temperatures are highlighted mainly in the variation of the first feature of the source bridge.

JDA is applied assuming ten iterations and using an SVM classifier to determine the pseudo-labels at each round. Fig. 48 and Fig. 49 show the latent features with the linear hyperplane and the estimated histograms. It is possible to note similar patterns to the results determined by the TCA method, presenting a correct separation of the target features using the source knowledge (Z-24 Bridge). These circumstances indicate that the most relevant distribution divergences are mainly related to marginal distributions, proving TCA's ability to transfer knowledge between structures. Meanwhile, the alignment of the histograms of the first two features under the same conditions can be noticed, presenting differences when there is structural damage and in the first latent feature of

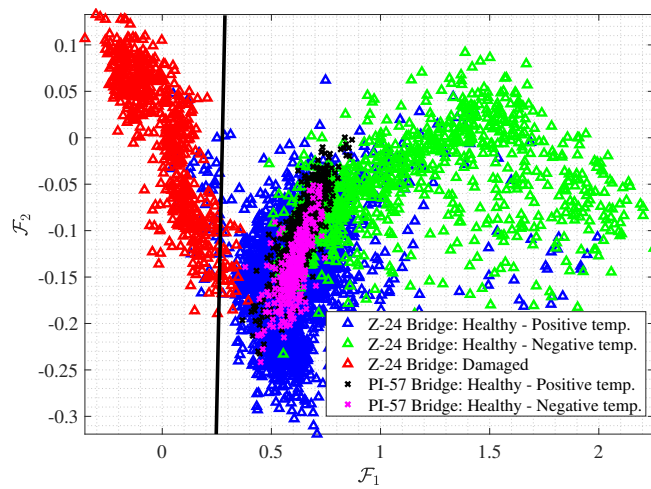
Figure 47 – Marginal distributions of the Z-24 Bridge (top) and PI-57 Bridge (bottom) after TCA application.



Source: Prepared by the author.

the source domain under negative temperatures.

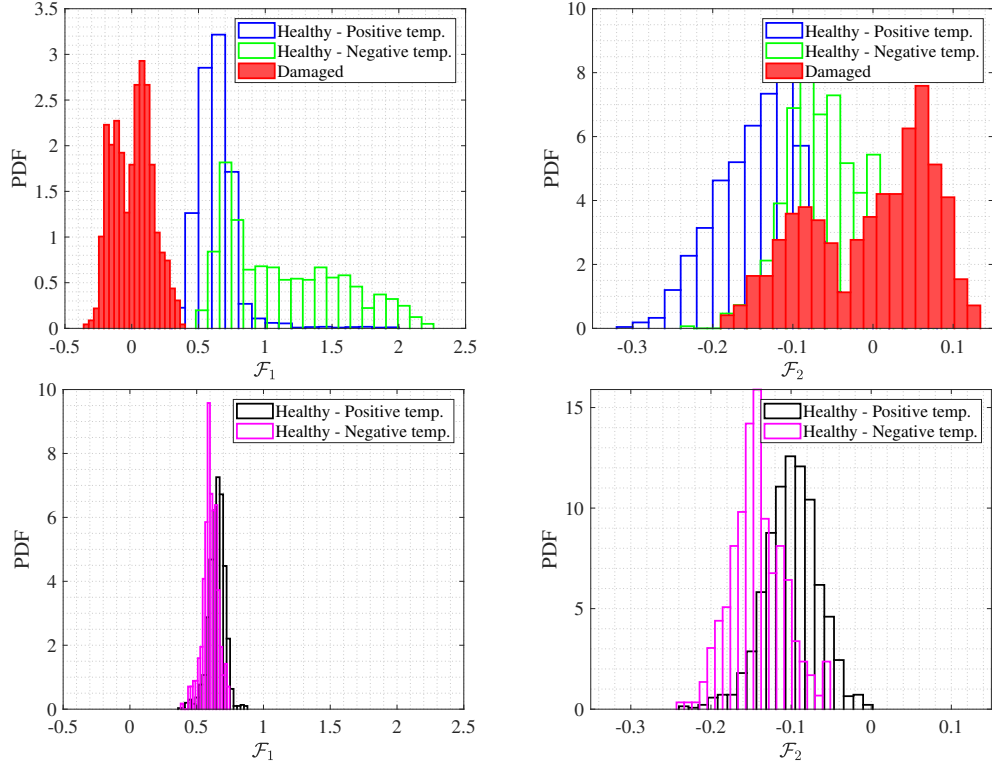
Figure 48 – Latent feature space after JDA application (Z-24 to PI-57 Bridges), where --- is the hyperplane estimated by the SVM classifier.



Source: Prepared by the author.

