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Railway Track Support Condition Assessment Through Vehicle-Based Modal Analysis

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Abstract

One established parameter for the assessment of railway track support conditions is vertical track stiffness. There are other parameters that can also be used to directly or indirectly assess track support conditions, such as track geometry or track irregularities. However, while these parameters are extensively used in current railway monitoring procedures, they also have some limitations in this context. For example, monitoring methods based on these parameters are intrinsically focused on assessing the conditions of the track superstructure, especially if performed using instrumented railway vehicles. This behaviour tends to overlook the track's subgrade layer. This is an important issue since subgrade condition represents one of the main factors that influences track dynamic response and overall track support conditions. However, there is a significant lack of reliable subgrade monitoring solutions. This issue is even more severe in the context of vehicle-based solutions, which are the generally recognized way to more efficiently monitor entire railway infrastructures. Therefore, this issue represents an important knowledge gap that is currently only partially fulfilled with some indirect methods or is more commonly ignored in favour of superstructure focused monitoring solutions.

In order to potentially mitigate the previous knowledge gap, a novel methodology to evaluate railway track support condition was developed in the present thesis. This methodology is based on modal analysis of the characteristic frequencies of the multi-element system composed by an instrumented railway vehicle and a railway infrastructure. The main theoretical concept used here belongs to the group of vibration-based structural damage identification methods. The concept employed in these methods is that modal parameters, such as natural frequencies or modal shapes, are correlated with the physical properties of a structure (mass, damping and stiffness). Therefore, changes in these physical properties, through the appearance of damage for example, will cause detectable changes in the modal properties of the structure under analysis. Thus, the concept proposed in this methodology is that by observing the characteristic frequencies of the combined system, from the point of view of the moving vehicle, it is possible to collect relevant information regarding overall track support conditions of the railway infrastructure and also monitor the conditions of the subgrade layer.

In the context of this thesis, a dedicated modelling solution and an unsupervised data-driven tool were developed in addition to the described track monitoring methodology. The first was created to provide the required testing dataset with the intended conditions, while the later was devised to apply the proposed track monitoring methodology. The developed data processing tool enabled the automatic extraction of results with the proposed methodology, with experimental data and data from numerical simulations.

Keywords: railway track subgrade, vehicle-track interactions, modal analysis, multibody numerical simulation, sparse autoencoder, Machine Learning

Resumo

A rigidez vertical da via é um dos parâmetros mais utilizados para a avaliação das condições de suporte de via ferroviária. Existem outros parâmetros que também podem ser utilizados para avaliar as condições de suporte de via, de forma direta ou indireta, como a geometria de via ou as irregularidades na via. No entanto, embora estes parâmetros sejam bastante utilizados nos procedimentos atuais, estes também apresentam algumas limitações neste contexto. Por exemplo, as soluções de monitorização baseadas nestes parâmetros estão intrinsecamente focadas na avaliação das condições da superestrutura da via, especialmente se forem aplicadas com recurso a veículos ferroviários instrumentados. Este comportamento tende a desprezar as condições da fundação da via. Isto é uma questão importante, dado que as condições da fundação representam um dos principais fatores que influenciam a resposta dinâmica da via e as condições gerais de suporte da via. No entanto, há uma falta significativa de soluções fiáveis de monitorização da fundação. Esta questão é ainda mais grave no contexto de soluções baseadas em veículos, que são reconhecidas como sendo as mais eficientes para avaliar toda a infraestrutura ferroviária. Logo, esta questão representa uma importante lacuna de conhecimento que atualmente é apenas parcialmente preenchida por alguns métodos indiretos ou é frequentemente ignorada a favor das soluções de monitorização focadas na superestrutura.

De forma a potencialmente mitigar esta lacuna de conhecimento, foi desenvolvida na presente tese uma nova metodologia para avaliar as condições de suporte da via ferroviária. Esta metodologia baseia-se na análise modal das frequências características do sistema multi-elemento composto por um veículo ferroviário instrumentado e uma infraestrutura ferroviária. Esta metodologia enquadra-se nos métodos de identificação de danos estruturais baseados em vibrações. O conceito subjacente a estes métodos é que os parâmetros modais, como as frequências naturais ou os modos modais, estão correlacionados com as propriedades físicas de uma estrutura (massa, amortecimento e rigidez). Logo, alterações nestas propriedades físicas, por exemplo através de um dano, causarão mudanças detetáveis nas propriedades modais da estrutura em análise. Assim, o conceito proposto nesta metodologia é que ao observar as frequências características do sistema combinado, do ponto de vista de um veículo instrumentado, é possível recolher informações relevantes sobre as condições gerais de apoio da via da infraestrutura ferroviária e também avaliar as condições da fundação.

No contexto desta tese foi desenvolvido um método de modelação dedicado para o efeito e uma ferramenta de análise de dados não supervisionada, como complementos à metodologia de monitorização de via mencionada acima. A primeira foi criada para fornecer os dados de teste nas condições pretendidas, enquanto a última foi concebida para aplicar a metodologia de monitorização proposta. A ferramenta desenvolvida permitiu a extração automática de resultados, por processamento de dados experimentais ou de dados de simulações numéricas.

Palavras-chave: subestrutura ferroviária, interações veículo-via, análise modal, simulação numérica multi-corpo, sparse autoencoder, Machine Learning

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List of Abbreviations

AE	Auto-encoder
AI	Artificial Intelligence
BC	Baseline case
CBM	Cement Bound Mixture
DC	Damaged cases
DCP	Dynamic Cone Penetrometer
DIC	Digital Image Correlation
DoF	Degree-of-Freedom
EOV	Environmental and Operational Variations
FEM	Finite Element Method
FFT	Fast Fourier Transform
FRF	Frequency Response Function
FWD	Falling Weight Deflectometer
GPR	Ground Penetrating Radar
LVDT	Linear Variable Displacement Transformers
LWD	Light Weight Deflectometer
MBS	Multibody Simulation
MD	Mahalanobis Distance
MDD	Multi-Depth Deflectometers
ML	Machine Learning
MS	Modelling Solution
NN	Neural Networks
OA	Outlier Analysis
PCA	Principal Components Analysis
RSMV	Rolling Stiffness Measurement Vehicle
SAE	Sparse Auto-encoder
SHM	Structural Health Monitoring
TMM	Track Monitoring Methodology
UDDT	Unsupervised Data-Driven Tool
UGM	Unbound Granular Materials
USP	Under Sleeper Pads

1 Introduction

1.1 Motivation

Since the inception of the railway industry in the early 19th century, this sector has always had an important role in the development of societies, in terms of social and economic aspects. Thus, it is no surprise that most modern and developing countries are still spending considerable efforts in creating, maintaining and modernizing their railway infrastructures and vehicles. Railway management and maintenance activities are a significant share of the overall activity in this sector. This importance represents one of the main drives for the current research efforts to develop new solutions, or to improve those that already exist, to facilitate all aspects of these railway related activities. Such efforts can be focused on multiple aspects, including on the development of more efficient methods to assess railway assets (i.e., railway vehicles and railway infrastructures). Railway transportation is now-a-days considered the most ecological way of transportation, both for goods and people. In this context, the European Commission designated 2021 as the European Year of Rail, as part of the European Green Deal's efforts to achieve climate neutrality by the year 2050, promoting and financing the transition to more rail-based transportation, Figure 1.1.

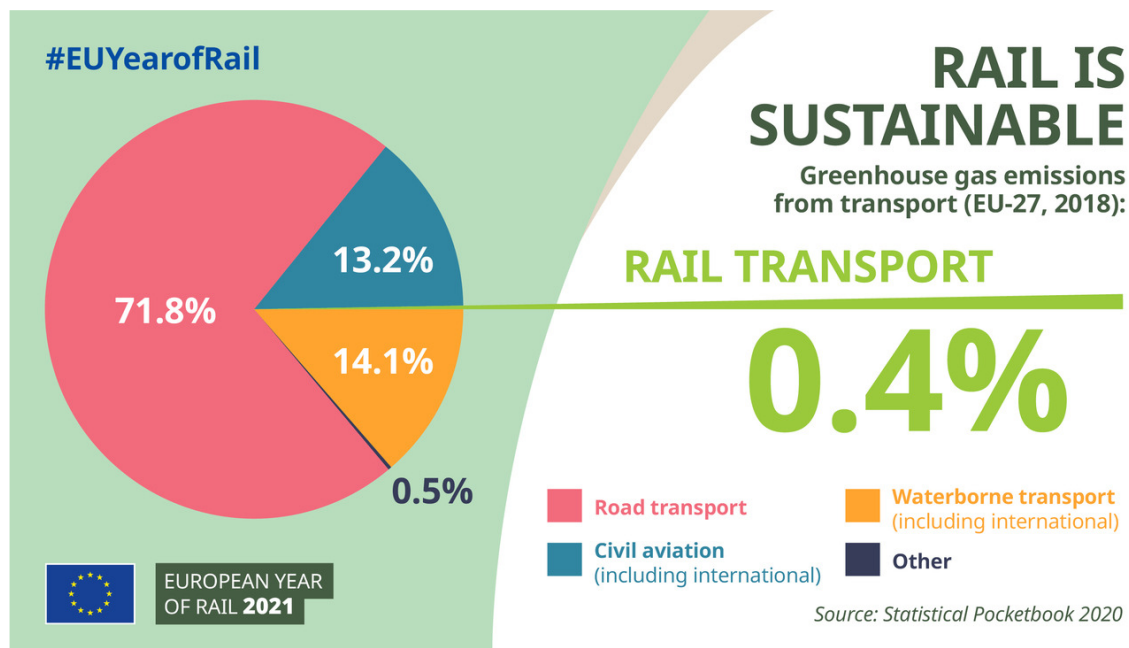


Figure 1.1: Emissions of greenhouse gases from the European transportation sector in 2018, published by the European Commission (2021).

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Another initiative on this subject is the 2030 Agenda for Sustainable Development of the United Nations, namely goal 9 “Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation” (Figure 1.2). Point 1 of this goal encourages the development of reliable, sustainable and resilient infrastructures, including regional and transborder infrastructures, to support economic development and human well-being, with a focus on affordable and equitable access for all. Point 4 states that by 2030, infrastructures and industries should be upgraded to make them sustainable, with increased resource usage efficiency and greater adoption of clean and environmentally sound technologies and industrial processes. Thus, one of the topics enclosed in this goal is the improvement of current Structural Health Monitoring (SHM) solutions applied to railway infrastructures. One of the objectives of this thesis is to support these endeavours, by participating in the ongoing efforts to improve methodologies to monitor railway infrastructures.

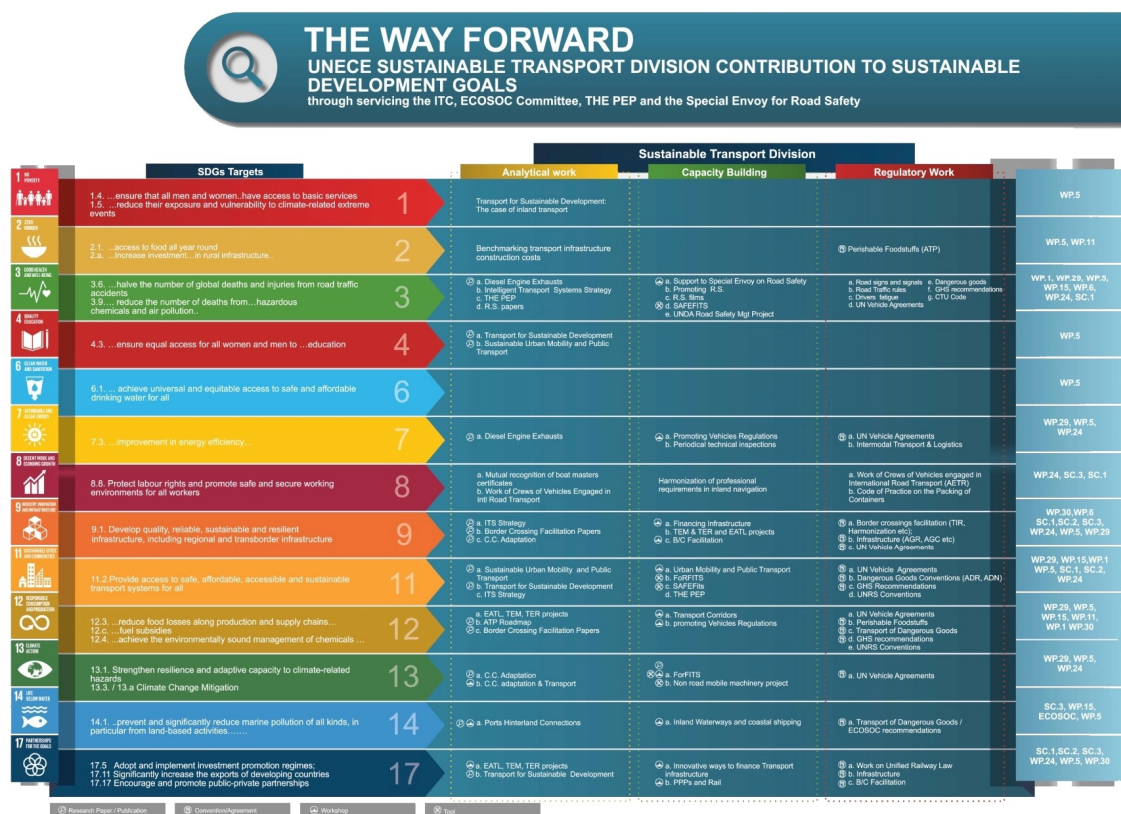


Figure 1.2: Sustainable Development Goals of the 2030 Agenda of the United Nations (2015).

Relevant for the present context, there are still unsolved challenges in the railway sector related with some traditional issues. One of these research challenges is the development of efficient and reliable railway track monitoring solutions, which includes the assessment of railway track subgrade conditions.

The degradation of railway track support conditions results from a complex process, which depends on several factors related with the superstructure, the substructure, or the dynamic interactions between the track and the different types of vehicles that run over it (Fröhling, 1997; Berggren, 2009; Berggren, 2010; Gallego et al., 2011; Milne et al., 2019).

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Among these factors, the substructure's subgrade layer is the well-recognized major influencer on overall railway track support conditions (Selig and Li, 1994; Esveld, 2001; Auersch, 2005; Berggren, 2009). However, subgrade condition is an aspect that is often overlooked in most track monitoring methods, due to a general bias towards monitoring the railway superstructure (Innotrack, 2008; Wang et al., 2016), which naturally is something that should be avoided. Thus, the development of a reliable subgrade monitoring method should represent a significant boon for the current railway maintenance improvement efforts.

Another relevant topic in this sector is the development and improvement of modelling solutions for railway vehicles and/or railway infrastructures, which can range from simple predictive maintenance-related models to digital twins of entire railway lines and vehicle fleets (Azimi et al., 2020; Avci et al., 2021). Among their several benefits, these models are important tools for railway managers to support efficient and timely maintenance actions. Most of the available solutions dedicated to modelling the railway infrastructure are focused on either the plain railway superstructure or on specific assets, such as bridges, viaducts or tunnels (INNTRACK, 2008; Wang et al., 2016; Sousa et al., 2023). Common applications for these models include SHM, the detection of track defects, or the prediction of track degradation (INNTRACK, 2008; Wang et al., 2016; Kong and Cai, 2017; Azimi et al., 2020; Sousa et al., 2023). Despite the major focus on railway superstructure, the railway substructure is still present on several modelling solutions. Most of those solutions involve either lumped-elements theoretical models that describe the substructure by layers of spring-damper elements, or complex numerical models using the Finite Element Method (FEM) or other similar methods, where every component is modelled in detail (Berggren, 2009; Pombo et al., 2013; Zhai, 2020; Fernández-Bobadilla and Martin, 2023; Lamprea-Pineda and Connolly, 2024). Modelling solutions that include the railway substructure can be used for several applications, such as to analyse noise and vibration propagation from the track (Auersch, 2005; Kouroussis et al., 2012) or assess soil stability conditions under traffic loads (Shi et al., 2023). However, there is a significant lack of modelling solutions for the railway substructure based on multibody simulation models. This group of numerical simulation solutions is amply used to model railway vehicles and the railway superstructure (Kong and Cai, 2017; Lesgidis et al., 2020; Shang et al., 2021), but to the author's knowledge, there is no dedicated method focused on modelling the substructure through a multibody software as a fully formed set of elements with their own independent and complete modal properties (mass, stiffness and damping). The alternative modelling solutions either oversimplify the substructure representation by modelling it with only spring-damper elements, thus inherently coupling its modal properties and dynamic responses to the surrounding elements, or use FEM models to fully represent the substructure, which naturally involves higher development and computation costs (Pombo et al., 2013; Zhai, 2020; Fernández-Bobadilla and Martin, 2023; Lamprea-Pineda and Connolly, 2024).

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Another research challenge that the railway sector faces nowadays is how to convert the abundance of data that is being collected from railway infrastructures and/or vehicles into usable information that can support decision-making by the railway managers regarding maintenance actions (Selig and Li, 1994; Berggren, 2010) and how to integrate the new AI based technologies into usable tools in this sector (e.g., digital twins of railway assets for continuous and online monitoring) (Tang et al., 2022; Zhang et al., 2022; Mishra et al., 2022).

1.2 Scope

This thesis proposes a novel methodology to evaluate railway track support conditions based on modal analysis of the characteristic frequencies of the multi-element system composed by an instrumented railway vehicle and a railway infrastructure. This methodology, which is integrated in the group of vibration-based structural damage identification methods, proposes the use of a lumped-element mechanical system as the underlying theoretical model to interpret the acquired data. The main concept behind these methods is that modal parameters, such as natural frequencies and mode shapes, are correlated with the physical properties of a structure, i.e., mass, damping and stiffness, (Doebeling et al., 1998; Kong and Cai, 2017; Avci et al., 2021). Therefore, changes in these physical properties, through for example the appearance of damage or defects, will cause detectable changes in the modal properties of the structure under analysis. Thus, by observing the characteristic frequencies of the combined system, from the point of view of the moving vehicle, it should be possible to collect relevant information on track support conditions of the railway infrastructure over its length, and over time by comparing different rides over the same railway track. The modal analysis concept is reinforced by the use of an unsupervised data-driven tool to process the frequency data and extract the intended track condition results.

One of the main advantages of the proposed methodology is that it allows to collect information regarding the conditions of the lower layers of a railway infrastructure (Doebeling et al., 1998), when compared with other vehicle-based methods that are more focused on monitoring the superstructure (Innotrack, 2008; Wang et al., 2016). This is because the superstructure, together with the substructure, are excited by the moving vehicle, thus their dynamic response can be monitored to gather information on their respective conditions. The broad band excitation created by the passage of a vehicle over the track, resulting from the inherent dynamics of this process, is an important feature that is being used by the proposed methodology. As opposed to other situations where the dynamics of the track-vehicle interactions can represent a hurdle to be overcome or mitigated, e.g., excessive vibrations levels that can reduce the quality of acquired data (Esveld, 2001); here the passage of a railway vehicle over the track is being used as a natural mechanism to excite a broad band of local natural frequencies from the combined mechanical system (Kourossis et al., 2012). Accordingly, the dynamic response of the

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combined system to this excitation can be perceived by monitoring the observable resonance frequencies using sensors installed in the moving vehicle and then assessed by analysing the variation of these frequencies over time and along the track. Thus, information regarding infrastructure support conditions can be extracted from these frequencies, including data on subgrade condition, which is important due to its major influence on track dynamic response and track support conditions (Esveld, 2001; Innotrack, 2008; Berggren, 2009; Wang et al., 2016).

