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Machine Learning approaches for damage detection strategy in Structural Health Monitoring: application to experimental data

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To my family

Abstract

Structural Health Monitoring (SHM) is a discipline born during the last decades of the 20^{th} century with the aim of implementing damage detection strategies in many engineering fields. These processes rely on structural observations that can be carried out through periodical dynamic response measurements coming from sensors installed on the structures. Datasets regarding a broad range of the lifetime of the structure are often required in order to implement efficient monitoring systems. Furthermore, analyses on the data should be fine evaluated in order to integrate and discern from the periodic or continuous measurements the noise (environmental) ones that may otherwise affect the results in a strong way. The first approach towards SHM is constituted by the model-driven methods: they can be developed starting from an updating of a Finite Element Model (FEM) by means of an inverse approach. The key concept relies on the definition of the modal parameters of the structure in order to minimize the discrepancy between the actual results and the prediction ones. The main problem related to the model-based approach concerns the noise data implementation, in which the environmental ones fall into. Instead, other SHM methods rely on the data-driven approach, which needs a big amount of data coming from permanent monitoring systems or from simulations aimed at describing accurately the actual behavior of the structure. Unlike the first approach, data-driven methods can predict environmental variations by exploiting the algorithms capabilities to discern through data the real pathological structural states from the fictitious ones.

This thesis is mainly focused on developing analyses embedded in the data-driven methods, more precisely focusing on exploiting a correlation between the amount of available data (or a limited part of them) and certain diagnostic characteristics of the structure. In the recent years, *Machine Learning* (ML) techniques have been used in order to enhance their properties related to extraction of information through a decision making approach: within a dataset, it is actually possible to “train” an algorithm and then test its capabilities to recognize a statistical pattern of information related to a possible damage in the structure. *Transfer Learning* techniques will be exploited to the behavior of different materials framed structures without having direct data from those, but only transferring knowledge between machine learning algorithms with damage detection objective.

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Chapter 1

Introduction

The importance in detecting structural damage at the earliest feasible stage is widespread over the civil, aerospace and mechanical engineering field. Since the beginning, damage detention methods are visual or they have been exploited through localized experimental methods such as acoustic or ultrasonic methods, magnet field methods and so on (Doebling et al., 1996). The needing of *a priori* knowledge of the area close to the damage and the accessibility of that portion of the structure are the main limitations of these experimental methods. To solve these issues, methods able to inspect changes in the structural vibration properties have been developed.

Modal parameters including natural frequencies, mode shapes and modal damping, are linked to physical properties of the structure such as mass and stiffness. Damage detention can be determined considering changes in physical properties associated to modal characteristics.

A monitoring system is thought to record variations in these physical parameters that must be sensitive enough to enable the damage identification

(Ceravolo, 2023). First of all, it is important to define the structural damage itself: it may embrace many events, e.g. cracks, delamination, corrosion, fiber pullout, loose joints and fasteners, buckling, creep, plastic deformation, weld defects, residual stresses, etc. Following, it can be introduced the concept of Structural Health Monitoring (SHM): it refers to the periodic or continuous assessment of the conditions of structure exploiting information from a system of sensors.

Nowadays, high performance sensors and instrumentations have been developed thanks to the technological progress. These are able to acquire high-frequency measurements with little cost and they allow to do an online monitoring of the structure by means of a continuous uploading of the structure measured data. Advantages of this technology are surely the availability of real time structural data and their trend observation feasibility in multiple places, only with an internet connection. A drawback can be noticed in the organization and the storage of a big amount of data could be difficult to manage and examine, leading us to find a way in order to synthetize the information. For this reason, recently, advanced technologies and algorithms of Machine Learning (ML), a branch of Artificial Intelligence (AI), started spreading in the civil engineering field for a diagnostic purpose above all. These technologies. exploiting a big amount of data, are able to create a diagnostic path on the acquired data, avoiding the needing for a physical model of the structure, that could be really difficult to define especially for historical buildings (Coletta, 2022).

Experimental data could be extracted from FE models in order to validate such technologies and understand whether or not their application can be conducted and which are the most suitable cases for it. Among all the possible quantities, the natural frequencies of structures represent a valuable “illness” indicator, due to their connection to a damage state. Experimentally, a damaged condition can be induced by means of mechanical or geometrical properties variations, for instance in the main structural elements of a FE model. Once extracted these data, a damage classification procedure can be performed if enough data are sufficient to train the algorithm. Usually, in real structures, data are not sufficient or they are not labelled. Transfer learning can be exploited in order to carry out, for instance, a classification problem on an adapted domain in which some data are “transferred” from another well-known system to a target system, often characterized by few data.

Damage detection and damage localization by means of Transfer Learning technologies will be described in the following Chapters, conducting a case study on two FE models.

Chapter 2

Structural Health Monitoring

2.1 Definition of damage and Structural Health Monitoring (SHM)

Structural Health Monitoring (SHM) is a process which involves the periodic monitoring of a structure by means of measurements, the extraction of features symptomatic to the phenomena under investigation and their statistical analysis to determine the actual state of the system (Farrar & Worden, 2012).

"The term structural health monitoring (SHM) usually refers to the process of implementing a damage detection strategy for aerospace, civil or mechanical engineering infrastructure. This process involves the observation of a structure or mechanical system over time using periodically spaced dynamic response measurements, the extraction of damage-sensitive features from these measurements and the statistical analysis of these features to determine the current state of system health. For long-term SHM, the output of this process is periodically updated information regarding

the ability of the structure to continue to perform its intended function in light of the inevitable ageing and degradation resulting from the operational environments. Under an extreme event, such as an earthquake or unanticipated blast loading, SHM could be used for rapid condition screening, to provide, in near real time, reliable information about the performance of the system during the event and about the subsequent integrity of the system."

The acronym SHM has been coined around the late 1980s, but is likely that these words have been previously defined with the origin of structural engineering (Boller, 2006). Essentially, a structural health monitoring system is the outcome of the combination of several sensors, devices and auxiliary tools (Fragonara Zanotti, 2012):

- a measurement system;
- an acquisition system;
- a data processing system;
- a communication/warning system;
- an identification system;
- a decision making system.

A big sequence of technical disadvantages however occurs in traditional diagnostic evaluation methods. The seldomness of visual inspections leads to a worsening of the predictions. Furthermore, non-superficial defects or invisible events of a damage process cannot be observed and they are neither objective due to the subjective judgement of the human operator. To improve the objectiveness of the evaluation techniques, destructive tests can be adopted but, especially for Cultural Heritage applications, they are forbidden.

Several techniques belong to the Non-destructive evaluations (NDE), such as: radiography, acoustic emission, thermography, ultrasonic testing, radiography, optical methods, vibration-based methods, electromagnetic testing, magnetic particle inspection, etc. (Ceravolo, 2023). Non-Destructive testing (NDT), belonging to the NDE field, refers to techniques carried out off-line and after damage location has been performed (Shull, 2002). This is not sufficient to guarantee a prompt damage detection because in the meantime an immoderate deterioration state could have been achieved. Furthermore, only a limited part of the structure can be analyzed due to the local nature of the diagnostic evaluations.

Structural Health Monitoring (SHM) systems, belonging to the modern NDE family, introduce a solution by showing a more detailed and exhaustive image of the structural health state. SHM, even though is based on innovative measures, algorithms, analyses and communication methods, follows the same aim as the traditional evaluation procedures. In particular, in this new approach (Ceravolo, 2023*)*:

i. Global quantities, dissimilarly from Non-Destructive testing (NDT), are inherently monitored, due to the remote (non-local) monitoring principal purpose.
ii. It is generally possible to adopt online implementation.

SHM, therefore, integrates these new technologies into a distinct smart system, hence it can be considered as a supplement to the traditional investigation methods.

For damage identification in existing structures, Vibration-based SHM techniques have been greatly exploited (Briard, 1970; Ceravolo & De Stefano, 1996; Loland et al., 1975). Anyway, one of the issue to be further investigated and to be solved is the requirement of a new way of thinking comprehensive of the importance of a rational design of a monitoring system. As a matter of fact, the needing of continuous or periodic observations and reliable analyses coming from different information sources must be condensed into a sensor network capable of doing it. Furthermore, another challenging task is the one taking into account environmental and operating conditions variability in the system (Ceravolo, 2023).

Talking about Cultural Heritage conservation (Ceravolo et al., 2019), monitoring applications are fundamental in proving data for decision making. The implementation of preventive conservation and the applicability of ready and target interventions can be done taking into account the global and continuous structural knowledge and the ability of monitoring procedures to achieve the complete information about the structural behavior. This can lead to a cost and invasiveness reduction, and to a lowering on irreparable damage occurrences.

2.2 Data-Driven *vs* Model-Driven approaches to damage detection

When designing a Structural Health Monitoring (SHM) system, independently of the monitoring method and technique considered, it is demanded to carry out preventively a careful analysis of the structural behavior in order to monitor the most expressive and sensitive parameters. The SHM procedure can thus be divided into two main classes: *model-driven* methods and *data-driven* methods (Ceravolo, 2023).

2.2.1 Model-Driven Approach

Model-driven methods rather apply an inverse approach to a law based model, making the updating of a Finite Element (FE) model their objective (Friswell, 2007). The aim of the process is to adjust some parameters of the model in order to reduce the residual between model predictions and experimental measurements. Hence, the damage in the structure can be deduced thanks to tests and simulations on the updated model (Coletta, 2022). When high-fidelity models of the structure are used to drive the approach, this last can potentially work without a validated damage model, with the drawback that noise and environmental effects are difficult to integrate. The traditional approach to engineering problems is constituted by the model-driven methods because they correspond to axiomatic thus more general formulations. Large number of parameters, anyway, characterize models and their settings need to be cautiously checked, in order to understand the underlying physics: for instance, it is necessary that a physical meaning is always maintained by the values of the "healthy parameters" and the ones responsible to simulate the state of damage. These last are really difficult to validate. A further issue that afflicts this approach is the unavoidable presence of errors due to the fact that the model is, by definition, a simplification of the reality. Another problem is the computational heaviness of the model-driven methods, because they require multiple runs of a Finite Element (FE) model in order to compute predictions. Inevitably, uncertainty will afflict the parameters that are not involved in the same process as the ones that have been chosen to be calibrated. Due to this, also the more refined models may differ from reality because of variation between these data and the ones used for the calibration. An example of this can be described by the environmental effects. Furthermore, when the objective is to model a historical structure, these problems become of a greater importance. Many difficulties in defining laws for a generalized application can be found in the uncertainties about the materials and their characteristics, the uncommon geometry, the lack of knowledge on the connections, on the interventions experienced and on the present crack pattern.

Regarding this, historical information and survey documentation can be seen as a key support. Guidelines for the seismic preservation have been proposed by the European project for the proposal of a performance-based approach to earthquake protection of Cultural Heritage, better known as PERPETUATE (Lagomarsino et al., 2012). The structural model of the building and the related artistic assets need to be defined by tools described in the survey program. These surveys are conducted in order to acquire several data taking into account the building geometry, the foundation, the mechanical parameters estimation, the chronological transformations of the structure via historical data, the state of maintenance, the identification of the damage mechanisms, if they are present, and the dynamic behavior. Furthermore, the identification of the main parameters to be investigated can be conducted by preliminary sensitivity analyses and, by doing so, it allows to concentrate the investigation to few significant points in order to achieve goals in limiting cost, time and destructive tests. Developing an accurate model, even though adequate tools, could be difficult (Coletta, 2022). Structural health monitoring makes use of models, being these an important support, but the deviation of the real behavior from the results can be very large and this must be taken into account (Brownjohn et al., 1999; Zhang et al., 2001).

The core of every model-driven SHM approach is surely system identification: these techniques are essential to realize a realistic structural model. This is even more important when it is considered uncertainty in the material properties and in scarcely-defined structural systems. Damage in permanent monitoring systems is usually function of a variation or anomaly in chosen parameters, and, by identification of quantities that reflect the damage (symptoms) reliability can be defined. When a structural scheme associated to an analyzed building is complex, a numerical model can be alternatively updated on the grounds of the identified parameters in order to overcome uncertainties by simulating the real behavior of the structure (Ceravolo, 2023). In standard structural problems mechanical models are the base on which safety assessment relies: the engineer is thus inclined to state any final evaluation, prognosis or decision on results coming from an updated model, rather on symptoms (Ceravolo et al., 2019).

2.2.2 Data-Driven Approach

Data-driven methods exploit monitoring data and make use of Pattern Recognition (PR), Machine Learning (ML), and other heuristic techniques in order to generate a statistical system representation (Worden & Manson, 2006). A huge amount of data is often needed for data-driven approaches: the information comes from the permanent monitoring systems and, if the dynamic behavior of the structure can be smoothly identified and reproduced, from simulations. In addition, the definition of the statistical models is easy and the evaluation of the environmental variation and the noise level is well described.

When data come from permanent or long-term monitoring systems, data-driven approaches are usually applied in structural health monitoring (SHM). This is because these methods need a lot of samples to be available in order to base reliable statistics. Within data-driven techniques, the data, already containing variations given by the external environment or by noise, can be analyzed. In data-driven approaches, differently from the model-driven ones, the knowledge of the phenomena that have effects on the structural behavior is independent from physical laws integrated in a model, but it is rather directly derived from measurements.

A generic algorithm is trained by the response acquired under the frequent conditions of the structure, taken as a reference. From this, the “not damaged” condition (or better, the “normal” condition, because the structure could have already experienced stable damages) is considered to deduced the damage due to the fact that the latter will modify the normal parameters. Data-driven methods need data from each damage state in order to be considered to set a generic pattern recognition algorithm, due to the needing of reaching the maximum efficiency. Taking into account architectural assets, the objective of getting these data can result to be really difficult and, in some cases, even impossible. To overcome these issues, an idea could be to exploit a Finite Element Model (FEM) in order to get data and thus, obtaining advantage from both methods: this is known in practice as a mixed-method, in which models are of supports of data-driven methods (Coletta, 2022).

Chapter 3

Strategies, problems and methodologies concerning Structural Health Monitoring

3.1 The diagnostic process: analogies and correlations with the medical diagnosis in the structural framework

Structural Health Monitoring (SHM), similarly to the medical and healthcare sector, in the structural rehabilitation framework requires anamnesis, diagnosis, therapy (prognosis) and controls (Fragonara Zanotti, 2012), thus translating into a research for significant data and information, identification of possible causes of damage and best remedial measures in order to get efficient interventions on the structure. The main difference with the medical framework is, of course, the type of patient: human on one hand and the structure in the engineering field. The parallelism seams to appear even more adequate talking about the Architectural

Heritage: indeed, the structure can be seen as a kind of "elderly patients", who own their scars, and have the sign of time expressed through damage and decay. Following the ICOMOS guidelines (ICOMOS, 2003):

"The peculiarity of heritage structures, with their complex history, requires the organization of studies and proposals in precise steps that are similar to those used in medicine. Anamnesis, diagnosis, therapy and controls, corresponding respectively to the searches for significant data and information, individuation of the causes of damage and decay, choice of the remedial measures and control of the efficiency of the interventions. In order to achieve cost effectiveness and minimal impact on architectural heritage using funds available in a rational way; it is usually necessary that the study repeat these steps in an iterative process."

It is thus of a great importance to monitor the vital signs to assess the patient's health. Pathologies can mostly be detected by providing a report about information comprehensive of blood pressure, respiratory rate, body temperature. Taking into account a structure, monitoring could be interpreted as odd due to the fact that the building, being an inanimate thing, has no vital parameters telling us the information about its condition (Coletta, 2022). Every structure has, anyway, a sort of heartbeat: it can be seen as a system characterized by a stiffness and a mass. The first is directly linked to the structural health, its variations lead to an effect in the presence of past interventions or damage appearance. The dynamics of the structural system is indeed defined by the mass and the stiffness: i.e. taking into account that the mass variations are negligible, or better, they do not occur in a spontaneous way, the stiffness of the structure can be indirectly monitored and consequently the health condition assessment can be conducted by monitoring its dynamic properties (Fan & Qiao, 2011).

Between structures and human beings, the main differences when they are seen as "patients" are surely their ability to reveal their illness. As a matter of fact, the structure is not able to autonomously communicate its diseases, but it can accumulate important damage quietly. Consequently, sudden collapse can happen without even noticing. In this sense, a monitoring system is seen as an apparatus from which measurements can be conducted: for instance, Structural Health Monitoring (SHM), by means of ML approaches, algorithms and other techniques, give a picture of the diagnostic information of the structure analyzed.

Firstly, for what concern structural monitoring, one needs to define the threshold beyond which a "healthy" condition becomes "unhealthy" to have a complete diagnosis. However, this is not complete at all: i.e. considering a minimum and a maximum breathing rate, some vital activities could exceed these limits, even though they are completely of a harmless nature and they are reversible. These false alarms can be seen as false positives. On the other hand, the real problem lies in the possibility to hide pathological manifestations within the data: an ongoing disease, which does not manifest itself at the data records, could be hidden and, in this case, we can talk about false negative. In the best scenario, this could lead to a delayed intervention and in the worst condition to an undesired irreversible damage condition, until failure.

In the structural framework, we should also mention how environmental conditions are able to alter briefly the diagnostic parameters without having a realistic impact on the health condition of the structure. Within these effects, the Structural Health Monitoring (SHM) community uses to refer to these as Environmental and Operational Variations (EOVs) because they are able to heavily influence the response of the structure. Ordinary Environmental phenomena are reversible and harmless for the structures, but they inevitably influence the uncertainty of the diagnostic response by modifying, also if temporarily, the dynamic parameters.

Finally, a needing for a “health indicator” that results to be sensitive enough to damage and as little as possible towards environmental effects plays a key role in the constitution of an accurate monitoring system (Coletta, 2022).

3.2 Environmental effects

Most of the structures are totally or partially exposed to meteorological and climatic phenomena. Some of these are rain, wind storms, positive and negative temperatures, high humidity, snow, etc.

A “direct” deterioration effect combined with a long period of time occurrence, make the environmental phenomena also cause problems on the precision of the diagnosis based on the monitoring data: static and dynamic structural response is, indeed, deeply influenced by climatic events due to errors in the interpretation of the measurements (Bassoli et al., 2017; Boller, 2006; Cross, 2012; Deraemaeker et al., 2008; Kita et al., 2019; Ni et al., 2005; Sohn, 2007).

What is important to notice is that no errors in the sensor measurement occur, but the actual structural behavior is changed due to these effects, and they are correctly measured by sensors. The real problem in the SHM system becomes the eased confusion in the diagnostic characteristics of the structure between the effects of the environmental variations and the actual structural damage (Coletta, 2022).

Environmental effects are mostly, as already said previously, harmless and reversible, but they may be confused as damage states in the diagnostic. The goal is to well interpret these phenomena to recognize only the dangerous permanent variations of structural stiffness in order to plan interventions and limiting the use of the structure during maintenance, where it is necessary.

Being this information confused, two consequences can occur:

- False positive error: this is experienced when a climatic phenomenon is mistaken for a structural damage. Within the “healthy” threshold, when this limit has a high safety margin. Whenever a false alarm occurs due to uncommon meteorological phenomena, the structure needs to be checked by a team of experts and, where it is necessary, the evacuation of people is required. This leads inevitably to a costly and inefficient structural monitoring protocol.

- False negative error: on the contrary, it is manifested when an actual damage measurement is diagnosed as an harmless environmental event. There can be two different consequences. In the less dangerous option, damage will progress more, but the interventions are delayed, leading to a more invasiveness nature. In the less fortunate case, however, the structural damage compromises the structural integrity thus leading this time to an impossibility of intervention scenarios. Monitoring in this last case will result completely useless due to the further delay in recognizing the serious damage. Furthermore, even life-safety is not guaranteed: the importance of preventing this type of error is fundamental in the engineering framework.

Furthermore, it is necessary to point out that climatic events can modify both stiffness and mass of the system. It could be a temporary effect, such as snow that could last for days modifying the mass of the structure, or a daily variation induced by temperature. The latter could also be responsible for stiffness variation due to the freezing phenomenon (Peeters & De Roeck, 2001).

One challenging aspect that one must pay attention is the prediction of the effects of these factors. Some relationships between temperature and modal frequencies could be found in literature within permanently or periodically monitored systems: directly proportional (Masciotta et al., 2017; Tronci et al., 2020), bilinear (Ramos et al., 2010), inversely proportional and also uncorrelated (Saisi et al., 2018).

The material and the structural disposition surely influences these relationships. Furthermore, other factors should be considered such as the contiguity with other structures, interventions realized with different materials and the foundation properties that may be influenced by the environmental events.

3.3 Machine Learning (ML) approaches to Structural Health Monitoring

In the recent years technological progress has allowed to make improvements on the procedures that required operators to be conducted. In the engineering field, the automatization of such procedures let it possible to implement new techniques that could be found also in the Structural Health Monitoring framework.

Progress ranges from hardware to software, including also methods and algorithms used in particular to analyze the more and more bigger amounts of data. Concerning monitoring systems, new sensors have been concepted in order to have measurements at higher frequencies that can be analyzed with a progressively faster and more efficient computers capable of collecting more and more data.

A tipping point, also in civil engineering, is surely the advent and the spreading of Machine Learning (ML) techniques with the objective of synthesizing and managing data taking into account their smart capabilities in order to apply a decision-making process on the extracted information (Farrar & Worden, 2012; Figueiredo et al., 2011; Flah et al., 2020; Smarsly et al., 2016).

Exploiting computers to gain direct knowledge and skills and by constantly improving performances automatically, Machine Learning combines these advantages to the emulation of the learning ability of human beings. The purpose of this technology is to derive the intrinsic links between the data starting from known data and ending in the efficient prediction of unknown data also analyzing their properties. Their application, concerning the monitoring of civil structures, have the purpose of connecting diagnostic characteristics from buildings measurements with a structural qualitative condition. The main issue with Machine Learning lies in the generalization of the input data.

Despite all, Machine Learning ability of knowledge acquisition is really similar to human learning (Mitchell, 2000). The intelligence is progressively chased in both machines and humans by improving algorithms on one hand and mental capabilities on the other. There are some main differences that can be described, though:

- While human learning needs time to be accomplished, Machine Learning knowledge is developed in a fast way.
- Forgetfulness of human beings is not present in ML and no knowledge limitations characterize only the artificial intelligence, as opposed to humans.
- Knowledge cannot be transferred between human beings by directly copying it. ML has the ability to make knowledge be transported from system to system.
- The human-learning can generate more ideas and filter the best option possible, while the mechanistic nature of the ML does not allow to do it.

- Rules obeisance is strictly a characteristic of the machines, including ML, while humans can think freely and for this reason their connections and logics are difficult to be simulated by a computer.

The hypotheses and instructions at the base of methods useful to analyze a set of input data in order to solve a practical problem must be explicit for ML. Unfortunately, this is not always reproducible: issues arise when some problems could not be solved by valid methods, i.e. dealing with an uncommon dynamically complex structure can represent a limitation also in terms of computational capabilities. Input-output associations learned from examples to synthetize connections are known as training data (learning methodology).

Relationships between the training dataset and the damage characterization can be exploited in order to help Structural Health Monitoring to learn from this information and use it as knowledge to apply again to unknown data. One can take advantage of these techniques to joint them with a structural monitoring system in order to allow the optimization and the automatization of the processes avoiding, where it is possible, the manual intervention. The consequence of having a very optimized algorithm lies in the capability of the same to exceed the technician ability due to the better data management skills, the low error rate probability and the unlimited speed and computational power compared to a human being (Coletta, 2022).

3.3.1 Supervised *vs* unsupervised ML approaches

When one talks about Machine Learning, two sub-categories can be described: the supervised learning and the unsupervised learning. The main difference between the two types of learning lies in the presence or not of the output (labels) of the training data.

Talking about supervised learning, the labels are available and one can exploit the ability of the algorithm to determine relationships between the measured data and the labels in order to use this knowledge to predict new labels starting from new data. Two distinct tasks can be assigned according to the label nature: classification or regression. Taking into account classification problem in a supervised learning, the aim is to determine a categorical class, whose label results marked, to every data comprised in both a single or multi-dimensional data set. Considering a real application, usually in SHM a structural diagnosis can be subdivided in two classes, function of the type of damage ("undamaged", "damaged"). If more damage locations can be detected, we can have even more classes, as we will see in the following Chapters. The other problem that can be solved with ML applications is the regression one, in which continuous variables constitute the labels: it is usually used in SHM by exploiting predictor variables represented by diagnostic parameters in order to predict unknown diagnostic structural parameters. By comparing the actual measurements with the predicted undamaged parameters, big differences arise when the structural behavior changes from its normal condition.

Analyzing an unsupervised problem, the final aim is different from the previous type of problem: here, no training label are available thus resulting in no basis on which the data can be categorized. The non possibility to associate a real meaning to data is due to the fact that the unsupervised procedure exploits information only from unlabelled data. The different tasks could be divided mainly in two for unlabelled data: clustering analysis and outlier analysis. Talking about clustering analysis, its aim is to derive a logical grouping by some pattern recognition in the data by the algorithm without mention the group classification, which previously was described for the supervised problem. Outlier analysis, instead (also known as anomaly or novelty detection) is really important for Structural Health Monitoring (SHM): if structural "healthy" data are known, it can be conducted a statistical analysis on such a data. Giving to the algorithm fresh data, these can be analyzed and tested in order to determine if they fit the undamaged condition of the structure or not. In the latter case, the structural diagnosis will be that of a damaged structure. This is similar to a classification problem with only two different classes (Coletta, 2022). Structural Health Monitoring exploits a lot outlier analysis due to the difficulties of finding available labelled data. An unsupervised algorithm needs only little information at the input point, anyway allowing to detect efficiently structural damage.

3.3.2 Training data

Even if the two types of problem (supervised vs unsupervised) are intrinsically different, both methods require an initial amount of input data to trigger the algorithm. Training, validation and test phases could be defined when dealing with supervised and unsupervised problems.

According to the different problem, the algorithm is provided by the initial data of the Training Dataset (TD) labelled or unlabelled. The parameters of the model can be evaluated by analyzing in a continuous way the data. Create a model able to generalize in a good way the additional unknown data and, of course, the TD ones, is the aim of this technique.

Validation is a phase really exploited in supervised problems that is performed on a small set of labelled data which are not for training purposes. The goal of the algorithm is to generalize unknown data and, to optimize this, validation avoids to incur the phenomenon of overfitting, which can be explained as the possibility of an algorithm to adapt itself too strictly to the Training Dataset (TD). In order to achieve this, a validation dataset is implemented in the algorithm to regularize its parameters: it can be considered as a sort of test on which accuracy can be tested. After the training and the validation phases, the testing phase is the final one on which the algorithm is expected to be able to determine discrete or continuous labels for supervised problems, or to provide output for the unsupervised one.

As already explained, the training, validation and testing datasets are essential to the algorithm. Concerning the Structural Health Monitoring (SHM), supervised classification problem would be the best but, in reality, it is not possible to get a sufficient amount of data from every structure and from each structural condition (Coletta, 2022). If this could be done efficiently, a dataset with all the diagnostic conditions would be used as training for the algorithm, then validation would be conducted on another dataset and, finally, the algorithm would be tested by applying real time measured data from the structure. Doing like that would allow the algorithm to detect and label each structural state because, supervising it with the training labelled set, it would be already able to recognize the properties. The main issue in SHM about supervised problems is the difficulty on finding data for each structural condition. Some questions arise about the possibility to know the evolution in time of the diagnostic parameters after a peculiar damage or about the ability of the algorithm of adapting its capabilities on detecting possible obstacles in the recognition of data patterns.

Past period related experimental data usage

Some hypotheses must be stated according to this application:

i. A specific damage has been noticed by the structure in a past period;
ii. The measurement of that particular condition has been recorded and stored as data;
iii. The previous structural condition has been reinstated after that event.

Dynamic monitoring is quite new and just a few structures have sufficiently long period monitoring data in order to have the building experienced in that time an episode of damage and repair, thus translating into a series of complete Training Dataset (TD). As time passes, this issue can be solved due to the inevitably variations in the structural conditions: these damages must be naturally caused, because it is not possible especially for AH structures to contrive and act a voluntary harm on them. But it can also be possible that the monitoring time period chosen is not enough to see any damage on the structure. Even if the damage has been experienced, it could be difficult to bring back the structure to its previous condition (Coletta, 2022). Furthermore, the initial behavior is improbable reachable for a series of reasons: the different materials involved in the interventions, the inevitable geometry changes and the new connections etc. The new structure would have, according to what has been just stated, different properties.