The MIDA method is applied and Fig. 50 and Fig. 51 illustrate the latent features from both bridges with a linear hyperplane applied for classification and the histograms

Figure 49 – Marginal distributions of the Z-24 Bridge (top) and PI-57 Bridge (bottom) after JDA application.



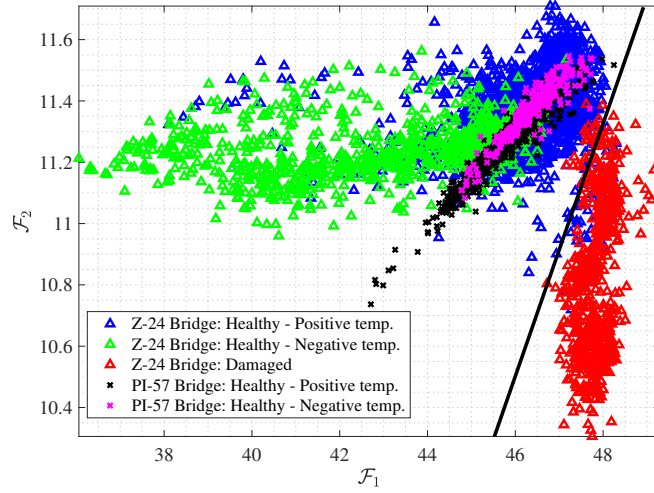
Source: Prepared by the author.

estimated, respectively. These results are significant due to the evident generalization of the classifier to correctly evaluate both bridges. Again, a proper evaluation of the source features is highlighted, while the target features are correctly separated based on their structural conditions. Meanwhile, the histograms of the latent features indicate the mitigation of the distances between the source and target domains under similar structural conditions.

Table 11 presents the classifier's performance in the original and latent space after applying the two knowledge transfer methods. In the original space, the SVM classifier fails to correctly categorize the features due to divergences between the data distributions, indicating a high rate of false positives of the target structure. Meanwhile, the classifier performance of TCA, JDA, and MIDA methods are similar for assessing the structural condition of the target bridge, as evidenced by the confusion matrix in Fig. 52. The results indicate the relevance regarding the divergence between the marginal distributions of source and target domains as the main factor to be minimized.

In this strategy, the importance of label knowledge in the training phase is highlighted to prevent potential problems of bridge safety assessment caused by the negative temperature effect, as shown in the previous section. Also, transfer learning implies using

Figure 50 – Latent feature space after MIDA application (Z-24 to PI-57 Bridges), where -- is the hyperplane estimated by the SVM classifier.



Source: Prepared by the author.

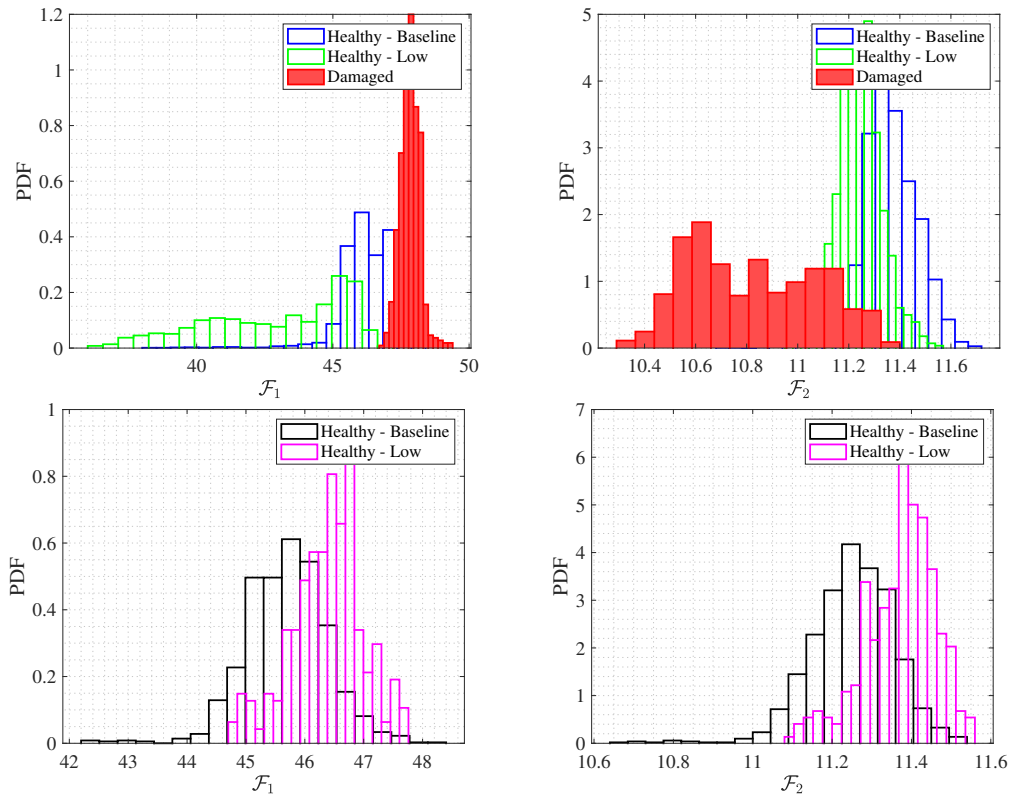
Table 11 – Performance of SVM classifier using TCA and JDA (Z-24 to PI-57 Bridges).