There are already studies on the natural frequencies of the different elements of railway infrastructures (Kouroussis et al., 2015), but to the author's knowledge, there is currently only one study on the development of a vehicle-based method to monitor subgrade natural frequencies to correlate them with railway track support conditions (Björklind, 2018). Additional details on this study, and some considerations on the similarities and differences between it and the methodology proposed here, are presented in chapter 2.

During the development of the previously mentioned methodology, the need to develop two additional important tools became apparent. First, in order to supply the required data to test and assess the methodology, a dedicated numerical modelling method was designed based on a multibody solution to be able to adequately model the subgrade layer and enable the extraction of the natural frequencies of interest. The designed modelling method had to solve the issue of establishing an alternative way to model these elements so that the obtainable results would be realistic, while not oversimplifying the subgrade representation and not requiring extensive computational resources for the intended simulations. The second important development was a data processing tool to enable the proper application of the proposed track monitoring methodology. After verifying that manual data analysis methods could not provide reliable results in this context, a dedicated Machine Learning based tool was developed to automatically apply the methodology and extract the intended results. The devised data processing tool was verified under different operational conditions, which included tests with realistic numerical data and tests with experimental data collected on Portuguese tracks.

1.3 Objectives

The present thesis entails the full development of a novel track monitoring methodology focused on assessing track subgrade condition, which will include the development of specific theoretical models that will be used for data interpretation and analysis. Overall, here are the main objectives:

1. Develop a **new monitoring methodology** to assess track support conditions, focused on assessing subgrade condition. This represents the main goal of this study;
2. Design a **numerical modelling method** that enables the representation of all relevant railway infrastructure elements in a multibody numerical model, including the ability to model the subgrade layer as an independent body element with its own complete modal properties;

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3. Create a **dedicated data processing tool** to enable the proper application of the proposed track monitoring methodology to provide reliable results regarding subgrade damage locations. An unsupervised data-driven strategy is envisioned as an appropriate solution for this task.

1.4 Thesis structure

This thesis, which is organized into seven chapters, presents the following structure:

Chapter 1: Introduces the background of the research topic and establishes the main objectives of the thesis. The chapter also outlines the objectives that guided this investigation and presents a complete list of the publications made in this context.

Chapter 2: Presents an overall discussion on the state-of-the-art in the railway monitoring topic, with a special focus on the infrastructure monitoring part. Additionally, some considerations on several topics relevant to the present study, namely an introduction to signal analysis and vibration-based methods in the railway context are also presented, followed by a focused discussion on railway subgrade monitoring methods.

Chapter 3: Contains a complete description on the proposed track monitoring methodology, including the developed theoretical models. The reasons that lead to the final configuration of the theoretical model are also presented. This is followed by a description of two proof-of-concept tests that were performed to preliminarily assess the proposed methodology.

Chapter 4: Describes the numerical models that were used to develop and test the proposed track monitoring methodology and assess the damage detection capabilities of the developed data processing tool.

Chapter 5: Provides a full description of the data processing tool, including a general reference to the different versions that were tested to reach the final solution. This chapter also describes some of the validations tests that were performed on the developed data processing tool using numerical data.

Chapter 6: Presents the assessment tests made on the proposed concepts using experimental data. The main batch of experimental data corresponds to two train rides with an instrumented railway vehicle over a section of the Portuguese *Linha do Norte*, which was further complemented with geotechnical data provided by *Infraestruturas de Portugal*.

Chapter 7: Concludes the thesis by summarizing the key outcomes, stating possible directions for future research and mentioning some of the advantages and drawback associated with the selected modelling method.

1.5 List of Publications

Below are listed the publications produced in the context of the present thesis, either published in journal articles or presented at international conferences:

Journal Articles

- Morais J, Morais P, Santos C, et al. (2021) Railway track support condition assessment – Initial developments on a vehicle-based monitoring solution through modal analysis. *Proc. Inst. Mech. Eng., Part F: J. Rail Rapid Transit* 236: 9. <https://doi.org/10.1177%2F09544097211064101>
- Morais J, Fortunato E, Ribeiro D, et al. (2023) Railway track support condition assessment — methodology validation using numerical simulations. *Engi. Fail. Anal.* 152: 107483. <https://doi.org/10.1016/j.engfailanal.2023.107483>
- Morais J, Fortunato E, Ribeiro D, et al. (2024) Railway Substructure Modeling Approach for Modal Analysis Using Multibody Simulation. *Appl. Sci.* 14: 6510. <https://doi.org/10.3390/app14156510>.
- Morais J, Silva P, Fortunato E, et al. (2026) Development of a railway track support condition assessment using a sparse autoencoder approach. *Submitted for publication*.

Book Chapter

- Morais J, Fortunato E, Ribeiro D, et al. (2026) Development of a railway subgrade monitoring methodology - concept description to practical implementations using Machine Learning. *Elsa platform, Elsevier. Accepted for publication*.

Conference Articles

- Morais J, Santos C, Morais P, et al. (2019a) Continuous Monitoring and Evaluation of Railway Tracks: System Description and Assessment. *Procedia Struct. Integrity*. 17: 448-455. <https://doi.org/10.1016/j.prostr.2019.08.059>.
- Morais P, Morais J, Santos C, et al. (2019b) Continuous Monitoring and Evaluation of Railway Tracks: Proof of Concept, *Procedia Struct. Integrity*. 17: 419-426. <https://doi.org/10.1016/j.prostr.2019.08.055>.
- Morais J, Mendes J, Fortunato E, et al. (2023) Railway Track Support Condition Assessment - Preliminary Validation Tests using a Multibody Simulation Software. In: *Young Researchers Seminar 2023*. <https://doi.org/10.5281/zenodo.8010597>
- Morais J, Fortunato E, Ribeiro D, et al. (2023) Studies on railway track support condition assessment using multibody numerical modelling. In: *XLIV Ibero-Latin American Congress on Computational Methods in Engineering*. <https://doi.org/10.5281/zenodo.10991636>
- Morais J, Meixedo A, Fortunato E, et al. (2024) Unsupervised Data-driven Tool for

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Track Support Conditions Assessment – First Results. In: *ECCOMAS 2024*.
https://www.scipedia.com/public/Morais_et_al_2024a

2 Railway track monitoring methods

This chapter provides a general overview on railway track monitoring methods with the goal of establishing the background that led to the development of the proposed track monitoring methodology focused on assessing subgrade conditions. This is done by progressively refining the scope of the state-of-the-art review, focusing on the advantages of monitoring the subgrade layer over monitoring other railway infrastructure elements. This chapter ends with a brief discussion on some topics that are specifically relevant for the proposed methodology regarding vibration-based methods and signal analysis in the railway context.

2.1 General overview

A typical ballasted railway infrastructure is constituted by several important elements, which are presented in Figure 2.1 along with the typical terminology used in the railway context. As can be seen, these elements can be separated into two groups: the superstructure that includes the rail, sleepers and the ballast layer; and the substructure that includes the remaining layered elements of the sub-ballast, capping layer and the natural soil layers. The subgrade is a further distinction to refer specifically to the soil layers of a railway infrastructure, including the pre-existent natural soils below the track and the prepared layers.

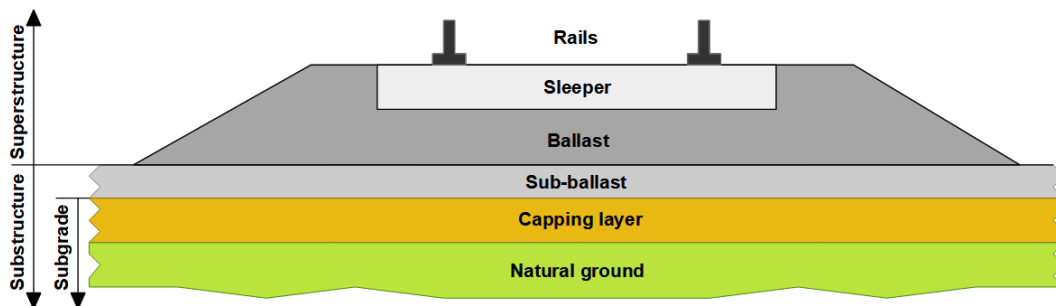


Figure 2.1: Schematic representation of a ballasted railway track.

All these elements have important roles in the overall process that allows a railway vehicle to carry passengers or freight in reliable and secure conditions, with relatively low energy consumption and low pollutant emissions when compared with other transportation modes (Zhai, 2020). The passage of a railway vehicle over a track imposes static and dynamic loads, which are respectively caused by the vehicle's weight and inertia plus impacts, which must be properly transmitted to the track's subgrade. Thus, one of the main roles of these railway elements is to distribute the loads throughout the depth and breadth of the railway infrastructure, to avoid compromising the subgrade layers' soil resistance

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due to stress concentration (i.e., compromising track bearing capacity). This load distribution effect can lower stress concentration levels by several orders of magnitude, from the wheel-rail contact points all the way down to the soil layers, and is dependent on several factors including the load per axle of the railway vehicles (Esveld, 2001). Other important roles of these elements include guiding the vehicle along the track (rails), enforcing a stable configuration of the rail profile (sleepers), and allowing rainwater drainage from the track (ballast and sub-ballast). A more in-depth description of these elements and information on other types of railway tracks (e.g., ballastless or slab tracks) can be consulted on several publication dedicated to the subject, including the book by Esveld (2001), and will not be presented here. Ballasted tracks are the focus of this study since this type of track represents the more common configuration used in Portugal and is still extensively used worldwide.

Railway infrastructures are subject to regular degradation of the initial conditions during their lifetime (Esveld, 2001). This degradation process depends on several factors that vary along the track and through time (Milne et al., 2019), thus requires the implementation of surveillance actions for an adequate monitorization of its progress. Managing railway maintenance tasks is one important factor that influences the technical and economic performance of this transportation system, because of the significant impacts on system availability and considerable financial costs that these tasks entail (Berggren, 2010). To efficiently monitor and maintain a railway track, large amounts of data related to the conditions of the railway should be collected and analysed. This data can be obtained by visual inspections, with dedicated auscultation vehicles, or with other methods (Esveld, 2001; Innotrack, 2008). With the advent of new and improved monitoring solutions over the years, this specific goal is now easier to achieve than in the past where visual inspections were the only available solution. However, railway managers are now facing the difficult task of converting this data collected from railway infrastructures into information to support decision-making regarding when to perform maintenance actions (Fernández-Bobadilla and Martin, 2023). This issue is one of main obstacles hindering further implementation of condition-based maintenance planning (Berggren, 2009; Berggren, 2010), as opposed to the preceding ideology of corrective maintenance planning with its potentially higher financial costs and longer track unavailability periods (Esveld, 2001; Milne et al., 2019).

The traditional visual inspection methods used to assess railway track support conditions are reliable in identifying sites that negatively affect the functional and structural performance of a railway (Paixão et al., 2016a; Paixão et al., 2019) and therefore are still established as common procedures by most railway network administrations around the world (Esveld, 2001; Innotrack, 2008). However, they do not provide useful information regarding the causes that lead to the degradation of the track support conditions. They are also not very efficient, in both time and financial resources. Consequently, maintenance actions based on these monitoring methods tend to be more corrective in nature than

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preventive or predictive, increasing operational and financial costs (Esveld, 2001; Milne et al., 2019). As part of the efforts to efficiently supply the required railway infrastructure condition data, a contemporary line of research consists of creating solutions to assess railway infrastructures based on in-service vehicles (i.e., vehicles of regular use for the transport of people or freight) (Innotrack, 2008; Rivas, 2013). In these methods, the vehicles are equipped with sensors to collect information on the structural health of the railway through which they move. These can include, for example, methods to detect damaged elements of the superstructure or measure the geometric profile of the rails. This concept allows the evaluation of a track in a sequential and continuous way, requires less resources than dedicated auscultation vehicles or conventional visual inspection campaigns, and does not cause significant impacts on railway availability (Berggren, 2010). As a result of the continuous monitoring of railway infrastructures, especially if performed with multiple vehicles, these methods can provide comprehensive information regarding its condition over time and space, allowing for a more efficient planning of maintenance actions (Fernández-Bobadilla and Martin, 2023).

Railway track support condition is important in the assessment of railway infrastructures because it refers to the resilient behaviour of the railway track, and the physical properties related with the resistance of the infrastructure to permanent track settlements. Thus, by monitoring it, information can be gathered regarding the structural health of a railway infrastructure and its ability to guarantee the safe passage of every railway vehicle that uses it. To fully assess railway track support conditions, every element of a railway infrastructure should be monitored, from the rails to the subgrade, to verify that each is able to fulfil its role. However, such extensive monitoring efforts are very time consuming, impractical and expensive. Thus, current methods tend to focus on just monitoring certain elements or parts of the railway infrastructure or use methods that can assess overall track support conditions through the evaluation of relevant parameters that are related to multiple elements of the railway infrastructure (Esveld, 2001; Berggren, 2009). Examples of parameters that can be relevant in the assessment of railway infrastructures include track geometry, track defects and ballast condition (e.g., contamination levels and particle sizes).

One of the established parameters for assessing railway track support conditions is vertical track stiffness, which is defined as the ratio between the vertical load applied on the rails and the maximum vertical displacement of the track (Esveld, 2001). Track stiffness is related to the bearing capacity of the railway track, i.e., with its ability to support the loads imposed upon it over its life cycle without undue permanent deformations or structural damage (Le Pen et al., 2016). According to relevant bibliography on this topic, a railway track should not have an excessively high track stiffness, nor should it be too low (Selig and Waters, 1994; Berggren, 2009; Wang et al., 2016; Roghani, 2017). High track stiffness causes an increase in the dynamic loads transmitted to the track, which leads to higher track deterioration rates due to additional fatigue damage, brittle fractures and excessive vibrations. On the other hand, low track stiffness entails large track settlements

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over time and increased structural damage rates, which also results in the need for additional maintenance actions. Additionally, significant spatial variations of track stiffness along a railway line should also be avoided because this will intensify transmitted wheel-rail contact loads, thus also increasing track degradation rates due to permanent deformation of the ballast and the subgrade (Dahlberg, 2009; Berggren, 2009; Paixão, 2014; Milne et al., 2019). Consequently, a track should ideally present an adequate and relatively homogeneous vertical track stiffness profile, which should be kept stable over time, for proper track resistance to the applied loads and acceptable track deflections levels. The difficulty is to determine the optimal stiffness range, since this is a complex multi-variable problem. Currently, there is no scientific or technical consensus on these values (Berggren, 2009; Kouroussis et al., 2015; Shi et al., 2023), only recommendations based on the type of track and expected traffic. Regardless, these recommendations on railway vertical track stiffness should be followed whenever possible.

Vertical track stiffness can be a difficult parameter to measure because it is dependent on the value of the applied load, due to the non-linear behaviour of the geomaterials present on railway infrastructures (Berggren, 2009; Paixão et al., 2016b). More specifically, the typical railway track load-deflection curve (Figure 2.2) exhibits two distinct regions, where the track's mechanical response changes significantly depending on the load levels being applied to it. Region 1 describes the response of the track where any gaps or voids are being closed during initial load application (e.g., the natural voids in the granular materials), thus displaying relatively low stiffness values. Then upon reaching a critical load value P_0 where all gaps are closed, the track exhibits a stiffer response that still depends on the applied load, but to a lower extent. Thus, track behaviour is always non-linear and load dependent, with these two distinct regions where the typical track response suffers a significant change in behaviour (Selig and Waters, 1994). The track response in region 2 corresponds to the nominal operational conditions of the track while being used by railway vehicles because their own weight is usually sufficient to place the track over the critical P_0 loading conditions (Selig and Li, 1994).

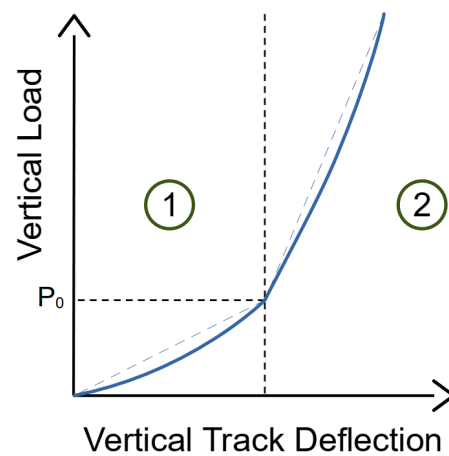


Figure 2.2: Typical load-deflection curve of a railway track, including its approximate bi-linear behaviour marked by regions 1 and 2.

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Apart from the arbitrary interference by track defects or other sporadic phenomena, a track response can be approximated by a bi-linear constitutive model with the fulcrum on the P_0 loading conditions (Selig and Li, 1994; Esveld, 2001, Sussmann et al., 2001). This approximation is a feature that can be used by methods dedicated to monitoring track stiffness or other parameters related with a track's mechanical response (Innotrack, 2008). However, the non-linear behaviour of the track should still be taken into consideration in most situations during data interpretation and analysis (Wang et al., 2021).

Among other factors, this non-linear response from railway tracks leads to some of the issues shared by most methods currently used to monitor vertical track stiffness, as reported in relevant reviews on the topic (Innotrack, 2008; Rivas, 2013; Wang et al., 2016). These issues include inconsistent measurement concepts and insufficient data analysis, resulting in values that are not directly comparable between methods, thus jeopardizing important tasks like creating track support condition standards based on vertical track stiffness values. Most of these methods can also suffer from a bias towards the conditions of the railway superstructure because they rely on measuring track deflections (Innotrack, 2008; Wang et al., 2016). This issue is described in the Innotrack report (2008), which states that some track defects (e.g., unsupported sleepers) can inadvertently influence track deflection measurements, since displacement transducers measure a combination of track deflection due to track flexibility (i.e., intrinsic component) and due to the presence of track defects (i.e., apparent component). This can result in inadequate values, due to localized defect on the track superstructure, that do not accurately represent overall track support conditions. This issue can inadvertently minimize the influence of subgrade conditions on track stiffness measurements, which is something that should be avoided because subgrade conditions represent one of the more important factors that influence track stiffness and overall railway track support conditions (Selig and Li, 1994; Esveld, 2001; Auersch, 2005; Berggren, 2009). Thus, these factors that can negatively impact track stiffness measurements should always be taken into consideration when using this type of track monitoring methods. However, the relationship between track deformation and the presence of track defects is an aspect that can be used in the detection of such defects (Sussmann et al., 2001). An additional issue that can cause the bias towards the superstructure in track stiffness monitoring methods is that the superstructure is naturally easier to monitor than the subgrade, since direct monitoring actions can be employed. Even with these challenges, vertical track stiffness is still one of the more used parameters for the assessment of railway track support conditions (Innotrack, 2008). These previous issues represent one of the main motivations that lead to the development of the present track condition monitoring methodology, i.e., the motivation that led to the development of a new method to assess subgrade condition. How this was achieved will be explained later in this chapter.

2.2 Track monitoring methods

The assessment of railway track support conditions has been an active research topic for several decades, with multiple studies and projects presenting different methods for the same base goal, each with their respective features, advantages and disadvantages. This section presents an overview of different approaches that have been presented over the years on this topic, including the more recent trends. It does not attempt to present a complete and thorough compilation of every available monitoring solution on this subject.

The second edition of the book *Modern Railway Track* (Esveld, 2001) presents a set of relevant parameters, or types of data, that can be used to assess railway track support conditions (Table 2.1). Naturally, the best data on track support conditions would be obtained through on-site excavations of the track, but this option is understandably not the preferred solution because of the inherent financial costs and massive interference with track availability. Thus, there is a need for alternative methods to monitor the parameters presented in Table 2.1, which should be able to provide the required information on track condition through non-destructive and less disruptive procedures.