Data from similar structure exploitation

A solution for the lack of data in Structural Health Monitoring (SHM) could be overcome by taking into account a multitude of different data sources.

One can, in fact, get data related to damages from other reproduced structures, can generate a training dataset able to create a model to apply on other structures, seen as duplicate products. This method can be exploited on structures that are simple enough to be reproduced, for example in the mechanical and aerospace fields and, as it can be clearly thought, not possible to be carried out in the civil engineering structures.

To partially solve this problem, the exploitation of other dynamically similar structures to extract data from the damaged condition can be done. The main difference with the previous approach is surely the management of these data: due to their dissimilarities in terms of data sources, they cannot be used directly to train the final algorithm whose goal is to analyze the monitored structure. The data need to be adapted to the targeted data to be used for this different system.

It is also important to take into account how noise and environmental effects are a crucial issue for the training data choice. The algorithm needs, in fact, to recognize both the damaged and undamaged condition and also the environmental condition. Damage can be more effectively detected if the algorithm has the ability to discern environmental condition from actual disease states. Including extreme climatic events in a chosen Training Dataset (TD) could be a good decision in order to let the algorithm have an exhaustive combination of both damage conditions and environmental conditions with the aim of recognizing them in the testing phase.

3.3.3 Transfer Learning

As already seen, ML techniques are not always able to adapt different training data between two different structures. The needing for generalization and synthetization of data, even in high-dimensional space, in addition to the previous issues leads to a new technology in the ML field.

The Transfer Learning (TL) comes to the aid of the labelled data lack issue. In fact, it allows training dataset coming from different "domains" to be implemented in order to initialize an algorithm even if these do not share the same tasks and distribution (Dai et al., 2007; Pan & Yang, 2009; Taylor & Stone, 2009; Weiss et al., 2016).

Transfer Learning concept can be found in many human habits and activities. Training in Machine Learning can be seen as the experience gained from past and similar actions in the human counterpart to overcome a present obstacle. For instance, considering a video game simulation, it can help effectively to get some skills useful in the same circumstances but in the real world (Coletta, 2022): in fact, the two systems (videogames and reality) even being so different, share information related to the same tasks needed to perform particular activities (i.e. riding a motorcycle).

As it will be described in a more detailed way in the next Chapters, the lack of labelled data about the damage structural condition, being the main issue of SHM, could be solved by exploiting Transfer Learning (TL) technologies.

Transfer Learning is applicable when information obtainable from a more available system (source) can be exploited, transferred and adapted to another system, characterized by a little data knowledge (target system), but having some characteristics in common with the first. In the scheme represented in Figure 1 (Pan & Yang, 2010) an overall description of Transfer Learning is shown:

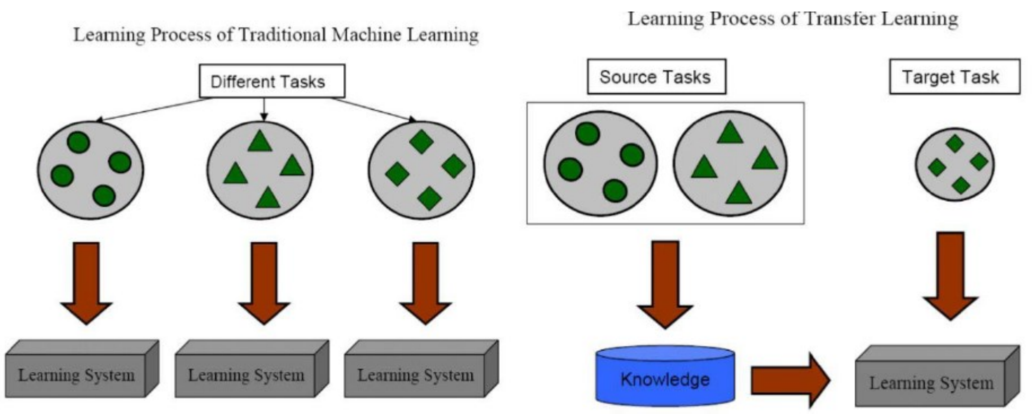


Figure 1: Traditional Machine Learning vs Transfer Learning conceptual difference (Pan & Yang, 2010)

In the structural engineering field, Transfer Learning applications are not so common and only few of them in the recent years have been released. For instance, Coletta (Coletta, 2022) solved the lack of labelled data referred to two different structural states by exploiting virtual data generated by means of a Finite Element Model (FEM) (Figure 2) in order to train Machine Learning (ML) algorithms in the frame of the *Sanctuary of Vicoforte* (CN, Italy), belonging to Architectural Heritage.

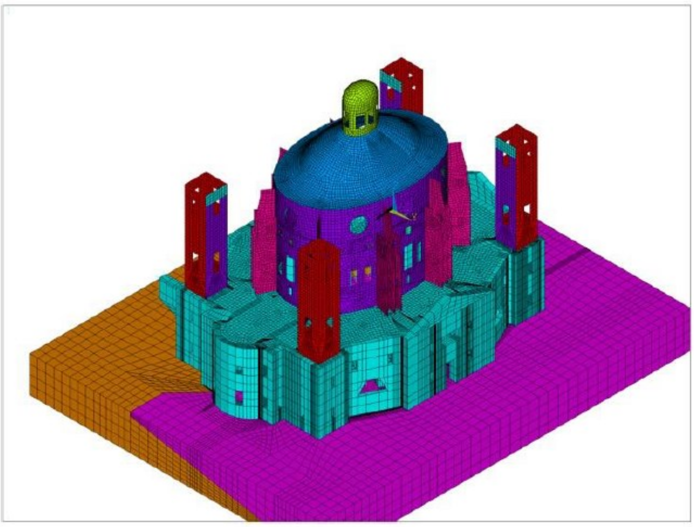


Figure 2: FEM of the Sanctuary of Vicoforte (Coletta, 2022)

Talking of deep learning instead, neural networks skills in cracks identification within images damage detection have been improved thanks to Transfer Learning applications. Dorafshan et al, on a set of 19 high definition images of concrete (319 images with cracks present and 3101 without, with a total of 3420 sub-images), were able to apply TL together with the AlexNet Deep Convolutional Neural Network (DCNN) architecture in classifiers (Dorafshan et al., 2018). Another example on concrete structures by Jang et al. is represented by the application to the GoogLeNet deep neural network architecture of the transfer learning in order to efficiently achieve cracks identification within hybrid images which put together both visual images and infrared thermography (Jang et al., 2019).

Gardner et al. defining a series of topological similar structures, deal with the application of TL on heterogenous population in order to solve a multisite damage location problem (Gardner et al., 2020).

Chapter 4

Finite Element modelling of real structures to obtain experimental data

4.1 Ventura's Yellow Frame

4.1.1 Benchmark problem

In the last decades, benchmark problems have been considered in order to validate structural control and structural health monitoring systems. A benchmark problem could be useful to allow a direct comparison between different methodologies, techniques and sensors thanks to an open-access test widely diffused in the research community. In particular, the American Society of Civil Engineering (ASCE), together with the International Association of Structural Control (IASC), started a project involved in the depiction of the first benchmark problem in Structural Health Monitoring (SHM). This problem outline was introduced in May 2000 at the 14th Engineering Mechanics Conference in Austin

(Texas). Contributions from several authors (Au et al., 2000; Bernal & Gunes, 2000; Corbin et al., 2000; Dyke et al., 2000; Katafygiotis et al., 2000) were considered in order to define the benchmark problem. At first, the conditions of this exercise were well stated, but the complexity of the problem grew over time. Since the different configurations of the problem could be several, other sessions during different conferences, focused on the development of the benchmark problem, were held in the following years. Just to mention, two sessions were dedicated at the ASME-ASCE Joint Mechanics and Materials Conference in San Diego (California, June 27-29, 2001). Another session was held during the 3rd International Workshop on Structural Health Monitoring (September 12-14, 2001), a session during the IMAC XXI Conference in Orlando (Florida, February 3-6, 2003) and one at the 16th ASCE Engineering Mechanics Conference in Seattle (Washington, July 16-18, 2003).

4.1.2 Benchmark Structure

The structure on which the benchmark problem is considered, relies on a modular 4 storey, 2 bay by 2 bay, steel frame structure scaled 1:3. It has been realized by the Earthquake Engineering Research Laboratory at the University of British Columbia (Figure 3). The total height of the structure is 3.6 m, and it is designed to be a squared plan, whose width is 2.5 m. The material involved in the structural members, beams and columns, is steel. In particular, steel hot rolled grade 300W sections have been involved in the realization of framed structure (Table 1). These sections were thought to be specifically used for this scaled model: B100x9 sections have been considered for the columns and S75x11 sections for the floor beams.

Taking into account the beam to column connections (Figure 4), their configuration allows to add a flexibility degree to the bracing system: this should be considered in order to build a numerical model of the structure. The sections involved in these members are angle braces L25x25x3, with the same material properties of the other structural elements.

Figure 3: Ventura Steel frame model (Ventura et al., 2003)

Figure 4: Beam to column connection (Ventura et al., 2003)

Property	Columns	Beam	Diagonal braces	Diagonal beams
Section	B100X9	S75X11	L25X25X3	HSS 51×51×6.4
Area (m^2)	$1{,}133\mathrm{x}10^{-3}$	$1{,}43\mathrm{x}10^{-3}$	$1{,}41\mathrm{x}10^{-4}$	$9{,}47\mathrm{x}10^{-4}$
Second moment of area in the strong dir. (m^4)	$1{,}97\mathrm{x}10^{-6}$	$1{,}22\mathrm{x}10^{-6}$	0	0
Second moment of area in the weak dir. (m^4)	$6{,}64\mathrm{x}10^{-7}$	$2{,}49\mathrm{x}10^{-7}$	0	0
Saint Venant torsional constant (m^4)	$8{,}01\mathrm{x}10^{-9}$	$3{,}82\mathrm{x}10^{-9}$	0	0

Table 1: Geometric characteristics of the Yellow Frame

Steel plates have been located at the four floor quadrants in order to consider the added mass on each slab: At the first floor a total mass of 1000 kg has been placed per quadrant; at the second and third floor a mass of 750 kg per quadrant was considered; lastly, in the top floor, 3 quadrants out of 4 have been loaded with 400 kg, while the fourth one with 800 kg, considering the added mass by shakers and instruments related to the forced-vibration for the various configurations.

In August 4-7, 2002, several vibration measurements have been carried out at the University of British Columbia Structure Laboratory. All the different tests configuration considered, have been analyzed including shaker, with hammer and ambient tests (Ventura et al., 2003). It is possible to depict all the possible configurations conducted during the tests:

Configuration I: The undamaged, fully braced structure was considered as first configuration.

Configuration II: Braced configuration in which braces located on the east side are removed.

Configuration III: Braced configuration in which braces located on the south-bay on the east side are removed.

Configuration IV: Braced configuration in which braces located on the top and bottom south-bay on the east side are removed.

Configuration V: Braced configuration in which braces located on the bottom south-bay on the east side are removed.

Configuration VI: Braced configuration in which second level braces located on the east side are removed.

Configuration VII: Unbraced configuration in which all the braces located on all sides are removed.

Configuration VIII: Unbraced configuration in which all the connections located on the north sides are loosened.

Configuration IX: Unbraced configuration in which the first and second level connections located on the north-bay of the east side are loosened.

Configuration X: Unbraced configuration in which the first level connections located on the north-bay of the east face are loosened.

Configuration XI: Same as configuration VII, added a mass of 100 kg on the top of the northwest corner of the structure.

The extractions of natural frequencies and mode shapes were performed using the different configurations previously described. To estimate the torsional frequencies, measured lateral motions derived from the opposite sides of the structure were exploited in order to compute their differences and then the torsional frequencies. Assuming the floor decks to be rigid in their plane, makes this hypothesis to be sufficient in order to get torsional frequencies in the previously described way. For the first configuration, Table 2 shows the first five natural frequencies of the frame, including the MAC (Modal Assurance Criterion) and the modal damping.

Mode number	Description	f_i [Hz] EFDD	SSI	MAC
1	1st mode, Y-direction	7,67	7,71	1
2	1st mode, X-direction	7,91	7,94	1
3	1st torsion	14,42	14,51	1
4	2nd mode, Y-direction	19,94	19,95	1
5	3rd mode, Y-direction	25,48	25,48	1

Table 2: Estimated natural frequencies (Ventura et al., 2003)

4.1.3 Finite Element Model: hypotheses and details

A finite element model has been realized in order to (i) validate the benchmark problem related to the Yellow Frame by Professor Ventura (Ventura et al., 2003), (ii) and to extract data useful for the analyses reported in the next Chapters, related to a damage classification via Machine Learning approaches.

Several methods can be exploited to well describe the physical reality, but surely Finite Element Modeling (FEM) represents one of the most suitable method, due to its capacity to best fit the structural behavior of real structures. This approach allows to determine approximate solutions thanks to algebraic equation systems able to solve analytical problems defined by differential equations of partial derivatives. The FEM method decomposes the overall structural arrangement in (i) monodimensional elements, (ii) bidimensional elements, (iii) solid elements. The main function of this approach relies on the structural discretization due to a numerical mesh generation.

The Finite Element Software considered for the modelling is ANSYS, which can be described by the following operative steps:

- Construction of the geometry;
- Element definition (solid, shell, beam or link element);

- Material properties attribution;
- Mesh definition;
- Boundary conditions;
- Load applications;
- Analysis;
- Post Processing.

It is possible, in ANSYS, to represent the element discretization by means of different element typologies. In particular, in order to generate the numerical model of the structures, the following elements have been adopted:

- Beam Element: Beam188;
- Link Element: Link180;
- Shell Element: Shell181;
- Structural mass element: Mass21.

Element Beam188

This element (Figure 5) can be used to analyze slender to moderate thick beam structures. Its main properties rely on the Timoshenko beam theory, allowing to consider also shear deformation in the element. Two nodes characterize the linear element, having six degrees of freedom. The DOFs related to each node describe the translations and the rotations in all the three different directions (x, y, z).

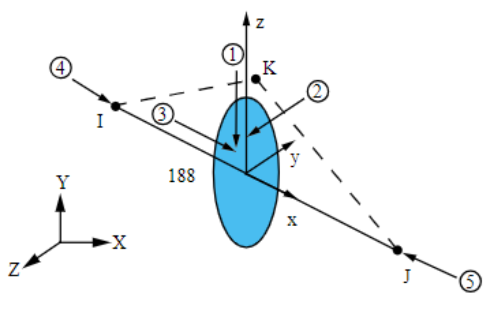


Figure 5: Beam188 element

Element Link180

The Link180 (Figure 6) represents a suitable element in several engineering applications, such as truss systems, cables, bracing systems and so on. It is a compression-tension uniaxial element with three degrees of freedoms for each of its two end nodes, corresponding to the translations with respect to the three directions (x, y, z). Flexure is not allowed by this element due to its capacity of taking into account only actions oriented along its axis. Deformation, sliding and plasticity are allowed.

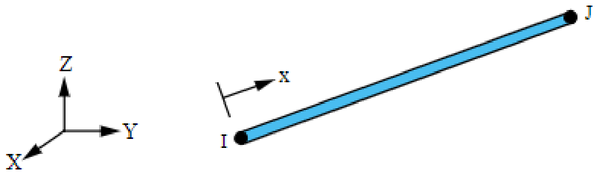


Figure 6: Link180 element

Element Shell181

The Shell181 element (Figure 7) is often exploited in order to model and analyze thin to moderately thick shell structures. It is represented by a four-node element with six degrees of freedom per node, allowing translations and rotations in all the three different directions (x, y, z). Shell181 can be also used to model different layers in a composite shell or sandwich construction.

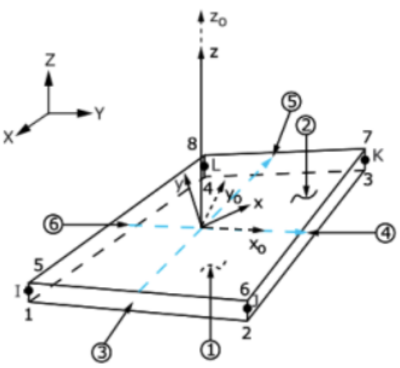


Figure 7: Shell181 element

Element Mass21

The element Mass21 (Figure 8) represents a point element with six degrees of freedom: translations and rotations about the x, y and z axes. It is possible to assign to this element different mass and rotary inertia for each coordinate direction.

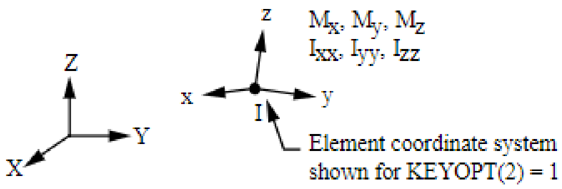


Figure 8: Mass21 element

The material properties used to model the Yellow Frame of Professor Ventura are shown in Table 3:

Material	E [GPa]	ν [-]	ρ [kg/m³]
Steel	207,83	0,28	7850

Table 3: Material properties (Ventura frame)

Each floor slab has added mass in form of plate elements and it is divided in four quadrants: The total mass of each quadrant can be observed in Figure 9:

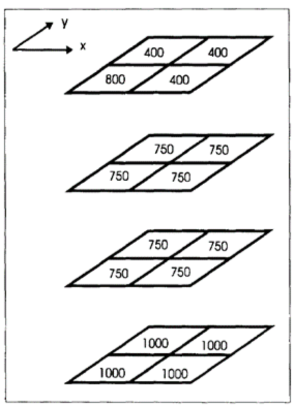
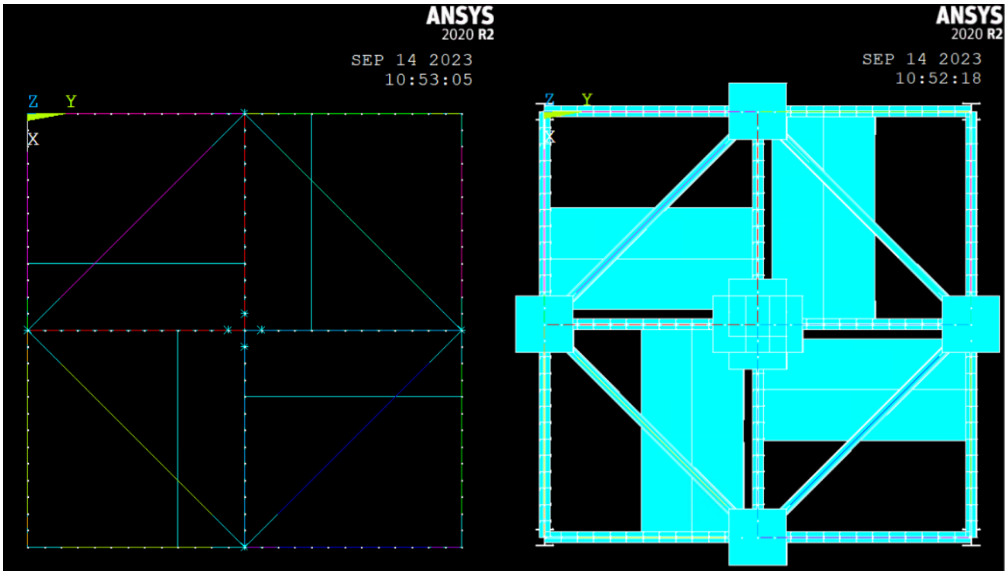


Figure 9: Ventura's Frame added mass [kg]

It is possible to consider this added masses as concentrated in the nodes, that are physically represented by the intersection between the plate elements and the frame structural beams (Figure 10).



a) *b)*

Figure 10: Steel frame plan view: a) elements and nodes for applied mass; b) meshed elements

The main hypothesis that stands behind the mass applications in the nodes relies in the uniform load transmission to the main structural frame. In order to conduct a proper modal analysis that would reproduce the same results as the experimental benchmark problem, it is also assumed that the columns are fixed constrained to the base.

It is possible to summarize also the other modelling assumptions. Firstly, the floors can be considered rigid in the horizontal plane; the diagonal braces are axial members considered pinned at the end-nodes connections and therefore cannot transfer bending moments; with the exception of the braces, all the beam-column connections can be considered as rigid.

The FEM of the Yellow frame benchmark problem is shown in Figure 11:

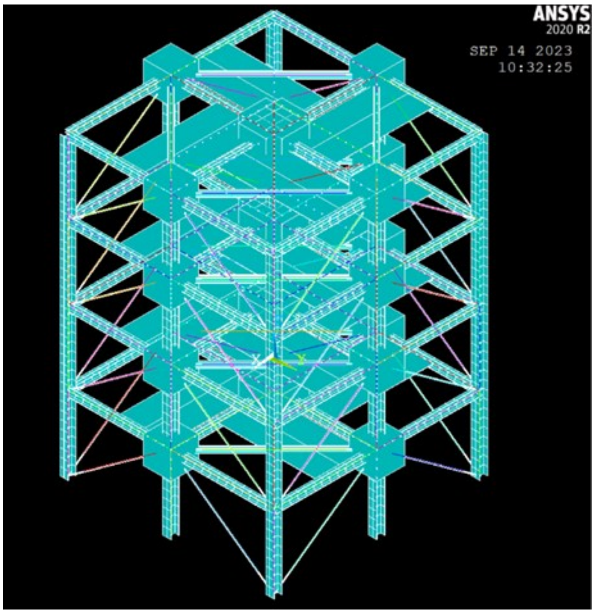


Figure 11: Yellow Frame FEM (ANSYS)

Using the information provided by the real frame, it has been possible to generate a FEM of the structure. Furthermore, a modal analysis can be conducted, allowing to construct mode shapes and estimate natural frequencies (Table 4) in order to compare the numerical results with the actual benchmark problem values represented in Table 2.

Mode number	Description	f_i [Hz] EFDD	f_i [Hz] SSI	f_i [Hz] FEM estimation
1	1st mode, Y-direction	7,67	7,71	7,42
2	1st mode, X-direction	7,91	7,94	7,93
3	1st torsion	14,42	14,51	14,21
4	2nd mode, Y-direction	19,94	19,95	19,40
5	3rd mode, Y-direction	25,48	25,48	21,38

Table 4: FEM estimated natural frequencies and comparison

In addition, a plot of the first three mode shapes can be depicted in the following (Figure 12).

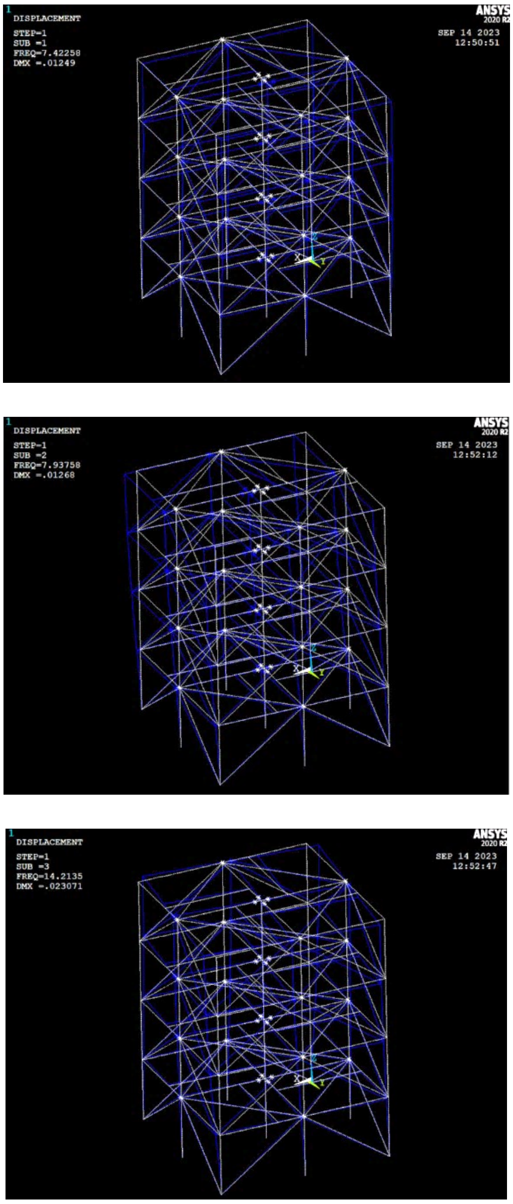


Figure 12: First, second and third mode shape illustrations

In order to conduct further analyses, as it will deeply described in the following paragraphs, another configuration of the previously defined benchmark problem related to the Yellow Frame has been modeled by means of ANSYS. In particular, it has been decided to model the unbraced configuration, with the same hypotheses in terms of connections, added mass and boundary conditions as the previous braced version (Figure 13). In Table 5 the estimated mode shapes and the natural frequencies are reported:

Mode number	Description	f_i [Hz] FEM estimation
1	1st mode, Y-direction	3,63
2	1st mode, X-direction	4,54
3	1st torsion	6,33
4	2nd mode, Y-direction	10,60
5	2nd mode, X-direction	13,94

Table 5: Estimated mode shapes and natural frequencies of the unbraced configuration

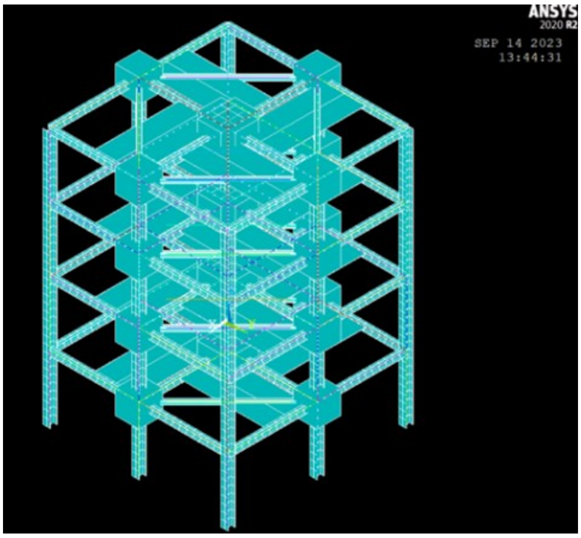


Figure 13: Unbraced Yellow Frame FEM model

4.2 Laboratory of Dynamics and Seismic's Frame

One of the aims of this thesis is to apply damage detection strategies to other little-known structures (target systems). The Yellow Frame by Professor Ventura (Ventura et al., 2003) can be seen as the target structure, while as source system another structure can be described in this Paragraph. The frame considered is a little structure located at the Laboratory of Dynamics and Seismic at Politecnico di Torino (Figure 14): this framed structure is a 3-storeys structure with a square plan 0.3 m wide, supported by 4 columns of a total height of 0.9 m, positioned at the edges and fixed at the base end to a steel plate, acting as a foundation plate. Most of the structural members are realized in aluminum, with exception of the bracing systems, realized in galvanized steel. The material properties can be found in Table 6.

Material	E [GPa]	ν [-]	ρ [kg/m^3]
Aluminum	69,00	0,32592	2600
Galvanized steel	210,00	0,27000	8000

Table 6: Material properties of the Laboratory's frame

The main structural elements are defined by the columns, the square plate elements, whose thickness is 5 mm, representing the slabs and the y-oriented bracing systems pinned to the first storey level. The geometric characteristics of the main structural elements are depicted in Table 7.

Property	Columns	Diagonal braces
Material	Aluminum	Steel
Section	20X3	L20X20X2
Area (m^2)	6,00x10^{-5}	7,60x10^{-5}
Second moment of area in the strong dir. (m^4)	2,00x10^{-9}	0
Second moment of area in the weak dir. (m^4)	4,50x10^{-11}	0
Saint Venant torsional constant (m^4)	1,69x10^{-10}	0

Table 7: Geometric characteristics of the Laboratory's frame

Figure 14: Laboratory's Frame

4.2.1 Finite Element Model: hypotheses and details

Some modelling assumptions can be stated as for the previous model: the floors can be considered rigid in their plane; the diagonal braces are axial members considered pinned at the end-nodes connections and therefore cannot transfer bending moments; with the exception of the braces, all the other connections can be considered rigid. An illustration of the Finite Element (FE) model can be depicted in Figure 15.