Classifier	Original space	Latent space		
Accuracy [%]	-	TCA	JDA	MIDA
Source domain	98.8	98.9	98.7	98.9
Target domain	0.0	100.0	100.0	100.0

Source: Prepared by the author.

more data sets and knowledge from one bridge to another under unknown conditions, improving the definition of a suitable transformation matrix. So, the greater amount of data sets and knowledge about the Z-24 Bridge concerning the PI-57 Bridge results in a better classifier performance in this strategy. Thus, the classification is straightforward, and the classifier's generalization to evaluate the unlabeled target data from the PI-57 Bridge is possible.

Figure 51 – Marginal distributions of the Z-24 Bridge (top) and PI-57 Bridge (bottom) after MIDA application.



Source: Prepared by the author.

Figure 52 – Confusion matrix of SVM classifier using TCA, JDA, and MIDA in the target domain (Z-24 to PI-57 Bridges).

		Predicted class				Predicted class				Predicted class		Predicted class			
Actual class	Healthy	0	1458	Actual class	Healthy	1458	0	Actual class	Healthy	1458	0	Actual class	Healthy	1458	0
	Damaged	0	0		Damaged	0	0		Damaged	0	0		Damaged	0	0
		Healthy	Damaged			Healthy	Damaged			Healthy	Damaged			Healthy	Damaged
		(a) Original Space				(b) TCA				(c) JDA				(d) MIDA	

Source: Prepared by the author.

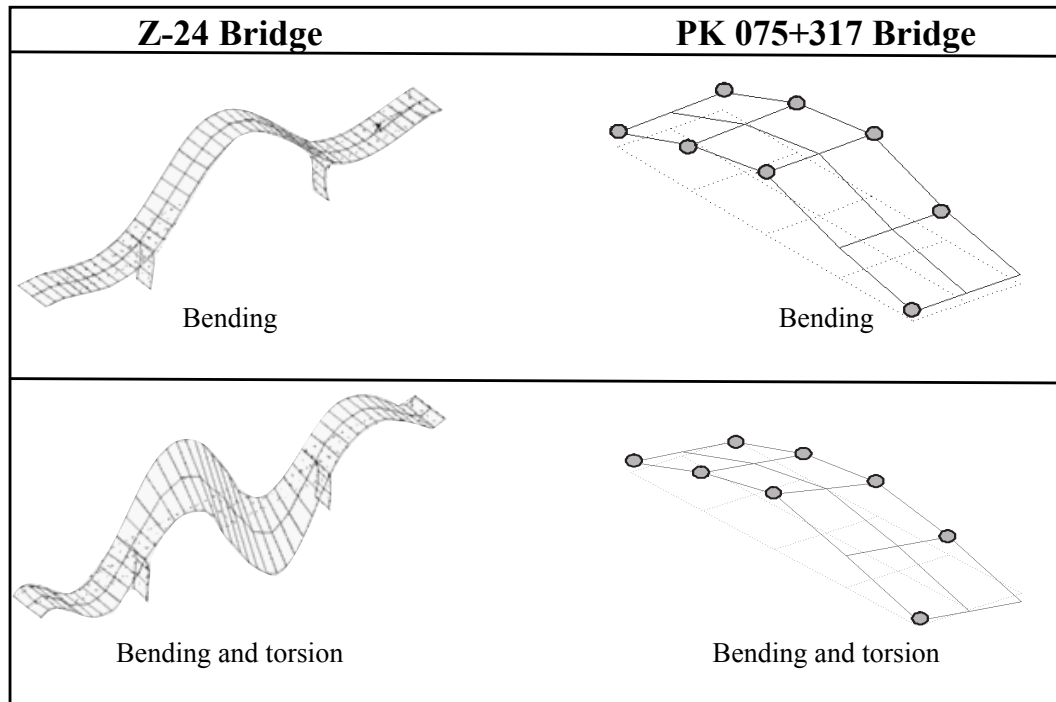
6.3 TRANSFER LEARNING BETWEEN THREE-SPAN AND ONE-SPAN BRIDGES: FROM Z-24 TO PK 075+317 BRIDGES

This section highlights the benefits of applying knowledge transfer even though the Z-24 Bridge and PK 075+317 Bridge present structural differences from an engineering perspective and serve different purposes. However, some similarities allow sharing of

structural knowledge between these bridges. In terms of environmental conditions, the natural frequencies are assumed under only positive temperatures to ensure the same knowledge in both bridges, and to avoid a potential negative transfer associated with the effects of negative temperatures.