Table 2.1: Relevant parameters for the assessment of track support conditions (Esveld, 2001).

- Track geometry	- Moisture Content
- Ground Penetrating Radar (GPR)	- Infrared Thermographic inspection
- Track stiffness	- Track Drainage
- Subgrade Strength	- Petrographic examination

Some of these parameters can provide information on overall track support conditions of a railway infrastructure (i.e., information on both the superstructure and the substructure), but that depends on the characteristics of the excitation mechanism, or monitoring depth, being used to assess them (Esveld, 2001). This means that the monitoring procedure must guarantee that the intended relevant elements of the track are being properly assessed, for the resulting data to be representative of said elements. This is particularly important for track stiffness and subgrade strength monitoring methods. These method classes must be able to obtain data from the entire infrastructure for the results to be representative of the overall condition of the track, and not focused on specific elements (Selig and Waters, 1994). On the other hand, these classes of methods can also be focused only on assessing a specific set of elements of a railway infrastructure, thus the influence of the remaining elements should be properly minimized in the acquired data. For example, a track stiffness monitoring method could be focused only on the conditions of the track superstructure, thus it should only mobilize a response from it. Alternatively, a railway monitoring method could be focused on assessing track stiffness from the entire railway infrastructure, thus requiring a monitoring procedure that can obtain a response from the whole system. On this topic, track geometry data should also be mentioned because the methods used to monitor this parameter are inherently focused on the conditions of the

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track superstructure (Esveld, 2001). Thus, while being capable of signalling sites with low track support conditions and being relatively simpler to implement than some of the other method classes (Innotrack, 2008), these solutions usually lack the means to provide information on the causes that lead to track degradation (Wang et al., 2016), especially if the source is on the track subgrade. The correlation between degrade track geometry and poor track support conditions is also not unequivocal, in that there are many causes that can lead to track geometry degradation and poor track support conditions is just one of them (Esveld, 2001; Selig and Waters, 1994).

The remaining parameters from Table 2.1 can usually only provide supplementary information on track support conditions because they are inherently focused on only some specific aspects or elements of the railway (Esveld, 2001). However, these methods can still be useful in this context. For example, moisture content data is a significant parameter to characterize the mechanical behaviour of geotechnical materials (Selig and Waters, 1994), and sometimes this parameter can be enough to characterize the poor response of a railway track. However, moisture content data is usually not enough to provide information on overall track support conditions (Selig and Waters, 1994).

Several of the methods that will be presented in this section can also be used to gather information on the condition of railway vehicles, vehicle running safety conditions and/or passenger comfort. This very broad topic falls out of this thesis's scope and will not be directly addressed here. However, this topic is one of the main reasons that justifies why track geometry monitoring methods are so commonly used in railway monitoring operations (Rivas, 2013). Railway track support condition monitoring methods can be classified into one of three categories (Figure 2.3): i) manually deployed methods, ii) on-site methods that use instrumentation installed on the railway infrastructure, or iii) vehicle-based methods that monitor the railway through instrumentation installed on railway vehicles. This section will present a brief introduction on these three categories, along with some examples. However, the discussion will be more focused on the third category since it includes the methodology proposed in this thesis.

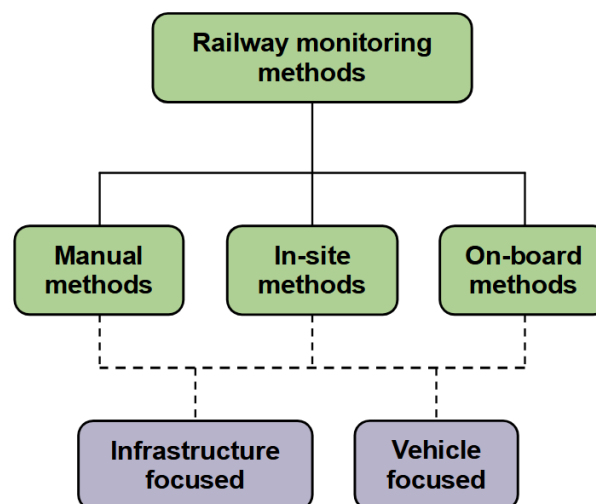


Figure 2.3: General categories of railway monitoring methods.

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2.2.1 Manually deployed methods

Manual methods to monitor railway tracks are solutions deployed by one or more human operators to carry out tests or monitoring campaigns on the track itself. These monitoring methods, which include most of the traditional solutions to monitor track condition (e.g., visual inspections), are usually employed when a specific track section needs to be assessed due to a suspicion of local degradation. These methods have multiple advantages, including being comparatively inexpensive and flexible to deploy in multiple situations, but also have significant drawbacks. The most notable are that these methods cause significant disruption on track availability due to the necessity of interrupting normal track operations, are not time efficient, and can be very labour intensive (Esveld, 2001).

Another significant aspect that must be taken into consideration when using this category of methods is that some of the parameters from Table 2.1, namely track stiffness, subgrade strength and track geometry, are dependent on the loading conditions of the track during monitoring (Selig and Waters, 1994; Wang et al., 2021). This means that data regarding these parameters is only representative of the conditions of the track during normal railway operations if said data is acquired in similar conditions. The most important distinction in this specific context, especially more relevant for manual methods when compared with the other two monitoring method categories, is if the monitoring procedure is being performed on a loaded or unloaded track. This aspect is related with the non-linear behaviour of railway tracks that was previously mentioned (Figure 2.2). It distinguishes between situations where the track is under loading conditions corresponding to the initial part of the typical track loading curve (i.e., unloaded track), and situations where the track is under conditions corresponding to the rest of the loading curve (i.e., loaded track). While most manual methods are unable to acquire data in loaded conditions, which is not desirable since loaded conditions is the situation that actually corresponds to the nominal operational conditions of a track, the acquired data can still be useful if this factor is taken into consideration when extracting conclusions from said data. However, methods in the other two categories are usually able to monitor the track in loaded conditions because railway vehicles are typically used as the loading source. While using methods from these two categories, different load values do provide distinct results on the previously mentioned parameters from Table 2.1, but these differences are far smaller than those that would be obtained when comparing results from a loaded and an unloaded track. The standard EN 13848-1 (CEN, 2019) on monitoring track geometry makes specific reference to the importance of this issue.

Nowadays, the methods in this category are mostly being used as supplementary tools in monitoring activities, or as part of data collection methodologies used in studies regarding new solutions to monitor railway infrastructures. Based on the author's research on studies regarding the development of new track condition monitoring methods, there are practically no recent studies in this category. Researchers working on this subject are more focused on developing new methods in the other two categories, since there are already

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multiple well-established manual inspections. In this category, there are methods dedicated to measure most of the parameters identified in Table 2.1, although the more commonly monitored parameters are track stiffness, track geometry and subgrade related.

There is a myriad of manual methods dedicated to measuring vertical track stiffness, or the related track modulus that also gives a measure of the mechanical strength of a railway infrastructure but without the influence of the rails' bending stiffness (Innotrack, 2008). Two common examples of these types of methods are the Light Weight Deflectometer (LWD) (Figure 2.4a) and the Falling Weight Deflectometer (FWD) (Figure 2.4b). A LWD monitors the deflection caused by the impact of a known weight on the soil, through a geophone installed in the base of the equipment. Then, an estimate of the soil's Modulus of Elasticity can be determined by using the measured deflection and the load applied on the impact. Likewise, an FWD is a device that uses a set of weights that are dropped on the soil through a metal plate to create a load impulse, similar to the passage of a vehicle axle, and then registers the load impulse propagation on the soil through a group of geophones. This method has a higher loading capability than the LWD, thus creating more representative loading conditions. The data collected with an FWD can then be used to estimate vertical track stiffness. These methods are more commonly employed in monitoring campaigns during the construction stages of new railway tracks, or during extensive maintenance actions to assess the conditions of the substructure (Fortunato, 2005; Sharpe and Govan, 2014; Park et al., 2020). The LWD, due to its more compact size, can also be employed to perform probing tests on sleepers or on the ballast layer to check for localized damage or defects, such as hanging sleepers or ballast voids (Sharpe and Govan, 2014; Bold et al., 2021).

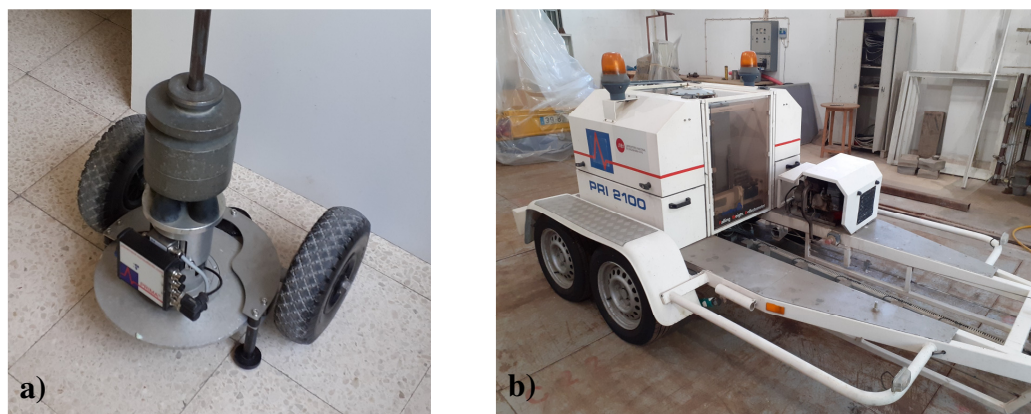


Figure 2.4: (a) a Light Weight Deflectometer and (b) a Falling Weight Deflectometer.

As for methods to measure subgrade strength, or other mechanical properties of the different layers of a subgrade, there are many commercially available solutions. Some of them only require relatively simple equipment setups to perform the tests but are only able to assess the upper subgrade layers, while others consist of more complex equipment setups that include auxiliary actuators to enable deeper probing tests. One common method employed in this context is the Dynamic Cone Penetrometer test (DCP). In a DCP test a set of impacts is applied to the soil using a probing cone, while measuring the depth of

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penetration after each blow. Although the DCP is a test designed to evaluate penetration resistance, its results are often related to the deformability of the soil material. Some tests that allow for the evaluation of track stiffness can also be used in this context, such as the FWD or the LWD. Although this type of testing is more commonly used during construction or rehabilitation of railway track, it can also be used to assess soil properties of the upper layers of a railway infrastructure in the context of monitoring operations of a track under assessment (Fortunato, 2005).

There are several manually deployed methods to measure track geometry and detect rail defects. According to EN 13848-1 (CEN, 2019), there is a list of parameters that must be measured to fully assess track geometry (Figure 2.5). The definition of each of these parameters, according to the standard, are described below. Based on these parameters, the differences between the current track configuration and the nominal configuration can be determined. These potential differences are the definition of a rail geometry irregularity. Examples of track geometry measuring methods in this category include track geometry survey trolleys that can measure all these parameters as they pass along the rails, or hand-held devices that can be used to measure these parameters individually.

- Track gauge – distance between the gauge faces of two adjacent running rails;
- Cross level – difference in height of the adjacent running tables calculated from the angle between the running surface of the rail and a horizontal reference plane;
- Longitudinal level – deviation in the direction perpendicular to the running surface of consecutive running tables on any rail;
- Alignment – deviation in the transverse direction of consecutive positions on any rail, in reference to a mean horizontal position;
- Twist – algebraic difference between two cross levels taken at a defined distance.

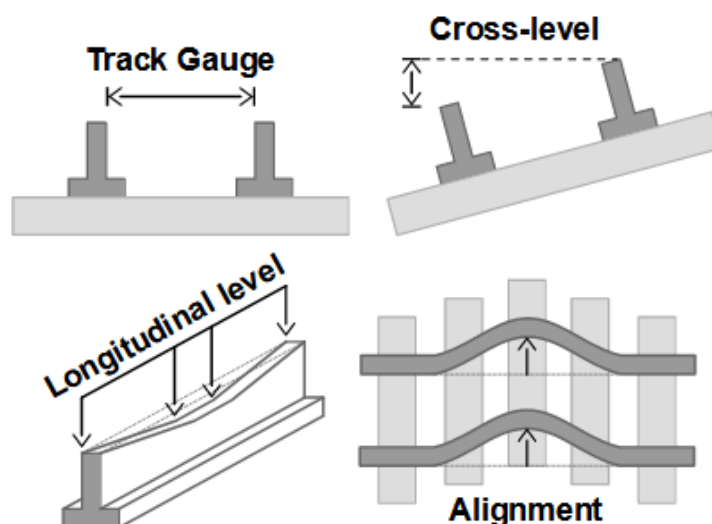


Figure 2.5: Schematic representations of track geometry parameters.

Another very common manual method is the impact hammer test or receptance test. This method is used in the railway context to assess the dynamic characteristics of railway infrastructure elements, similarly to its use in many other civil engineering applications. In

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this method, the structure under analysis is instrumented with accelerometers that are used to register the dynamic response of that structure to the impact generated by the impact hammer. The hammer is equipped with a load cell to register the impact load. Then, by combining the acceleration with the load from the impact test, receptance curves of the local response of the structure can be calculated. In the railway context, the receptance curves allow to estimate track flexibility in the frequency domain and to monitor resonance frequencies of the superstructure. There are many monitoring solutions that incorporate this method in their experimental setups. Some examples include when the focus of the monitoring solution is on assessing dynamic response of the rails and/or the sleepers to detect track defects, or to assess local track support conditions of the superstructure (De Man, 2002; Zhang et al., 2020; Bold et al., 2021).

Sometimes there is the need to collect samples from the different soil layers of a railway substructure for a full geotechnical characterization. For the upper layers, these samples can be collected using mundane manual tools, but for the lower layers of the subgrade there is the need for dedicated soil sampling systems to avoid having to remove the upper layers. After laboratory analysis, these samples can provide information on physical and mechanical properties of soils, moisture content, petrographic configurations of the sampled soil layers and track drainage conditions (Esveld, 2001).

2.2.2 On-site monitoring methods

On-site monitoring methods are based on sensors installed on the railway track, either just on critical locations with higher deterioration rates or with intensive traffic conditions, or on widespread configurations. Examples of these critical railway locations include rail switches, railway crossings or transition zones to and from embankments or bridges (Dahlberg, 2009; Wang et al., 2016). Compared with the other two categories, on-site monitoring methods can also be relatively inexpensive to deploy but lack the capability of the vehicle-based methods to assess entire railway networks for a reasonable financial investment (i.e., a single instrumented railway vehicle can, over time, monitor entire railway lines). On the other hand, on-site methods can be the more cost-effective solution to assess entire railway vehicle fleets, by placing adequate instrumentation on critical nodes of a railway line with high traffic (Ngigi et al., 2012).

There are multiple on-site monitoring methods described in available literature that can be used to gather information on the current state of railway tracks and/or railway vehicles. Two common parameters measured by on-site monitoring methods are track deflection and track dynamic response, which can be used to assess track stiffness and/or subgrade strength (Figure 2.6). Vehicle related parameters that can be measured by these methods include vehicle running speed and vehicle vertical loads transmitted to the track. Since this category is not the focus of this thesis, this sub-section will only present a brief list of instrumentation setups that can be used in this context and some applications of on-site monitoring methods.

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Figure 2.6: Examples of on-site instrumentation: accelerometers (black boxes) plus active and passive targets for a vision-based system to measure track deflections.

In this category, track deflection can be measured using several different types of devices or technologies, including: displacement transducers, accelerometers, geophones, particle image velocimetry systems, Digital Image Correlation techniques (DIC) or optical detection systems (Kouroussis et al., 2015). Common examples of displacement transducers include Linear Variable Displacement Transformers (LVDT), Multi-Depth Deflectometers (MDD), and laser transducers. Optical, laser and DIC based solutions can be used to assess global track deflection of a specific section if the reference point of the measurement is placed outside of the railway track (i.e., if an undisturbed reference location is used), because these are long range non-contact monitoring technologies. Similarly, geophones and accelerometers can also achieve this goal if these sensors are used to acquire displacement data through numerical integration in the time domain. This is due to how these sensor types inherently make measurements in an absolute reference frame (i.e., inertial reference frame) (Selig and Waters, 1994), thus enabling overall deformation measurements. Meanwhile, a LVDT can only measure track deflection between components on the superstructure (e.g., between one rail and the layer ballast), because they represent a contact monitoring technology. When there is the need to measure in-situ elastic and permanent deformations in the various soil layers of a test section, MDD is one of the more common methods used. In this method, several parallel rods are anchored at different depths inside the MDD tube wall. Using these rods as reference points, linear potentiometers measure each rod's movement relative to the surface, thus providing partial and integrated deflection measurements along the depth under assessment.

Common on-site methods to measure track dynamic response use accelerometers, strain gauges or geophones, installed on the rails or on sleepers. These sensors collect their respective data types during the passage of railway vehicles, which can then be processed to assess a wide range of relevant parameters, including: wheel-rail contact loads (Innotrack, 2008; Kouroussis et al., 2015), natural frequencies of superstructure components (Milne et al., 2017), or ground borne vibrations transmitted to the surrounding

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area (Colaço, 2019). Fibre optics sensors can also be used in this context. The work by Kouroussis (2015) presents a brief review on on-site railway monitoring methods, along with detailed considerations on the use of fibre optic sensors installed on the rails to monitor either track or vehicle condition. Relevant features of fibre optic sensors include the ability to operate over long distances (several dozens of kilometres), being light weight and easy to install, having good resistance to corrosion and high temperatures, and being immune to electromagnetic interferences.

2.2.3 Vehicle-based monitoring methods

Vehicle-based monitoring methods rely on instrumented railway vehicles to collect relevant data, regarding a wide array of possible parameters, as they travel along a railway track (Figure 2.7). These can be vehicle related such as the vertical and lateral loads transmitted from the vehicle to the track, the condition and degradation rates of specific vehicle elements (e.g., suspension systems, wheels or dampers), or transmitted vibrations that can be evaluated in the scope of passenger comfort or vehicle running safety (Zhai, 2020; Zhang et al., 2022). They can also be used to collect data on track deflection, track geometry, track defects, vertical track stiffness and other parameters related with track support conditions.

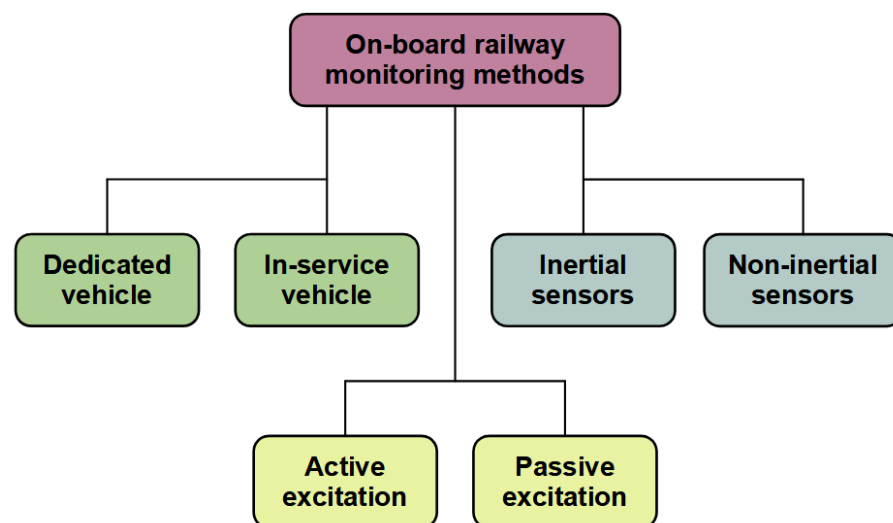


Figure 2.7: Sub-categories of on-board railway monitoring methods.