As already done for the previous structure, a modal analysis can be carried out in order to estimate, by means of the numerical FE model, the mode shapes and the natural frequencies (Table 8).

Mode number	Description	f_i [Hz] FEM estimation
1	1st mode, Y-direction	4,31
2	1st mode, X-direction	8,27
3	2nd mode, Y-direction	12,17
4	1st torsion	15,22
5	2nd mode, X-direction	34,44

Table 8: Estimated mode shapes and natural frequencies of the Laboratory's frame

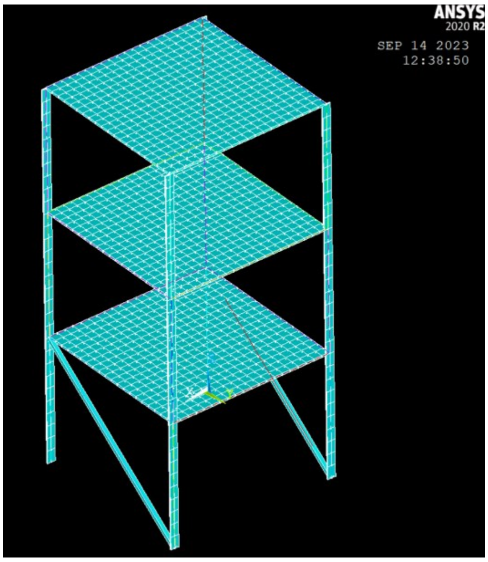
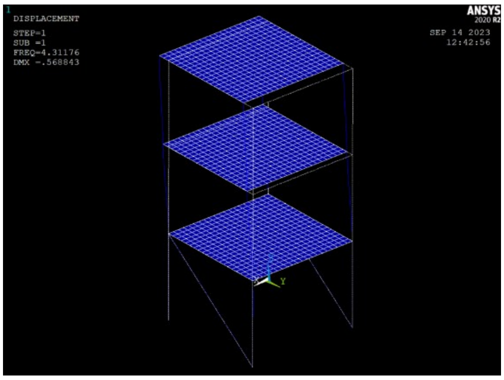
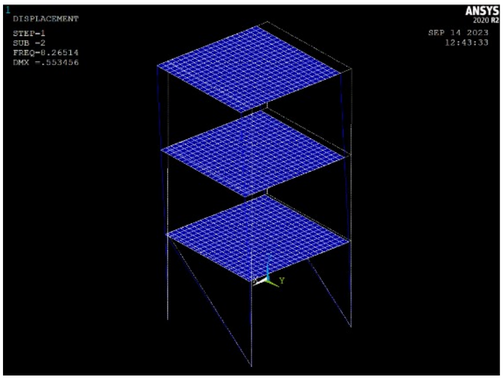


Figure 15: FEM of the Laboratory's Frame

Concerning the next Chapter, the most important modes that will be considered in order to conduct ML approaches for damage detection are the first flexural modes in X and Y directions and the first torsional mode (Figure 16).





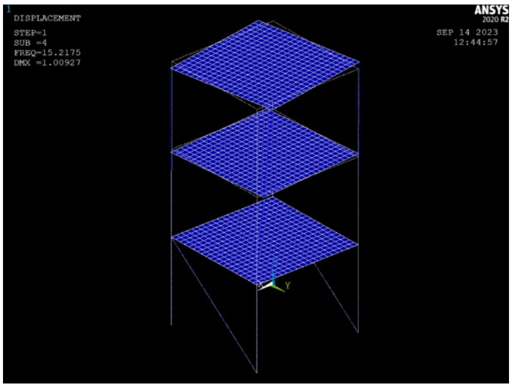


Figure 16: First, second and fourth mode shape illustrations

With the same purposes of the Yellow Frame (described in paragraph 4.1.1., pag. 32) in order to conduct the same kind of analysis between the two structures, also an unbraced version of the frame located at the laboratory has been modeled (Figure 17):

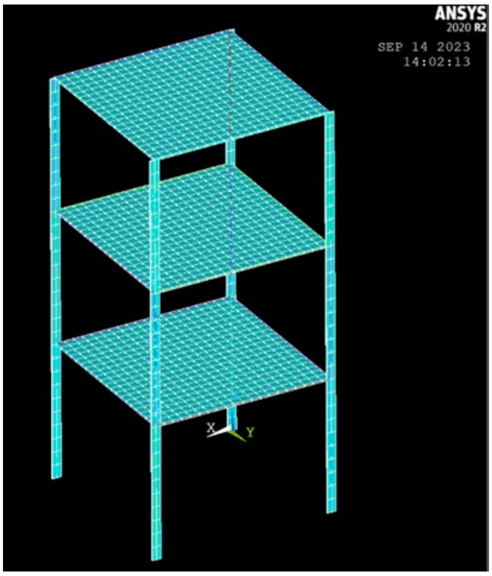


Figure 17: FEM of the unbraced Laboratory's Frame

Finally, a modal analysis has been conducted to estimate modes shapes and natural frequencies (Table 9):

Mode number	Description	f_i [Hz] FEM estimation
1	1st mode, Y-direction	3,11
2	1st mode, X-direction	8,27
3	2nd mode, Y-direction	9,10
4	1st torsion	10,62
5	3rd mode, Y-direction	13,90

Table 9: Estimated mode shapes and natural frequencies of the unbraced Laboratory's frame

Chapter 5

Obtaining labelled data for SHM through Transfer Learning

5.1 The lack of labelled data for SHM

Recently, considering the SHM applications, ML algorithms have been widely exploited in order to make predictions managing a big amount of data, as already explained in the previous chapters. Statistical models dealing with supervised or unsupervised learning problems allow the algorithm to be trained on a dataset (TD) that can have or not output labels, respectively. Between these two approaches, when the labelled data are not sufficiently enough to apply a supervised learning problem, these can be used together with unlabelled data in order to train the algorithm. This approach, that stays in the middle, is known as semi-supervised learning problem.

Labels, especially in the Architectural Heritage framework, can be obtained by means of investigations and visual inspections on the structure in order to get knowledge about its structural condition. Then, expert technicians are hired to get these operations done, thus reflecting in high costs especially if these investigations need to be repeated in order to obtain different measurements for several combinations of environmental and operating conditions (Boller, 2009). As said in Chapter 3, according to the "Past period related experimental data usage", the damage of a structural asset is rarely present when a monitoring system is performing and it is even more improbable that the repairing of a damage condition could bring back the structure to its original undamaged state without any modifications allowing us to use those damaged state data to train ML algorithms for the future of the asset. In fact, to get a complete training dataset (TD), all the structural components need to undergo damage and a situations in which the entire structure is completely undamaged is required.

The data used to train these ML problems in the case of SHM are taken from the same distributions, thus meaning that they derive from the same structure and in the same time period in order to neglect possible drawbacks in terms of degradations between the measurements.

With the objective to solve this issue, damage data coming from some similar structures can be collected to create a training dataset (Bull et al., 2021). This method can be efficiently used in a frame of mass-produced structures constituting a homogenous population. Fields like mechanical and aerospace engineering, where mechanical components and prefabrications are largely employed, results to be very appropriated towards this technology due to the possibility to damage an object belonging to the population in order to obtain data useful to train the algorithm.

In the civil engineering and architectural sectors it is difficult to imagine this concept to be applicable for different reasons:

i. Available datasets concerning dynamic structural monitoring are scarcely diffused and even if present, they are not sufficiently complete. The youngness of this applications makes difficult to find datasets including damaged conditions data related to buildings.

ii. Dissimilar dynamic behaviors related to differences in terms of geometry, materials, state of degradation and cracking, foundations soil and the interventions experienced, make the data of a structure really difficult to be used for the creation of a training dataset for another structure. In particular, the uniqueness of architectural heritage structures geometry and the uncertainties related to material properties make this approach even more challenging.

iii. If the previous point is annihilated, in the presence of two almost identical structures, building a dataset needs to have damage condition data. Furthermore, if these structures are Cultural Heritage buildings (CH), it is deeply forbidden to cause damage in the structures in order to get data for a series of countless reasons (artistically, historically, culturally and economically).

On first impression, the concept of using data provided by a system to create a training dataset useful to monitor another system may seem really difficult to be implemented in the SHM field. In fact, in order to apply it, one needs to define a really similar structure that has been monitored for enough time to allow a collection of data at least useful for the training dataset of the other structure, taking into account also the inevitable differences in terms of measurements methods.

Transfer Learning (TL) theory, as briefly described in Chapter 3, is introduced in order to solve the lack of labelled data by taking advantage of similar enough structures (without the limitation of being identical) from which data can be acquired and transferred to the algorithm.

This method implies that tasks, distributions and so, domains (as it will be described in the next paragraphs) are not the same within the training and the testing sets. Domain Adaptation techniques are exploited in order to achieve this objective (Pan et al., 2011; Pan & Yang, 2010).

5.1.1 Transfer Learning (TL) idea for SHM

Pan & Yang gives a unified definition of TL (Pan & Yang, 2010):

> "Given a source domain $\mathcal{D}_S$ and learning task $\mathcal{T}_S$, a target domain $\mathcal{D}_T$ and learning task $\mathcal{T}_T$, transfer learning aims to help improve the learning of the target predictive function $f_T(\cdot)$ in $\mathcal{D}_T$ using the knowledge in $\mathcal{D}_S$ and $\mathcal{T}_S$, where $\mathcal{D}_S \neq \mathcal{D}_T$, or $\mathcal{T}_S, \neq \mathcal{T}_T$."

In the previous paragraph, TL has been introduced explaining its benefits in SHM issue related to the lack of labelled data, in particular about damage conditions. The similarities between two different structural dynamic behaviors can be exploited in order to apply a Transfer Learning application.

To get advantage of this, an easier system that allows to collect monitoring data from a dynamic point of view can be found in the FEM of the structure, being really useful for its capability to mirror the real structure's main characteristics.

The ease to generate data, especially damaged condition, makes this tool perfect to be used for simulations according different structural conditions injuries. In fact, the real structure does not need to undergo damage but the ML algorithm can exploit these fictitious data generated by the FEM in order to solve in the future, for instance, a classification problem.

The data extracted by the model, anyway, have some intrinsic differences from the real measurement data, even with a careful calibration of the model. In fact, the model is inevitably a simplification of the main structural characteristics: different hypotheses made on the geometry representation can bring to some variations on the final results, i.e. the mesh could be refined according to the designer preference in order to have practical computational timing and even more, crack patterns are really difficult to be accurately reproduced in a FEM. Furthermore, another hitch that may occur is the fact that the real system could undergo different environmental conditions while it is monitored: for instance, also variations on the operating conditions or geotechnical characteristics of the foundation soil could result in altering the training dataset for the real structure. In this sense, domain adaptation algorithms could be really useful to reduce the variations between the virtual and the real system.

The Finite Element Model (FEM) data results to be a key factor in the generalization of the real data with thus representing a valuable model updating procedure.

The domain adaptation procedure allows to collect the data from both system in order to train and test a classifier on these new adapted data. A KNN cross validated classifier has been considered in this thesis (Guo et al., 2003) in Transfer Learning problems about two numerical models of real structures, as it is described in the next paragraph. A comparison of the results and the improvements in the accuracy will be described in order to highlight the benefits of TL applications.

In the next paragraphs a discussion about the basic theory of domain adaptation techniques is reported, with a focus to the Transfer Component Analysis (TCA). Finally, a case study is stated.

5.2 Domain Adaptation for SHM

A sub-sector of Transfer Learning methods is constituted by domain adaptation. Given different systems, as long as they are related in some way, domain adaption has the purpose of transferring knowledge between them by exploiting associated domains of data (Pan et al., 2011; Pan & Yang, 2010). Two different components can be described within the term *domain*:

- Feature space of input $\mathcal{X}$;
- Marginal distribution $P(X)$ of a set of inputs $X = \{x_1, \dots, x_n\}^T \in \mathcal{X}$.

With reference to the different systems, two domains can be determined according to Transfer Learning theory: a *source* domain $\mathcal{D}_S$ and a *target* domain $\mathcal{D}_T$. A *task*, indicated as $\mathcal{T} = \{\mathcal{Y}; f(\cdot)\}$, can be assigned to each domain, where $\mathcal{Y}$ represents the label space and $f(\cdot)$ defines the objective predictive function that is used to predict the associated label. The latter could also be defined as $P(y|x)$.

It can be described in a synthetic way:

- The labelled data is contained in $\mathcal{D}_S$, and they are the information needed to be transferred. It can be analytically defined as:

$$\mathcal{D}_S = \{(x_{S,1}, y_{S,1}), \dots, (x_{S,nS}, y_{S,nS})\}^T;$$

- The data coming from the final system is contained in $\mathcal{D}_T$ and they can be unlabelled or only partially labelled:

$$\mathcal{D}_T = \{(x_{T,1}, y_{T,1}), \dots, (x_{T,nT}, y_{T,nT})\}^T;$$

Where $x_{S,i} \in \mathcal{X}_S$ represent the n_s observations and the related output $y_{S,i} \in Y_S$ can be seen as the structural conditions in the case of SHM. On the other hand, $x_{T,i} \in \mathcal{X}_T$ represent the n_T observations in the target domain, whose data can be unlabelled or partially labelled, and $y_{T,i} \in Y_T$ can or cannot be present for every feature observation $x_{T,i} \in \mathcal{X}_T$.

Feature and label spaces can be considered to be identical for both source and target domains in domain adaptation methods, i.e. having $\mathcal{X}_S = \mathcal{X}_T$ and $\mathcal{Y}_S = \mathcal{Y}_T$ in the Structural Health Monitoring (SHM) field it means that both systems shares the same diagnostic properties and the same structural conditions. In reality, the systems differ in the marginal distribution and, not always, in the conditional one. It means that the diagnostic features are distributed in a different way, $P(X_S) \neq P(X_T)$, and also expresses the differences in the probabilities related to the occurrence of the structural conditions (labels), $P(Y_S|X_S) \neq P(Y_T|X_T)$, being these features happening could be dissimilar between the source and the target domain.

Due to these differences, training a classifier on the source domain and directly testing it on the target domain may induce in error the algorithm. In order to solve this issue, several methods have been introduced allowing to reduce the distance within the densities of source and target domains. These techniques exploit a nonlinear mapping function $\phi(\cdot)$, which makes the distributions to be equal, allowing to get $P\big(\phi(X_S)\big) \approx P\big(\phi(X_T)\big)$ and $P\big(Y_S|\phi(X_S)\big) \approx P\big(Y_T|\phi(X_T)\big)$.

In this master thesis the Transfer Component Analysis (TCA), a novel developed learning algorithm, has been exploited in order to shorten the distance between data distributions related to data collected by different FE numerical models associated to real structures.

5.2.1 Transfer Component Analysis (TCA)

Pan et al. introduced in 2011 a domain adaption technique known as Transfer Component Analysis (TCA) (Pan et al., 2011). This algorithm is implemented to learn some transfer components across the source and target domains in a Reproducing Kernel Hilbert Space (RKHS) using as embedded criterion the Maximum Mean Discrepancy (MMD). By exploiting the transfer components ability to span this subspace, data distributions of the two domains remain close and their data properties are preserved. Machine Learning methods can be applied within this subspace in order to get classifiers or regression models trained in the source domain (that contains labels) for use in the target domain, which is unlabelled or partially labelled.

TCA, as most domain adaptation techniques, relies on the hypothesis that $P(X_S) \neq P(X_T)$, but $P(Y_S|X_S) = P(Y_T|X_T)$. The Transfer Component Analysis (TCA) technique aims (i) at finding the mapping function $\phi(\cdot)$ by minimize the distance between the marginal probabilities $P\big(\phi(X_S)\big)$ and $P\big(\phi(X_T)\big)$, (ii) and at keeping in the mapping function $\phi(X_S)$ and $\phi(X_T)$ the significant properties of X_S and X_T. This approach is based on the assumption that $P\big(Y_S|\phi(X_S)\big) \approx P\big(Y_T|\phi(X_T)\big)$ is satisfied by ϕ. The function ϕ can be found as feature map determined by a universal kernel. By minimizing the distance between the empirical means of the source and target domains a highly non linear function ϕ can be found due to the probability of getting trapped in a poor local minimum by a direct optimization problem. To solve this issue, a domain adaptation method based on a dimensional reduced law, known as MMDE can be applied in order to avoid defining the $\phi(\cdot)$ with an intrinsic non linearity (Pan et al., 2008).

The Maximum Mean Discrepancy (MMD) distance between the two different data distributions may be measured through the distance between the empirical means of the source and target domains. This sentence can be analytically reported:

$$Dist(X'_S, X'_T) = tr(KL)$$

Where X'_S and X'_T represents the transformed inputs from the two different domains, $K = k(X, X')$ is associated to the Kernel matrix, that collects the kernel matrix of target, source and also cross domains, where $X = \{X_S, X_T\}^T$. Finally L represents the MMD matrix, that can be defined in the following:

$$L(i,j) = \begin{cases} \frac{1}{n_S^2} & if\ x_i, x_j \in X_S \\ \frac{1}{n_T^2} & if\ x_i, x_j \in X_T \\ \frac{-1}{n_S n_T} & otherwise \end{cases}$$

By means of a kernel matrix K decomposition, one can obtain the empirical kernel map exploiting a $(n_S + n_T) \times m$ weight matrix, W, which aims at converting and reducing the feature vector in a space defined by m dimensions.

$$\widetilde{K} = \left(KK^{-\frac{1}{2}}\widetilde{W}\right)\left(\widetilde{W}^T K^{-\frac{1}{2}}K\right) = KWW^TK$$

Then, by replacing $\widetilde{K}$ the distance between the two empirical means of the source and target domain can be defined:

$$Dist(X_S', X_T') = tr(W^TKLKW)$$

In order to control the complicated nature of the weight matrix, a regularization term is needed in the distance minimization. In this way, we can write the kernel learning problem as:

$$\min_{s.t. W^THKW=I} tr(W^TKLKW) + \mu\, tr(W^TW)$$

In which μ is a regularization / trade-off parameter, I is the identity matrix, H is a centring matrix and the W^THKW corresponds to the variance of the projected samples that, in the Transfer Component Analysis (TCA), is tried to be preserved. The constraints on the latter are important in order to avoid the trivial solution $W = 0$. It can be demonstrated by writing the Lagrangian, that the latter equation can be solved by optimizing the equivalent trace problem in the following:

$$\max_W tr((W^T(KLK + \mu I)W)^{-1}W^TKHKW)$$

One can solve W from the latter equation by deriving the m principal eigenvectors of $(KLK + \mu I)^{-1}KHK$, where $m \leq n_S + n_T - 1$, that describe the space of the transformed features by means of $Z = KW$, with $Z \in \mathbb{R}^{(n_S+n_T)\times m}$.

5.3 Case study

The difficulty to manage a damage detection strategy is further enhanced in civil engineering structures: in particular, referring to Chapter 2, lack of monitoring data and the scarcity of labels associated to those, makes Machine Learning approaches focused in Transfer Learning applications one of the possible methods to overcome these issues. In this thesis, experimental data are obtained by numerical Finite Element (FE) models of two real framed structures (Chapter 4). To simulate an "illness state" of the structures, damages have been applied to the two models by means of drops in the mechanical properties of the main elements, as it will be further investigated in the next paragraphs.

5.3.1 Source structure

The main hypothesis of the analyses relies on the choice of the "source" systems: these will be constituted by the different configurations of the framed structure located at the Laboratory of Dynamics and Seismic of Politecnico di Torino (Chapter 4). The numerical models will provide features data by means of estimated natural frequencies of the first flexural modes in direction y and x (1st and 2nd mode shapes) and torsional mode (4th mode shape). On the other hand, not all these data will provide a label: the associated damage, realized with variations of a material property (i.e. Young modulus) or geometric characteristic (i.e thickness of the element) is not always present in the data, due to the fact that it is experimentally difficult to obtain this information in a real monitoring system application.

5.3.1.1 Laboratory's Frame configurations

The source systems considered, as previously said, are the different configurations of the laboratory frame. In particular, two different FE models have been realized in order to exploit Transfer Learning analyses.

Configuration I: Frame braced in y direction at the first storey (Figure 18):

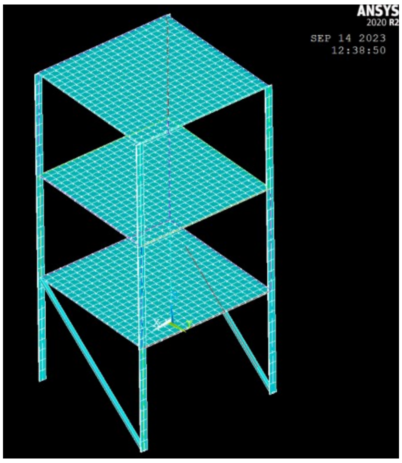


Figure 18: Source structure: configuration I

Configuration II: Unbraced frame (Figure 19):

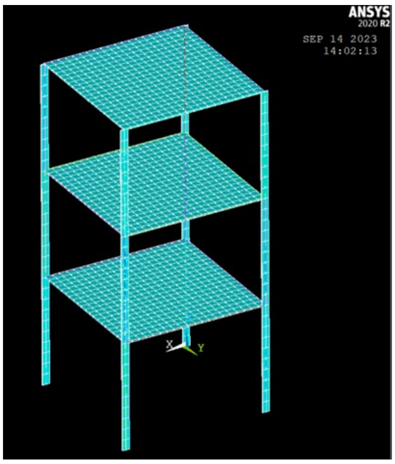


Figure 19: Source structure: configuration II

5.3.2 Target structure

The real system that needs to be investigated is represented by the target system. It consists in a little-known structure whose data are usually far less numerous with respect to the well-known source structure. In this thesis, the finite element model of the Yellow Frame by professor Ventura (Chapter 4) has been chosen as target system. As stated for the source system, also in the target one the features extracted are the estimated natural frequencies of the first flexural modes in direction y and x (1^{st} and 2^{nd} mode shapes) and torsional mode (3^{rd} mode shape). The main difference between the source and the target structure relies on the amount of available data, as it will be deeply explained in the next paragraphs. The labelled data are represented by the values of the mechanical properties of the structure (i.e. Young modulus), but in this case they are very few. All these problems have as a direct consequence the needing for TL applications.

5.3.2.1 Yellow Frame configurations

Two different finite element models of the Yellow Frame have been realized in order to extract a realistic amount of data that will be used together with the data provided by the source structure to help the algorithm in improving its performance in a classification problem related to damage detection.

Configuration I: Braced Yellow Frame (Figure 20):

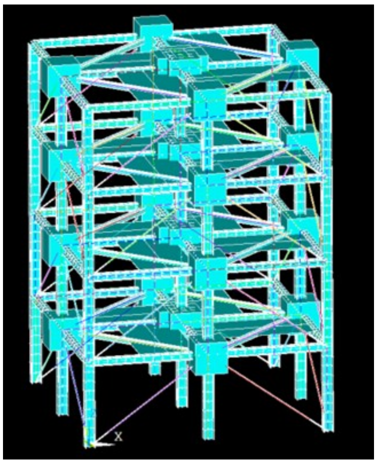


Figure 20: Target structure: configuration I

Configuration II: Unbraced Yellow Frame (Figure 21):

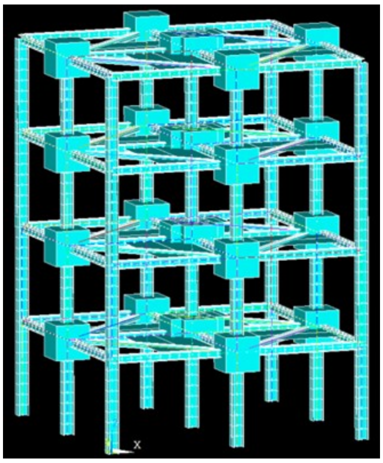


Figure 21: Target structure: configuration II

5.4 Damage in the structures and features extraction

In order to have a dataset that could reflect both damaged and undamaged situations, a variation of both material and geometric characteristics of the structures have been considered. These damages are located in different portions of the structural main elements in order to collect different classes for a further damage localization on the target structure. The material property investigated in order to detect the damage is the Young modulus: the source system, as explained in previous Chapter 4, is an aluminum structure whose Young modulus is $E_{aluminum} = 69$ GPa for an undamaged condition. Instead, the target structure is made of steel and presents a big difference in terms of material properties: in particular, its Young modulus for an undamaged state is $E_{steel} = 208$ GPa.

Furthermore, other discrepancies arise in the comparison between the natural frequencies of the source and target structure, as a consequence of the big differences in terms of material and geometry. Some of them can be stated:

i. The source structure is a 3-storeys structure with 0.9 m height, while the target structure is a 3.6 m, 4-storeys structure;
ii. As previously described, the source structure is an aluminum structure, while the target structure is made of steel.
iii. The dynamic behavior of the two structures is not the same, i.e. the first torsional mode is present as 4th mode for the source structure, while as 3rd mode for the target structure.
iv. No edge beams connecting columns in the plane are present for the source structure, but only plate elements working as slab floors. On the contrary, the target structure has beams connected to the columns.

Even if the material in terms of properties are different, we could notice how the ratio between the Young modulus and the density of the two materials is similar:

$$\frac{69\ GPa}{2.6\ g/cm^3} \approx \frac{208\ GPa}{7.85\ g/cm^3} \cong 27$$

In the following paragraphs a complete description of the damages applied to the finite elements of the different source-target structureal configurations is reported, even noticing the differences in terms of natural frequencies.

5.4.1 Damage cases applied to the structures

Within the TL structural configurations, different damages are applied in order to investigate the ability of the algorithm in (i) detecting and (ii) localize a “pathological” structural state instead of another. Briefly, a description of the damages is reported:

I. **Configuration I (braced structures):**

A. Damage applied to the base column located at the origin ((x,y) = (0,0)), up to the first storey;
B. Damage applied to the entire bottom to top column ((x,y) = (0,0));
C. Multiclass damage detection on the first part of the column ((x,y) = (0,0), 0 m < z < 0.9 m);
D. Multiclass damage detection on the second part of the column ((x,y) = (0,0), 0.9 m < z < 1.8 m);;
E. Multiclass damage detection on the third part of the column ((x,y) = (0,0), 1.8 m < z < 2.7 m);;
F. Multiclass damage detection on the fourth part of the column ((x,y) = (0,0), 2.7 m < z < 3.6 m);;
G. Damage applied to the y-oriented bracing systems for configuration I;

II. **Configuration II (unbraced structures):**

A. Damage applied to the base column located at the origin ((x,y) = (0,0)), up to the first storey;
B. Damage applied to the entire bottom to top column ((x,y) = (0,0));

C. Multiclass damage detection on the first part of the column ((x,y) = (0,0), 0 m < z < 0.9 m);

D. Multiclass damage detection on the second part of the column ((x,y) = (0,0), 0.9 m < z < 1.8 m);;

E. Multiclass damage detection on the third part of the column ((x,y) = (0,0), 1.8 m < z < 2.7 m);;

F. Multiclass damage detection on the fourth part of the column ((x,y) = (0,0), 2.7 m < z < 3.6 m);;

III. Localized damage on the Laboratory Framed structure;

IV. Multiclass damage localization (cases A., B., G.) for Conf. I;

V. Multiclass damage localization on columns (cases C., D., E., F.) for Conf. I.

VI. Multiclass damage localization on columns (cases C., D., E., F.) for Conf. II.

In order to apply a progressive damage to the structure, data are extracted with a linear variation of the Young modulus of the two different materials. In particular, in cases A. B. and G. both the moduli range between 1 GPa and their actual values, meaning 69 GPa for aluminum and 208 GPa for steel, while for cases C., D., E. and F. the lower bound of the moduli is represented by the 20% of the undamaged value. In the analysis G, the thickness varies in a range between its actual one, corresponding to 2 mm, up to a lower bound that can be assumed numerically zero.

5.4.2 Source and target systems features and labelled data

A complete dataset is available for the source structure: this system, as already explained previously, needs to provide a contribution by means of data that can be processed by the algorithm through the Transfer Component Analysis (TCA) in a domain adaptation approach. The labels are present in a percentage that varies in each analysis.

On the other hand, the target structure has very few data: a damage classification based on these would not be efficient, even because the labelled data are not enough. For this reason, several analyses between the various configurations have been conducted in order to improve the accuracy of the damage detection.