The mode shapes are demonstrated in Fig. 53, highlighting the physical correspondence between the bridges that provide a proper knowledge transfer. Therefore, the analysis is focused on the first and third natural frequencies of the Z-24 Bridge and the first two natural frequencies of the PK 075+317 Bridge as features that represent the bending mode and the combination of bending and torsion modes.

Figure 53 – Comparison of the configuration of the mode shapes associated with the natural frequencies.

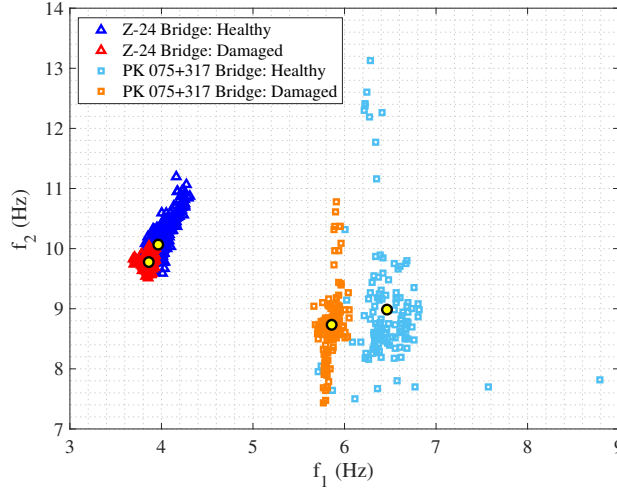


Source: Adapted from Peeters and Roeck (2001) and Cury and Cremona (2012a).

Fig. 54 show the natural frequencies of both bridges in a two-dimensional feature space. The Z-24 Bridge has 4103 observations, with 3501 observations in the healthy assuming only positive temperatures and 602 observations in the damaged condition. Meanwhile, the PK 075+317 bridge has 280 observations, with 130 and 150 observations under healthy and damaged conditions, respectively. The differences related to structural and operational between the bridges lead to divergences in their natural frequencies, with the railway bridge presenting higher frequencies due to its construction. Additionally, the excitation related to the trains crossing Bridge PK 075+317 may have affected the

feature extraction, resulting in a higher dispersion of its features.

Figure 54 – Two-dimensional feature space of the original feature space, where $\bullet$ is the average frequency values of each cluster.



Source: Prepared by the author.

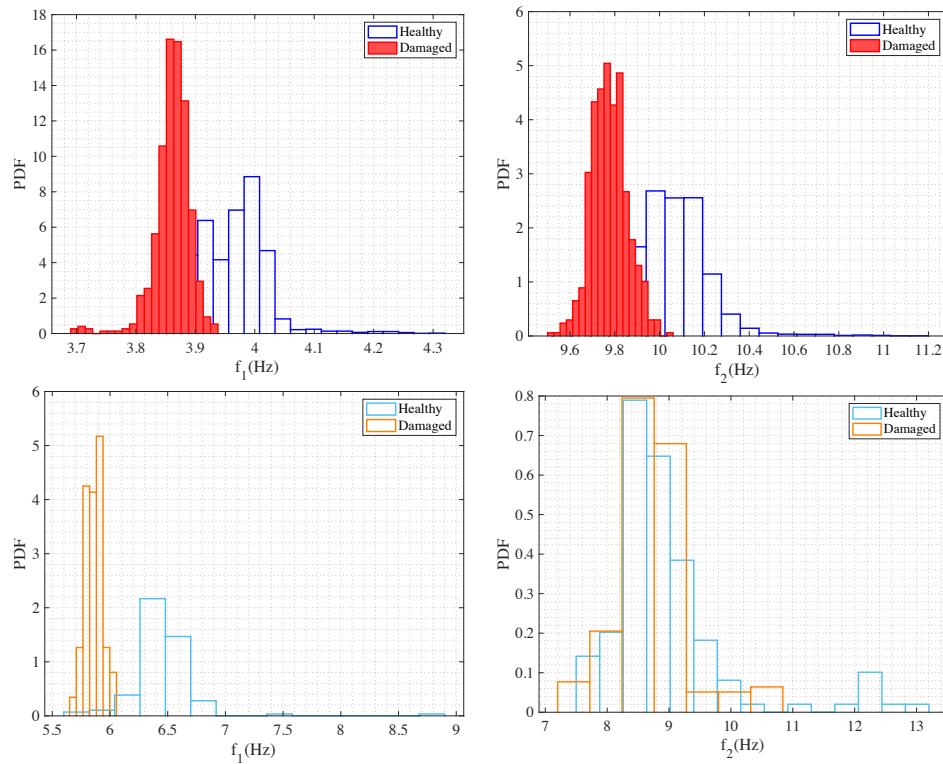
From Fig. 55 and Fig. 56, one can observe the histograms and box plots of the natural frequencies extracted from both bridges. The probability distributions and box plots of the PK 075+317 Bridge highlight a significant dispersion as observed in the feature space. In addition, its second feature represents the healthy and damaged conditions overlap, which can impair structural integrity assessment.