There are two main groups of vehicle-based monitoring methods to assess railway infrastructures depending on the type of monitoring vehicle being used: solutions based on dedicated auscultation vehicles, and solutions implemented using in-service vehicles. Dedicated auscultation vehicles correspond to integrated monitoring solutions, usually provided by a commercial supplier, which can simultaneously assess multiple track related parameters using extensive on-board sensor setups (Innotrack, 2008; Rivas, 2013). The data provided by these solutions is of high quality, thus justifying their extensive use by several railway managers around the world to monitor their railway networks. But they have some disadvantages in common, most notably that inspections with these vehicles are expensive

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mostly due to the high financial cost of these vehicles. Additionally, they also impose significant constraints on track availability for normal operation and thus can only be applied sparsely (i.e., it is common for these methods to be applied to monitor a particular line only once or twice a year) (Ward, 2011). Methods based on in-service vehicles consist of smaller instrumentation setups installed in common passenger or freight railway vehicles, which can gather data on relevant track related parameters during normal operational conditions. The instrumentation setups, and their respective operational conditions, should be simple enough as to not interfere with the safety and the functional aspects of the selected vehicle during normal service. These methods can provide data with similar quality levels as the dedicated auscultation vehicles, while having significant advantages over them. They are cheaper to install and use, do not interfere with the availability of the track during operation, and have the potential to provide data with much higher frequency over any particular line. The increase in data availability provided by these methods, which can be further reinforced if multiple instrumented vehicles are being concurrently used to monitor an entire railway network in real time, is a cornerstone in the recent trend to move from corrective maintenance actions to condition-based maintenance solutions (Berggren, 2010; Ward, 2011). All these advantages justify the current interest of the scientific and railway industry communities in developing track monitoring methods based on in-service vehicles. Of note in this specific topic, there are several well-established methods based on dedicated auscultation vehicles to monitor track geometry and track defects that are still currently used by today's railway managers (Rivas, 2013), which were developed in the late 1990's and early 2000's. This aspect can be further verified by the fact that there are standards dedicated to regulating how these vehicles must operate during track geometry and track defects monitoring operations (CEN, 2020a; CEN, 2020b).

On the other hand, there are no standards for the measurement of track stiffness with vehicle-based methods (Innotrack, 2008; Berggren, 2009), showcasing the need for further research on the subject. This is likely related with the known issues shared by most of the current track stiffness vehicle-based monitoring methods that are described in relevant literature (Innotrack, 2008, Rivas, 2013). Wang (2016) mentions four key issues that can be attributed to these methods: i) inconsistent measurement concepts, ii) incapability for high-accuracy measurements, iii) low measurement speed rates and iv) insufficient data analysis. Issue i) refers to the fact that the evaluated track stiffness monitoring methods target different stiffness concepts (i.e., static track stiffness, dynamic track stiffness, or the stiffness of specific track components), which are not interchangeable because they depend on distinct aspects of the experimental setup being used or refer to different characteristics of the mechanical system under analysis (e.g., dynamic track stiffness depends on the excitation frequency being used, while static track stiffness does not) (Esveld, 2001). This severely hampers any attempt of comparing results obtained with different track stiffness monitoring methods. Additionally, most of the methods analysed in this work present measurements with relatively low accuracy in field conditions (issue ii), because the

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sensors used in their experimental setups are sensitive to the vibrations that are naturally present in the railway context. This issue is made worse in the several methods that apply time integration to the acquired data, which can amplify noise and other defects commonly present in acquired experimental data. Issue iii) refers to the fact that the methods evaluated in Wang's paper either have low measurement speed rates that impose a limit on the application of the monitoring method, or have self-imposed constraints to allow for higher measurement speed rates but at a cost of reduced data quality. Finally, issue iv) refers to the lack of sufficient research on the topic of dynamic track stiffness and its relationship with excitation frequency, excitation amplitude and vehicle running speed, all of which are important parameters in the evaluated methods. The methodology proposed in this thesis was designed to circumvent these issues by using an alternative monitoring method, while still sharing similar overall goals as the methods described in this paper.

In the context of vehicle-based methods to monitor railway infrastructures and/or vehicles, a relevant distinction that can also be made is between methods based on inertial sensors or on non-inertial sensors. The prevalence of the inertial based methods, when compared with other solutions, is shown below in Table 2.2. Inertial methods use accelerometers and/or gyroscopes installed in the railway vehicle to measure the dynamic response of the interactions between the vehicle and the railway infrastructure. This data is then used by each different method to assess either relevant parameters of the vehicle or the track. Non-inertial methods use other types of sensors, including displacement transducers (e.g., LVDT or Lasers), vision-based sensors, GPR, or strain gauges to collect relevant data on their respective monitoring subjects.

On top of the two previous sets of distinctions (type of railway vehicle and type of sensor technology), another important aspect that can also be relevant is the excitation mechanism used by the vehicle-based monitoring method to induce the dynamic response from the railway infrastructure that is under analysis. This aspect is particularly relevant for track stiffness monitoring methods, due to the previously reported non-linear mechanical behaviour of railway tracks. The distinction here is between methods that use active solutions as the excitation mechanism (i.e., solutions that apply controlled loads, at specific frequencies, with dedicated equipment) and passive solutions that rely on the natural excitation caused by the passage of railway vehicles over the tracks. Active solutions have the intended advantage of creating more controlled conditions for data collection, which is important since track stiffness is dependent on several factors, including excitation amplitude and excitation frequency (Innotrack, 2008; Berggren, 2009). However, this aspect also represents one of their disadvantages since comparing results obtained with different active methods is unreliable due to the non-linear behaviour of the track (Innotrack, 2008; Wang et al., 2016). Additionally, due to their inherently more complex equipment setups, active solutions can only be implemented in dedicated auscultation vehicles. These downsides, together with the recent need for higher amounts of track condition data (i.e., higher quantity and with higher periodicity), are some of the main

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reasons for the move from active solutions to methods that rely on the natural excitation created by railway vehicles (Wang et al., 2016).

The natural excitation created by the passage of a railway vehicle over the track is the result of vertical track stiffness variations that exist along the line (Esveld, 2001). These track stiffness variations can either be inherent from track design (e.g., localized track stiffness variations created by the intermittent, but periodic, presence of the sleepers below the rails (Figure 2.8); transitions between subgrades with different mechanical properties, etc), or the result of the natural degradation of track support conditions (Zhai, 2020). At each of these stiffness variations, which most of them are sudden but not very intense, the passage of the vehicle creates a load impulse on the track like a small impact (Zhai, 2020). It is the combination of these successive impacts along the track, primarily caused by the interaction between the vehicle and the intermittent sleepers, which represent this natural excitation mechanism. Due to the impact like nature of these impulses, the result is a broad band excitation of the natural frequencies of the combined mechanical system under analysis (Cohen, 1995; Zhai, 2020). This feature is one of the main aspects that is being exploited in the proposed methodology to assess track support conditions, including the conditions of the subgrade, thus removing the need for an active excitation solution. The concept of using passive excitation solutions is suitable for implementation on in-service vehicles, since the simpler equipment setups required for their implementation agree with the technical limitations that this category imposes. Data obtained through vehicle-based passive solutions are more subject to the circumstances imposed by the vehicle's running conditions (i.e., the current operational and environmental conditions that include vehicle running speed and temperature changes), but have the feature of being inherently more representative of normal track-vehicle operational conditions (i.e., the data is more representative of the dynamic response of this system, considering all non-linearities present) (Esveld, 2001; Kouroussis et al., 2012).

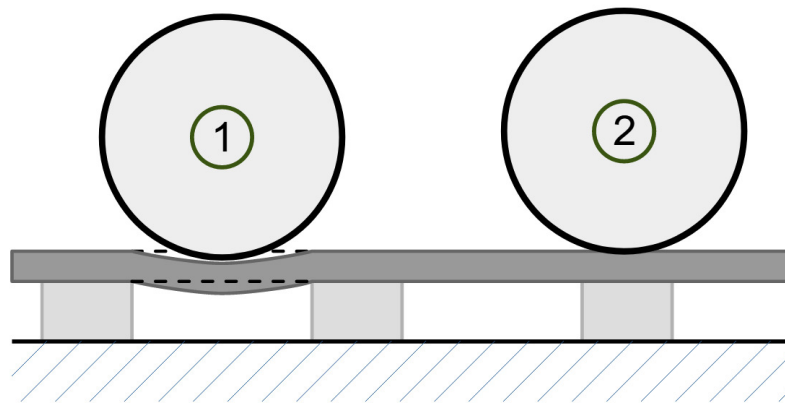


Figure 2.8: Schematic representation of the sleeper related track stiffness variation that promotes the natural excitation mechanism, presenting the rail deformation differences between (1) the more deformable position between sleepers and (2) the more rigid position right on top of a sleeper.

Table 2.2 provides a list of methods/studies known to the author, along with their respective categorization in the previously mentioned sub-categories and some additional

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relevant information. This table results from the author's research on the topic, performed in the context of the present thesis, but only contains one paper per method/author. It does not represent every research on the general topic of vehicle-based railway monitoring methods, either read by the author or published on the topic. However, precautions were taken for this research to be as comprehensive, representative and non-biased as possible. The rest of this sub-section will present a brief description on most of these methods (Table 2.2), relevant comments on them, and some conclusions on the current state of this category of railway monitoring methods.

Table 2.2: List of studied papers on vehicle-based track monitoring methods. (* These methods are references to commercial methods. The remaining papers are mentioned in the References section).

Year	Country	1 st Author	Vehicle	Excitation	Sensors	Monitored Parameter/s
1997	China	Wangqing	Dedicated	Active	Inertial	Stiffness
2000	Japan	Naganuma	In-service	Passive	Inertial	Geometry, Defects
2002	USA	Li	Dedicated	Active	Inertial	Stiffness
2002	Czech Rep.	Vymtal	Dedicated	Passive	LVDT	Stiffness
2002	Netherlands	Rasmussen	Dedicated	Passive	Lasers	Stiffness
2004	USA	Norman	In-service	Passive	Lasers	Stiffness, Geometry
2006	UK	Weston	In-service	Passive	Inertial	Geometry, Defects
2007	Italy	Caprioli	In-service	Passive	Inertial	Defects
2007	Switzerland	Soldati	Dedicated	Active	Inertial	Stiffness
2007	USA	Sussmann	Dedicated	Passive	Inertial	Stiffness, Geometry, Defects
2009	Sweden	Berggren	Dedicated	Active	Inertial	Stiffness
2010	Spain	Real	In-service	Passive	Inertial	Geometry, Defects
2010	Poland	Uhl	In-service	Passive	Inertial	Defects
2011	Korea	Lee	In-service	Passive	Inertial	Geometry, Defects
2011	Germany	Heirich	In-service	Passive	Inertial	Geometry
2011	Russia	Boronakhin	In-service	Passive	Inertial	Geometry
2011	France	Hosseingholian	Dedicated	Active	Inertial	Stiffness
2012	Japan	Tsunashima	In-service	Passive	Inertial	Geometry, Defects
2013	China	Qin	In-service	Passive	Inertial	Defects
2014	Netherlands	Molodova	In-service	Passive	Inertial	Defects
2014	UK	Louis Le Pen	In-service	Passive	Inertial	Geometry, Defects
2014	Netherlands	Núñez	In-service	Passive	Inertial	Geometry, Defects
2014	Hungary	Vinko	In-service	Passive	Inertial	Defects
2015	China	Xiao. Zhang	In-service	Passive	Inertial	Geometry, Defects
2015	Netherlands	S. Li	In-service	Passive	Inertial	Defects
2016	Spain	Salvador	In-service	Passive	Inertial	Defects
2016	China	X. Wei	In-service	Passive	Inertial	Geometry, Defects
2016	Ireland	Quirke	In-service	Passive	Inertial	Geometry
2016	Brazil	Barbosa	In-service	Passive	Inertial	Geometry, Defects
2016	China	Ning	In-service	Passive	Inertial	Defects
2017	USA	Lederman	In-service	Passive	Inertial	Defects
2017	Australia	Lingamanaik	In-service	Passive	Inertial	Geometry, Defects
2017	Japan	Saito	In-service	Passive	Inertial, Vision	Geometry, Defects
2017	Canada	Roghani	In-service	Passive	Lasers	Stiffness
2018	Sweden	Vinberg	In-service	Passive	Inertial	Defects
2018	Sweden	Berggren	Dedicated	Passive	Inertial	Stiffness, Geometry
2018	Belgium	Germonpré	Dedicated	Passive	Inertial	Geometry, Defects
2018	Sweden	Björklind	In-service	Passive	Inertial	Subgrade properties
2019	Iran	Mehrali	In-service	Passive	Lasers	Stiffness, Geometry
2019	Portugal	André Paixão	In-service	Passive	Inertial	Geometry, Defects
2019	India	Lathe	In-service	Passive	Inertial	Geometry, Defects
2020	Italy	A De Rosa	In-service	Passive	Inertial	Geometry, Defects
2020	China	Y. Wang	In-service	Passive	Inertial	Defects
2021	Netherlands	H. Wang	In-service	Passive	Vision	Geometry
2021	China	C. Chang	Dedicated	Passive	Vision	Defects
*	Switzerland	SBB	Dedicated	Passive	Inertial, Vision	Geometry
*	Sweden	Infranord	Dedicated	Passive	Inertial	Geometry
*	UK	Network Rail	Dedicated	Passive	Inertial	Geometry

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Most of the vehicle-based railway monitoring methods developed and implemented prior to the year 2010 were based on dedicated auscultation vehicles (Innotrack, 2008; Rivas, 2013). A possible explanation for this is that researchers at the time preferred to use this solution because the overall concept of monitoring railways with instrumented vehicles was still new. The use of dedicated vehicles provided a more controlled monitoring environment than trying to use in-service vehicles, since methodology development is easier if there is control of the entire system than trying to adequately match an instrumentation setup with the functionalities and requirements of an in-service vehicle. Thus, the research efforts could be focused on developing the actual monitoring technologies. All the methods presented in Table 2.2 that use active excitation solutions were also developed in this period. This was likely due to a similar reason as the choice of using dedicated auscultation vehicles, where the more controlled track loading conditions provided by active excitation solutions represented a better monitoring setup.

In this early period, the more established and widely used monitoring methods were based on assessing track geometry (Innotrack, 2008), likely due to how this parameter is capable of simultaneously assess track support conditions and vehicle running safety (Rivas, 2013). While track geometry data cannot provide direct information on track subgrade conditions (Wang et al., 2016), it still is a vital source of data on some aspects of track structural health (Innotrack, 2008, Roghani, 2017). Examples of such methods from this period, provided in Table 2.2, are the Swiss SBB, the Swedish Infranord and the UK Network Rail New Measurement Train (Rivas, 2013) (Figure 2.9). Most of these methods were developed in the decades prior to the year 2000 and have been extensively used ever since by multiple railway managers around the world (Rivas, 2013). All these methods are based on an extensive instrumentation setup dedicated to measuring every relevant parameter of track geometry, all according to the standards EN 13848-1 (CEN, 2019) and EN 13848-2 (CEN, 2020a).



Figure 2.9: (a) the Swiss SBB monitoring vehicle, (b) the Swedish Infranord monitoring vehicle, and (c) the UK Network Rail New Measurement Train (adapted from Rivas, 2013).

The Swiss SBB track monitoring vehicle (Figure 2.9a) was equipped with an inertial track geometry measurement system. This non-contact monitoring method consisted of two sets of optical measurement boxes that were used to assess, record and analyse track geometry. This vehicle was also equipped with a GPS system to geo-locate the collected data. The system, according to the manufacturer, was capable of highly accurate track geometry measurements at vehicle running speeds up to 120 km/h. The resulting sampling

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distance of the track was 0.25 m. In the Infranord monitoring vehicles (Figure 2.9b) longitudinal level was measured with accelerometers mounted in the car body and with LVDTs mounted between the axles and the car body. Some of these vehicles were also equipped with a mechanical chord measurement system that was used to monitor longitudinal level and alignment even in harsh weather conditions. Others were equipped with systems to measure overhead wire condition, detect the presence of rail corrugation and assess rail profile. All vehicles used a sampling distance of 0.05 m for track geometry measurements, which was resampled to 0.25 m during post-processing. The UK Network Rail New Measurement Train was a converted high-speed vehicle used to monitor track geometry and overhead wire equipment conditions at vehicle speeds up to 200 km/h (Figure 2.9c). Data geo-referencing was achieved by the combined use of an on-board GPS, odometry tachometers to measure train speed and distance travelled, an inertial unit to know when the train changed tracks, and an underlying map of the network. On each side of the vehicle there was a displacement transducer between the bogie frame and the axle box. An inertial system containing a triaxial accelerometer and a rate gyroscope was suspended from the bogie frame. On the underside of the vehicle there were also optical scanners that located the relative position of each rail. It was the combination of the data from all these sensors that provided information on track geometry. The reported sampling distance of this system was in the order of 0.25 m. An example of this type of monitoring method used in Portugal is the EM 120 track recording car. This vehicle is employed by *Infraestruturas de Portugal* (IP) (the Portuguese company responsible for the entire railway network) as part of their track monitoring activities to collect data over the entire Portuguese railway network. Over the years, this data has also been used by Portuguese researchers to investigate relevant issues on track support conditions, such as the effects of transition zones and buried culverts on track geometry deterioration rates (Fortunato et al., 2007; Paixão et al., 2016a; Varandas et al., 2014, 2017).

Considering the positive and negative aspects of assessing track support conditions based on monitoring track geometry that were previously presented, the railway sector also developed and implemented alternative methods based on monitoring vertical track stiffness to achieve this goal. The Innotrack report (2008) identifies the two main reasons that led to this move in the years prior to 2010: i) track stiffness is a better parameter than track geometry to provide information on most of the root causes that lead to track degradation; and ii) track stiffness is a parameter that can provide relevant information on track subgrade conditions, contrary to track geometry monitoring methods. These reasons were particularly relevant at that time because there was also a general intent to implement more high-speed railway tracks, since track stiffness is a very important parameter in studies focused on evaluating if a track is fit for the high-speed railway standards (i.e., to check if a track is compatible with the higher vehicle running speeds and higher axle loads) (Esveld, 2001).

From the multiple track stiffness monitoring methods based on dedicated auscultation

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vehicles developed in this period, some of them became hallmarks of the efforts developed in this context at that time (Innotrack, 2008; Rivas, 2013). One of them was the Swedish method developed by Berggren during his PhD thesis (2009) named Rolling Stiffness Measurement Vehicle (RSMV) (Figure 2.10).

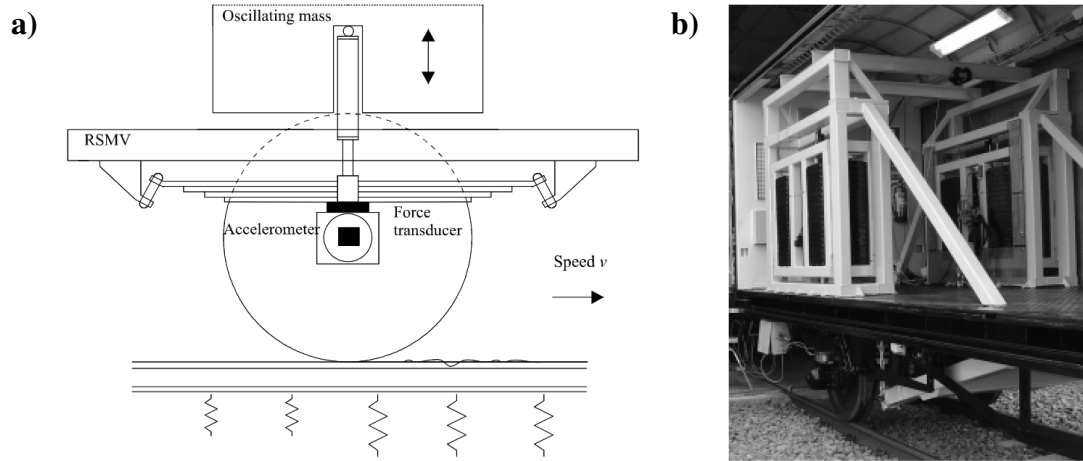


Figure 2.10: (a) Schematic representation of the RSMV system, and (b) a picture of the RSMV system (Berggren, 2009).