The features datasets are constituted by the natural frequencies corresponding to the first flexural mode in y and x, and the first torsional mode of the two structures: damaging the structure through a reduction of mechanical properties (E) or geometric characteristics (thickness of the elements) in the FE models, a consequent change in the natural frequencies array constituting a dataset will arise. It will be shown the difference in terms of datasets related to the source and target structures in the following TL analyses, with a focus on the domain adaptation capability to overcome this big issue in the damage classification problem.

The value of the mechanical or geometrical property related to a damage condition has been selected to be all the values below the 50% of the Young modulus or thickness associated to an undamaged structural state.

5.5 Transfer Learning applications in damage detection

In this paragraph a complete description of the analyses is reported, focusing on the details related to the amount of data extracted in each case study.

The Transfer Learning technique adopted in these analyses is the TCA. A simple damage detection between different sets of source and target structures has been evaluated: with these datasets, further analyses related a damage localizations in the target structure are conducted.

I.A. Source and target structures (configuration I) damage detection for case A.

The two structural configurations are the braced ones (Figure 22):

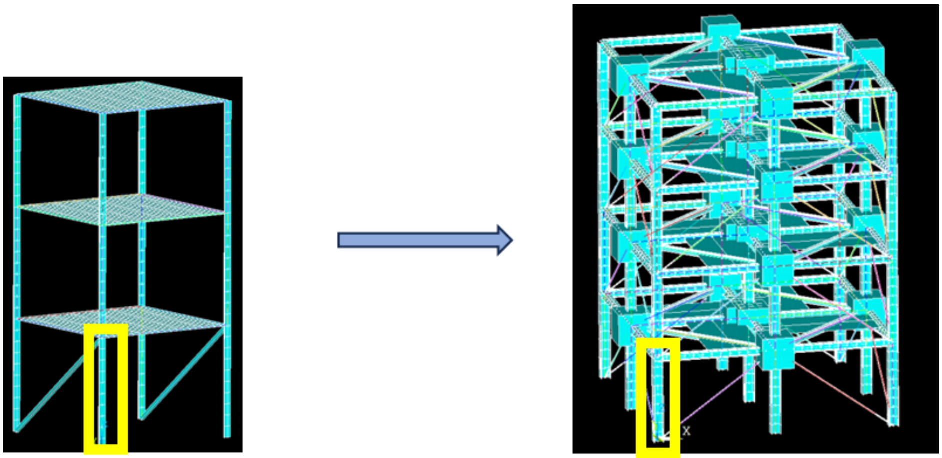


Figure 22: TL analysis: I.A.

I.B. Source and target structures (configuration I) damage detection for case B.

Braced structures associated to a damage occurring in the entire column (Figure 23):

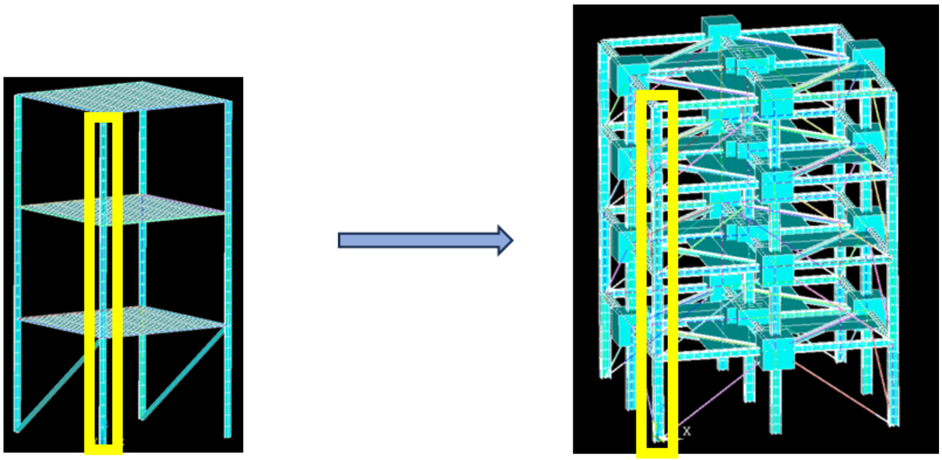


Figure 23: TL analysis: I.B.

I.C. Source and target structures (configuration I) multiclass damage detection for case C.

In the framework of the structural damage localization in a particular element, this analysis could be useful to test the algorithm in this task. A damage through a reduction of the 80% of the Young modulus has been applied to the three different subdivisions of the first storey column (Figure 24).

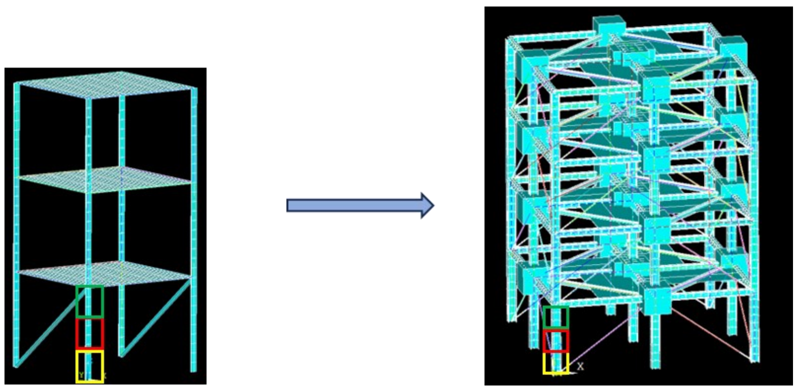


Figure 24: TL analysis: I.C.

I.D. Source and target structures (configuration I) multiclass damage detection for case D.

Following the same idea of the previous analysis, a damage detection on localized damages on the second portion of the column is performed (Figure 25):

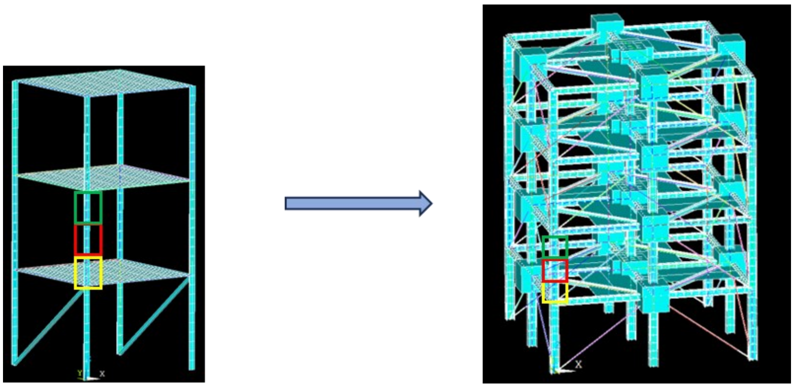


Figure 25: TL analysis: I.D.

I.E. Source and target structures (configuration I) multiclass damage detection for case E.

The same could be performed on the third portion of the column (Figure 26):

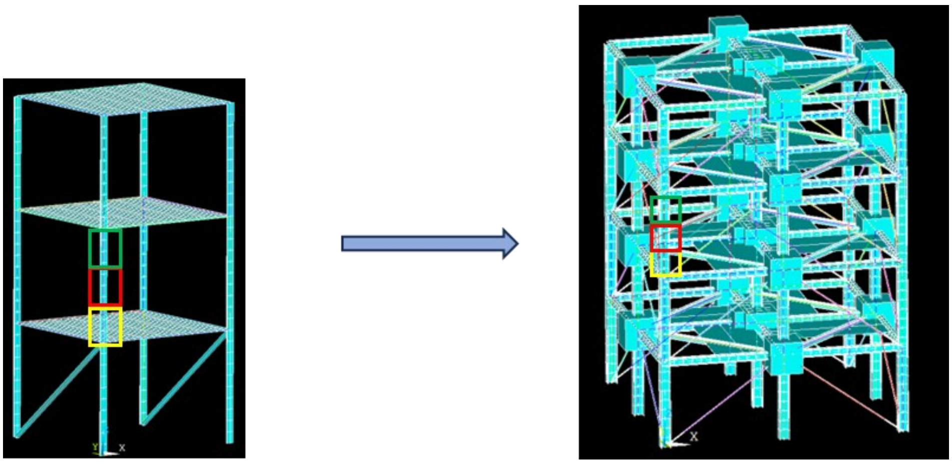


Figure 26: TL analysis: I.E.

I.F. Source and target structures (configuration I) multiclass damage detection for case F.

Finally, a multiclass damage detection on the fourth part of the column (Figure 27):

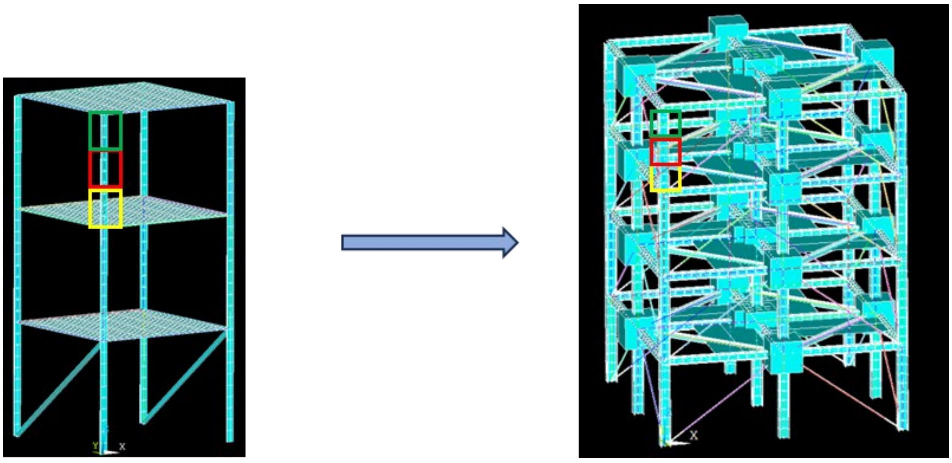


Figure 27: TL analysis: I.F.

I.G. Source and target structures (configuration I) damage detection for case G.

In this case, the damage has been applied in the y-oriented bracing systems of the structures belonging to configuration I (Figure 28):

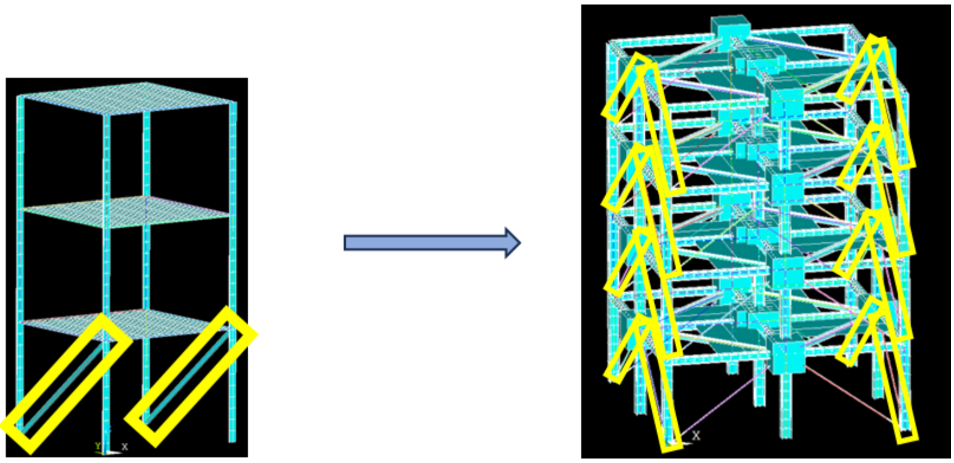


Figure 28: TL analysis: I.G.

II.A. Source and target structures (configuration II) damage detection for case A.

Unbraced structures configuration related to the damage case A (Figure 29):

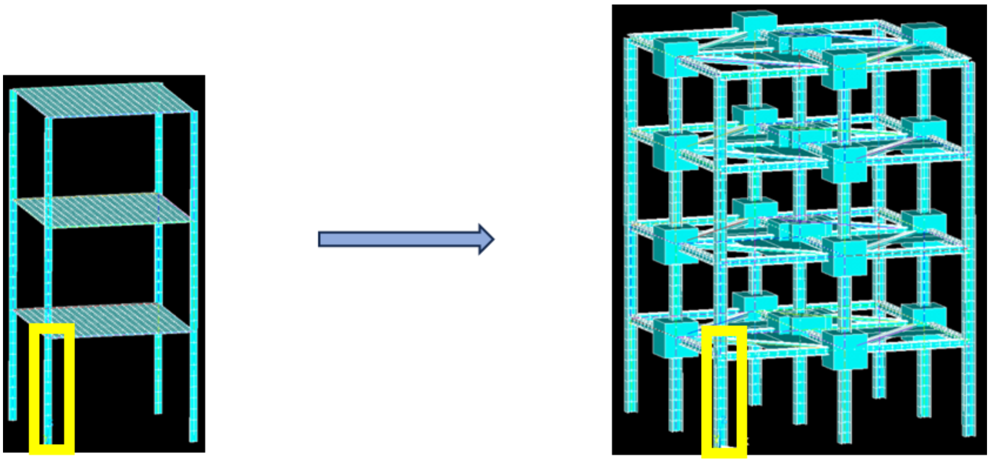


Figure 29: TL analysis: II.A.

II.B. Source and target structures (configuration II) multiclass damage detection for case B.

Unbraced structures configuration related to the damage case B (Figure 30):

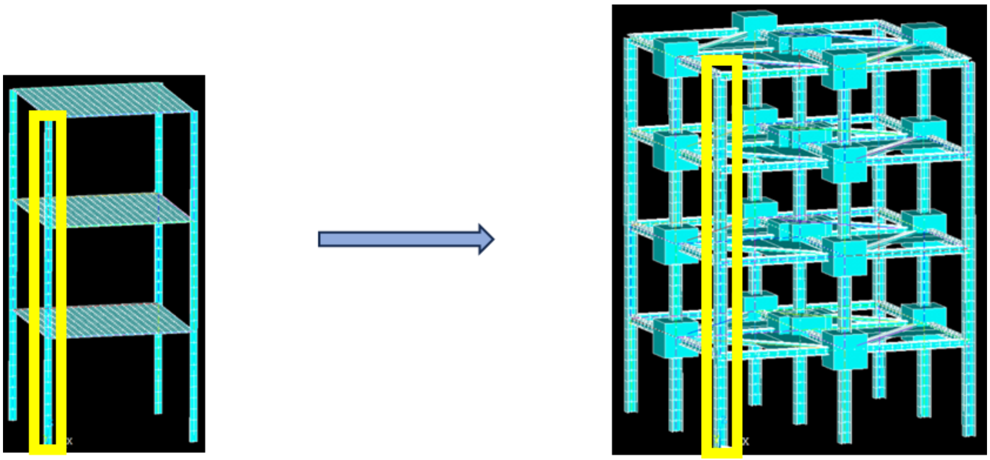


Figure 30: TL analysis: II.B.

II.C. Source and target structures (configuration II) multiclass damage detection for case C.

This analysis is analogue to the I.C., but related to the unbraced configuration II (Figure 31):

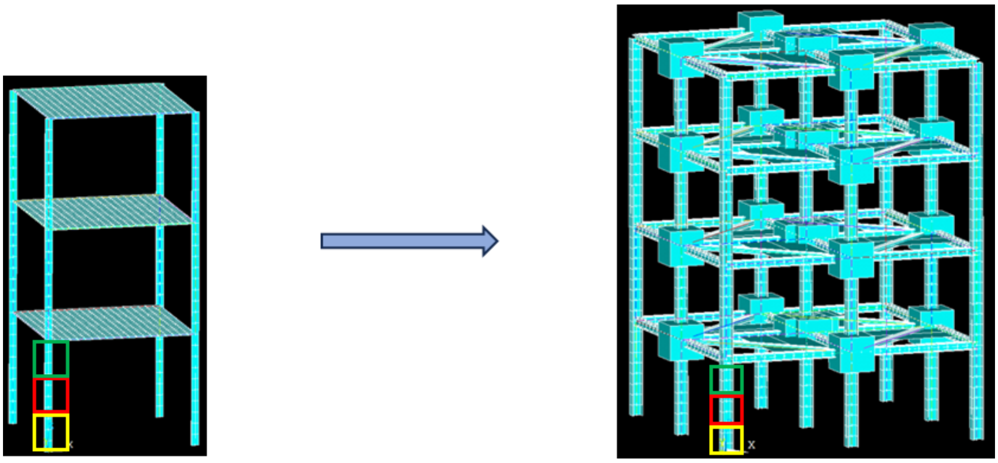


Figure 31: TL analysis: II.C.

II.D. Source and target structures (configuration II) multiclass damage detection for case D.

This analysis is analogue to the I.D., but related to the unbraced configuration II (Figure 32):

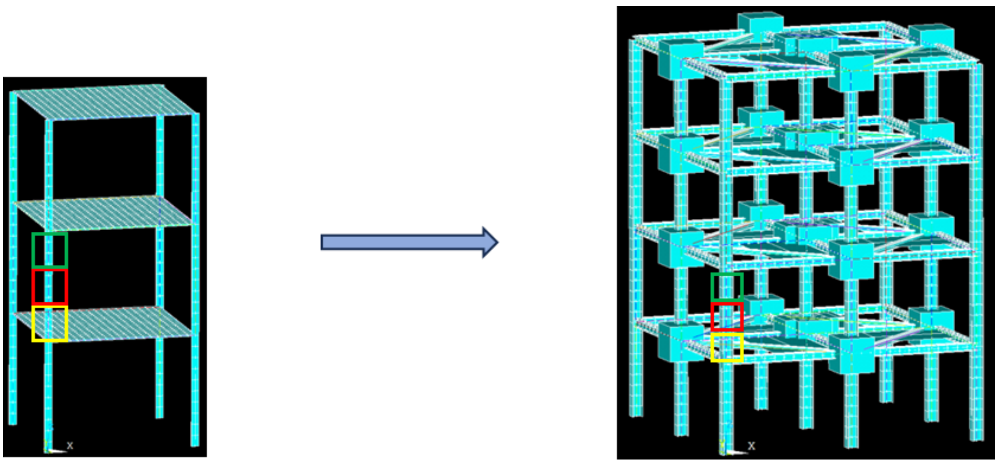


Figure 32: TL analysis: II.D.

II.E. Source and target structures (configuration II) multiclass damage detection for case E.

This analysis is analogue to the I.E., but related to the unbraced configuration II (Figure 33):

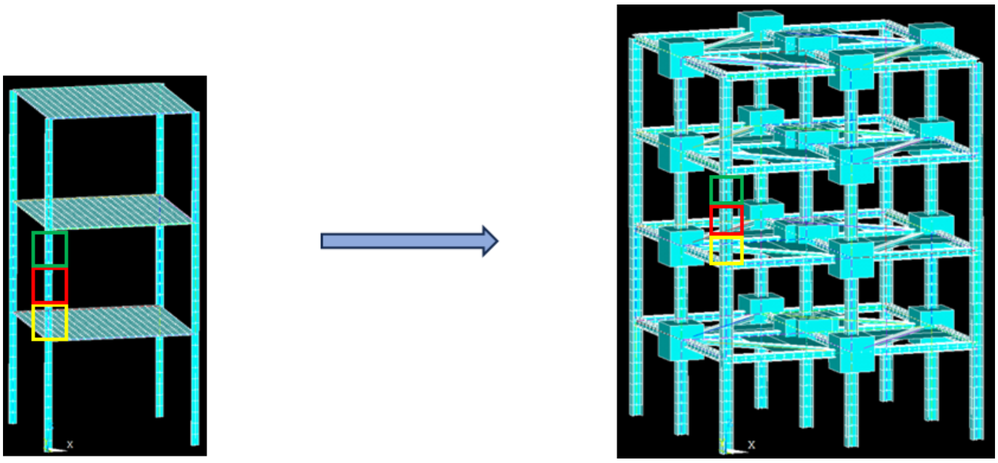


Figure 33: TL analysis: II.E.

II.F. Source and target structures (configuration II) multiclass damage detection for case F.

This analysis is analogue to the I.E., but related to the unbraced configuration II (Figure 34):

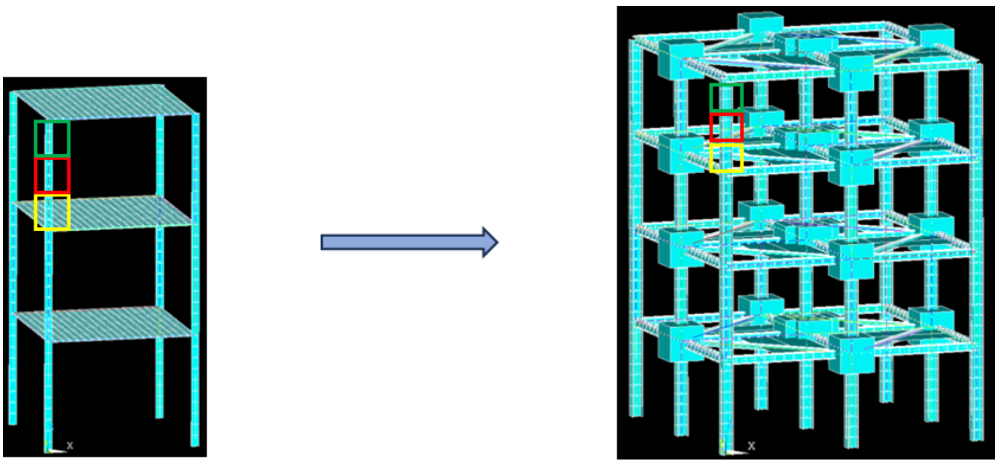


Figure 34: TL analysis: II.F.

III. Localized damage in the Laboratory's Frame

Here, two configurations of the Laboratory's frame are taken into account for a TL analysis regarding two different induced damages: in the source system (configuration II) a damage has been applied by varying the Young modulus of the material, while the damage on the target system (configuration I) has been considered through a thickness reduction on the middle third part of the bracing systems (Figure 35).

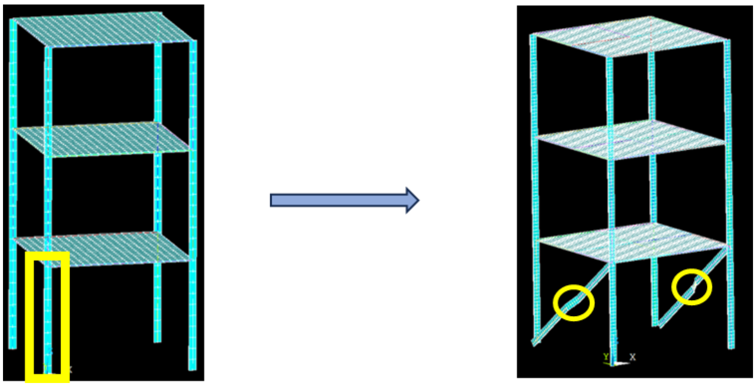


Figure 35: TL analysis: III.

IV. Multiclass damage localization for configuration I, case A., B., G.

In this analysis, the ability of the algorithm in localizing a damage in the target structure (Yellow Frame) is tested: a set of four different structural conditions (classes) are present in the classification problem. As it will be discussed in the next paragraphs regarding the training and test data that have been chosen in each case, here the total amount of data are the sum of the previous analyses (A., B., G.). This study will inform on the possibility of detecting different structural damages on a structure (Yellow frame) starting from datasets relating to another structure (Laboratory Frame) and represents one of the most complex problem that will be faced in this master thesis (Figure 36).

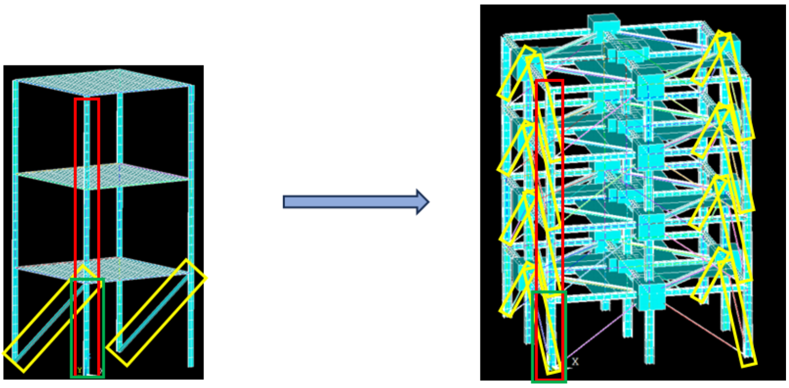


Figure 36: TL analysis: IV.

V. Multiclass damage localization for configuration I, case C., D., E., F.

A global damage detection problem has been performed in order to test the algorithm on its ability to discern different damages in the entire height of the column for configuration I (Figure 37):

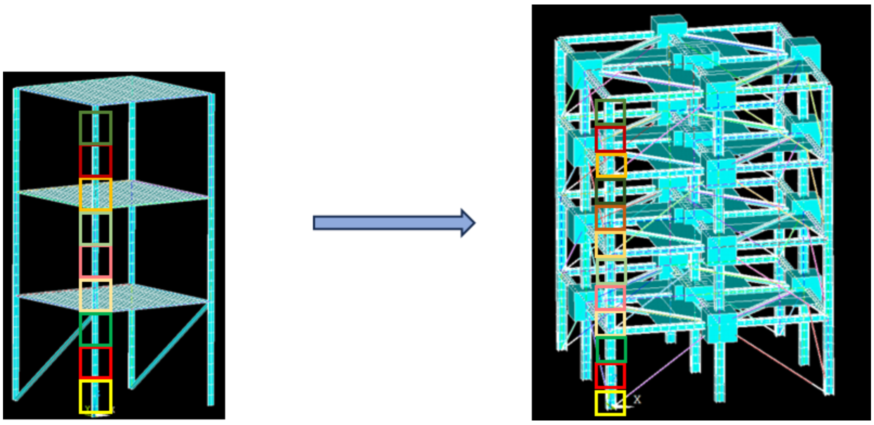


Figure 37: TL analysis: V.

VI. Multiclass damage localization for configuration II, case C., D., E., F.

An analogue global damage detection analysis to the previous one (V) has been conducted on configuration II (Figure 38):

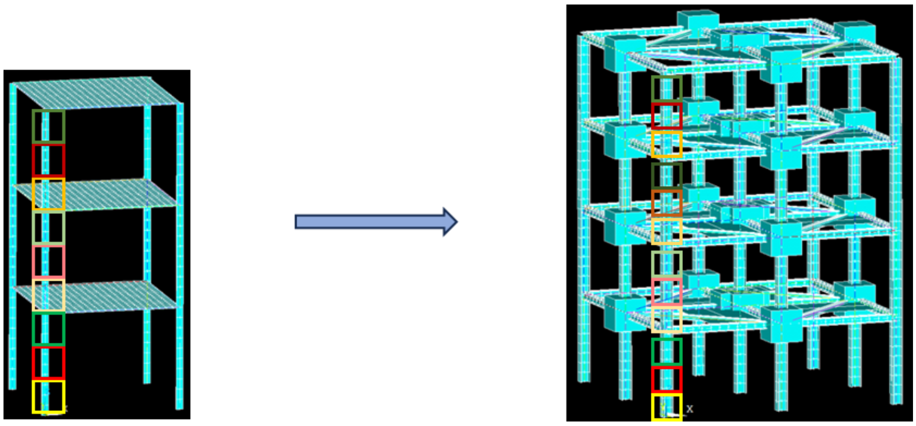


Figure 38: TL analysis: VI.

5.6 Classification

5.6.1 Original dataset

A KNN cross validated classifier (Guo et al., 2003) has been applied to the target structure (Yellow frame), before considering the domain adaptation technique. Additionally to the source data, a limited subset of labelled data provided by the target system has been used to maximize the classification accuracy.

5.6.2 Adapted domains

The TCA, belonging to the domain adaption techniques, was applied to the data of the target system selected for the analyses. For the transformation, a linear kernel was considered. Then, as previously said, a KNN cross validated classifier was used for the problem.

In the adaptation, the three natural frequencies components are transformed in a reduced number of transfer components m equal to 2, with a regularization parameter μ that varies according to the analysis (Table 10).