In this analysis, the transfer learning strategy relies on applying the MIDA method assuming the Z-24 bridge as the source and the PK 075+317 bridge as the target. The reason for applying this method is its ability to perform feature augmentation by embedding the domain features before the features mapping, which allows projecting the features onto a two-dimensional latent space ($m = 2$). In contrast, the TCA and JDA methods are not recommended due to the consequent dimensionality reduction that may not allow an adequate physical interpretation of the behavior of bridge features.

The same pre-processing applied in the previous section is considered, and a supervised classification is performed based on the SVM classifier, as there is extensive knowledge of the historical data of the source bridge. To address the MIDA application, a linear kernel is assumed and the hyperparameters are defined according to a sensitivity analysis, where the trade-off parameter, μ , is set to be 1×10^{-5} .

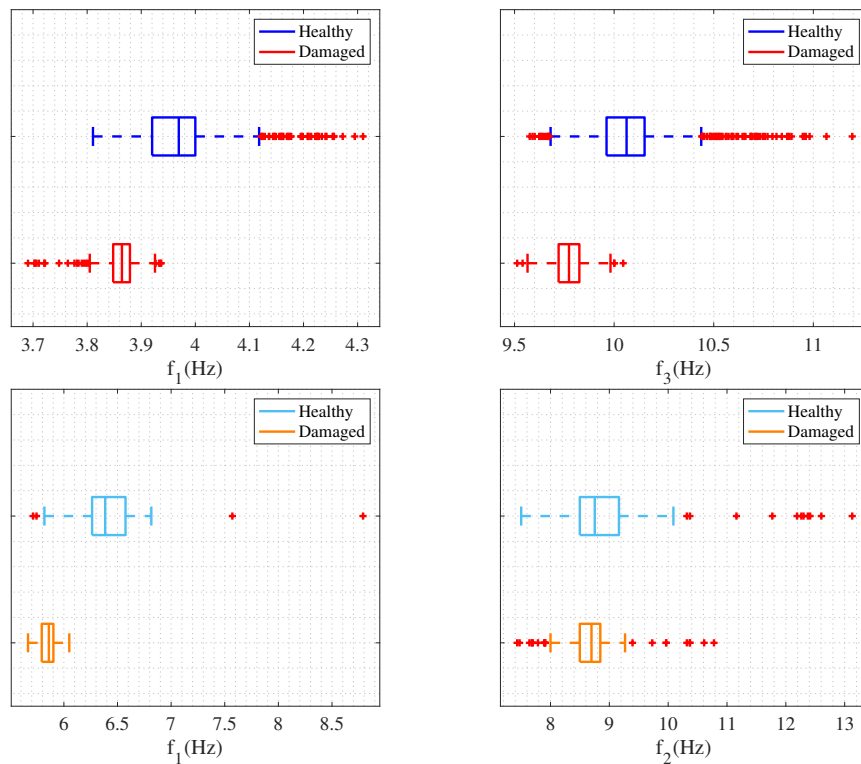
Fig. 57 and Fig. 58 show the features in latent space along with the linear hyperplane and their corresponding histograms. The divergences between the features of both bridges

Figure 55 – Marginal distributions of the Z-24 Bridge (top) and PK 075+317 Bridge (bottom) in the original space.



Source: Prepared by the author.

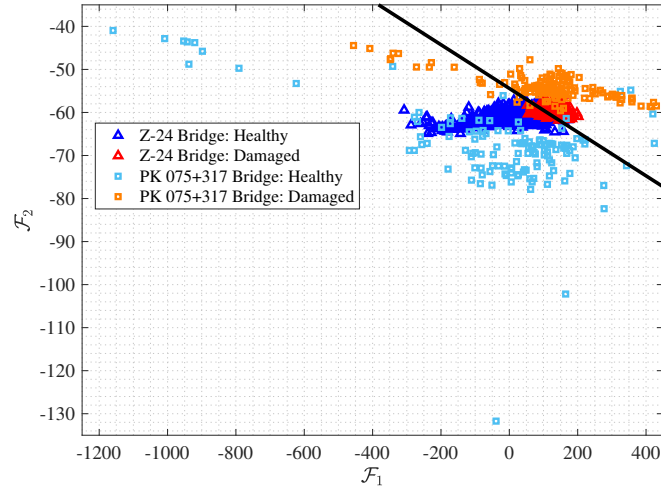
Figure 56 – Box plot of the Z-24 Bridge (top) and PK 075+317 Bridge (bottom) in the original feature space.