This vehicle consisted in a rebuilt two-axle freight wagon equipped with a dedicated track loading equipment and monitoring sensors. The method proposed in this research was focused on assessing track support conditions by monitoring dynamic track stiffness. The track was excited by two masses oscillating at specific frequencies (up to 50 Hz) and amplitudes, through one of the axles of the vehicle. The dynamic track stiffness was estimated based on vertical loads and accelerations measured on the axle box level by the on-board instrumentation. The static axle load applied by this system was 180 kN and the maximum dynamic load was 60 kN. The system had two monitoring configurations depending on the vehicle's running speed: a high measurement rate mode that allowed vehicle speeds up to 50 km/h with one to three simultaneous sinusoidal excitation frequencies in the same excitation signal, or a configuration designed for detailed investigations at lower speeds (below 10 km/h) with broad band excitation signals. Berggren gave two main reasons for measuring dynamic track stiffness, as opposed to measuring static track stiffness. The first reason was that when using the full range of excitation frequencies available to his system, a significant portion of the track infrastructure could be assessed including the subgrade. The second part was that when using just a higher excitation frequency range, the obtained data was more focused on the superstructure, since higher frequencies do not excite the lower layers of railway infrastructures. Thus, by using a methodology based on monitoring dynamic track stiffness, employing different excitation frequencies, Berggren claimed that more thorough information on railway track support conditions could be obtained than with static track stiffness measurements. Most of the features and limitations presented by Berggren for his method (e.g., dependence between vehicle running speed and allowed excitation frequency ranges) correspond to some of the issues identified later by Wang on his paper (2016)

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regarding track stiffness monitoring methods. In the scope of Wang's analysis, the more crucial issue in Berggren's method was the difficulty entailed in monitoring dynamic track stiffness using complex active excitation solutions and then compare the results with data obtained with other methods (i.e., the issue regarding inconsistent measurement concepts). But at the time, this method represented a significant advancement in the field of vehicle-based monitoring methods to assess track support conditions using track stiffness and served as inspiration for subsequent developments on this topic.

One such development made by a research group that also included Berggren was presented on a research paper in 2018 (Nielsen et al., 2018). This work describes the developments on Berggren's original concept made by this group, which consisted in two main steps: the first was adding a new instrumented axle to the monitoring vehicle to measure track deflection in unloaded conditions; and the second consisted of a new track stiffness monitoring concept based on measuring track deflection and from it estimate track stiffness. The first step was implemented to allow the method to separate between the contributions to track deflection due to track longitudinal level and track defects from the contributions due to track stiffness. The concept behind this first step is that an unloaded instrumented axle would only observe the contributions of track geometry to track deflection monitored through it, while the loaded axle from the original concept would observe the contributions of both aspects to track deflection. The combination of the data obtained in this setup enabled the removal of track geometry contributions to the measured track deflection, thus creating a more accurate track stiffness monitoring method. The second step, which represented a significant drift from the original track stiffness measurement method, was based on measuring simultaneous track deflections at six points along a track with laser transducers installed on the dedicated auscultation vehicle. These measurement points were spaced to be able to monitor track deflection in six different track loading conditions, based on their relative position to the vehicle's axles. These deflection values were then processed through a track-vehicle computational model to estimate the deflection curve of the track, and from it obtain the respective track stiffness profile. This was done by iteratively tuning the model's structural parameters until an adequate match was achieved between its results and the measured data. The model employed a single beam to represent the rails, which was placed upon a Winkler type elastic foundation representing the rest of the track (i.e., rail pads, sleepers, ballast, and subgrade). This second evolution forwent the concept of monitoring dynamic track stiffness directly with a dedicated actuator setup, which was used in prior solutions presented by Berggren, and opted for a method based on estimating static track stiffness. This solution cannot assess some of the finer aspects of a track's response that a dynamic track stiffness measurement enables, like estimating overall damping properties of a track. However, this new concept corresponds to a much simpler and easier to implement method, which can provide reliable data on track support conditions, and does not have some of the issues identified by Wang et al (2016) and Berggren on other track stiffness monitoring methods. Nevertheless, this new method

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now suffers significantly more from the superstructure bias issue that was previously mentioned regarding track deflection monitoring solutions (Innotrack, 2008; Wang et al., 2016), thus leaving room for improvements.

Another important hallmark of track stiffness monitoring methods from the early 2000's period was the *Portancemetre* method developed by Hosseingholian et al (2011). This French project presented another method to continuously measure dynamic track stiffness with a dedicated vehicle (Figure 2.11). The system was based on a carriage that contained a dynamic actuator and the sensors, another carriage that carried the power supply for the actuator, and a regular railway locomotive to tow the entire system. The general concept behind this dynamic actuator, similarly to the one used by Berggren, consisted of applying a sinusoidal excitation to the track with varying frequencies and amplitudes (frequencies up to 25 Hz). Then, track response was measured by a set of accelerometers installed on the oscillating masses and on the actuator carriage. From this acceleration data, track deflection and applied load was calculated. Track deflection was calculated by double integration of the acceleration data, while the load data was calculated through a mathematical model that used the acceleration on multiple elements of the carriage and their respective mass values. From this processed data, dynamic track stiffness values were then estimated. Like Berggren's first method, this system represented a significant development at the time on track support conditions monitoring methods. But it also contained several of the issues identified later by Wang et al (2016) and other relevant publications regarding track stiffness monitoring methods (Innotrack, 2008).



Figure 2.11: Composition of the railway *Portancemetre* system (Hosseingholian et al., 2011).

The remaining track stiffness monitoring methods developed in this period (i.e., prior to 2010), mentioned in Table 2.2, used variants similar to the previously presented dedicated railway vehicle concepts. Wangqing's method (1997), Li's method (2002), Soldati's method (2007) and Sussmann's method (2007) employed separate axles on the monitoring vehicle to apply loaded and unloaded conditions to the track, relying on the same concept used in Berggren's second method. From those two distinct loading situations, track deflection and/or track geometry was monitored using appropriate sensor arrangements, from which track stiffness was then estimated. Vymtal's method (2002) was based on measuring track deflections in loaded and unloaded conditions, to then infer track stiffness, but required two runs of its dedicated railway vehicle over the track region under

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evaluation. On the first run, the monitoring axle was unloaded. Then in the second run a hydraulic actuator installed on the vehicle applied a constant rolling load on the track. Rasmussen's method (2002) proposed an interesting concept based on laser doppler sensors installed on a dedicated vehicle to measure rail bending velocity, but he never presented a prototype system. Like Berggren's second method, this method used rail bending velocity measurements to estimate track stiffness through a dedicated track-vehicle computational model.

In Table 2.2 there are only two more papers pertaining to the use of dedicated monitoring vehicles that have not been mentioned yet. The first paper, by Germonpré et al (2018), does not report on the development of a new monitoring method, but describes a research study on the individual contributions of longitudinal track unevenness and track stiffness variations to railway induced vibrations. It also presents how track stiffness variations can be modelled as equivalent track unevenness to reduce the modelling effort while only introducing small modelling errors. The data used to test the proposed hypothesis was collected with one dedicated auscultation vehicle from Infranord, demonstrating that this type of method was still being used in more recent years. The second paper, by Chang et al (2021), presented an innovation at the time on the use of dedicated auscultation vehicles to monitor railway tracks. It describes the development of an unmanned railway inspection vehicle (Figure 2.12) and the obtained preliminary test results. This vehicle is used to monitor track geometry and track defects through an embarked vision system. The authors justify the use of this concept, instead of using in-service vehicles, because it imposes less restrictions on the instrumentation setups and can potentially be used at any time of the day in between regular train runs on a track. The reported results are promising, but this implementation had several practical limitations due to the low structural sturdiness of the vehicle and low maximum running speeds. While this specific implementation had some issues, the overall concept has the potential to be a significant contribution to the field. In this topic, the work by Jing et al (2022) presents a review on developing and implementing railway monitoring methods based on unmanned vehicles (railway and aerial). General advantages and disadvantages of this concept are mentioned here, along with the reasons that have led to their relatively low usage by today's railway managers.

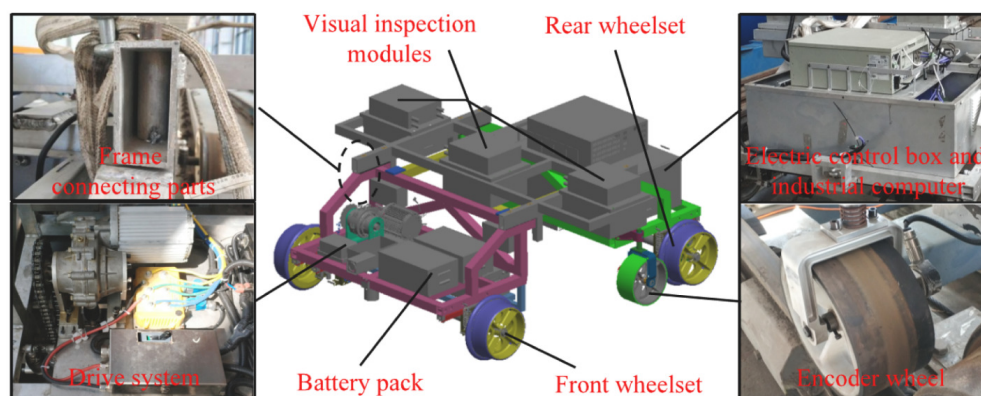


Figure 2.12: Unmanned rail inspection vehicle developed by Chang et al. (2021) (adapted figure).

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In the years after the development of the methods described in the Innotrack report (2008) up to nowadays (i.e., from 2010 up to today), the development of new vehicle-based monitoring methods using the concept of dedicated auscultation vehicles was mostly abandoned in favour of developing methods based on using in-service vehicles equipped with sensors and other monitoring equipment. This was due to the previously mentioned advantages of this concept over the use of dedicated vehicles, particularly their capability to provide higher amounts of data. However, some methods using dedicated vehicles are still used today by railway managers and researchers to collect information on track support conditions (e.g., Björklind, 2018). This is especially true regarding the track geometry and track defects monitoring methods developed in the period prior to 2010. These methods proved to be very reliable sources of data on these parameters, even if they have the previously mentioned downsides regarding the use of dedicated auscultation vehicles (Rivas, 2013).

In-service vehicle-based methods

By analysing the methods that use instrumented in-service vehicles presented in Table 2.2, it is possible to perceive some trends that were established over the years regarding some common aspects. Most of these methods use inertial sensors as the main or only source of data in their instrumentation setups. A significant portion of these methods are also dedicated to monitoring track geometry and/or track defects, and only a minority is focused on assessing other parameters like track stiffness and subgrade properties. The proliferation of methods using inertial sensors is likely related with how these sensors have comparatively low acquisitions costs, are readily available on the market, are easy to install in multiple situations due to their small dimensions and mechanical sturdiness and can provide data with adequate quality in many scenarios (Heirich et al., 2011; Chia et al., 2019). Another significant feature of this type of sensors is their capability to provide non-contact measurements in an absolute reference frame (i.e., the inertial reference frame). The reasons for the high numbers of track geometry and track defects monitoring methods are likely related with the advantages of monitoring these parameters, which have been presented previously in this section (i.e., these methods are comparatively simple and inexpensive to implement, and these data types are relevant sources of information on track support conditions and vehicle running safety).

There are the four methods presented in Table 2.2 dedicated to monitoring other track related parameters using in-service vehicles, namely track stiffness and track subgrade properties. Norman's method (2004), which was mentioned in the Innotrack report (2008), is probably one of the first methods based on in-service vehicles dedicated to monitoring track stiffness. The first step of this method is to evaluate track geometry with laser displacement transducers measuring track deflection. Then, this data is used to estimate track stiffness through a Winkler type mathematical model. This paper reported that this solution could provide accurate estimates of track stiffness, but also that this method suffers

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from most of the issues on track stiffness monitoring methods identified by Wang in his paper (2016) and described in the Innotrack report (2008). Mehrali's method (2019) uses a data processing methodology based on Norman's method (2004) but improves on it by employing Big Data tools in the data processing routines. This work describes the effects of using the Classification method, the Decision Tree method, the Clustering method, and the Dominant Wavelength filtering method in this specific context. The last two methods (Roghani, 2017; Björklind, 2018) will not be described in this section, because they will be used as relevant examples later in this chapter.

The sub-group of methods from Table 2.2 dedicated to monitoring track geometry and/or track defects using in-service vehicles is presented now in Table 2.3. From the methods presented in this table, three specific trends were perceived. However, each individual method has relevant features that makes it distinct from each other. These can include different specific aspects on their data processing methodologies (e.g., the method by Real et al. (2010) proposes the application of digital filters to further process deflection data after the frequency analysis), or methods that are focused on analysing specific track features such as frequency-based methods focused on observing track corrugation (Caprioli et al., 2007) or track squats (Molodova et al., 2014).

Table 2.3: List of studied papers that use in-service vehicles and are dedicated to monitoring track geometry and/or track defects (sub-group from Table 2.2), including perceived monitoring trends.

Year	Country	1 st Author	Trend	Monitored Parameter/s
2011	Korea	Lee	Advanced Tools	Geometry, Defects
2014	Netherlands	Núñez	Advanced Tools	Geometry, Defects
2016	Brazil	Barbosa	Advanced Tools	Geometry, Defects
2016	Ireland	Quirke	Advanced Tools	Geometry
2019	India	Lathe	Advanced Tools	Geometry, Defects
2020	Italy	A De Rosa	Advanced Tools	Geometry, Defects
2007	Italy	Caprioli	Frequency Analysis	Defects
2013	China	Qin	Frequency Analysis	Defects
2014	Netherlands	Molodova	Frequency Analysis	Defects
2015	Netherlands	S. Li	Frequency Analysis	Defects
2016	Spain	Salvador	Frequency Analysis	Defects
2016	China	Ning	Frequency Analysis	Defects
2017	USA	Lederman	Frequency Analysis	Defects
2018	Sweden	Vinberg	Frequency Analysis	Defects
2020	China	Y. Wang	Frequency Analysis	Defects
2000	Japan	Naganuma	Numerical Integration	Geometry, Defects
2010	Spain	Real	Numerical Integration	Geometry, Defects
2011	Germany	Heirich	Numerical Integration	Geometry
2011	Russia	Boronakhin	Numerical Integration	Geometry
2012	Japan	Tsunashima	Numerical Integration	Geometry, Defects
2014	UK	Louis Le Pen	Numerical Integration	Geometry, Defects
2015	China	Xiao. Zhang	Numerical Integration	Geometry, Defects
2016	China	X. Wei	Numerical Integration	Geometry, Defects
2017	Australia	Lingamanaik	Numerical Integration	Geometry, Defects
2019	Portugal	André Paixão	Numerical Integration	Geometry, Defects
2017	Japan	Saito	Vision sensors	Geometry, Defects
2021	Netherlands	H. Wang	Vision sensors	Geometry
2006	UK	Weston	-	Geometry, Defects
2010	Poland	Uhl	-	Defects
2014	Hungary	Vinko	-	Defects

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The following descriptions of each trend mentioned in Table 2.3 represent general and adequate explanation on the methods in each group.

i) The first trend corresponds to methods that apply numerical integration in the time domain to collect inertial data to estimate track deflections. More specifically, all these methods apply double integration to collected acceleration data to obtain track deflections and rail position relative to the monitoring vehicle. From these results, track geometry information is inferred. Some of these methods are also able to detect some types of track defects. While this type of methods represents a reliable category on some important aspects related with track support conditions, they all suffer from some issues, namely: the noise amplification effect that the numerical integration procedure entails (Wang et al., 2016) and the potential bias towards railway superstructure conditions that was previously described.

ii) The second trend corresponds to the group of methods that apply frequency analysis to collected inertial data to monitor specific track defects (e.g., squats or rail corrugation). This data processing trend is either based on detecting the characteristic frequencies of these track defects (Figure 2.13), or on detecting specific disturbances in the time-frequency representation of the collected data that are caused by some track defects (more information on this topic will be presented in section 2.3). Most of these papers rely on derivations of the Fast Fourier Transform (FFT) to calculate the frequency spectra, but some of them also use more advanced time-frequency analysis tools, namely: the Wavelet distribution (Caprioli et al., 2007; Molodova et al., 2014) and Cohen's Class distributions (Ning et al., 2016).



Figure 2.13: Picture of railway corrugation on the rail head, illustrating its periodic pattern that enables the use of frequency-based methods to detect this type of track defect.

iii) The third trend represents the group of methods that propose the use of more advanced data processing tools in their methodologies. The examples presented in Table 2.3 include three methods that propose the use of Kalman filters to process the acquired acceleration data into track deflection results, and from that assess track geometry and track defects (Lee et al., 2011; Barbosa, 2016; Lathe and Gautam, 2020). There is also a paper describing the application of Machine Learning (ML) tools to determine vehicle safety indicators based on track geometry and the presence of track defects (De Rosa et al., 2020). The last method in this group represents a review on the application of Big Data concepts in the context of railway monitoring methods based on instrumented railway vehicles (Núñez et al., 2014).

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As a relevant side note, the railway sector has also been investing in the development of tools and methods based on ML and Artificial Intelligence (AI) to improve almost every aspect of its activities, taking advantage of recent developments in this field. As examples, some of these undertakings have been focused on developing new railway vehicle concepts (e.g., by creating self-driving railway vehicles) or on finding new and improved solutions for maintenance related activities on railway assets (e.g., by developing digital twins of the railway vehicles and/or the railway infrastructure for online and continuous maintenance planning) (Tang et al., 2022; Zhang et al., 2022; Mishra et al., 2022). Naturally, SHM developments in the railway sector are also benefiting from improvements based on AI and ML solutions, which have been focused on a myriad of topics. Some of these topics include the creation of better monitoring methods using ML integrating sensors, or on developing new solutions to process acquired data and/or to assess railway assets. Examples of such applications are well documented in relevant bibliography (Tang et al., 2022; Mishra et al., 2022), demonstrating the practical benefits of employing these technologies, which overall translate into efficiency, reliability and/or efficacy improvements over conventional solutions. However, using ML and AI based tools can also entail some relevant shortcomings in this context. Bobadilla and Martin (2023) present some considerations on this topic, namely that such methods can be very data dependant and thus can be unreliable if precautions are not taken in this regard (e.g., if inadequate data is used during the training step of an encoder-based data processing method, the outputs can be completely unrelated with reality). Moreover, this work states the following additional possible disadvantages of such methods: reduced availability of labelled data sets and small number of defective observations to enable adequate implementation of ML based tools, and low explainability of the ML and AI algorithms that sometimes not even their designers are able to explain how the tool came out with a specific result or to prove its validity.