Analysis	**I.A.**	**I.B.**	**I.C.**	**I.D.**	**I.E.**	**I.F.**	**I.G.**
μ	1,00E+00	1,00E+01	1,00E-01	1,00E-10	1,00E-03	1,00E-06	1,00E-03

(a)

Analysis	**II.A.**	**II.B.**	**II.C.**	**II.D.**	**II.E.**	**II.F.**
μ	1,00E-03	1,00E+01	1,00E-03	1,00E-08	1,00E-02	1,00E-05

(b)

Analysis	**III.**	**IV.**	**V.**	**VI.**
μ	1,00E+10	1,00E-01	1,00E-03	1,00E-03

(c)

Table 10: Regularization parameter for the analyses: (a) Conf. I. (b) Conf. II. (c) Damage localization

5.7 Training and testing datasets

In the Machine Learning framework, a prevalent objective involves the investigation and development of algorithms able of learning from data and making predictions. The input data utilized for model creation are typically divided into distinct datasets. Notably, three primary datasets – training, validation and test sets – are typically employed at various stages in the model development process (paragraph 3.3.1).

A training dataset comprises data used during the learning phase, aiming to adjust parameters (i.e. weights) or, for instance as in this case, a classifier.

When it comes to classification tasks, a supervised learning algorithm examines the training dataset to ascertain or acquire the most effective combinations of variables that will yield an accurate predictive model. The objective is to generate a well-adapted model that is able to perform on new data. The model's performance is assessed using novel data from other datasets (such as validation and testing ones) to gauge the model's accuracy in classifying new data. To mitigate risks like over-fitting, it is crucial not to use data from the validation and testing dataset for the model training, and vice-versa.

To prevent overfitting, it is essential to include a validation dataset in addition to the training and testing datasets aiming at adjusting any classification parameter. Finally, the test dataset is used to assess performance metrics like accuracy, sensitivity, specificity, F-measure and so forth. The validation dataset serves a dual purpose, acting as training data for testing without being part of the initial training or final testing phases.

The test dataset refers instead to a collection of data that stands independently from the training dataset but follows the same probability distribution as the training dataset. If a model also fits the test dataset effectively, that means minimal overfitting. On the other hand, a superior fit to the training dataset compared to the test dataset typically suggests overfitting. Therefore, a test set involves a set of examples used uniquely to evaluate the performance of a classifier. To achieve this, the final model is used to predict classifications in the test set. These predictions are then compared with the true classifications (labels) to evaluate the model's accuracy. In a situation where the original dataset is divided into two subsets as in this case (training and test datasets), the test dataset might evaluate the model only once. Method like cross-validation can effectively employ two partitions, reducing bias and variability by averaging results over repeated rounds of model training and testing.

5.7.1 Information on the datasets exploited in the TL analyses

Through the Transfer Learning applications, it is important to describe accurately the data available both for the source and target systems, with a particular focus on the labelled data. As following, all the analyses will be described.

Analysis I.A.

ANALYSIS I.A.		
TL	**SOURCE (Lab structure)**	**TARGET (Yellow Frame)**
Dataset	570	81
% training	70%	70%
% testing	30%	30%

Table 11: TL application: datasets for analysis I.A.

Analysis I.B.

ANALYSIS I.B.		
TL	**SOURCE (Lab structure)**	**TARGET (Yellow Frame)**
Dataset	570	81
% training	70%	70%
% testing	30%	30%

Table 12: TL application: datasets for analysis I.B.

Analysis I.C.

ANALYSIS I.C.		
TL	**SOURCE (Lab structure)**	**TARGET (Yellow Frame)**
Dataset	1854	270
% training	65%	65%
% testing	35%	35%

Table 13: TL application: datasets for analysis I.C.

Analysis I.D.

ANALYSIS I.D.		
TL	**SOURCE (Lab structure)**	**TARGET (Yellow Frame)**
Dataset	1854	270
% training	65%	65%
% testing	35%	35%

Table 14: TL application: datasets for analysis I.D.

Analysis I.E.

ANALYSIS I.E.

TL	SOURCE (Lab structure)	TARGET (Yellow Frame)
Dataset	1854	270
% training	65%	65%
% testing	35%	35%

Table 15: TL application: datasets for analysis I.D.

Analysis I.F.

ANALYSIS I.F.

TL	SOURCE (Lab structure)	TARGET (Yellow Frame)
Dataset	1854	270
% training	65%	65%
% testing	35%	35%

Table 16: TL application: datasets for analysis I.F.

Analysis I.G.

ANALYSIS I.G.

TL	SOURCE (Lab structure)	TARGET (Yellow Frame)
Dataset	570	81
% training	70%	70%
% testing	30%	30%

Table 17: TL application: datasets for analysis I.G.

Analysis II.A.

ANALYSIS II.A.

TL	SOURCE (Lab structure)	TARGET (Yellow Frame)
Dataset	570	81
% training	70%	70%
% testing	30%	30%

Table 18: TL application: datasets for analysis II.A.

Analysis II.B.

ANALYSIS II.B.

TL	SOURCE (Lab structure)	TARGET (Yellow Frame)
Dataset	570	81
% training	70%	70%
% testing	30%	30%

Table 19: TL application: datasets for analysis II.B.

Analysis II.C.

ANALYSIS II.C.

TL	SOURCE (Lab structure)	TARGET (Yellow Frame)
Dataset	1854	270
% training	65%	65%
% testing	35%	35%

Table 20: TL application: datasets for analysis II.C.

Analysis II.D.

ANALYSIS II.D.

TL	SOURCE (Lab structure)	TARGET (Yellow Frame)
Dataset	1854	270
% training	65%	65%
% testing	35%	35%

Table 21: TL application: datasets for analysis II.D.

Analysis II.E.

ANALYSIS II.E.

TL	SOURCE (Lab structure)	TARGET (Yellow Frame)
Dataset	1854	270
% training	65%	65%
% testing	35%	35%

Table 22: TL application: datasets for analysis II.E.

Analysis II.F.

ANALYSIS II.F.		
TL	**SOURCE (Lab structure)**	**TARGET (Yellow Frame)**
Dataset	1854	270
% training	65%	65%
% testing	35%	35%

Table 23: TL application: datasets for analysis II.F.

Analysis III.

ANALYSIS III.		
TL	**SOURCE (Lab structure (conf. II))**	**TARGET (Lab structure (conf. I))**
Dataset	570	114
% training	70%	70%
% testing	30%	30%

Table 24: TL application: datasets for analysis III.

Analysis IV.

ANALYSIS IV.		
TL	**SOURCE (Lab structure)**	**TARGET (Yellow Frame)**
Dataset	1200	120
% training	80%	80%
% testing	20%	20%

Table 25: TL application: datasets for analysis IV.

Analysis V.

ANALYSIS V.		
TL	**SOURCE (Lab structure)**	**TARGET (Yellow Frame)**
Dataset	6708	984
% training	70%	70%
% testing	30%	30%

Table 26: TL application: dataset for analysis V.

Analysis VI.

ANALYSIS VI.

TL	SOURCE (Lab structure)	TARGET (Yellow Frame)
Dataset	6708	984
% training	70%	70%
% testing	30%	30%

Table 27: TL application: dataset for analysis VI.

Within these datasets, the algorithm will be able to conduct a classification problem after a component reduction from three to two (transfer components) in order to obtain a bidimensional nature of the features to be classified. In the following paragraph, a detail on the natural frequencies pattern in the original domains will be reported, with a focus on the unavoidable distance between the source and target original input data.

5.8 Natural frequencies pattern on the original domains.

In order to study the application of Transfer Learning methods, the feature datasets of the different structures are investigated in order to recognize some differences or, if there are present, some similarities. In this case study, the first flexural modes in y and x directions, together with the first torsional one, are the main features analyzed: in particular, the natural frequencies associated to those are computed applying a progressive damage to the structures (Paragraph 5.4).

Hereinafter, a comparison between the natural frequencies datasets (input data) of the source and target systems is reported, with a particular attention on the distances in terms of dynamic properties of the two structures.

A gaussian noise has been applied to all the natural frequencies vectors:

$$f_{n,i,noise} = f_{n,i} + errper * std\big(f_{n,i} * random(length(f_{n,i})\big)$$

Where:

$f_{n,i}$ represents the natural frequencies variation vector of the i-th mode shape [Hz];

$errper = 5\%$ is the error introduced randomly into the natural frequency vector.

Analysis I.A.

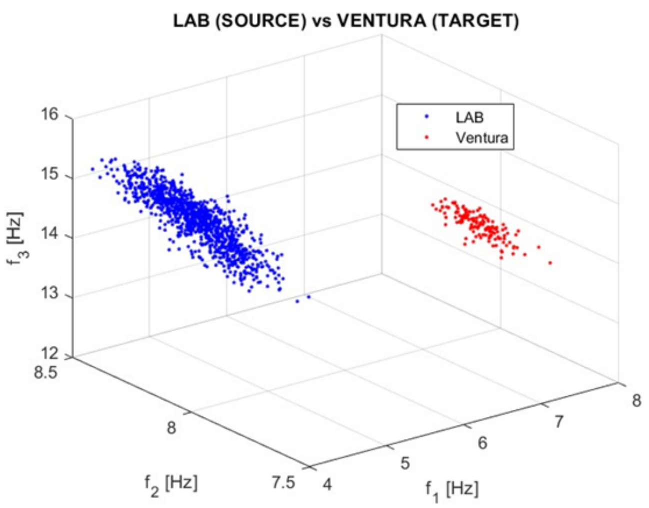


Figure 39: Natural frequencies 3D plot: analysis I.A.

Analysis I.B.

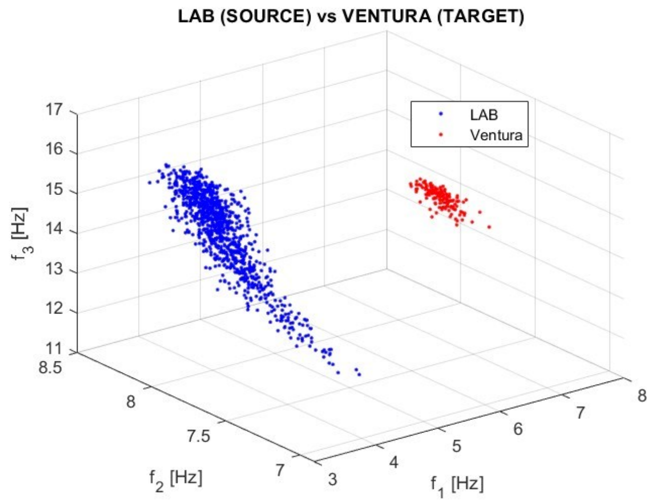


Figure 40: Natural frequencies 3D plot: analysis I.B.

Analysis I.C.

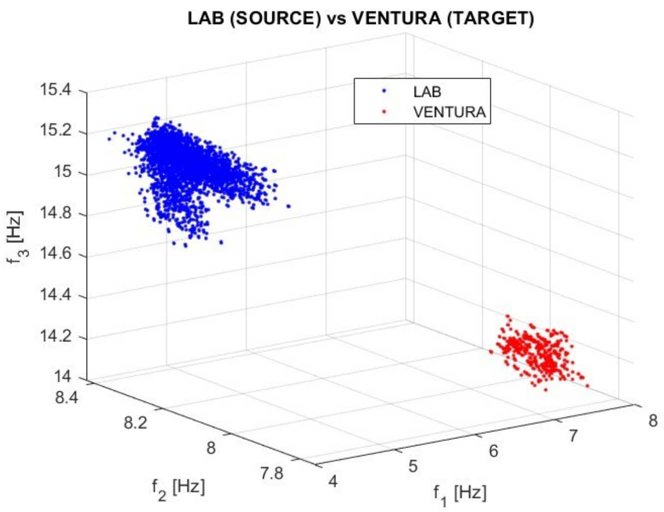


Figure 41: Natural frequencies 3D plot: analysis I.C.

Analysis I.D.

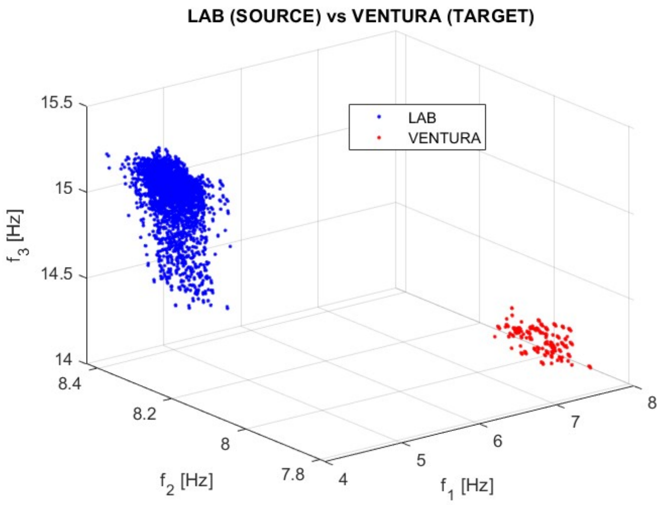


Figure 42: Natural frequencies 3D plot: analysis I.D.

Analysis I.E.

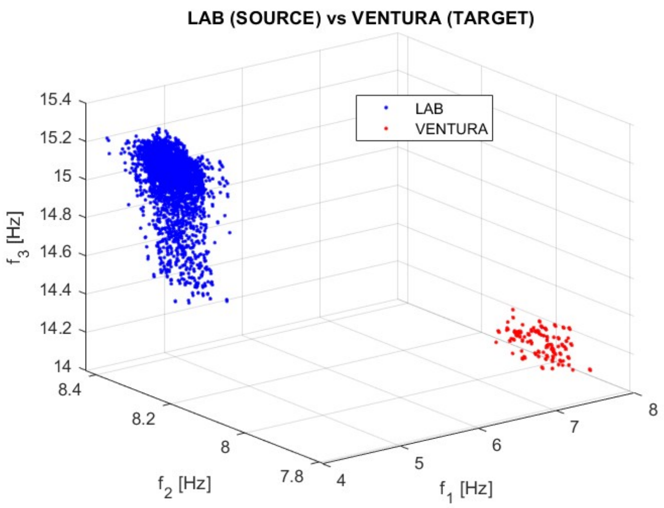


Figure 43: Natural frequencies 3D plot: analysis I.E.

Analysis I.F.

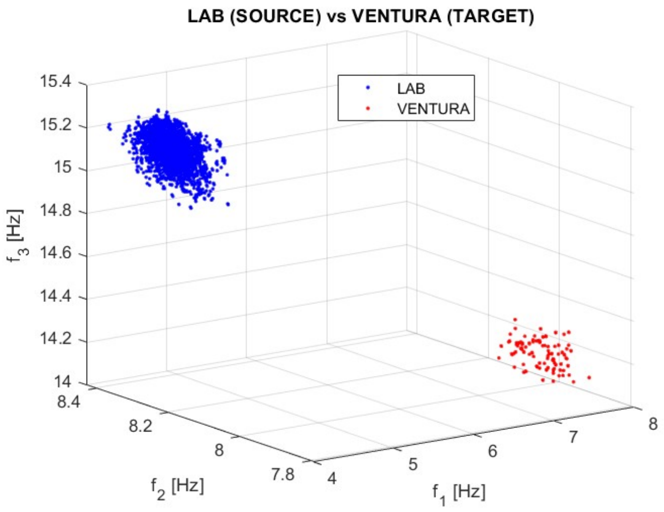


Figure 44: Natural frequencies 3D plot: analysis I.F.

Analysis I.G.

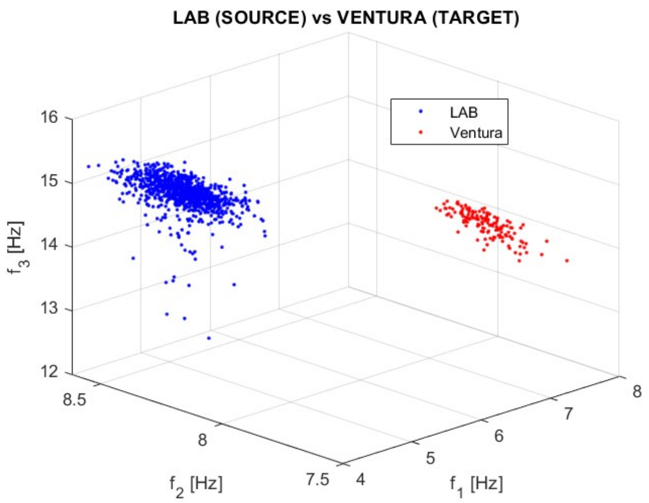


Figure 45: Natural frequencies 3D plot: analysis I.G.

Analysis II.A.

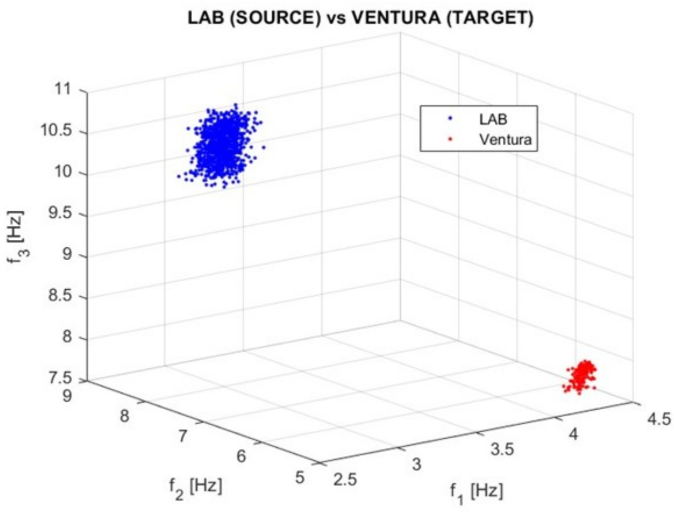


Figure 46: Natural frequencies 3D plot: analysis II.A.

Analysis II.B.

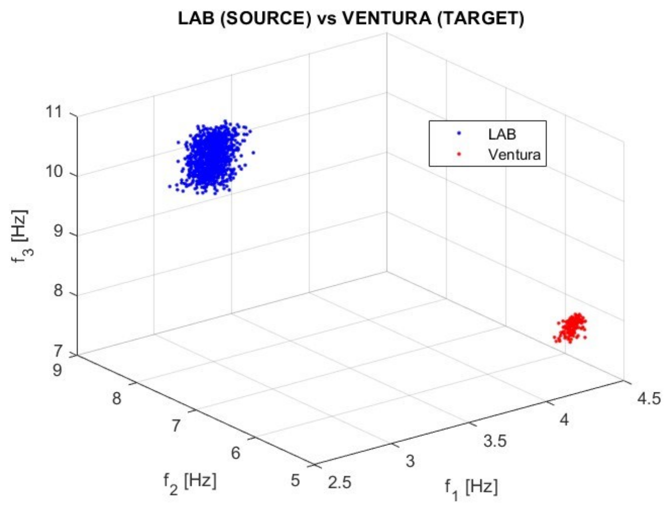


Figure 47: Natural frequencies 3D plot: analysis II.B.

Analysis II.C.

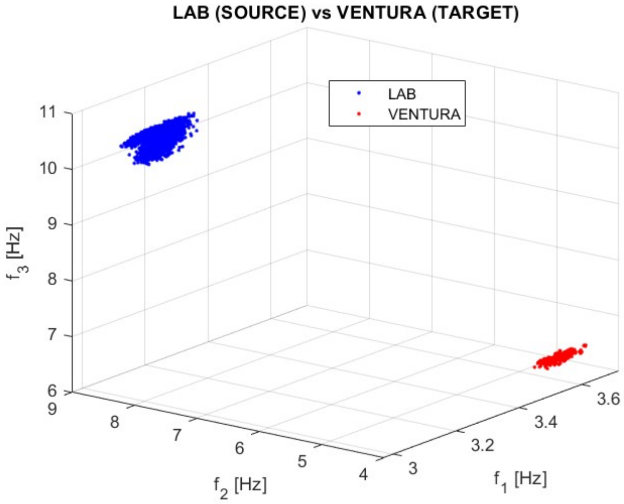


Figure 48: Natural frequencies 3D plot: analysis II.C.

Analysis II.D.

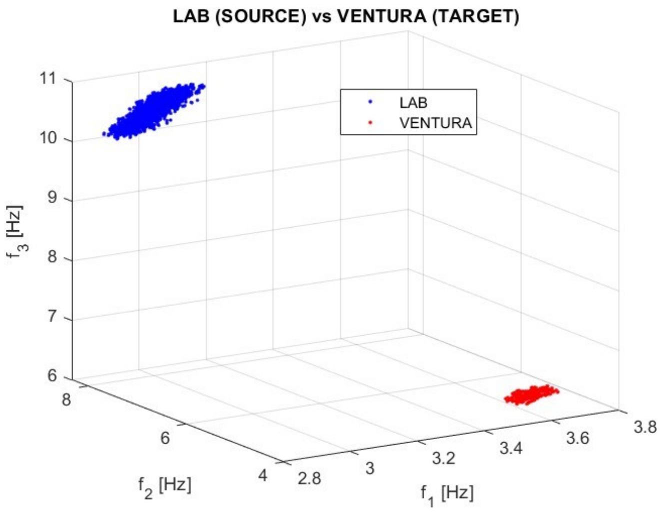


Figure 49: Natural frequencies 3D plot: analysis II.D.

Analysis II.E.

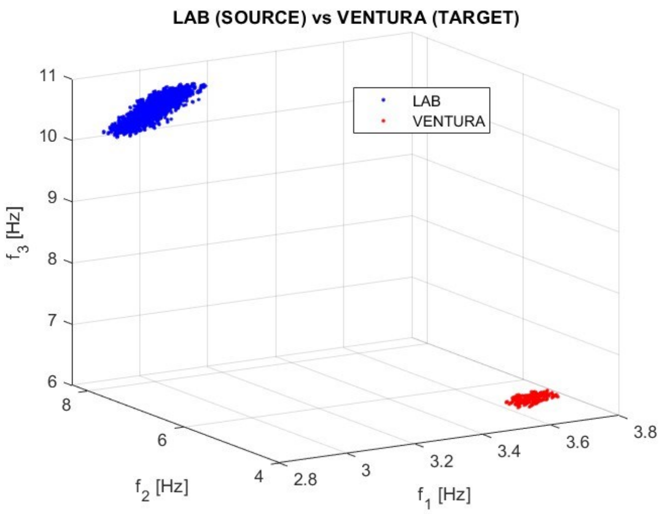


Figure 50: Natural frequencies 3D plot: analysis II.E.

Analysis II.F.

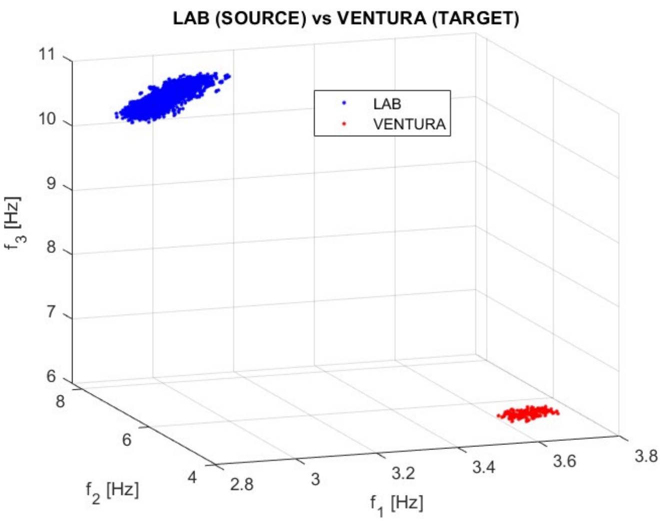


Figure 51: Natural frequencies 3D plot: analysis II.F.

Analysis III.

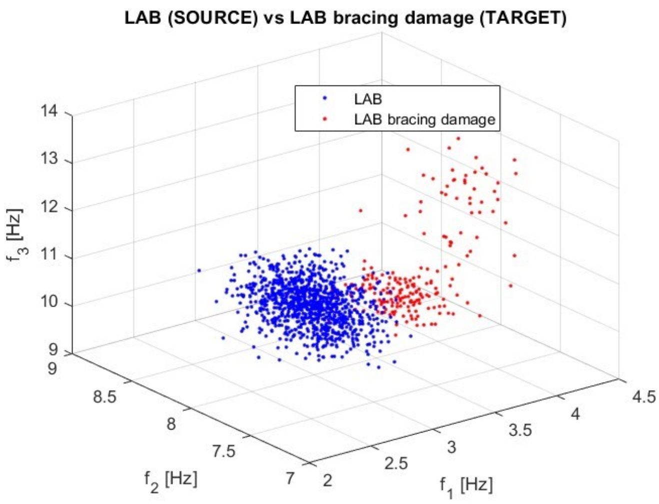


Figure 52: Natural frequencies 3D plot: analysis III.

Analysis IV.

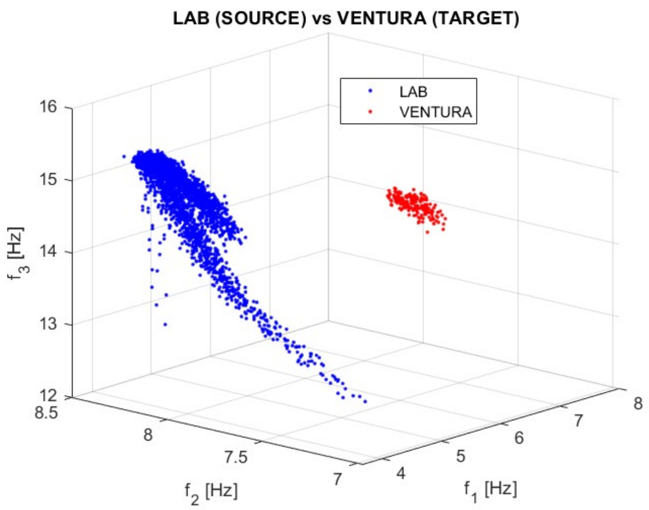


Figure 53: Natural frequencies 3D plot: analysis IV.

Analysis V.

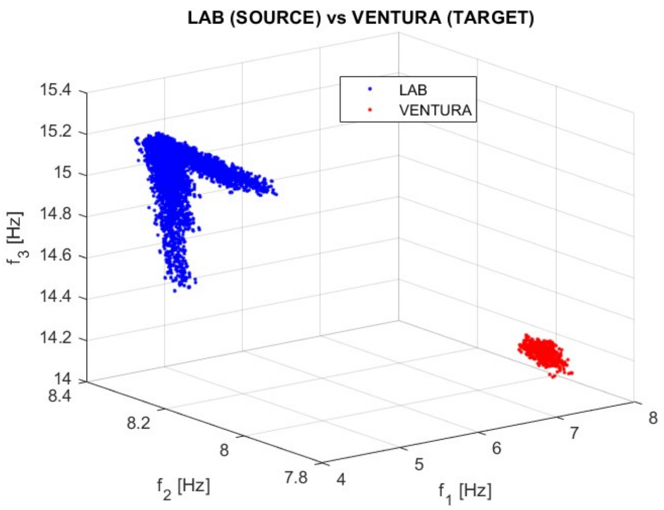


Figure 54: Natural frequencies 3D plot: analysis V.

Analysis VI.

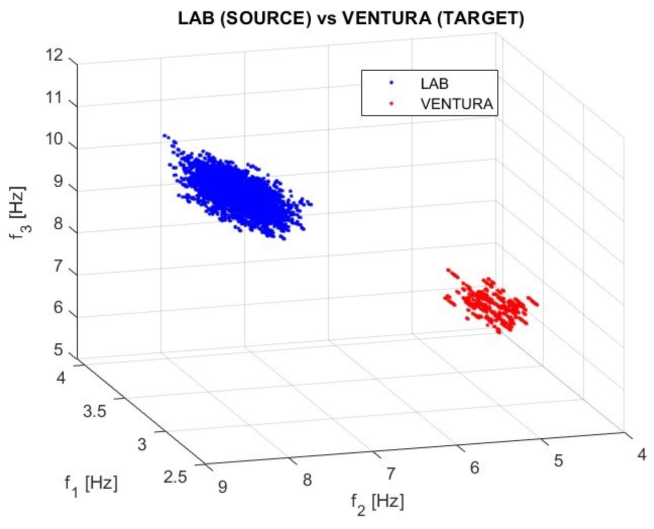


Figure 55: Natural frequencies 3D plot: analysis VI.