Source: Prepared by the author.

were effectively reduced, while the data properties were maintained after the MIDA application. In addition, the alignment of the histograms according to their corresponding structural conditions is highlighted, while a significant variability of the target data is mainly concentrated in the first latent feature.

Figure 57 – Latent feature space after MIDA application (Z-24 to PK 075+317 Bridges), where — is the hyperplane estimated by the SVM classifier.



Source: Prepared by the author.

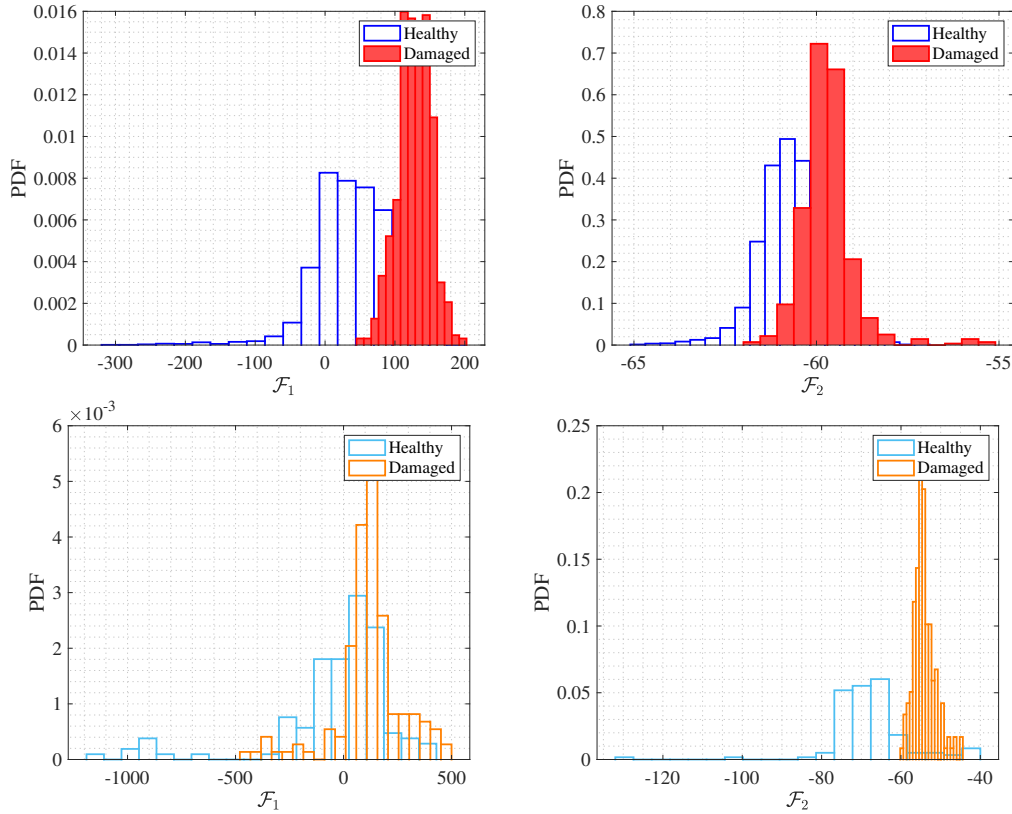
Table 12 presents an overview of the classifier performance for damage detection. The benefits of knowledge transfer through the MIDA method are highlighted by improving the classifier accuracy, from 46.43% in the original space to 91.79% in the latent space. In the original space, the SVM classifier fails to correctly evaluate the healthy features and indicates the presence of false positives concerning the target bridge. However, applying the MIDA method effectively aligns the probability distributions, resulting in a significant improvement in the assessment of the structure by the classifier.

Table 12 – Performance of SVM classifier using MIDA (Z-24 to PK 075+317 Bridges).

Classifier	Original space	Latent space
Accuracy [%]	-	MIDA
Source domain	95.3	95.3
Target domain	46.4	91.8

Source: Prepared by the author.

Figure 58 – Marginal distributions of the Z-24 Bridge (top) and PK 075+317 Bridge (bottom) in the latent space.



Source: Prepared by the author.

6.4 CONCLUSIONS

This chapter proposed the application of transfer learning to evaluate a bridge under unknown structural conditions by leveraging prior knowledge from the known bridge, assuming the existence of similarities between the structures that allow the knowledge transfer. The knowledge from the Z-24 Bridge in Switzerland was transferred to detect damage in the PI-57 and PK 075+317 Bridges in France using two independent classification strategies to highlight the importance of the source knowledge data.