Returning to Table 2.3, an outlier that can be perceived in the presented methods is the use vision-based sensors, instead of inertial sensors, to acquire track deflection data and/or detect the presence of track defects. The number of methods using this concept is far below the number of methods using inertial sensors, which is likely related with how these sensors are comparatively more expensive to acquire and install, are more complex to use and maintain, are relatively more susceptible to environmental conditions (e.g., the presence of fog or smoke severely hampers their use), and the collected data usually requires significant computational resources to process. But this type of sensors has the significant benefit of being a non-contact solution to directly monitor track deflections, something that inertial based methods can only do indirectly by using time integration procedures or other equivalent techniques. This benefit is also shared by other non-contact sensor types like laser displacement transducers, which are also still underly used when compared with inertial-based solutions. The two methods identified in Table 2.3 that use vision sensors represent vehicle-based monitoring solutions where these sensors are used to provide additional information on track related aspects, complementing other types of monitoring

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solutions (Saito et al., 2017; Wang et al., 2021).

Finally, the three remaining papers from Table 2.3 do not follow any of the previous trends on solutions to monitor track geometry and/or track defects. The work by Weston et al (2006) describes a method that uses pitch-rate gyroscopes to monitor track geometry and track defects. While pitch-rate gyroscopes are inertial sensors, this method forgoes the need to use time integration to obtain track deflections by instead estimating this parameter based on the relative position between each monitoring point on the vehicle. This method provides an interesting solution to monitor track deflections by overcoming the issue of relying on time integration procedures while using inertial sensors, but still suffers from some of the other issues of these methods like to potential bias towards superstructure conditions. Uhl's method (2010) presents a solution to monitor track defects based on using a model to solve an inverse problem to detect track defects. In this method, track defects profiles are estimated and tested in the proposed model to obtain estimates of vehicle dynamic response. Then, the track defects profile that more closely recreates the monitored acceleration data is this method's estimate of the track defects on the line under analysis. While there is potential in this method, the authors of this paper report that the obtained results were only obtained at low vehicle running speeds, and the results were not compared with actual track defects data from the monitored railway track. The last paper, by Vinko (2014), describes several methods dedicated to observing track corrugation and rolling contact fatigue. One of them is based on vehicle wheels instrumented with accelerometers to monitor wheel slippage and its relationship with the corrugation phenomenon. In this method, the acceleration data is used directly to assess this topic. The remaining methods rely on Eddy current sensors, digital microscopes and high-speed cameras to monitor these issues.

In conclusion, from the entries on Table 2.2, the abundance of inertial methods and passive excitation solutions becomes evident when compared with the alternative options. This disproportion can be attributed to several reasons, one of which is related with how these two types of solutions tend to be simpler and cheaper to implement (Innotrack, 2008). The previously mentioned prevalence of track geometry and track defects measuring methods is also made evident, when compared with monitoring methods based on the other parameters from Table 2.1. This is likely due to the reasons previously given in this section, which include the fact that track geometry can simultaneously be used to assess track support conditions and vehicle running safety (Rivas, 2013). The lack of vehicle-based methods dedicated to assessing subgrade properties is also evident. This is possibly related with the added difficulty of monitoring the subgrade from the point of view of a moving vehicle, which does not represent an easily accessible direct contact between the observation point and the subgrade when compared with the manual and on-site monitoring methods. A work authored by Bobadilla and Martin (2023) represents an extensive review on modern tendencies in vehicle-based condition monitoring of railway tracks, including an analysis on methods proposed over the years beginning from the 1980's. This work also

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provides insights in several relevant topics in this context, thus representing a very interesting reference for further information in this subject.

2.2.4 Final remarks

From the considerations presented in this section, the reasons that justify the lack of a preferred general solution for monitoring railway track support conditions becomes evident. Track monitoring represents a complex problem, with multiple variables and influencing factors. Thus, it is naturally difficult to find a solution that can attend to every factor. While there are already several adequate methods to monitor specific aspects of track support conditions, there is also still room for improvement. This is one of the main drives for the ongoing research on the topic around the world, which includes the present work.

The proposed methodology to monitor track support conditions is based on a parameter that is not specifically mentioned in Table 2.1, namely the vibration characteristics of the railway infrastructure. However, this parameter is indirectly related with track stiffness and subgrade strength (Esveld, 2001). According to the classification systems described in sub-section 2.2.3, the proposed vehicle-based monitoring methodology was developed for deployment using in-service vehicles, is based on the passive excitation solution, and utilizes inertial sensors as the data source. Thus, the proposed methodology also benefits from the previously described advantages of using them. The following section will present more information on this topic, including an introduction on the proposed methodology and its underlying concepts.

2.3 Signal analysis and vibration-based methods

This section provides an overview on several relevant concepts related with signal analysis and vibration-based methods in general and then presents some of these concepts in the railway context. This is done here to facilitate the discussion of important aspects regarding the methods that will be presented in the following section and to add further context and insight on the reasons that led to the development of the methodology proposed in this thesis. This section starts with a brief introduction on the general topic of time and frequency signal analysis, followed some considerations on the application of these concepts to railway monitoring. The second sub-section provides an introduction on the topic of vibration-based methods in the railway context.

2.3.1 Frequency-based analysis

The representation of how a signal varies in the time domain is a very common and often fundamental tool used in most signal analysis situations (Cohen, 1995). However, in some situations it is often advantageous to also study a signal using different domains, such as the spatial or the frequency domains. One of the main reasons to employ frequency-based analysis is the possibility to characterize the physical properties of matter, including the

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capability to characterize the propagation and attenuation characteristics of a medium. This reason is the main aspect that justifies the value of using frequency analysis in several engineering contexts, where the focus is on studying physical phenomena, such as in SHM and vibration-based damage detection methods. The process of applying signal analysis in the time-frequency domain, to describe how the spectral content of a signal evolves over time, is based on the projection or decomposition of that signal into a set of well-known base functions (i.e., a distribution) (Cohen, 1995). This type of analysis corresponds to a very important tool in several areas of research where it is important to be able to locate and distinguish the spectral content of a signal over its duration, such as in the analysis of audio signals.

The most common methodology for analysing a signal with time varying frequency content is to divide that signal into multiple segments in the time domain, by using finite-duration time windows and then applying the Fourier transform to each segment. This description corresponds to a brief explanation on the short-time Fourier transform (STFT). The representation of each of these Fourier transforms in the time scale of the original signal represents the concept of the spectrogram graph. The application of Fourier transforms is the basis of numerous time-frequency analysis methodologies and historically represents the first linear distribution to be developed for this purpose (Cohen, 1995). However, to obtain more refined time-frequency analysis tools (e.g., have improved time and/or frequency resolutions), there are other linear distributions that have been proposed over the years (Cohen, 1995; Chen and Ling, 2002). Some examples are the adaptive Gaussian representation, the matching pursuit algorithm and the adaptive spectrogram. While these distributions have improved features when compared with the more basic distributions, they are also more resource intensive to implement and so are not always the better solution for every situation (Chen and Ling, 2002). The proposed track monitoring methodology uses the Fast Fourier Transform (FFT) during the data processing phase, and the spectrogram form for the graphical representation of the obtained spectrums. This topic will be further addressed in the following chapters.

In the context of railway related monitoring methods, frequency-based analysis can be used to detect the presence of damaged railway elements or even characterize relevant components of the infrastructure or of a vehicle. Alternatively, frequency-based analysis can also be used to assess changes in the dynamic response of an element or group of elements from these mechanical systems. Examples of studies on this topic include detecting the presence of rail corrugation on a track (Caprioli et al., 2007), estimating soil layer thickness (Björklind, 2018) and monitoring the frequencies excited by the passage of a vehicle to assess superstructure support conditions (Le Pen et al., 2016).

However, the frequency-based methods used in this context often rely on specific concepts related with the railway infrastructure and vehicles, especially on the several situations that require the use of time-frequency tools, due to the non-stationary frequency spectra that characterize the signals being analysed. One of these concepts is that each main

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component from the combined mechanical system under analyses (i.e., railway superstructure, substructure and vehicle) has a distinguishable dynamic response (Kouroussis et al., 2015; Salvador et al., 2016). These different dynamic responses translate into distinct frequency spectrums, each with a typical frequency band of interest. There is no consensus on specific values for these frequency bands from the multiple references on the topic, because they depend on a multitude of factors that are complex to assess. However, there is consensus on average values for each of these bands. The work by Kouroussis (2015) reports the following frequency ranges for each component of the combined mechanical system:

- Vehicle dynamic response is usually concentrated in the low-frequency range (frequencies up to 15 Hz), which mostly contains the natural frequencies and modes of vibration of the structural elements of railway vehicles;
- Track substructure elements, especially the subgrade, have natural frequencies in the frequency range from 15 Hz to 150 Hz. These frequencies are related with track flexibility and soil natural frequencies;
- The rest of the frequency spectrum (frequencies over 150 Hz) contains the characteristic frequencies related with elements from the superstructure, including multiple vibration modes from the rails and sleepers.

The vehicle related characteristic frequencies result from the excitation of natural frequencies of specific vehicle components (e.g., suspension systems), or natural vibration modes from the vehicle itself (Zhai, 2020). Examples of these vibration modes are the lateral hunting motion of the vehicle's chassis over the suspension system, and the bending and torsional natural frequencies of the chassis' platform. These vehicle related frequencies are inherently dependent on the characteristics of the vehicle under analysis. For instance, the first vertical vibration mode of suspension systems is usually designed to be around 1 Hz for passenger vehicles, and is between 2.5 and 4 Hz for freight cars depending on their cargo (Iwnicki et al., 2019). While not the focus of the proposed methodology, by knowing the expected values of the vehicle related natural frequencies, these can be more easily identified in acquired data and properly sorted according to the desired goal.

On the other end of the spectrum, superstructure related natural frequencies that are commonly present in acquired data correspond to specific vibration modes involving the rails and the sleepers, or are related with the presence of periodic track defects (De Man, 2002; Kouroussis et al., 2015; Salvador et al., 2016). The more common superstructure related natural frequencies for ballasted tracks are (Figure 2.14): i) a lower frequency where the rails and sleepers vibrate vertically in phase over the ballast layer (located between the 50 to 300 Hz band), ii) another frequency where the rails vibrate over the sleepers' support layer (200 to 600 Hz), iii) and a third frequency related with the rails vibrating on their fastening points to the sleepers (800 to 1000 Hz) named pin-pin frequency. These frequency ranges are common values for the first vibration mode of each of these natural frequencies

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(Kouroussis et al., 2015). There are also anti-resonance frequencies that can be observed in these elements. A common one corresponds to the iv) vibration of the sleepers over the surrounding track elements (80 to 300 Hz), which can only be observed when the monitoring point is on the rails or above them (e.g., on a railway vehicle) (Kouroussis et al., 2015).

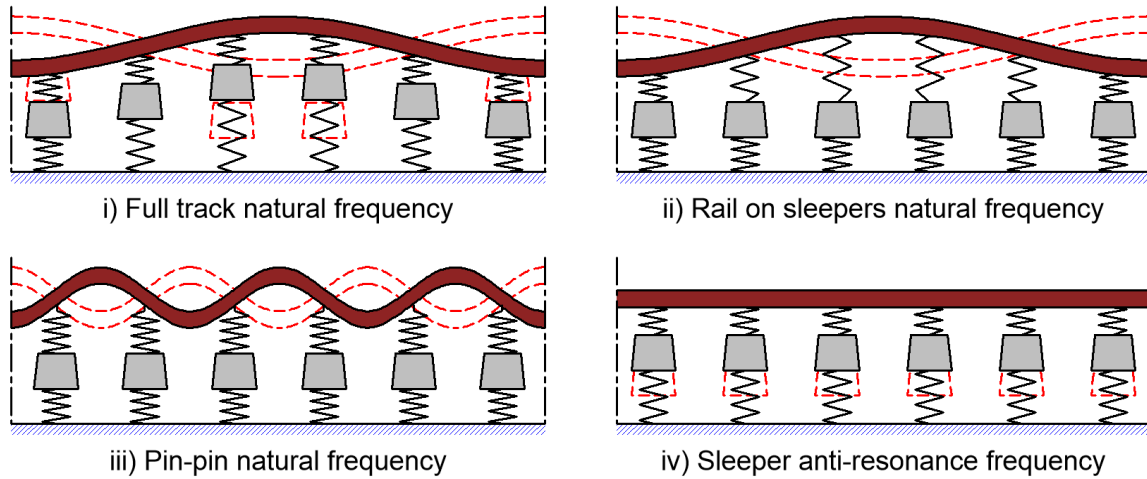


Figure 2.14: Typical ballasted railway track vibration modes.

The observable values of these superstructure natural frequencies depend on several factors, including the specific mechanical characteristics of the superstructure components (e.g., rail mass and stiffness). Another relevant factor is if the mechanical system being monitored is just the track superstructure or the entire system (i.e., the vehicle and the track). This is important because the presence of a railway vehicle influences the values of the resonance frequencies related with the track superstructure (Zhai, 2020; Shang et al., 2021). Regarding rail defects with identifiable frequencies, a typical example is the phenomenon of rail corrugation, which has a characteristic frequency ranging from 1000 to 30000 Hz depending on the magnitude and periodicity of the defect (Kouroussis et al., 2015; Salvador et al., 2016). Overall, by monitoring this group of frequencies, relevant information can be gathered on track support conditions of some superstructure components. Relevant examples include monitoring sleeper physical properties (De Man, 2000) or detect the presence of rail corrugation (Caprioli et al., 2007).

Finally, observable track substructure characteristic frequencies are mostly related with the properties of the track subgrade. More specifically, these natural frequencies are mainly dependent on the configuration and mechanical properties of the soil layers beneath the track (Knothe and Wu, 2005; Auersch, 2005; Kouroussis et al., 2012). Esvelde (2001) presents in his book the mathematical formulation and the theoretical background for estimating soil resonance frequencies, in the geotechnical framework. The concept is that in natural soil deposits, which are often stratified, resonance effects can occur as if the soil was a conventional structure with multiple natural frequencies. Estimates of these n natural frequencies are given by Equation 1 (i.e., n for each potential vibration mode), which are dependent on the shear wave propagation velocity of the soil (c_P for P type waves) and the

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vertical thickness of the soil layer (h). In turn, the shear wave propagation velocity is dependent on the soil's mechanical properties, namely its shear modulus (G), its density (ρ), its Young's modulus (E) and its Poisson's ratio (ν). Of these n vibration modes, the more prevalent vibration mode is normally the first ($n=1$) (Kouroussis et al., 2012), which has values ranging from 10 to 100 Hz. It is this relationship between soil mechanical properties and soil resonance frequencies that supports the proposed methodology of monitoring soil resonance frequencies to assess subgrade support conditions.

$$f_n = (2n - 1) \frac{c_p}{4h} \quad (1)$$

Several research groups have studied the effects that different soil properties and compositions have on soil shear wave propagation velocity and ground vibration amplitudes through numerical simulation models (Knothe and Wu, 2005; Auersch, 2005; Kouroussis et al., 2012). Based on equation (1), these studies also give some insight on how these soil parameters affect the soil resonance frequencies that can be observed. The work by Kouroussis et al (2012) describes the influence that different soil configurations have on overall soil dynamic response, by simulating different scenarios with multi-layer models. One example of these scenarios is a model where each soil layer has increasing stiffness along the model's depth (Figure 2.15). However, the theoretical formulations and models used in these studies can only provide estimates of soil dynamic responses, due to natural approximations made by these models regarding reality (e.g., soil boundaries between the different layers are not usually perfect horizontal planes). However, they still represent an important tool for geotechnical studies regarding railway infrastructures. The method proposed in the master's dissertation by Björklind (2018) is based on the use of this theoretical formulation in the context of railway monitoring and contains several comparisons between frequency estimates obtained with this formulation and experimental data.

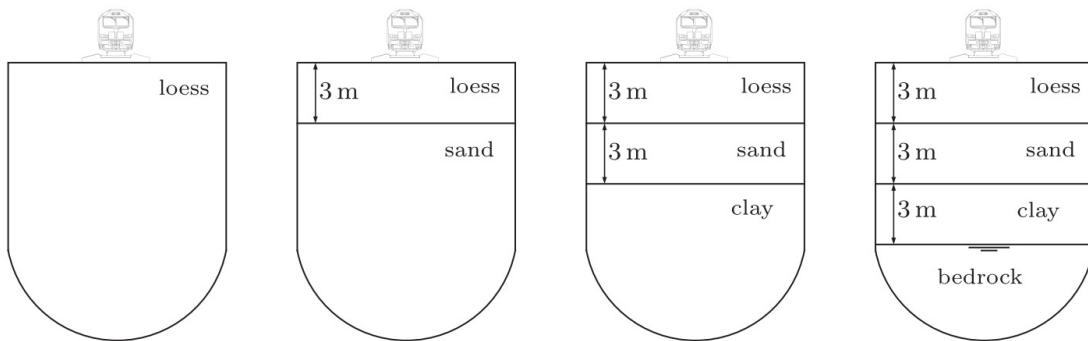


Figure 2.15: Example of a multi-layer models group used by Kouroussis et al. (2012) to study the influence of soil properties and configurations on soil dynamic response.

The previous description presented a brief introduction on the potential complexity and diversity of railway related frequency spectrums. Based on information collected from the previous bibliographic resources (Esveld, 2001; Kouroussis et al., 2015), the graph from Figure 2.16 presents typical values for the frequency ranges of relevant railway related

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phenomena. This includes common resonance frequencies of the combined mechanical system, and frequencies related with vehicle running speed (e.g., a frequency created by a wheel defect). Knowledge of the ranges of the multiple frequencies that might be present in acquired railway data facilitates the process of extracting the resonance frequencies of interest for any given railway monitoring application based on frequency analysis.

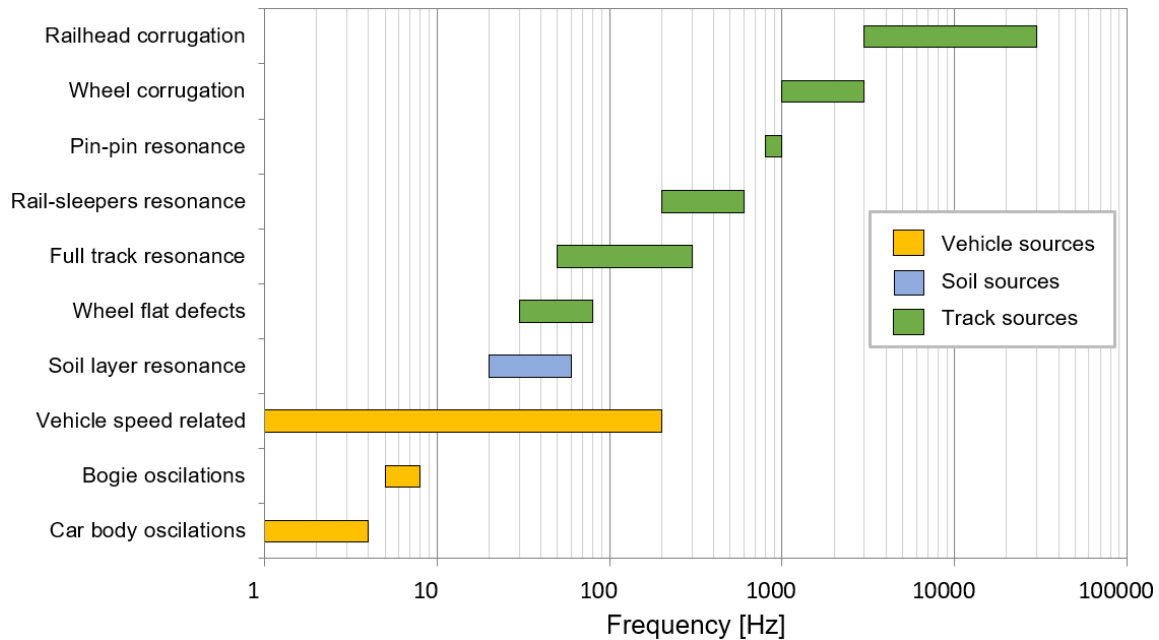


Figure 2.16: Typical frequency ranges from the main sources on a railway infrastructure and vehicle.