As it is clear from Figure 39 - Figure 55, the source and target structures have a completely different behavior: their natural frequencies associated to an undamaged state (Table 4, Table 5, Table 8, Table 9) have no common values neither in their flexural modes (y or x) nor in the torsional one. This is not an optimum scenario in order to reproduce a good Transfer Learning application because, as we will partly confirm in Chapter 6, the domain adaptation will suffer a lot the different trends of each natural frequencies to individuate a clear damage state for both the structures. In particular, the differences between the undamaged triplets of natural frequencies and the ones corresponding to a damage state are even larger, as we could expect, when the damage is applied to an entire main element (Figure 53). Instead, when only a portion is damaged, it is even more difficult to diagnose an actual structural “illness” due to the similarity between these natural frequencies triplets.

Chapter 6

Analysis of the results

In this Chapter, the results of the previous stated analyses are reported. A double distinction could be performed in order to understand two different aims in these studies. In the first paragraph, all the results related to a simple damage detection are stated: the algorithm in these analyses is focused on determining whether or not a condition could be classified “damaged” or “undamaged”.

In paragraph 6.2, instead, all the analyses focused on a classification problems related to more than two classes are described: having more classes associated to different induced damages in the structures, will allow the algorithm to “identify” the damage, thus conducting a localization process.

6.1 Damage detection

A binary classification is described in this paragraph, taking into account all the analyses having a single damage induced. Both the configurations (I. and II.) have been affected by the same main element damage, with exception of analysis

I.G., in which only the bracing systems are damaged. Once applied the Transfer Learning procedure by means of the TCA algorithm, a common bi-dimensional domain is obtained: the classifier, which is trained by the target data and the source data in this adapted space, will be able to conduct a binary classification problem, with a focus on the accuracies on the testing data objective of this case study: the target domain testing dataset.

6.1.1 Adapted domains

To classify the damage condition, two different plots are shown both for the training and testing sets: the training set accuracy can be compared to the testing set accuracy in order to determine if overtraining is reached. In the following sub-paragraphs the (i) training and testing data classification in the adapted domain, (ii) accuracies between the different analyses and (iii) target domain testing data accuracy comparisons between the classifier trained before and after being applied TL procedure are described.

6.1.1.2 Training and testing data classification

In the TL adapted domains, both data coming from the source and target systems are used to train the classifier. The lack of data in the target structure is, in this way, apparently solved. The index useful to measure these improvements is represented by the accuracy index, which is the ratio between the prediction corresponding to the actual response on the total number of the predictions carried out. The following plots describe all the features used to train the algorithm, the cross elements are the testing data on which the accuracy can be computed by a direct comparison with the circled points, which represent the predictions of the algorithm.

Every analysis corresponding to a binary classification (“damaged”, “undamaged”) is reported in the following:

Analysis I.A.

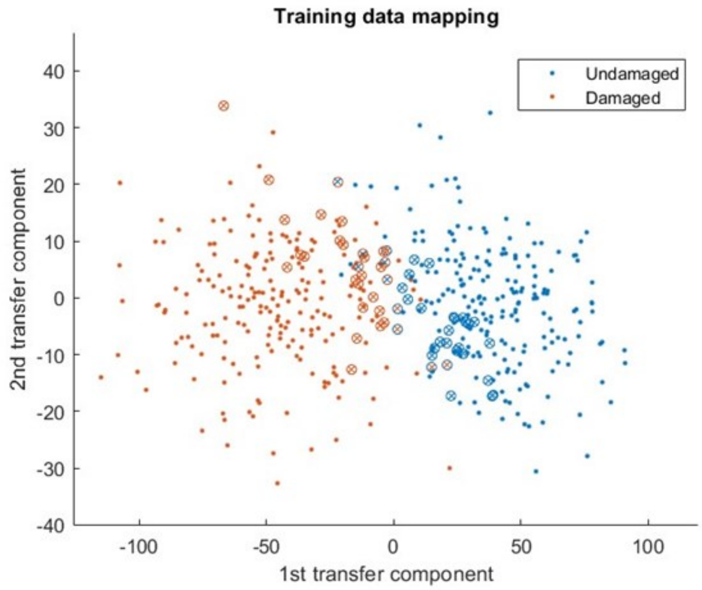


Figure 56: Training data mapping for analysis I.A.

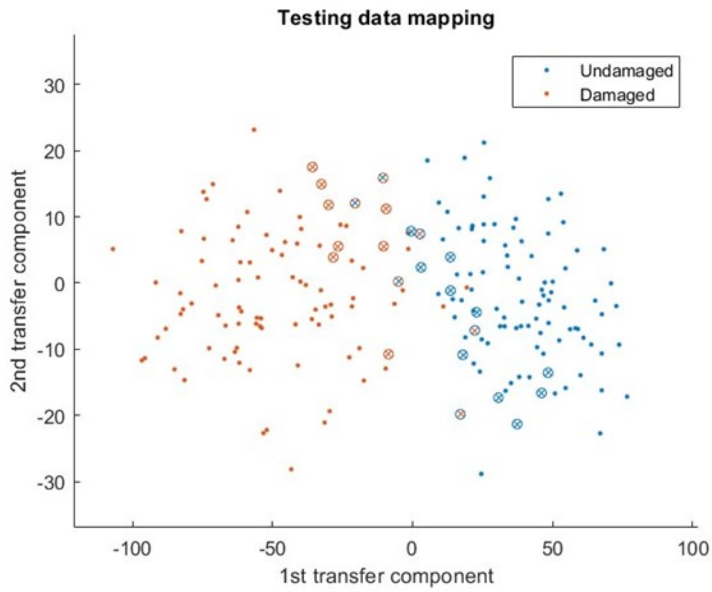


Figure 57: Testing data mapping for analysis I.A.

Analysis I.B.

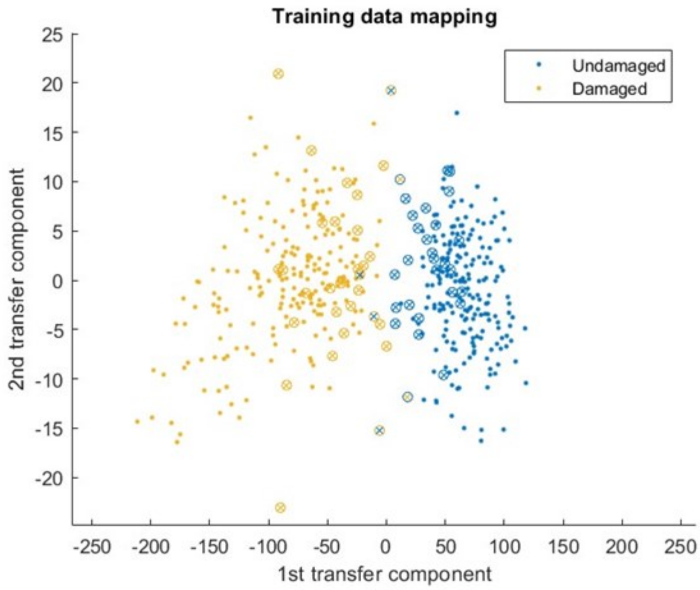


Figure 58: Training data mapping for analysis I.B.

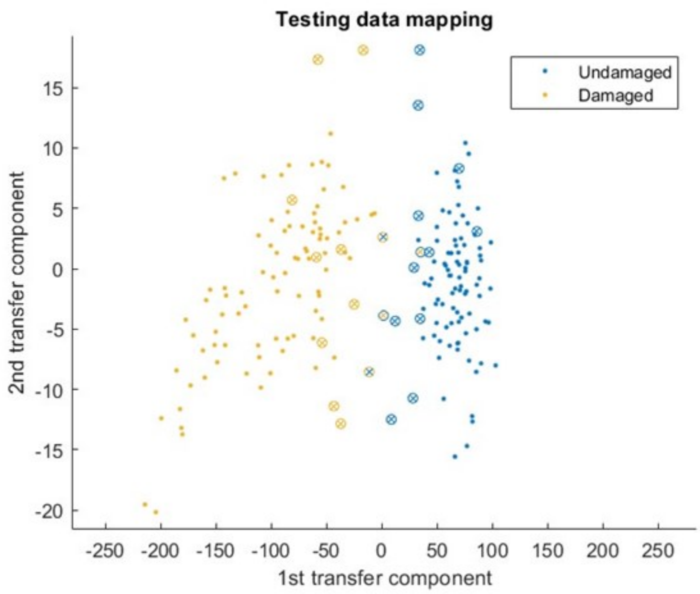


Figure 59: Testing data mapping for analysis I.B.

Analysis I.G.

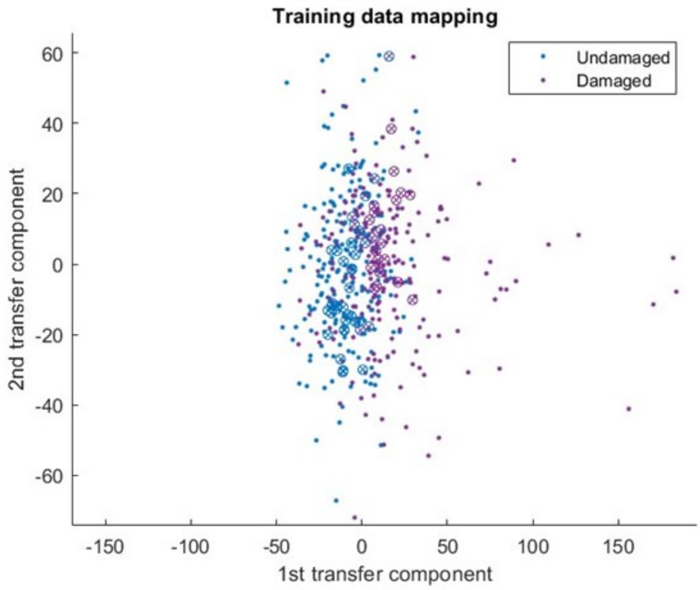


Figure 60: Training data mapping for analysis I.G.

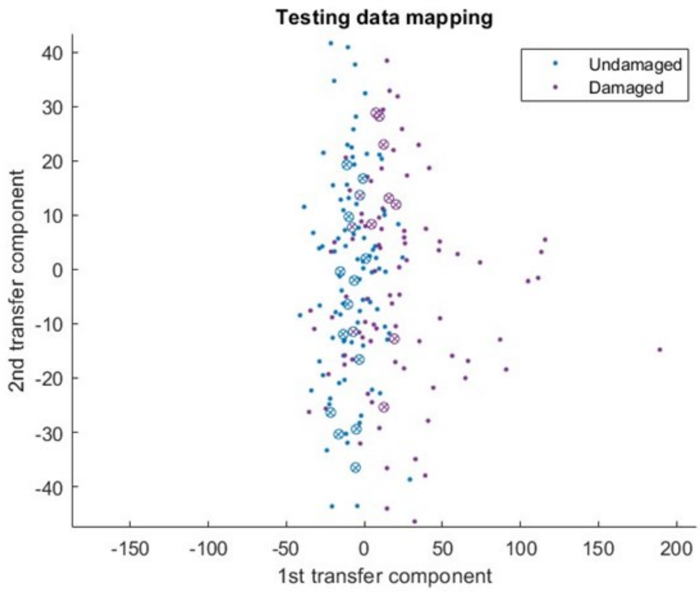


Figure 61: Testing data mapping for analysis I.G.

Analysis II.A.

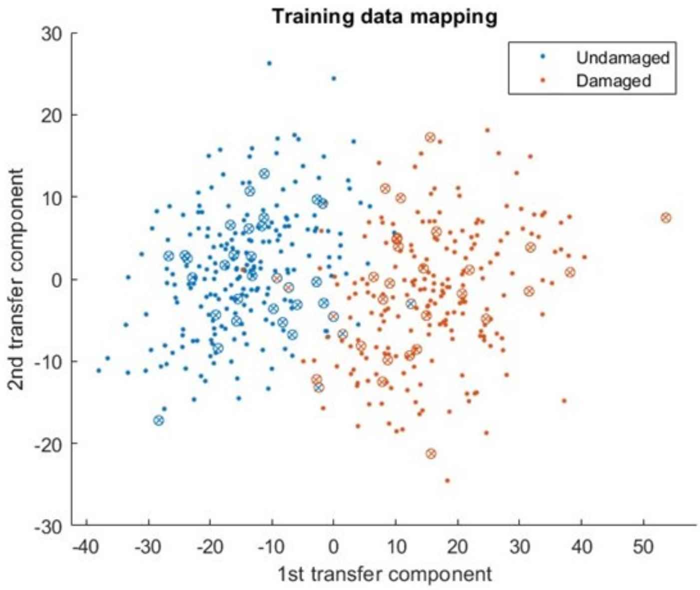


Figure 62: Training data mapping for analysis II.A.

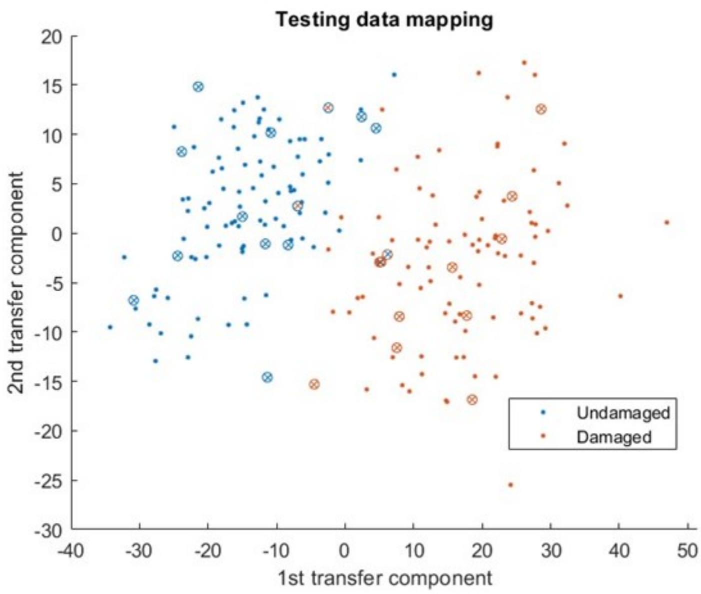


Figure 63: Testing data mapping for analysis II.A.

Analysis II.B.

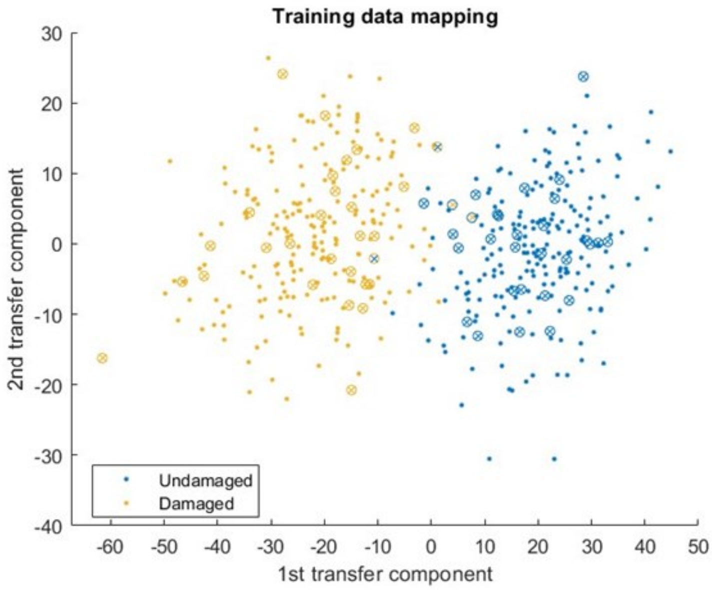


Figure 64: Training data mapping for analysis II.B.

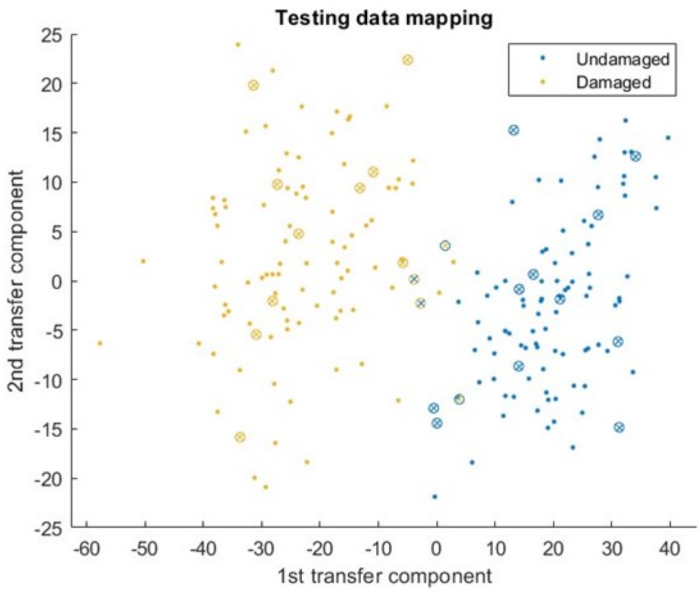


Figure 65: Testing data mapping for analysis II.B.

Analysis III.

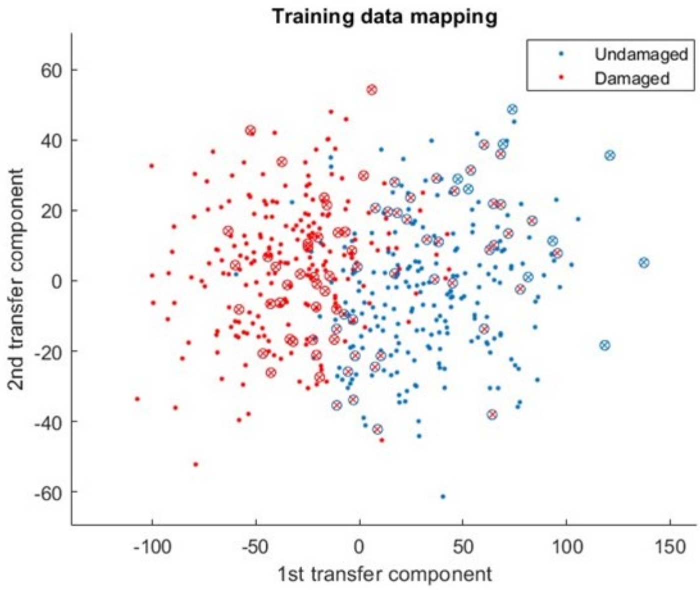


Figure 66: Training data mapping for analysis III.

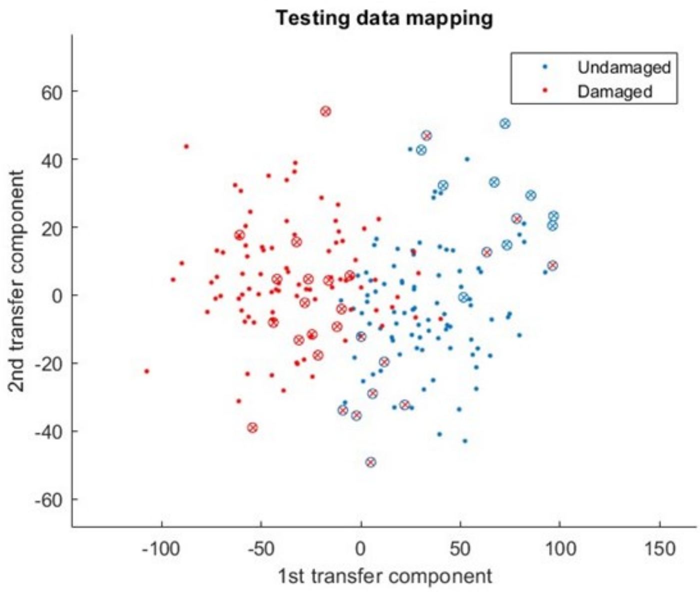
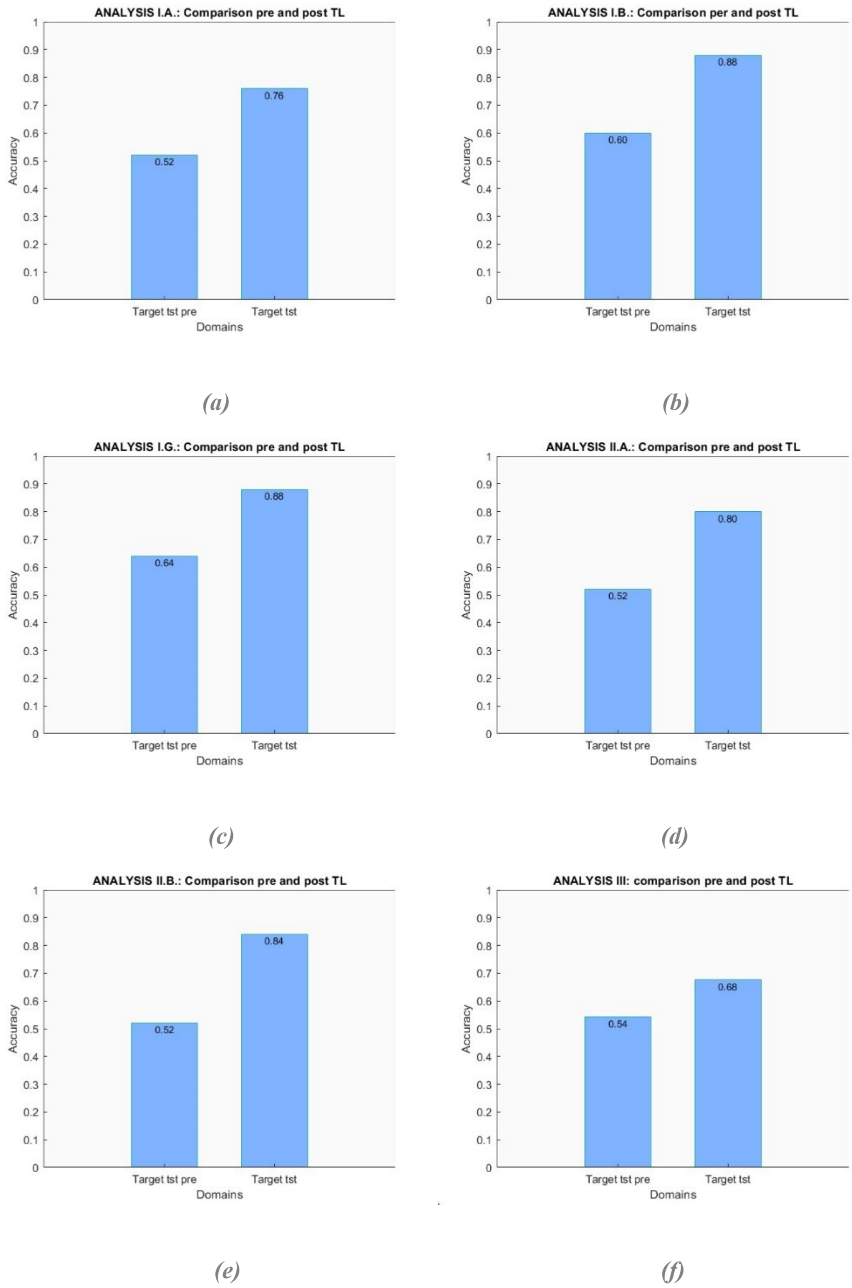


Figure 67: Testing data mapping for analysis III.

6.1.2 Accuracy comparison



(a) *(b)* *(c)* *(d)* *(e)* *(f)*

Figure 68: Accuracy comparison for the different analysis (a-f)

Accuracy	I.A.	I.B.	I.G.	II.A.	II.B.	III.
Pre Transfer Learning	52%	60%	64%	52%	52%	54%
Post Transfer Learning	76%	88%	88%	80%	84%	68%

Table 28: Accuracy comparison in analyses I.A., I.B., I.G., II.A., II.B., III.

Here is a summary of the accuracy improvements after transfer learning for each scenario:

- I.A.: 24% increase (from 52% to 76%);
- I.B.: 28% increase (from 60% to 88%);
- I.G.: 24% increase (from 64% to 88%);
- II.A.: 28% increase (from 52% to 80%);
- II.B.: 32% increase (from 52% to 84%);
- III: 14% increase (from 54% to 68%).

As it can be noticed, Transfer Learning constitutes for these case study an important technology in the damage detection in the two different structural configurations (I. and II.). Considering the unbraced version (II.A. and II.B.) of the source and target domains, it can be observed the highest improvements within all the analyses (+28%, +32%). Good performance in the classification can be found also for the braced configurations (I.A., I.B., and I.G.). Analysis III. presents a different scenario: it takes into account two similar structures (conf. I and conf. II of the Laboratory Frame), but they differ both in the bracing systems, present only in the target system and also in the type of damage induced. The source system damage has been applied by a reduction in the mechanical properties of the material constituting the column (Young modulus of the aluminum), while the target damage has been applied considering a pure geometrical variation of the thickness in the central part of the bracing system. It can be seen how in this analysis a good improvement by TL in the accuracy has been evaluated (+14%) but it is not the highest of these analyses. It can be concluded that the nature of the damage coming from the source system input data (natural frequencies variation) is really important, such as the geometrical and mechanical properties, for a good result in the transfer learning application about the algorithm classification process.

6.2 Multiclass Damage localization

All the analyses concerning the classification of more than one state of damage in the structure are reported in this paragraph. Having more than one damage allows the algorithm to associate a class to a damage, and doing like that, it is possible to identify where the damage is occurring. Transfer Learning techniques will be exploited in order to gain data from a source system and share them in an adapted domains containing the little datasets of the target structures. Having more than two classes, it is allowed to image the accuracy to be lower with respect to the simple damage detection shown in the previous paragraph.

6.2.1 Adapted domains

All the data coming from different structural damage conditions and their corresponding undamaged states are collected in order to be adapted, by means of the TCA algorithm in the TL framework, in a domain also containing the little target data, coming from different structural conditions. In particular, for analyses C. D. E. and F. four different classes are present: the undamaged conditions, and the bottom, middle and top end damage states of the corresponding column. For what concern analysis IV., V. and VI. a major distinction can be performed: analysis IV. corresponds to a four classes localization problem, three of them related to a damage applied on a main structural element (column up to the first storey, entire column height, y-oriented bracing systems) and their undamaged condition. Analyses V. and VI. take into account a damage localization problem in all the third portions of the column, comprehensive of cases C. D. E. and F.. Thirteen different classes can be determined for scenario V. (conf. I) and VI. (conf. II.): bottom, middle and top damages of the four portions from the ground to the top of the column, added to their undamaged condition. Hereinafter, the training and testing data classification plots are reported.

6.2.1.2 Training and testing data classification

Analysis I.C.

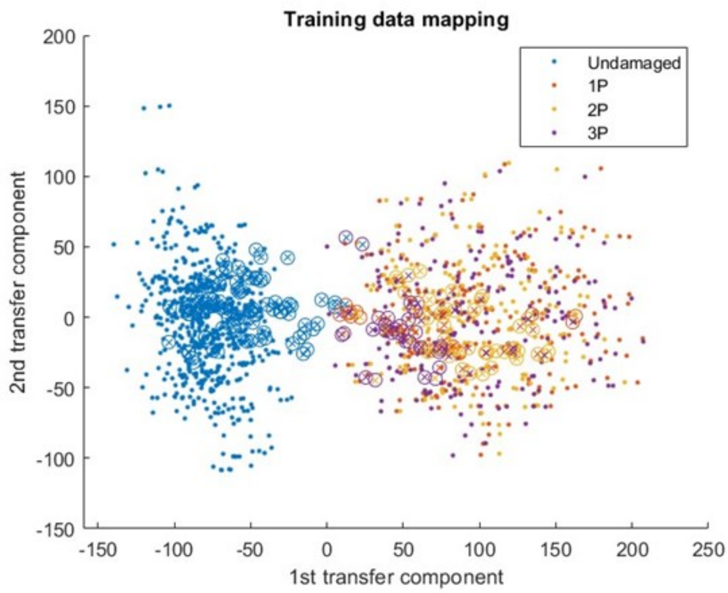


Figure 69: Training data mapping for analysis I.C.