The effectiveness of the TCA, JDA, and MIDA methods was proven by the similarity of the latent features in the same structural conditions and the reduction of the divergences between their probability distributions, allowing the classifier generalization to evaluate the structural condition of different bridges. It was found that the quality of the knowledge present in the source data and the number of observations (in the source and target domains) have a relatively strong influence on the classification performance.

In the transfer learning from the PI-57 Bridge to the Z-24 Bridge (unsupervised classification using outlier detection), the performance of the proposed methods was not

satisfactory due to the lack of knowledge present in source data about the effects of negative temperatures on the bridge's global stiffness. In contrast, the knowledge present in the source data of the Z-24 Bridge was successfully transferred to the PI-57 Bridge (supervised classification), as indicated by an accurate classifier performance for both methods. Meanwhile, the successful knowledge transfer from the Z-24 Bridge to the PK 075+317 Bridge highlighted the potential of the proposed methodology even when the bridges present different frameworks and purposes, as these structures present similarities in terms of their dynamic behavior represented by their modes shapes in this case. Thus, the correct assessment of the bridge's safety through transfer learning relies on the useful knowledge present in the source bridge that is relevant to the target one.

Therefore, this study noticed a better transfer performance from the Z-24 Bridge to the other bridges, as the data sets from the Z-24 Bridge have deeper structural knowledge acquired under different operational and environmental conditions. Besides, the data sets from the Z-24 Bridge have more observations to characterize those conditions, which improves the training process of each classifier, i.e., better classification performance is achieved as more quality data sets are available, both in terms of structural knowledge and quantity of observations.

7 FINAL REMARKS

This final chapter describes the final remarks from the results obtained during the development of this thesis in Section 7.1. The suggestions with different ideas for possible future works that can be developed are listed in Section 7.2. Finally, the papers written as a result of this work are presented in Section 7.3, which presents the contributions to the literature.

7.1 CONCLUSIONS

Based on the discussions and results on transfer learning methodology presented throughout this thesis, we can outline the main conclusions regarding the development of this work:

- Transfer learning generalizes the knowledge from a known structure to different situations, including populations of homogeneous and heterogeneous structures. As such, this robust methodology not only overcomes many machine learning limitations but also facilitates comprehensive analysis, leading to the development of robust models. This minimizes the need to collect new data sets and the computational cost. Nonetheless, the success of the knowledge transfer is subject to certain prerequisites imposed by the methodology, including the consistency of the labels, data labeling and the quality of the transferred data;
- Transfer learning represents an attractive solution to solve several problems in the process of monitoring a structure. There are situations in which data collection is often unfeasible, expensive, or even impossible to carry out due to difficulties in installing a monitoring system in the structure. To address this problem, the data history of one known structure can be reused to evaluate another one. Furthermore, it is possible to minimize the influence of environmental and operational effects on data sets, as well as facilitate the calibration of FE models through the application of transfer learning methods;
- The application of a similarity analysis to validate the application of transfer learning methods was not necessary in this work, as the investigated structures were

equivalent and they were under similar environmental and operational conditions. Additionally, the dynamic behavior of the structures indicated the similarities between the bridges and consequently contributed to the success of the knowledge transfer. The implementation of a similarity analysis is important in evaluating whether the structures represent a homogeneous or heterogeneous population to minimize the possibility of a negative transfer occurring;

- Model-based and feature-based represent the main approaches for evaluating the integrity of different structures. In this case, the latter is considered in this work, as SHM is traditionally carried out using features for statistical pattern recognition. TCA, JDA, and MIDA methods were applied in different case studies to prove their ability to minimize the divergences between the features extracted from different structures to perform damage identification. Thus, it is possible to generalize the source knowledge to accurately assess the structural condition of the target structure;
- The opportunities provided by the application of transfer learning were demonstrated in the results presented in the chapters of this thesis. Firstly, the difficulties inherent in calibrating FE models of a bridge under temperature effects were minimized by the application of TCA, which can increase the use of numerical modeling for long-term monitoring consequently. Then, the importance of label and knowledge consistency between the investigated structures was demonstrated by combining TCA with GPR models for quantifying levels of structural damage. Finally, one of the first works in the literature to deal with bridges under realistic conditions presented the application of TCA, JDA, and MIDA to detect structural damage, and highlight the importance of similarity between the dynamic behavior of bridge.