An additional aspect that can also assist in the process of frequency identification and extraction is proper selection of instrumentation placement, considering the type of method being used and the subject under analysis (i.e., railway infrastructure or vehicle). For instance, the previously described rail natural frequencies are inherently easier to observe if the instrumentation is placed on the rails or on an adjacent element (e.g., on the sleepers or on the wheels/axles of a railway vehicle). This is especially important when instrumented railway vehicles are the data source for the monitoring method being used (Ward, 2011; Rivas, 2013), because of the presence of the suspension systems. These elements are natural low-pass filters that prevent the transmission of higher frequencies from the track and the wheels to the rest of the vehicle (Zhai, 2020). This can either be an asset or a limitation on instrumentation position in a vehicle, depending on the natural frequencies of interest. Annex E from the standard EN 13848-1 (CEN, 2019) provides information on expected frequency ranges and acceleration amplitudes for the detection of different categories of rail defects, depending upon the position of accelerometers on a railway vehicle (i.e., on an axle box, on a bogie or in the chassis). Following a similar concept, the standard EN 14363 (CEN, 2005) prescribes the position of accelerometers on several components of a railway vehicle for the assessment of parameters relevant for vehicle running behaviour. Proper selection of instrumentation placement, taking into consideration the subject under analysis, can be vital to determine the viability and quality of the data obtainable with any given railway monitoring method (Rivas, 2013; Zhai, 2020).

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A final aspect to consider when monitoring frequencies in the railway context is that the different components of the combined mechanical system are not the only sources of distinct frequency patterns. In fact, there are some specific frequencies, which are only observable depending on the position of the instrumentation, which can increase the complexity of the obtainable railway related spectrums. Two common examples of these frequencies are: i) the frequency excited by the passage of a vehicle over the sleepers and ii) the frequency related with the distance between the axles of a railway vehicle. The frequency from example i) is related with the stiffness variation created by the spacing between the sleepers of a railway track and the vehicle running speed. This frequency can only be observed if the monitoring point is on the vehicle, since from the track's point of view this stiffness variation is localized. On the other hand, example ii) is related with the frequency that appears due to the excitation created by the passage of railway vehicle's axles over a track and thus is related with the distance between the vehicle's axles and vehicle running speed. This frequency can only be observed if the monitoring point is on the track, and not on the vehicle. Although these two examples showcase how these additional frequencies do not correspond to natural frequencies of specific railway elements, they can still be used to gauge the dynamic response of certain parts of the combined mechanical system. For example, the work by Le Pen et al. (2016) reports the use of the frequency ii) to estimate track stiffness by employing a monitoring method using on-site instrumentation.

This sub-section presented a brief introduction on railway related concepts concerned with frequency-based analysis. While not being an extensive report on the subject, the objective here was to present a solid foundation on this topic. Based on these concepts, adequate decisions can be made on how to monitor each of the frequencies presented in Figure 2.16 regarding monitoring method selection and instrumentation setup. While not every railway monitoring method based on frequency analysis needs to use time-frequency tools, some situations do benefit if the collected data is analysed in the time-frequency domain, so that the frequency patterns can be perceived and studied (Salvador et al., 2016). This is the case of the proposed methodology, as will be explained in section 2.4.

2.3.2 Vibration-based methods

Vibration-based damage detection methods utilize the fact that changes on the physical properties of a structure (i.e., mass, damping and stiffness), due to the appearance of damage or defects for example, cause corresponding changes in its vibration characteristics (Maia and Silva, 1997). This includes the structure's natural frequencies, its mode shapes, and its damping factors (Doebling et al., 1998; Kong and Cai, 2017), thus justifying the assessment of these parameters in the context of SHM applications (Avci et al., 2021). Since resonance frequencies are usually much easier to monitor than the other vibration characteristics, they represent the main parameter that is normally used in vibration-based methods (Doebling et al., 1998). A railway infrastructure can also be monitored through

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the use of these concepts, since there are already studies on models dedicated to estimate the natural frequencies of several railway infrastructure elements and on the correlation between the natural frequencies of specific track elements with the manifestation of defects or changes in their mechanical properties (De Man, 2002; Knothe and Wu, 2005; Auersch, 2005; Kouroussis et al., 2012). However, currently there is a lack of validated methods based on monitoring these vibration characteristics to assess overall railway track support conditions (Shi et al., 2023). In the railway context, the concept of vibration-based damage detection methods can also be used to assess the conditions of important elements of railway vehicles (Alemi et al., 2017). Although important in multiple studies, this specific topic will not be addressed here since it falls outside of this thesis's subject.

The methodology proposed here to evaluate railway track support conditions is based on modal analysis of the multi-element system composed by a railway infrastructure and a moving railway vehicle. In general, by assessing the characteristic frequencies of this combined system at each point of the infrastructure and the corresponding changes of these values over time, considering the modal characteristics of the moving vehicle, this methodology states that it is possible to obtain relevant indicators about the current state and the rate of degradation of the railway infrastructure under evaluation. More specifically, information related with subgrade modal stiffness should be obtainable by monitoring its characteristics frequencies. This is then used to gain insights into the subgrade's vertical stiffness and actual support conditions, which are particularly relevant in railway track support conditions (Selig and Li, 1994; Esveld, 2001; Auersch, 2005; Berggren, 2009). These two types of stiffness concepts cannot be compared directly, because the first is an approximation of the second, but they are naturally related with each other (Esveld, 2001) (Figure 2.17).

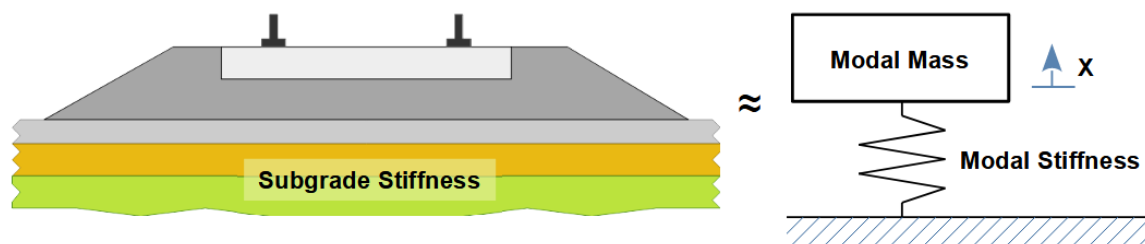


Figure 2.17: Concepts disambiguation: railway subgrade stiffness vs equivalent modal stiffness. The vertical stiffness of a subgrade layer can be modelled as a modal stiffness, but these are not equal.

An important aspect of railway tracks, relevant in the context of vibration-based damage detection methods, is that they can be considered as an infinite structural system without major discontinuities if the supplementary civil engineering structures are excluded (e.g., bridges). This means that, unlike a bridge or similar structures that have clearly defined physical boundaries, a railway track can be described as an unbound system in the longitudinal direction (Zhai, 2020). Thus, it is reasonable to expect that track support conditions should change gradually along a railway track. These gradual changes should form perceivable patterns if the related characteristic frequencies of the mechanical system are represented in the time-frequency domain (Doebeling et al., 1998; Salvador et al., 2016;

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Vinberg et al., 2018). Abrupt changes on these patterns should either represent evident physical disturbances of the track mechanical system (e.g., the presence of a civil engineering structure), or the appearance of a non-localized defect or degradation on the track. This specific feature is one of the main aspects that is utilized in the proposed methodology.

In general, there are some immediate advantages of using modal analysis and frequency-based methodologies in the railway monitoring context, when compared with the more conventional methodologies that analyse data in the time domain:

i) The modal properties of a linear system are independent of the characteristics of the excitation signal used to assess it (amplitude and frequency) (Doebling et al., 1998). In this context, this property means that the characteristic frequencies of the combined system, which are the main parameters under observation, are not correlated with the vehicle running speed, nor with any other parameter related with the excitation source (Esveld, 2001). Thus, there is no need to limit the running speed of railway vehicles to values below normal operational conditions due to this aspect. This is one of the main advantages of the proposed methodology, which will solve some of the issues identified by Wang et al (2016) on other track stiffness monitoring methods, where the results are dependent on vehicle running speed and/or on the characteristics of the excitation signal being used. This feature allows for easier comparisons between results from different train rides on the same track regions, since there is no need to compensate for the speed differences between rides.

ii) The modal properties of a structure, including its natural frequencies, are well defined parameters that enable direct comparisons between results obtained from different experimental campaigns and with distinct methods (Maia and Silva, 1997). The only major precaution to consider when comparing results is to verify if it is the same mechanical system that is being monitored. Thus, if the system under analysis didn't suffer any damage or major changes in its constitution, the same resonance frequency values are to be expected. This advantage of the proposed methodology over other track stiffness monitoring methods solves the inconsistent measurement concepts identified by Wang et al. (2016).

iii) There are three types of physical data that can normally be interchangeably used to assess the characteristic frequencies of a system (displacement, velocity or acceleration data), but only if they correspond to the same movement of interest (i.e., vertical movement of the system, in the current case). This is true because the observable frequency content is approximately the same between all these data types, in that each resonance frequency has the same value in every data type. However, the amplitude of the frequency content is usually not the same between these three cases, thus the resonance frequencies that are observable in each data type can change. In practice, since accelerations are more reliable in the typical frequency ranges of interest, they represent the main type of data that is usually used in vibration-based methods (Doebling et al., 1998). The direct use of acceleration data also avoids the need for integration procedures that other methods employ

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in the railway monitoring context (Milne et al., 2019). This is another advantage of the proposed methodology, since integration procedures can amplify noise and other defects commonly present in acquired experimental data (Wang et al., 2016).

iv) This type of methodology is also reasonably insensitive to amplitude disturbances in the data, either of electrical or mechanical nature. This happens because the important aspects under evaluation are specific frequencies present in the data, and not the actual amplitude of said frequencies. For example, the data provided by two separate vehicles regarding the same railway track, with different data acquisition systems, should still provide comparable results regarding the characteristic frequencies of the combined system. These results would only need to be adjusted based on the specific mechanical characteristics of each vehicle, such as suspension stiffness and vehicle mass. This aspect also mitigates some of the issues identified by Wang (2016) on other track stiffness monitoring methods, mainly the issue related with the low-quality measurements.

However, there are also drawbacks of applying modal analysis in this context, when compared with time domain methodologies. If the frequency content in the acquired data is non-stationary in the time domain, it is not possible to know when and for how long each frequency existed on the obtained signal if it is only analysed in the frequency domain (Cohen, 1995). This issue represents one of the main reasons for the use of time-frequency analysis tools, and should be taken into consideration to avoid significant losses in information. This potential issue is particularly important when using vehicle-based monitoring methods to assess track support conditions, because the non-stationarity of the data in the time domain is inherent. Therefore, while this issue requires the use of additional data processing resources, the previously mentioned advantages usually outweigh this potential inconvenience.

Another drawback that should be considered is that isolated phenomena with short duration, when compared with the time window being used to process the data for the frequency domain, can be naturally filtered from the results (Doebling et al., 1998). This is an intrinsic consequence of these data processing methodologies and not an unexpected defect. An example of this type of phenomenon in the railway context would be a single damaged sleeper on a track, which represents a very localized defect. On the other hand, a sufficiently long track stretch with a defective support layer should have a perceivable impact on the resulting frequency spectrums. This specific drawback is not overly relevant in the proposed methodology, since this type of phenomena is not the focus of the methodology, but should still be considered during results analysis. Additionally, this drawback can also be naturally overcome if the short duration phenomena have the capability to create a disturbance in the frequency domain similar to a Dirac impulse (i.e., an impact on the track), which results in a large band excitation of the lower frequencies of the spectrum, making them visible again in the obtainable frequency spectrums (Randall, 1987).

2.4 Railway subgrade monitoring: why and how

Has already stated, the degradation of railway track support conditions depends on several factors, which can be related with the superstructure, with the substructure, or with the dynamic interactions between the track and the railway vehicles (Fröhling, 1997; Berggren, 2009; Berggren, 2010; Gallego et al., 2011; Milne et al., 2019). One of the reliable parameters used for the assessment of railway track support conditions is vertical track stiffness (Esveld, 2001; Le Pen et al., 2016), albeit it has some relevant constraints in this context (INNOTRACK, 2008; RIVAS, 2013; Wang et al., 2016). Monitoring methods based on track stiffness tend to be intrinsically more focused on assessing the conditions of the track superstructure (Esveld, 2001; Berggren, 2009; Li et al., 2020; Lai et al., 2022), leaving the track subgrade completely unmonitored or at most poorly assessed (INNOTRACK, 2008; Wang et al., 2016). This is an important issue since subgrade conditions represent one of the main factors that influences track dynamic response and track support conditions (Selig and Li, 1994; Esveld, 2001; Auersch, 2005; Berggren, 2009). Yet, there is a major deficit of dedicated and reliable subgrade monitoring methods. This deficit is even more severe in the context of vehicle-based methods, which are acknowledged as the more efficient way to monitor entire railway infrastructures (INNOTRACK, 2008; RIVAS, 2013). The previous considerations are repeated here to reinforce the importance of subgrade condition monitoring, which corresponds to one of the main reasons that lead to the development of the present thesis.

Before moving forward in this section, an important distinction should be made regarding the two different stiffness parameters that are relevant in this context: vertical track stiffness and subgrade stiffness. Vertical track stiffness is the term used to encompass the stiffness properties of the entire railway infrastructure, from the rails to the subgrade soil layers beneath the track (Esveld, 2001). This parameter includes the contributions of every railway element in this mechanical system, where the significant impact of the subgrade layer is well acknowledged. Another element that also has a significant impact in this parameter are railway pads, which correspond to ductile elements that can be placed between the rails and the sleeper and/or between the sleepers and the ballast layer to further enhance the load bearing capabilities of a track (Esveld, 2001). On the other hand, subgrade stiffness refers to only the vertical stiffness contributions of the soil layers beneath a track (Esveld, 2001). While the goal of the proposed track monitoring methodology is to assess overall track support conditions, which can be accomplished through monitoring vertical track stiffness, its focus is on obtaining data on subgrade condition/stiffness through its characteristic frequencies and from that infer information on track support conditions.

From the information presented in section 2.3, there are already several methods dedicated to monitoring track support conditions. But despite the influence that the subgrade has on this parameter (Esveld, 2001; Auersch, 2005; Berggren, 2009), only a few of those methods specifically take its influence into consideration as part of their monitoring procedures. Additionally, it can also be perceived that the track stiffness

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monitoring methods presented in Table 2.2 shares some or all the monitoring related issues mentioned by Wang (2016) and the Innotrack report (2008), including the more recent studies. Nowadays, the subgrade layer has been gaining some relevance in recent studies, as can be perceived in a new review paper focused on geotechnical studies using AI (Hasheminezhad et al., 2026). However, according to this work, there are still no monitoring method similar with the one proposed here, which is focused on assessing subgrade conditions using an instrumented railway vehicle and a less complex modelling approach that can potentially represent an overall more efficient solution.

A relevant example of a study that takes into consideration the major effect that the subgrade has on track support conditions is the method proposed by Roghani in his PhD thesis (Roghani, 2017). This method uses a monitoring system based on laser transducers and a video camera to measure track deflections from an in-service vehicle. This data is then used to assess track support conditions, by converted it into track stiffness estimations through a mathematical model (Figure 2.18).

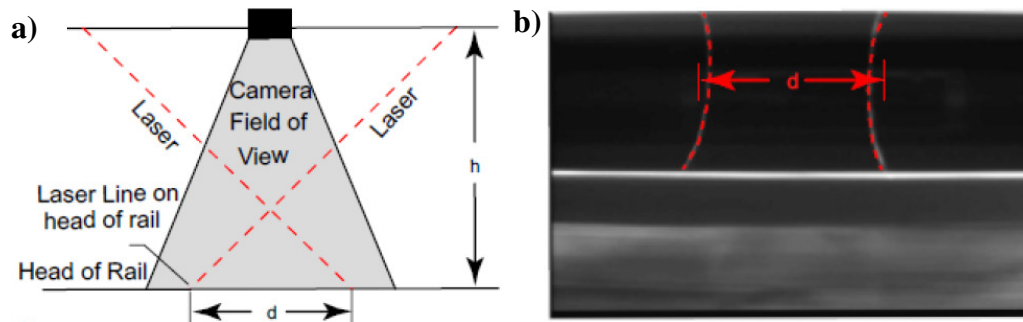


Figure 2.18: (a) Schematic representation of the experimental setup used in Roghani's PhD thesis, and (b) a typical image taken with his experimental setup (adapted from Roghani, 2017).

This method takes into consideration the subgrade's effects on track support conditions through a filtering procedure in the data processing method to separate between the subgrade stiffness related effects on deflection measurements from other influencing aspects (e.g., track defects). The presented results show an adequate agreement between the subgrade stiffness estimations and the known characteristics of the monitored subgrade layers (Figure 2.19). However, one of the reported case studies shows that a track retrofit operation to a heavier rail type had a higher impact on the estimated track stiffness value than the reconstruction of the subgrade in the same region. The effects on estimated track stiffness caused by each of these two modifications to the original track configuration were evaluated separately, since five sections of this track region were tested with different combinations of these two aspects. This specific result is not enough to prove that the proposed method cannot monitor track support conditions without a bias towards superstructure condition, because the change to the heavier rails could indeed represent a higher improvement to overall track support conditions than the subgrade modifications (i.e., it depends on specific characteristics of the studied situation). However, this conclusion still represents a possible example of this issue, which is shared by other methods that use track deflection measurements to estimate track stiffness (Innotrack,

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2008). As previously explained, track deflection monitoring methods tend to be more focused on superstructure condition (Esveld, 2001; Wang et al., 2016; Milne et al., 2019), which can negatively impact the track support conditions results of the entire infrastructure. Thus, this result can be an indicator to this issue because a change on the superstructure had a bigger impact on the estimated track stiffness than a change on the subgrade, despite the focus of this method on subgrade properties. By comparison, the methodology proposed in the current thesis overcomes this potential issue by instead monitoring the characteristic frequencies of the track-vehicle mechanical system, since natural frequencies are inherently focused on the conditions of their respective elements (Maia and Silva, 1997). Thus, the separations between each of the major elements that influence overall track support conditions is a natural result of this methodology, according to the underlying concept.