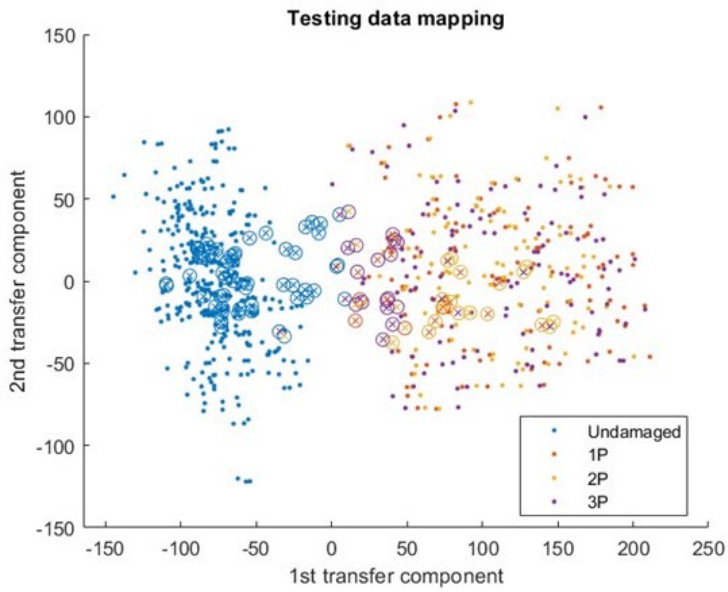


Figure 70: Testing data mapping for analysis I.C.

Analysis I.D.

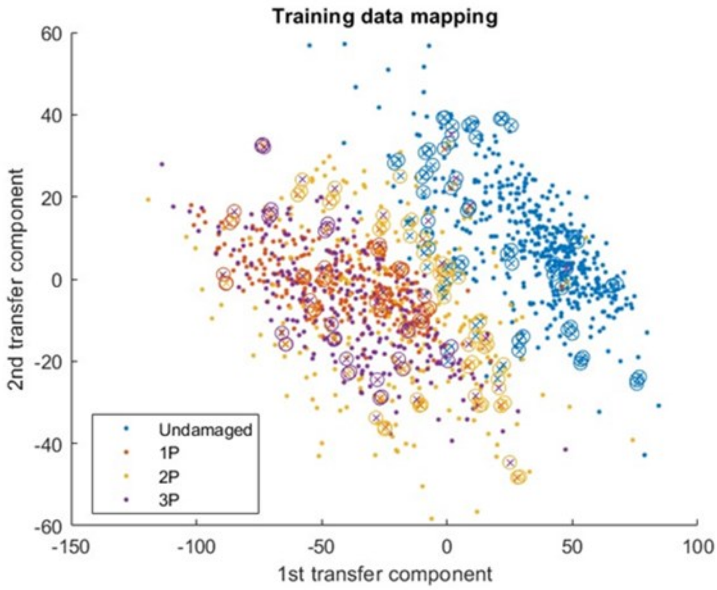


Figure 71: Training data mapping for analysis I.D.

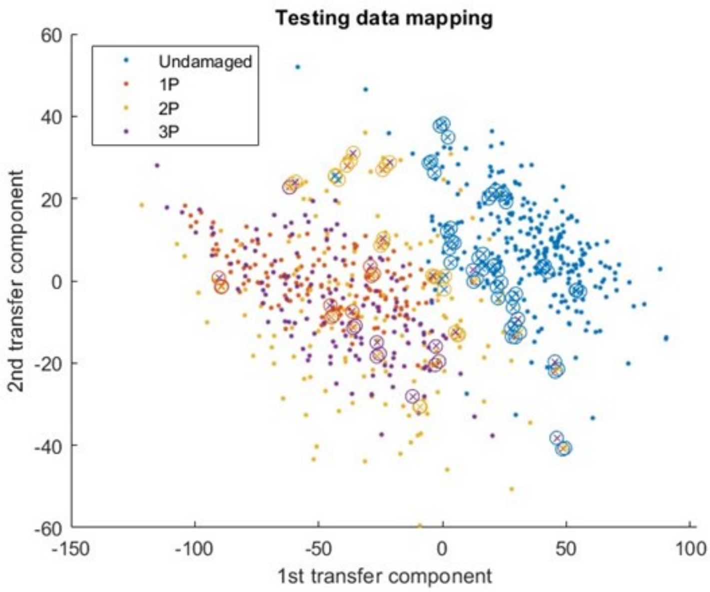


Figure 72: Testing data mapping for analysis I.D.

Analysis I.E.

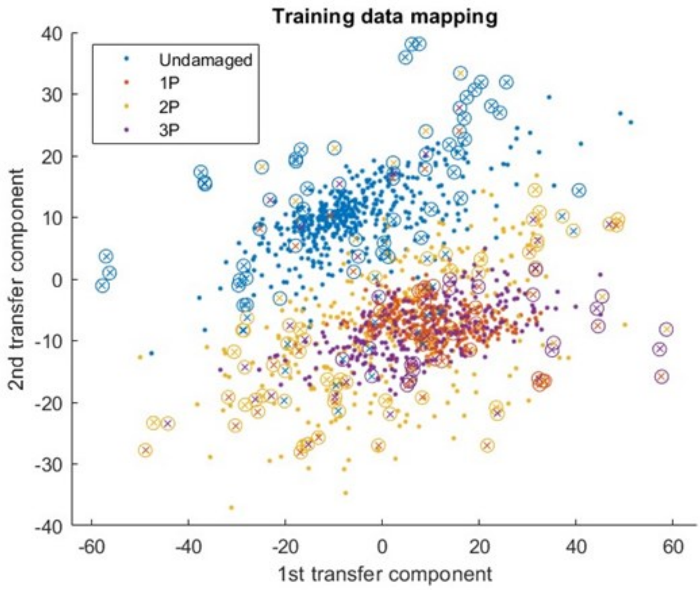


Figure 73: Training data mapping for analysis I.E.

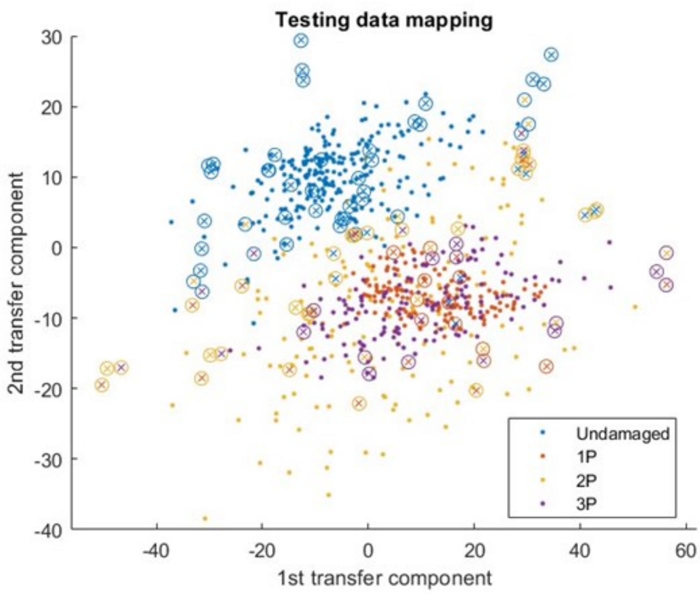


Figure 74: Testing data mapping for analysis I.E.

Analysis I.F.

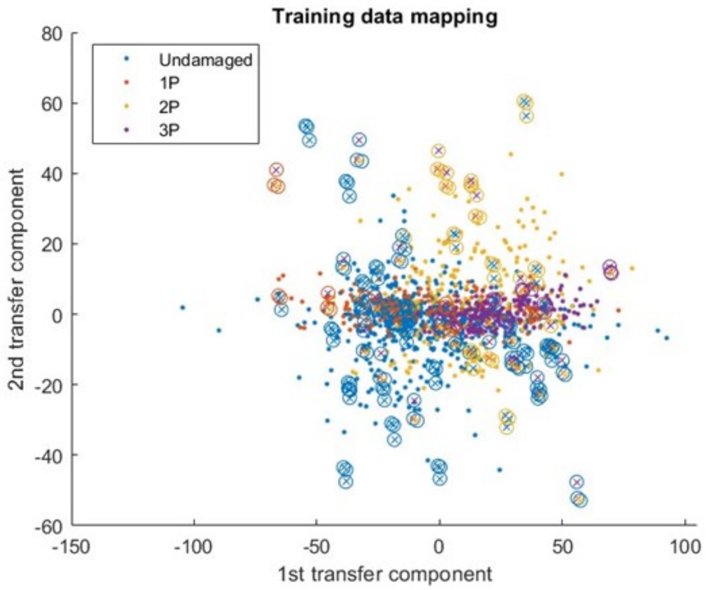


Figure 75: Training data mapping for analysis I.F.

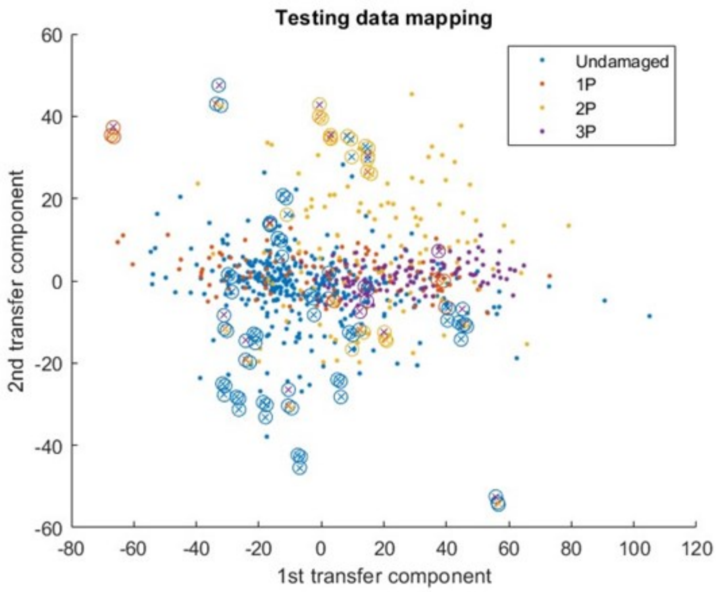


Figure 76: Testing data mapping for analysis I.F.

Analysis II.C.

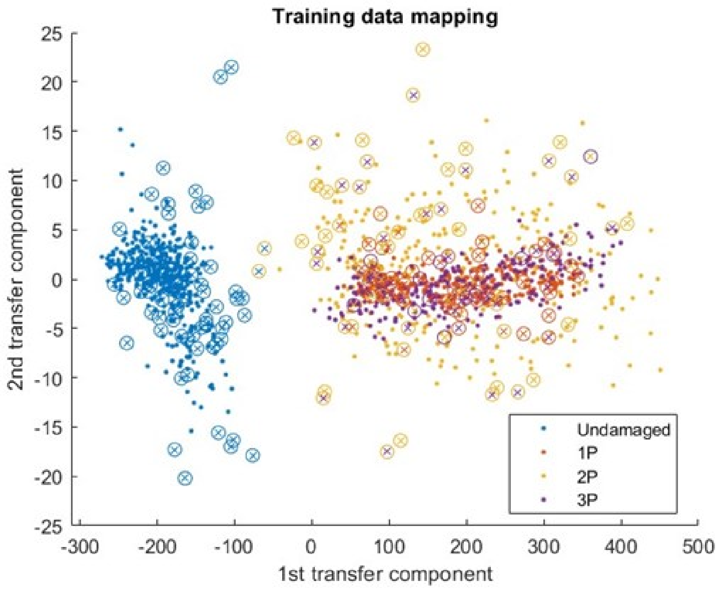


Figure 77: Training data mapping for analysis II.C.

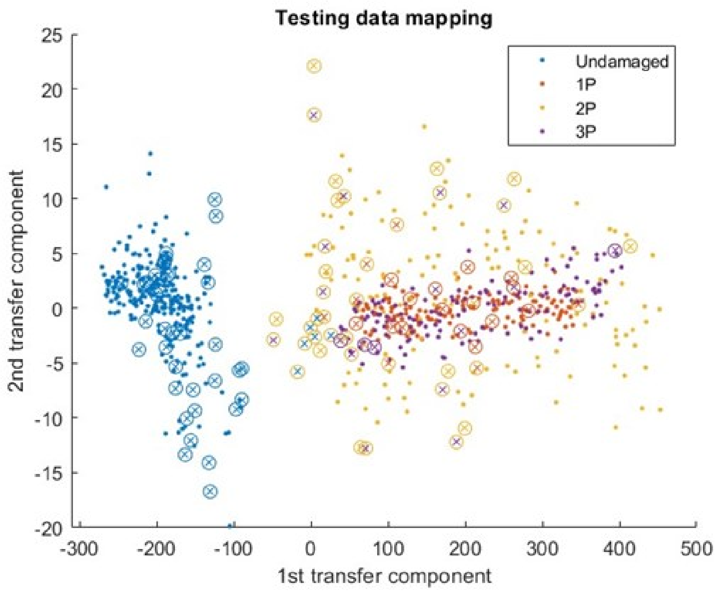


Figure 78: Testing data mapping for analysis II.C.

Analysis II.D.

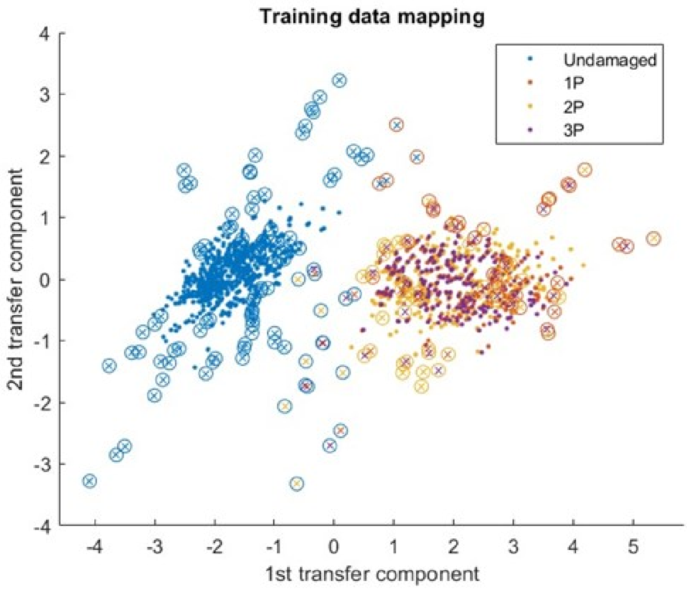


Figure 79: Training data mapping for analysis II.D.

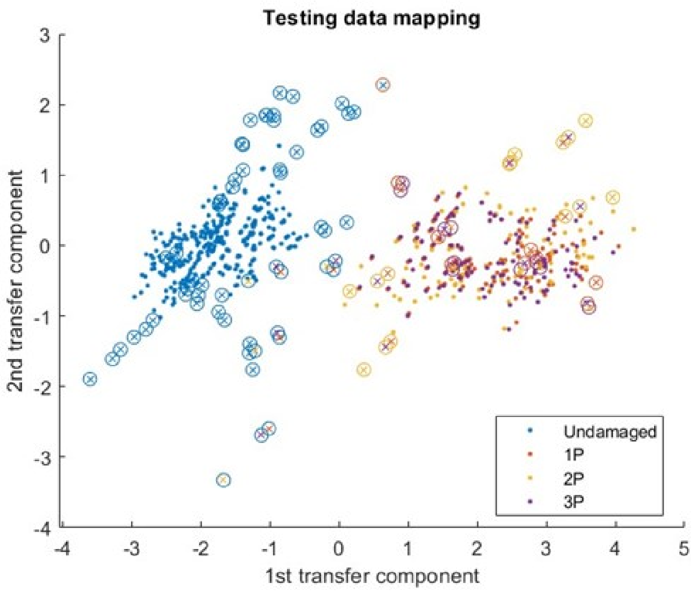


Figure 80: Testing data mapping for analysis II.D.

Analysis II.E.

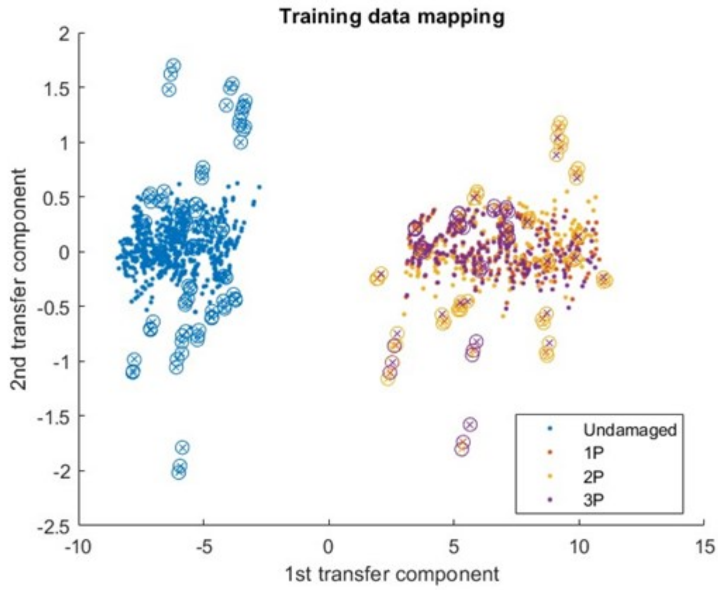


Figure 81: Training data mapping for analysis II.E.

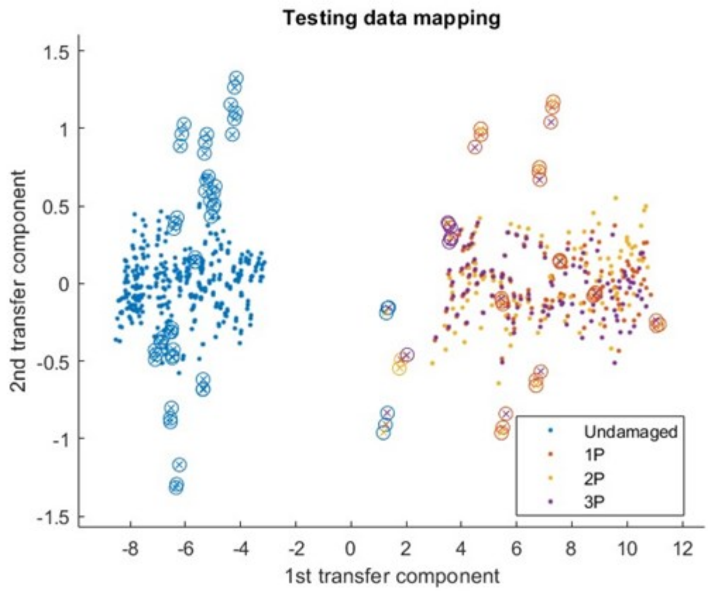


Figure 82: Testing data mapping for analysis II.E.

Analysis II.F.

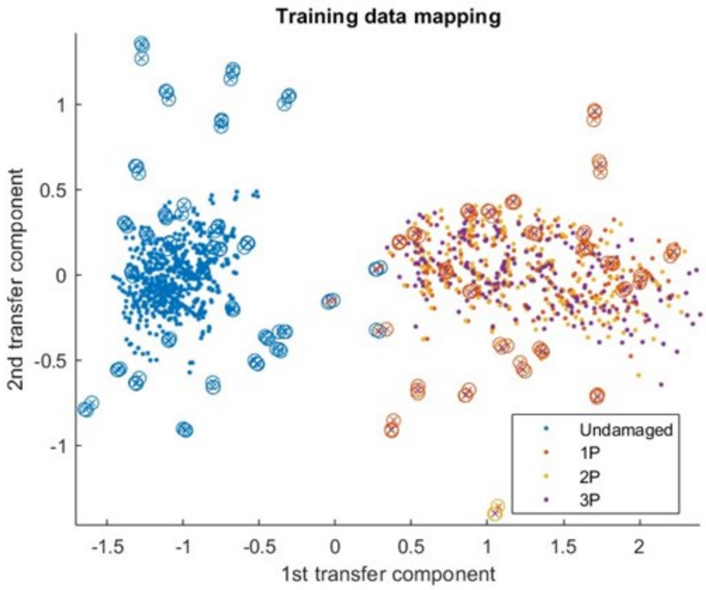


Figure 83: Training data mapping for analysis II.F.

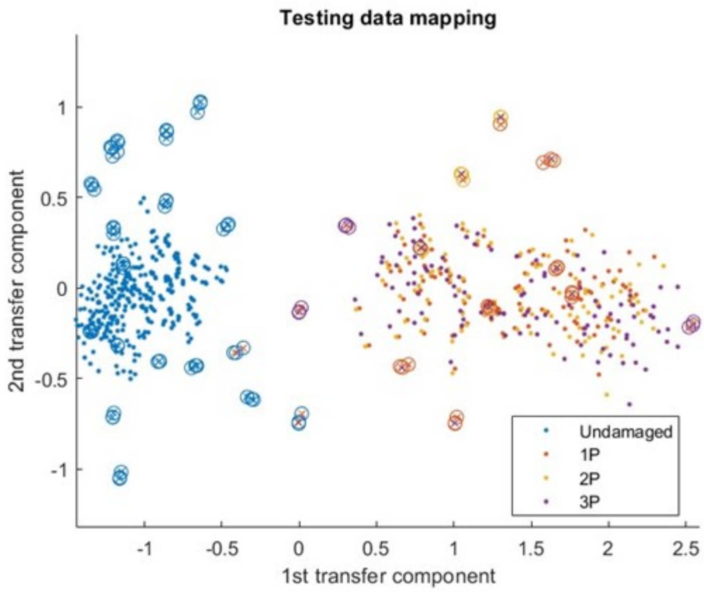


Figure 84: Testing data mapping for analysis II.F.

Analysis IV.

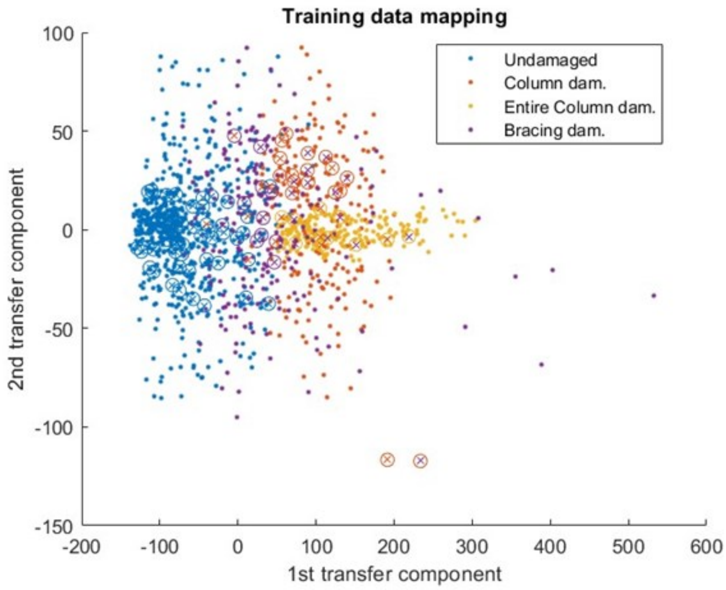


Figure 85: Training data mapping for analysis IV.

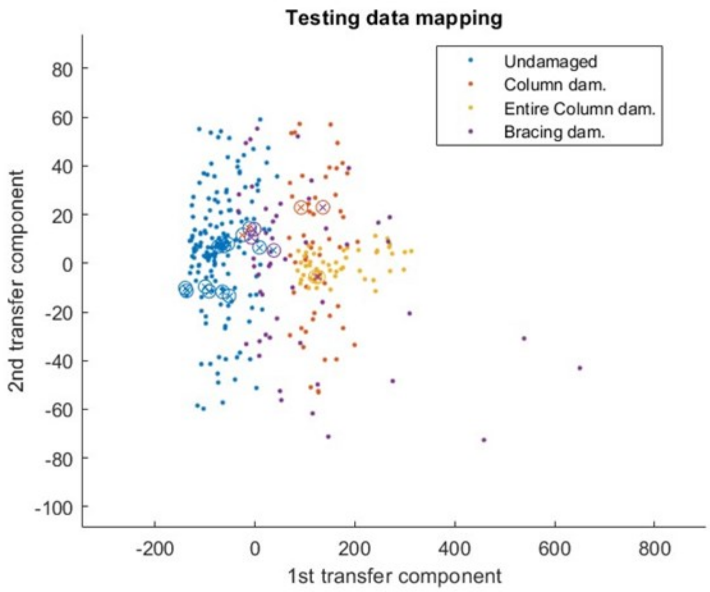


Figure 86: Testing data mapping for analysis IV.

Analysis V.

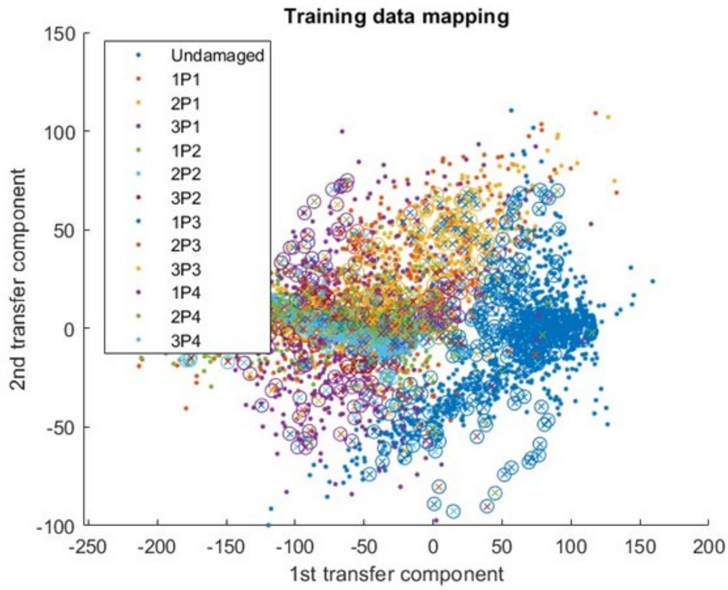


Figure 87: Training data mapping for analysis V.

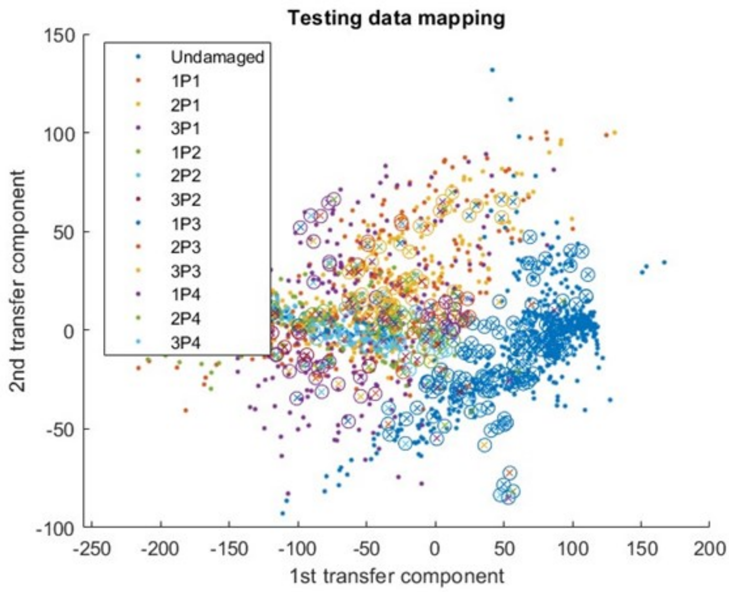


Figure 88: Testing data mapping for analysis V.

Analysis VI.

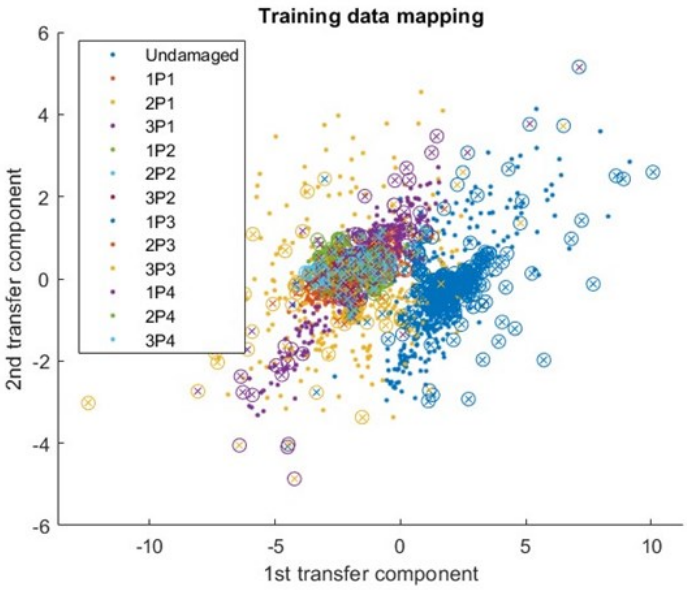


Figure 89: Training data mapping for analysis VI.