7.2 SUGGESTION FOR FUTURE WORKS

There are some topics related to knowledge transfer that can be investigated in future work, which can provide better results and new approaches for the analysis of different structures. These topics are:

- As mentioned in Section 2.4, there are different types of approaches that can be used in an analysis in agreement with the type of knowledge. In this thesis, only the feature-based approach is proposed to investigate the structural condition of

bridges. Therefore, the application of different approaches can be carried out with the purpose of evaluating possible better performance when using another knowledge type to be transferred;

- The methods proposed in this work are capable of mitigating divergences between the distributions of the data sets measured from the investigated domains. However, these methods do not present suitable performance for any type of analysis, including more complex situations when the features exhibit anomalous behavior without defined patterns. Therefore, it is possible to use other more robust and effective methods for a more comprehensive analysis that can provide adequate results;
- The purpose of similarity analysis can provide a more comprehensive analysis between structures with different characteristics. The idea is to determine specific similarities even between distinct structures with significant frameworks, including different topology, geometry, and type of materials. Some studies proposed this type of analysis in recent years, but there are no consolidated methodologies that are effective in validating transfer learning based on similarity index;
- One interesting topic related to transfer learning that has not been deeply investigated in the scientific community is the negative transfer. A holistic analysis should be proposed to provide a better understanding when the knowledge transfer should be carried out and what motivated the loss of performance in a situation where the negative transfer occurred;
- In the SHM context, it is possible to use different strategies for structural analysis that are not based on data sets collected by data acquisition systems embedded in the structure. For instance, methods based on deep learning models that perform image processing are interesting due to their versatility and robustness. Transfer learning can be proposed using a model-based approach that uses the prior knowledge of a pre-trained neural network to process new images collected from a structure, reducing the computational cost associated with the training phase and the need to collect a large amount of data.

7.3 CONTRIBUTIONS TO THE LITERATURE

This thesis contributes to the literature by proposing a new way of investigating the integrity of populations of different structures. The foundations of transfer learning for SHM were laid down by describing the motivations that led to its application in the

analysis of structures, the main questions to decide the necessity for knowledge transfer, the definitions of the terms that provide the particularities of transfer learning, and the main approaches proposed according to the type of knowledge to be transferred. Finally, a comprehensive analysis using transfer learning is proposed to perform damage identification in different structures under realistic situations and the importance of the quality of knowledge transferred across different structures was highlighted. The manuscripts written during the doctorate were published in the following journal papers:

- **Marcus Omori Yano**, Eloi Figueiredo, Samuel da Silva, Alexandre Cury. "Foundations and applicability of transfer learning for structural health monitoring of bridges". *Mechanical Systems and Signal Processing*, 2023. 204, 110766. DOI: 10.1016/j.ymssp.2023.110766;
- **Marcus Omori Yano**, Eloi Figueiredo, Samuel da Silva, Alexandre Cury, Ionut Moldovan. "Transfer Learning for Structural Health Monitoring in Bridges That Underwent Retrofitting", *Buildings*, 2023. 13(9), 2323. DOI: 10.3390/buildings13092323;
- Samuel da Silva, **Marcus Omori Yano**, Rafael de Oliveira Teloli, Gael Chevallier, Thiago G. Ritto. "Domain Adaptation of Population-Based of Bolted Joint Structures for Loss Detection of Tightening Torque", *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering*, 2023;
- **Marcus Omori Yano**, Samuel da Silva, Eloi Figueiredo, Luis Gustavo Giacon Villani. "Damage quantification using transfer component analysis combined with Gaussian process regression". *Structural Health Monitoring*, 2023. 22(2):1290-1307. DOI:10.1177/14759217221094500;
- Eloi Figueiredo, **Marcus Omori Yano**, Samuel da Silva, Moldovan, I., Adrian Bud, M. (2023). Transfer Learning to Enhance the Damage Detection Performance in Bridges When Using Numerical Models. *Journal of Bridge Engineering*, 2022. 28(1), 04022134. DOI: 10.1061/(ASCE)BE.1943-5592.0001979
- Samuel da Silva, **Marcus Omori Yano**, Gonzalez-Bueno, C. G. (2021). Transfer component analysis for compensation of temperature effects on the impedance-based structural health monitoring. *Journal of Nondestructive Evaluation*, 2021. 40(3), 64. DOI: 10.1007/s10921-021-00794-

There are manuscripts referring to this thesis that were published in conferences:

- Leonardo Ferreira, **Marcus Omori Yano**, Samuel da Silva, Carlos Cimini,(2022). "Damage quantification on composite structures using neural networks and hybrid data". 33th Congress of the International Council of the Aeronautical Sciences, 2022. (pp. 3723-3736);
- **Marcus Omori Yano**, Leonardo Ferreira, Samuel da Silva, Carlos Cimini, Eloi Figueiredo. "Gaussian process regression using hybrid data for damage quantification". 6th Brazilian Conference on Composite Materials, 2021. DOI: 10.29327/566492

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