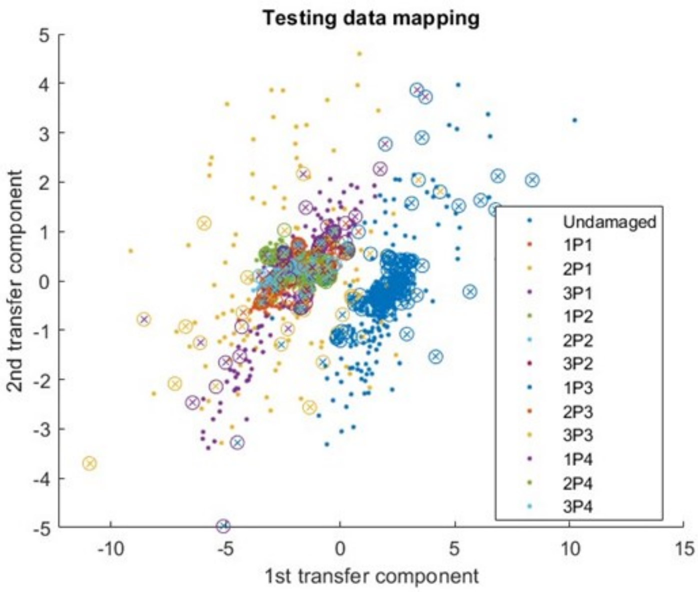


Figure 90: Testing data mapping for analysis VI.

6.2.2 Accuracy comparison

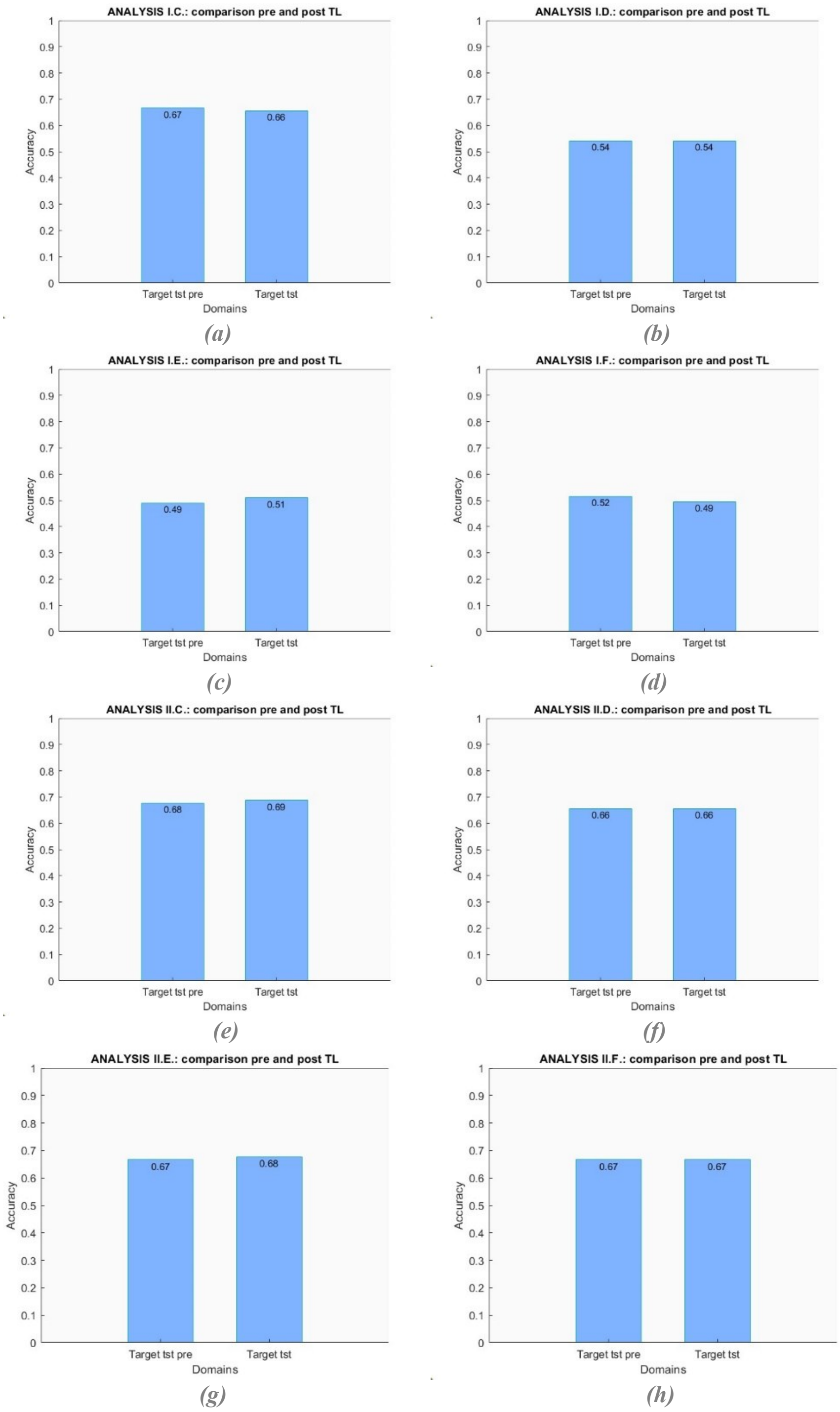
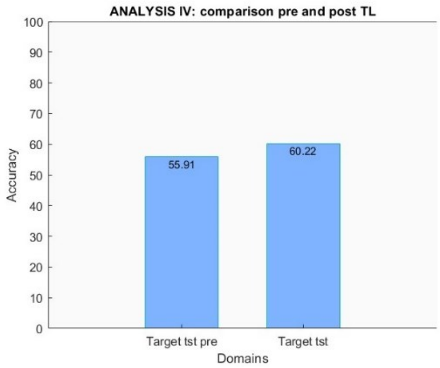
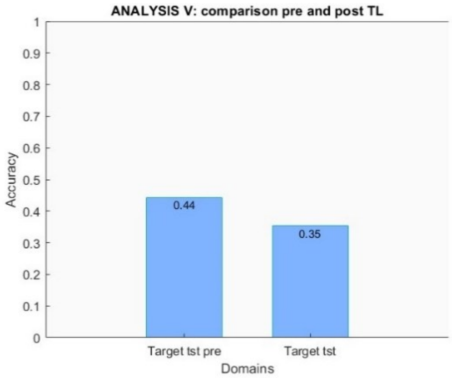


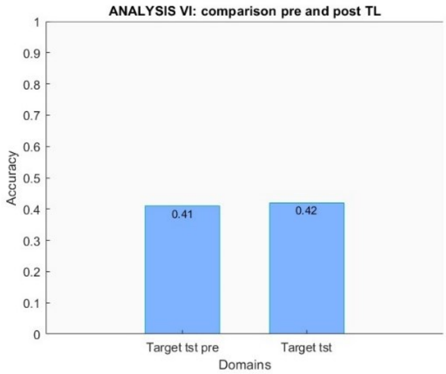
Figure 91: Accuracy comparison between the analysis (a-g)



(i)



(j)



(k)

Figure 92: Accuracy comparison between the analyses (i-k)

In these analyses concerning the damage localization, only few of them lead to improvements thanks to transfer learning. In a better way, the differences between the pre and post TL application in the classification are almost unnoticeable. Analyses I.C., I.D. and V. performed in a worse way, while all the other performed better or in an equal way. A particular interpretation could be done for analysis IV., V. and VI.: within all the analyses, these present the highest variations in a positive direction (analysis IV.) and in a negative one (analysis V.). The algorithm is more able to detect damage when it is well established in the entire element, like in IV., while for the same configuration (I.) a localized damage in a main element results more difficult to be classified and that even brought to a worse result than a pre-trained algorithm without TL (-9%) one. A slight improvement can be, anyway, found in the same analysis (VI.) conducted in an unbraced configuration (II.): the algorithm here performed better, even if only of 1 percentage point, than the algorithm trained with only the few data coming from the target dataset.

6.2.3 Classes accuracy

In these plots, the accuracy is spread in all the classes related to the previous descriptions:

Analysis I.C.

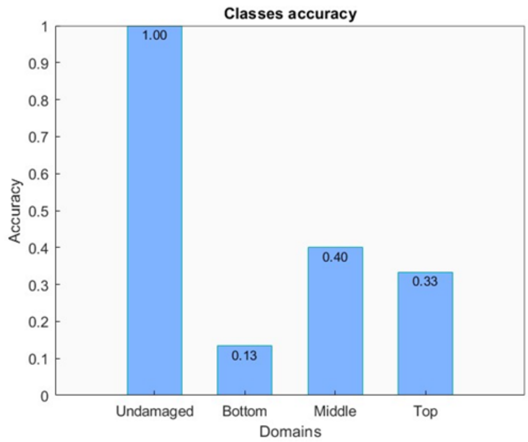


Figure 93: Accuracy between the classes: analysis I.C.

Analysis I.D.

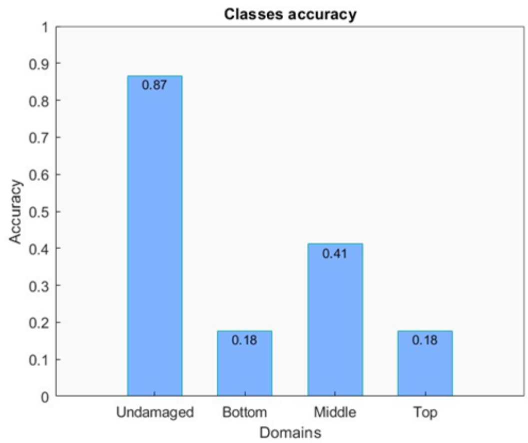


Figure 94: Accuracy between the classes: analysis I.D.

Analysis I.E.

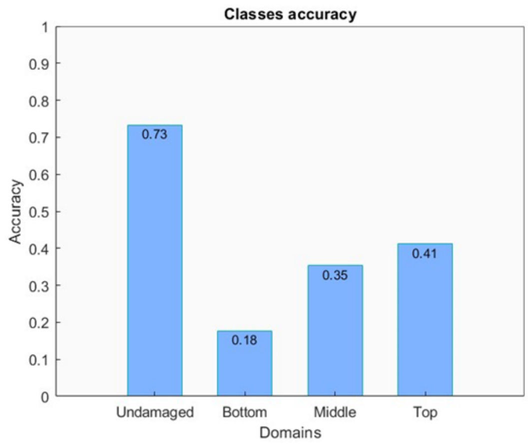


Figure 95: Accuracy between the classes: analysis I.E.

Analysis I.F.

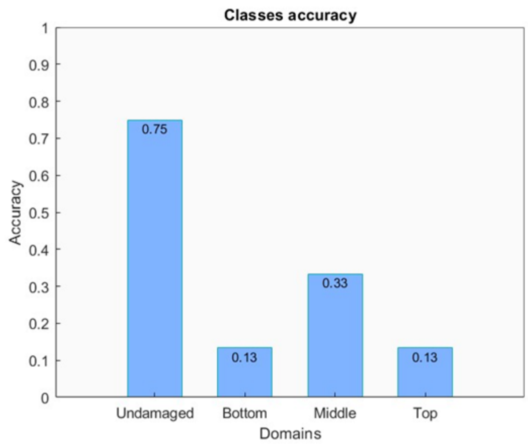


Figure 96: Accuracy between the classes: analysis I.F.

Analysis II.C.

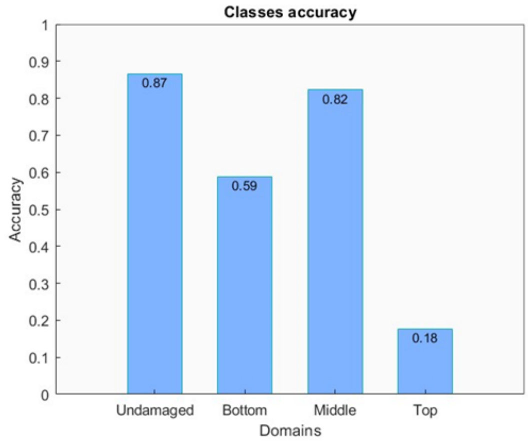


Figure 97: Accuracy between the classes: analysis II.C.

Analysis II.D.

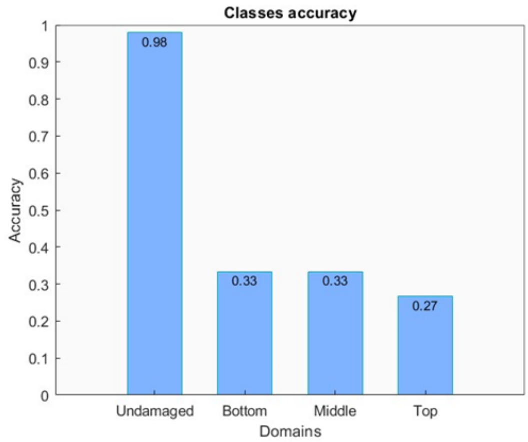


Figure 98: Accuracy between the classes: analysis II.D.

Analysis II.E.

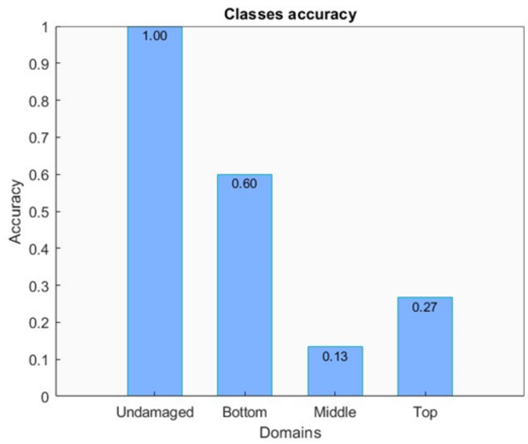


Figure 99: Accuracy between the classes: analysis II.E.

Analysis II.F.

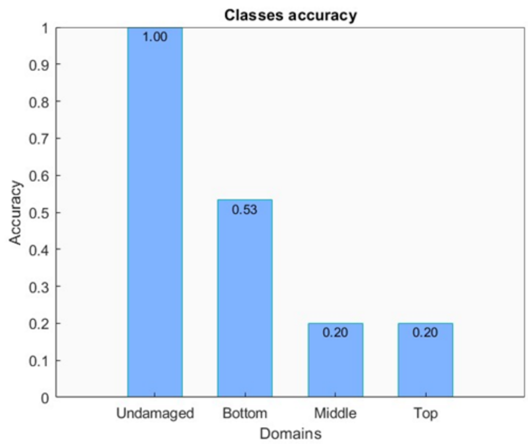


Figure 100: Accuracy between the classes: analysis II.F.

It can be referred to the following tables (Table 29 - Table 32) in order to have a clear comparison between the two different problems configurations (I. and II.):

	Accuracy	I.	II.
	Undamaged	100%	87%
	Bottom end dam.	13%	59%
C.	Mid dam.	40%	82%
	Top end dam.	33%	18%
Accuracy (pre)		67%	68%
Accuracy (post TL)		66%	69%

Table 29: Classes accuracy comparison for C.

	Accuracy	I.	II.
	Undamaged	87%	98%
	Bottom end dam.	18%	33%
D.	Mid dam.	41%	33%
	Top end dam.	18%	27%
Accuracy (pre)		54%	66%
Accuracy (post TL)		54%	66%

Table 30: Classes accuracy comparison for D.

	Accuracy	I.	II.
	Undamaged	73%	100%
	Bottom end dam.	18%	60%
E.	Mid dam.	35%	13%
	Top end dam.	41%	27%
Accuracy (pre)		49%	67%
Accuracy (post TL)		51%	68%

Table 31: Classes accuracy comparison for E.

	Accuracy	I.	II.
	Undamaged	75%	100%
	Bottom end dam.	13%	53%
F.	Mid dam.	33%	20%
	Top end dam.	13%	20%
Accuracy (pre)		52%	67%
Accuracy (post TL)		49%	67%

Table 32: Classes accuracy comparison for F.

From the previous tables, it can be seen the major improvement in accuracy for the unbraced configurations (II.) rather than the braced ones (I.). The undamaged condition is well predicted for all the analyses, while the damage predictions are better for the middle damage in configurations I., and, exception made for case C., the bottom damage is the best predicted for configuration II.

Analysis IV.

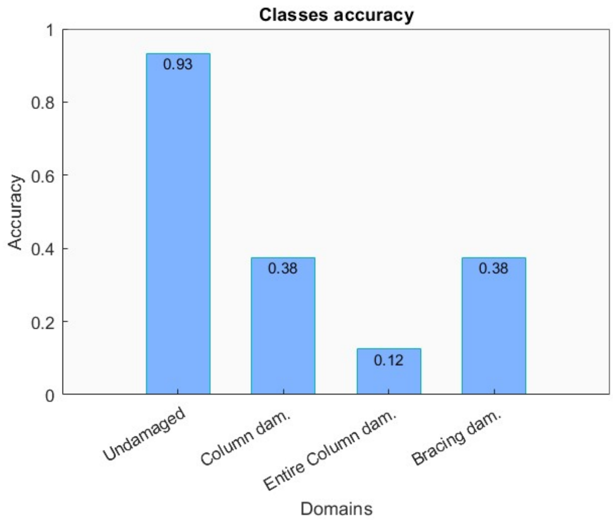


Figure 101: Accuracy between the classes: analysis IV.

Accuracy	IV.
Undamaged	93%
Column 1 dam.	38%
Entire Column dam.	12%
Y-oriented bracing dam.	38%
Accuracy (pre)	56%
Accuracy (post TL)	60%

Table 33: Accuracy between the classes for analysis IV.

Analysis V.

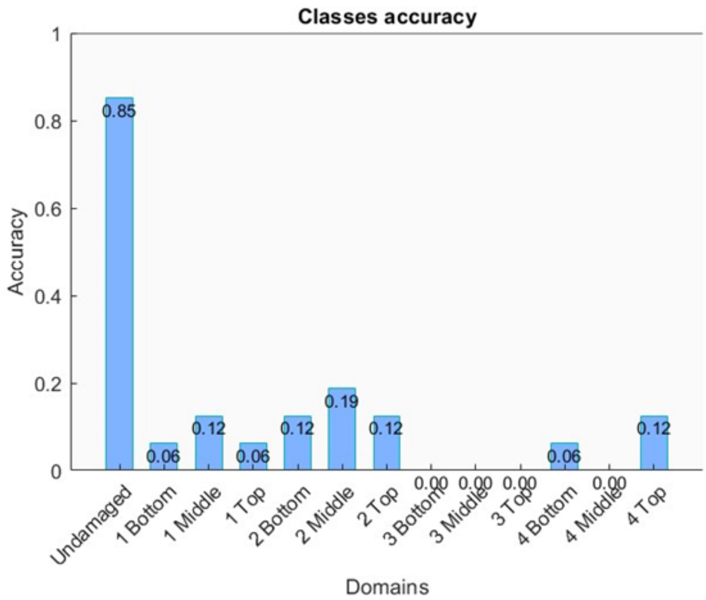


Figure 102: Accuracy between the classes: analysis V.

Analysis VI.

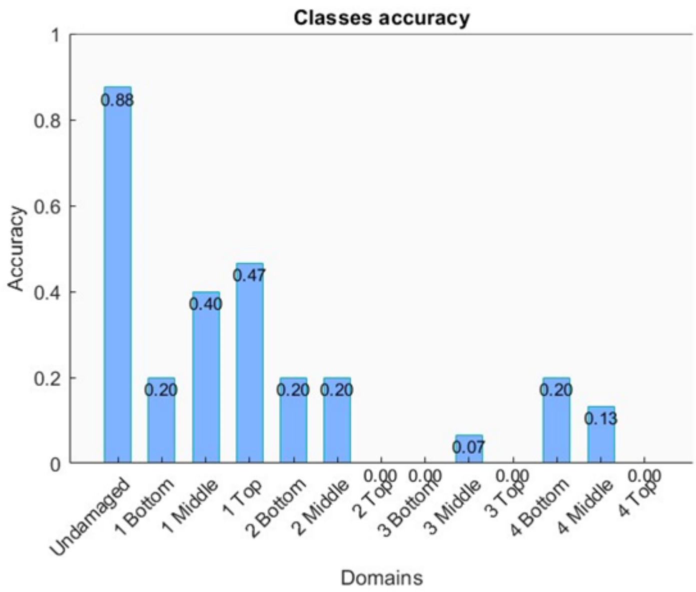


Figure 103: Accuracy between the classes: analysis VI.

	Accuracy	V.	VI.
	Undamaged	85%	88%
1	**Bottom end dam.**	6%	20%
	Mid dam.	12%	40%
	Top end dam.	6%	47%
2	**Bottom end dam.**	12%	20%
	Mid dam.	19%	20%
	Top end dam.	12%	0%
3	**Bottom end dam.**	0%	0%
	Mid dam.	0%	7%
	Top end dam.	0%	0%
4	**Bottom end dam.**	6%	20%
	Mid dam.	0%	13%
	Top end dam.	12%	0%
	Accuracy (pre)	44%	41%
	Accuracy (post TL)	35%	42%

Table 34: Accuracy between the classes for analysis V. and VI.

For analyses V. and VI. we have (Figure 92):

- Analysis V.:
    - Accuracy before Transfer Learning: 44%;
    - Accuracy after Transfer Learning: 35%;
- Analysis VI.:
    - Accuracy before Transfer Learning: 41%;
    - Accuracy after Transfer Learning: 42%.

At first, it seems that transfer learning did not significantly improve accuracy in analysis V. (it is actually lower than the accuracy gained by the classifier prior the domain adaptation), but there was a slight improvement in accuracy for analysis VI. after the TL application. Analysis V. experienced a decrease in accuracy that may indicate difficulties in effectively adapting the pre-trained model to the properties of the dataset or non-optimal fine-tuning strategies.

Analysis VI., on the other hand, showed a more consistent performance in terms of accuracy, demonstrating a small improvement after TL application. This could be related to the better suited pre-trained model and fine tuning process of this scenario (conf. II. “unbraced” structures).

Once described the overall performance of the algorithm, we can focus on the accuracy distribution between the 13 different classes for analysis V. (Figure 102) and VI. (Figure 103). The accuracy in both the analysis is generally higher for undamaged conditions and lower for damaged conditions, whose localizations result to be inherently harder to classify accurately.

The braced configurations (analysis V.) show higher accuracy in detecting damage in the lower columns, even though their percentage is not sufficient to be consistently considered valuable. On the other hand, the column between the second and third floor is classified adapting domains of features coming from different topological situations: indeed, the source system is a 3-storeys structure and the target system a 4-storey structure. In order to classify damage in the second-to-third floor of the target system, data should come not from the same position of the source structure: being the top end portion of the column, it should be considered to detect damage in the top end portion of the column of the target structure (third-to-fourth storey). This led in assuming the same input data both for the second and third portion of the column for the Yellow Frame (target), represented by the second portion of the column of the Laboratory Frame (source). By using the same source data in the classification of these six different damage classes (2 Bottom, 2 Mid, 2 Top, 3 Bottom, 3 Mid, 3 Top), only the portion of the damaged column closest to the ground and describing the more similar dynamic behavior compared to the source column considered is actually better identified (12%, 19%, 12%).

Analysis VI., taking into account the unbraced configurations of source and target structures, shows superior performance in identifying damage across the categories, especially for bottom and mid-level damage. In particular, the highest accuracies can be seen in the first and second column, representing a common characteristic with the previous analysis. The first column damage detection accuracies are the highest (20%, 40%, 47%). The same problem can be noticed also for this analysis: due to the structural dissimilarities between the structures, also here the third portion of the column cannot being identified in a good way, even if all the other percentages are higher comparing to the braced configuration analysis.

Finally, it can be stated that analysis V. represents a good example of negative transfer learning application, for which small and localized damages in systems represented by too much different structural characteristics (geometry and material, overall) could be hardly identified and, in this case, the lack of data in the target structure cannot be solved by means of TCA application in transferring source data coming from this structure in a common adapted domain in order to train the classifier.

Analysis VI., on the other hand, shows a slight improvement: even if also the unbraced structural configurations of the source and target domain present different geometrical and mechanical properties, these differences are not so marked such as the braced configurations ones. This can be seen also in the input data variation of the first three natural frequencies: in these last analyses the variational distances are lower with respect to the original configuration ones.

Chapter 7

Conclusions

The aim of this case study is to embrace some kind of knowledge about the potentiality of data driven techniques in the framework of Transfer Learning applications. This concept is mainly important in the Structural Health Monitoring approach by the fact that a lot of structures in the civil engineering field do not support a direct data management and exploitation in order to detect a damage only by using algorithms trained on the very few data available due to (i) the insufficient time needed to extract measurements or (ii) the lack of labelled data in the structure.

The first step in the damage identification process can be associated to the simple awareness in the presence of a damage in the whole structure, and this can be done by a recognition of a sudden drop in the natural frequencies of the structure. In the ML application, the classification procedure is one of the methods that allow a direct association of input data to a structural state. On the other hand, the second step consists in the damage localization: the algorithm is trained on datasets coming from different structural damaged conditions and the number of classes identified are dependent on the types of damage allocated. Pattern recognition in these tasks is harder than in the first one, due to the needing of finding paths within the given input data, that are usually characterized by natural frequencies.

Transfer Learning comes in help in the Machine Learning techniques due to its capabilities to merge data from different structures in order to boost up the performance, in instance, of a classifier. Transfer Component Analysis (TCA) relies on the domain adaptation techniques for which as hypothesis $P(X_S) \neq P(X_T)$, but $P(Y_S|X_S) = P(Y_T|X_T)$. The TCA technique, in particular aims (i) at finding the mapping function $\phi(\cdot)$ by minimize the distance between the marginal probabilities $P\big(\phi(X_S)\big)$ and $P\big(\phi(X_T)\big)$, (ii) and at keeping in the mapping function $\phi(X_S)$ and $\phi(X_T)$ the significant properties of X_S and X_T, where these last represent the input data features domain of a source and a target structure.

In the case study analyzed in this master thesis, some general considerations on TL can be given:

- A deep analysis on the main characteristics of the domain of interest (target system) should be done in order to understand the main properties of its datasets. This is essential to select an appropriate source system from which data could be handled with the aim of being used in the target tasks. In particular, geometry and material properties are the main aspects involved in the dynamic behavior of the structures.
- If one can relate to the previous point, also the type of damage and its location plays an important role in input data distribution, for instance, natural frequencies of the structures associated to a "disease" condition.
- A different choice of the classifier or the use of a different TL algorithm can be considered proper options in dealing with these kinds of problems

in order to improve the adaption in the common domains and, as consequence of this, the accuracy of the damage detection.

- Fine-tuning strategies should focus on further improving the model's skills to identify the structural conditions and enhancing performance across all damage categories.

7.1 Future perspective: Modal similarity for Optimal Sensor Placement

A possible development of this work can be exploited in studying the degree of similarity between structures. In fact, this could lead on determining the level of available knowledge transfer between different systems. It is important to assess the way in which two structures are similar and focus the attention only in those parameters that really matter: in order to develop this aspect, is necessary to introduce a method of analysis in structural similarity.

A question may arise: which properties does one need to consider when similarity is measured? The answers can be multiple, but good properties that characterize uniquely the dynamic behavior of structures are modes shapes and natural frequencies. Taking into account the first ones, strictly associated to a value of the second, analyses can be conducted to find a "similarity path" between two systems.

The degree of similarity could not only improve TL applications in its strict sense, but it could be a possible solution in the measurements extraction from the target system. One of the main limitations in SHM is the discrete number of sensors that can be installed on a permanent or temporary monitoring system on a structure. An Optimal Sensor Placement (OSP) analysis could be done taking into account the modal similarity. OSP refers to strategically determining the best locations in a system or environment to position sensors for collecting data in an efficient manner, with the aim of maximizing the information obtained and allowing accurate monitoring procedure.

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