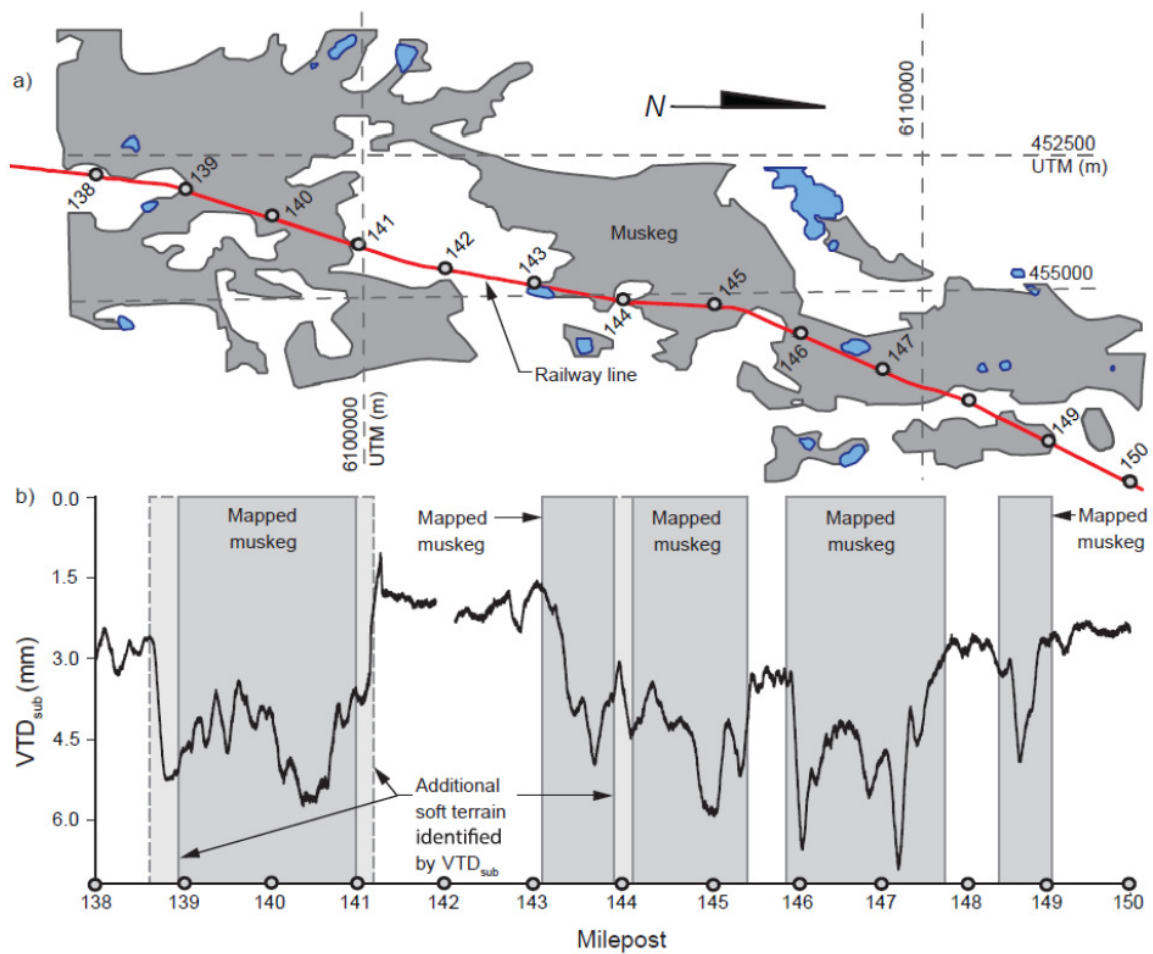


Figure 2.19: Comparison of obtained vertical track deflection (VTD) data, processed with the filtering procedure, with the geological composition of a track section in Andriashek, Canada (Roghani, 2017).

The method proposed by Björklind in his master's dissertation (2018) also attempts to avoid this issue by using a similar concept as the one proposed in the present thesis. Björklind's main concept is to monitor the resonance frequencies of every relevant soil layer beneath the track under analysis, using instrumented railway vehicles (Figure 2.20). This data is then used to assess track support conditions by comparing the obtained frequencies with estimates of each layer's natural frequency using prior knowledge of the

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subgrade's constitution. These soil natural frequency estimates are calculated according to the previously mentioned formulation presented in Equation 1 (Esveld, 2001).



Figure 2.20: (a) Instrumented railway vehicle used in Björklind's experimental campaigns, and (b) position of one accelerometer on the vehicle's bogie (Björklind, 2018).

While Björklind's method shares the same base concept as the methodology proposed in the current thesis (i.e., monitoring track support conditions through the analysis of subgrade resonance frequencies) there are multiple differences. The more significant differences are: i) Björklind's method does not take into account the influence of the railway vehicle in the dynamic response of the combined mechanical system under analysis, ii) the current thesis proposes the use of a single dominant frequency for the characterization of overall track support conditions, instead of trying to determine the resonance frequency of each soil layer present on the track, and iii) the current thesis also proposes the use of additional tools, from the time-frequency field of signal analysis, to improve the frequency identification process and provide additional information for the assessment of track support conditions. In the current author's opinion, distinction i) represents the cause for the significant differences between frequency spectrums obtained from the same studied track sections that are reported in Björklind's dissertation (Figure 2.21). The issue is that each pair of compared spectrums was obtained using two different instrumented railway vehicles. The vehicle's influence in the dynamic response of the combined mechanical system is something that should never be disregarded, considering that it is a significant part of the combined mechanical system that is effectively under analysis (Zhai, 2020). Distinction ii) refers to an advantage of the methodology proposed in the current thesis over other methods used to monitor track support conditions, including Björklind's method, in that the process of assessing the intended parameter under evaluation (i.e., subgrade condition in this case) is simpler by only having to monitor one dominant characteristic or parameter. This is in opposition of having to monitor multiple physical quantities, used to obtain estimates of the relevant parameters, as part of the procedure to assess track support conditions (e.g., monitor track deflections and applied loads to estimate track stiffness). In this context, another advantage of this aspect is that it removes the need to have extensive prior knowledge on the subgrade's constitution, creating a simpler and more flexible method that can be applied to any railway track without having prior data on this aspect. The work by Kouroussis (2012) provides an analysis on

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the significant effects that different subgrade configurations have on overall dynamic response of railway tracks, thus showcasing the benefit of this last feature.

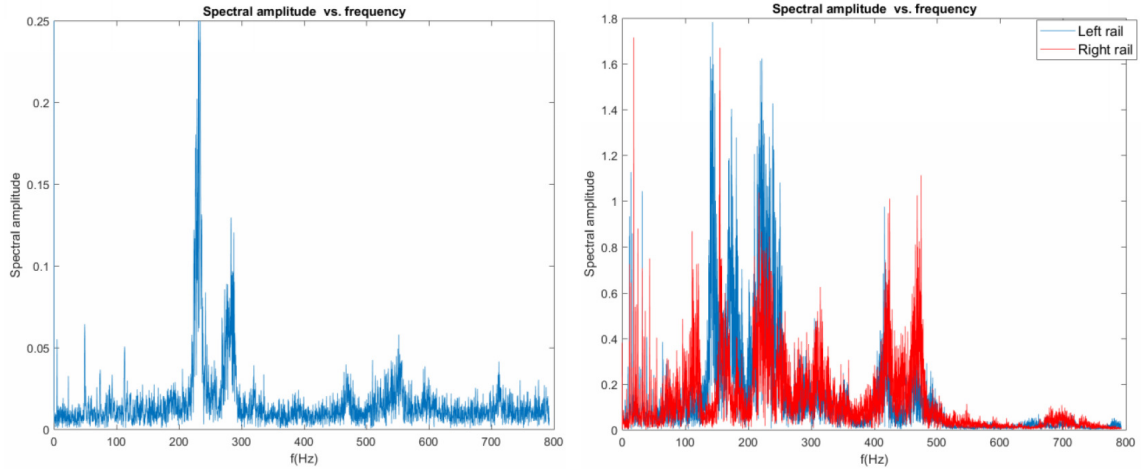


Figure 2.21: Example of the results obtained by Björklind in his dissertation regarding the same track location observed by two distinct instrumented railway vehicles (adapted).

The current methodology proposes the use of the spectrogram form to represent the processed frequency data, which simplifies the identification and monitoring of the intended characteristic frequency (distinction iii). The main intent of the spectrogram form is to allow the observation of the various frequencies present in the data, thus making it possible to identify relevant characteristic frequencies of the combined system under analysis from the typically complex frequency spectrums that are obtainable in this context (i.e., distinguish frequencies related to the vehicle, which can then be discarded, from frequencies related with the track). The spectrogram form also allows to check the patterns or curves of variation of these frequencies along a railway track (in the same spectrogram) or over time (by comparing multiple spectrograms from the same track), which can be used to obtain additional relevant information on a railway track (Salvador et al., 2016; Vinberg et al., 2018). Figure 2.22 highlights these differences in the data processing sequences, from raw data to the final spectrogram representation of the frequency content. Björklind's method stops in step 2, where he only compares different frequency spectrums with each other. From this figure the benefits of using the spectrogram representation in this context is made evident, due to the additional information that can be extracted from the perceivable frequency patterns. For instance, by comparing the perceivable frequency curves in this spectrogram (i.e., the well-defined red lines) with the vehicle running speed curve from graph a), a clear distinction between two types of frequencies can be perceived: frequencies that depend on the vehicle running speed (F_{ds}) and frequencies that are independent of the vehicle running speed (F_{is}). Contrary to the F_{ds} curves, F_{is} frequency curves share no comparable pattern with the vehicle running speed curve. As previously explained in section 2.3, this feature is an inherent characteristic of natural frequencies, thus simplifying the task of identifying them in the spectrogram form. Another example of application of this concept to experimental data can be checked in section 3.4, pertaining to a specific case study that was performed in the present context. In this example, known data on track layout

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(the presence of track structures and embankment configuration) is provided and cross-checked against the obtained spectrogram results. The obtained correlations between these two aspects represented a preliminary validation on the proposed methodology by showcasing the relationship between the perceivable F_{is} frequency curves and relevant aspects of track support conditions. It also showed the potential of the methodology to detect the presence of certain structures on the track, such as the technical blocks from an underpass that were detected in this case.

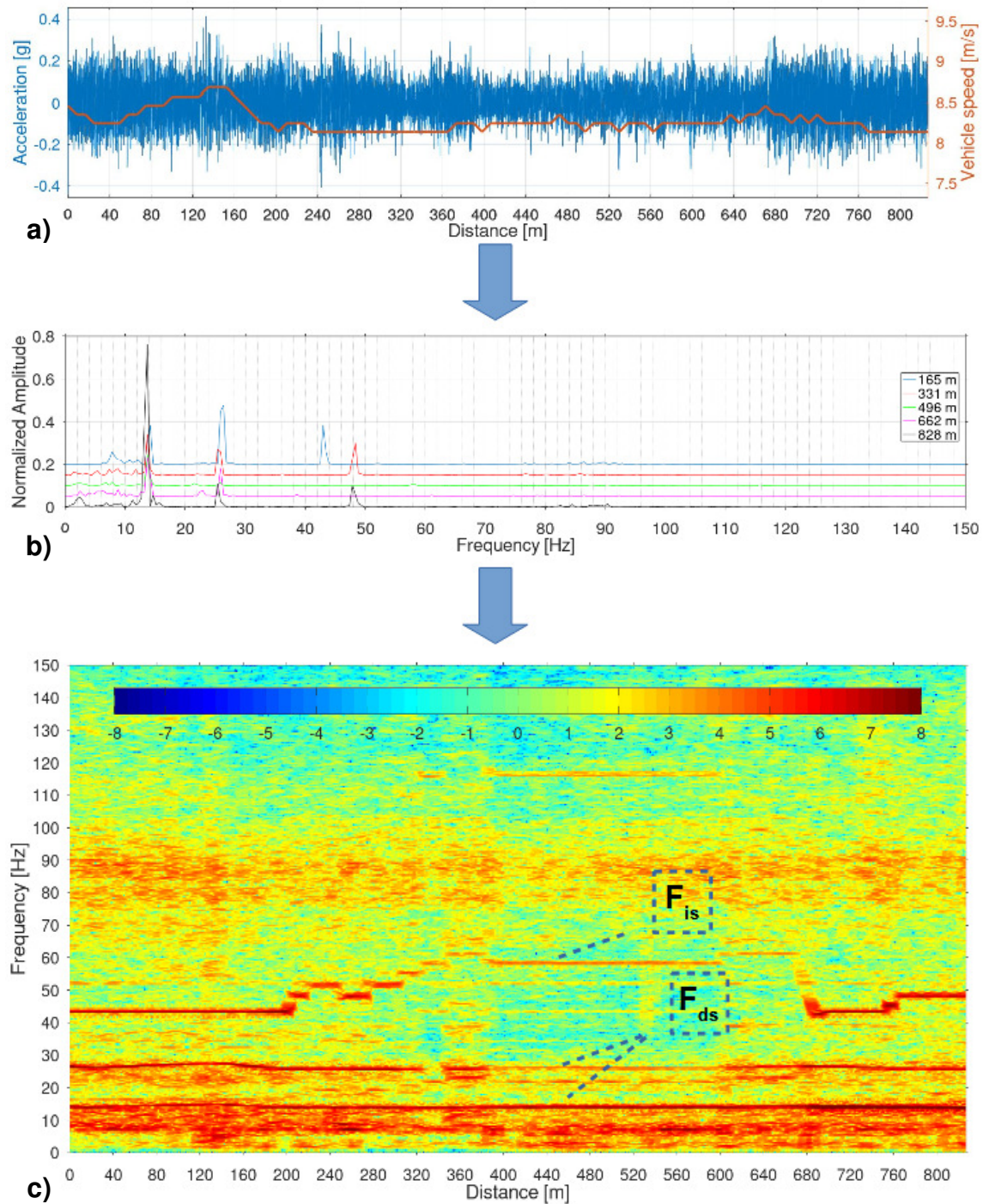


Figure 2.22: Main steps of the proposed data processing methodology: (a) raw acceleration data collected with the in-service vehicle, (b) frequency spectrums extracted, (c) final spectrogram form.

2.5 Chapter final remarks

This chapter presented a general overview on the overall background that fomented the development of the present thesis. Several considerations were made on the state-of-the-art on track monitoring methods, along with the description of multiples examples of methods that are used in this context. Additionally, several relevant concepts were introduced to further showcase the potential of the proposed track monitoring methodology. Two track monitoring methods were compared in more detail with the proposed solution and finally the results from a preliminary test campaign were shown here. Overall, this information should offer a clearer picture on the motivations behind this study and provide the reader the tools to understand some of the decisions that were made during the methodology's development.

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3 Proposed theoretical models

The initial sections of this chapter are focused on describing the theoretical model behind the proposed Track Monitoring Methodology (TMM), and the theoretical background that was established to support the Modelling Solution (MS) specifically developed to support this study. In the final sections, two proof-of-concept tests that were performed in the early development stages of this study are described and discussed. The topic of describing the theoretical model behind the TMM is a subject that has been addressed in every publication made in the context of this study, each focused on different stages of the methodology's development. Similarly, a full description on the developed MS was also the focus of the third scientific paper published in the context of this thesis (Morais et al., 2024a).

The theoretical model behind the proposed TMM was developed by combining different independent concepts to create the means to interpret the acquired frequency data and enable the extraction of relevant information regarding track support conditions. During the TMM development process, preliminary results demonstrated its potential as an alternative track monitoring method that could assesses subgrade conditions. However, some difficulties were exposed when attempts were made to manually extract results from numerical simulations or from experimental data. After testing multiple solutions to solve this specific issue and to improve upon the overall reliability of the proposed methodology, an unsupervised data-driven tool was developed to apply the TMM in a more efficient way. Details on this data processing tool will be provided in chapter 5.

In order to supply the required testing data for the methodology's development and validation, an adequate modelling solution was essential since relying only on experimental data was unfeasible given the available resources. This is usually also undesirable since a solid foundation built on numerical data allows for additional flexibility in the sort of scenarios that can be more promptly used in this task. Like in other railway subgrade related studies, this thesis was also affected by the general lack of geotechnical data, or equivalent subgrade related information, which could be used during the testing and validation processes of the TMM (Powrie, 2024). However, the available numerical models that could be used to represent a subgrade layer were not adequate for the established goal of employing a modelling solution that could simulate considerable track extensions while not requiring extensive computational and/or time resources. Therefore, these issues imposed the development of a dedicated modelling solution that could achieve the previous goal and still allow for the representation of the subgrade as a fully independent element, especially in terms of its modal properties and resulting natural frequencies. These requirements

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eventually lead to the selection of a multibody simulation (MBS) software as the framework for the numerical models developed in this context. In the end, the developed MS also required the development of a theoretical background to support the proper representation of a subgrade layer in a MBS model, which was integrated into the overall theoretical model developed for the TMM.

3.1 Initial model considerations

Before describing the several elements behind the proposed theoretical model, this subsection starts with an important premise that enables the underlying logic that was used in its design, in terms of physical and mechanical principles. The premise in question is:

- The values of the natural frequencies of the soil layers beneath a railway track do not depend directly on the presence of a railway vehicle on the track.

This means that the observable values of the natural frequencies of the soil layers do not directly change due to the presence of a vehicle above those layers, and do not change based on the modal parameters of that vehicle. This statement does not disregard the expected smaller changes in the values of the resonance frequencies from the soil layers due to the dynamic interaction between the two mechanical systems in question (i.e., the railway infrastructure and vehicle). Instead, it just states that there is no direct change in these natural frequencies caused by the presence of a railway vehicle, since the characteristic frequencies of a linear mechanical system are independent from the properties of the excitation source used to assess them (Doebeling et al., 1998). This concept is applicable in the context of this complex multi-element system for the purpose of modal analysis in the same way that it is acceptable in the context of analysing other common engineering structures (Maia and Silva, 1997). This premise is clearly presented here first since this is something that is not commonly stated in the bibliography that deals with the natural frequencies of soil layers in the railway context (Selig and Water 1994; Esveld, 2001; Wang et al., 2016). While this statement does not present anything new in general, for the author it represented an important step in this study since it removed the potential for many misconceptions regarding the parameters that can actually influence the natural frequencies of a subgrade layer.

Another useful topic relevant for the next section is the following: in an MBS model based only on rigid body elements, there is an inherent detachment between the mechanical properties of a body element and its geometric dimensions. While total mass can be established using a body's geometry and density, parameters related with other mechanical properties cannot be directly linked to body elements (e.g., Young's modulus). These other mechanical properties are usually simulated through other element types connected with the respective body elements, such as springs and dampers. In the present context, this means that there would be a disconnection between the geometry/mass of a subgrade layer body element and its equivalent stiffness characteristics. Furthermore, this means that the

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natural frequency values of the simulated subgrade layer would be dependent on the combination of the mass of the subgrade body element and the stiffness of the associated spring element, which would have no intrinsic relationship in such a model. This is in opposition to other modelling software (e.g., FEM model), where the mechanical properties of a subgrade layer can be intrinsically established during model setup. Another aspect related to this issue is the difficulty in obtaining realistic values for the modal properties of a soil layer, as opposed to a common steel beam, which hinders the option of simply imposing these values on an MBS model. The proposed MS solves these issues by providing a concrete solution for the geometry that a subgrade layer element should use in an MBS model to provide realistic natural frequencies. More specifically, by selecting a cylindrical shape for the numerical models of the railway's layered elements (e.g., a subgrade layer and a ballast layer) and some input parameters related with their mechanical properties, this MS provides an equation that gives the diameter of these cylindrical elements as a function of subgrade layer height. This relationship thus imposes a connection between the subgrade's geometry/mass and its relevant mechanical properties, resulting in realistic values for the obtainable natural frequencies related with the simulated subgrade element. The proposed MS represents a potentially interesting innovation in the specific field of soil layer modelling in the geotechnical context, since this solution enables the numerical representation of soil layers in a computationally efficient manner while providing adequate data for modal analysis and vibration related studies on this subject.

3.2 Model description

The basis of the theoretical model behind the proposed methodology consists of a lumped-elements type model that is used to provide the framework to parse the acquired frequency data. The model has two Degrees-of-Freedom (2-DoF) composed by a series of two spring-mass sub-systems, in a vertical arrangement, which represents the vehicle and the railway infrastructure (Figure 3.1).

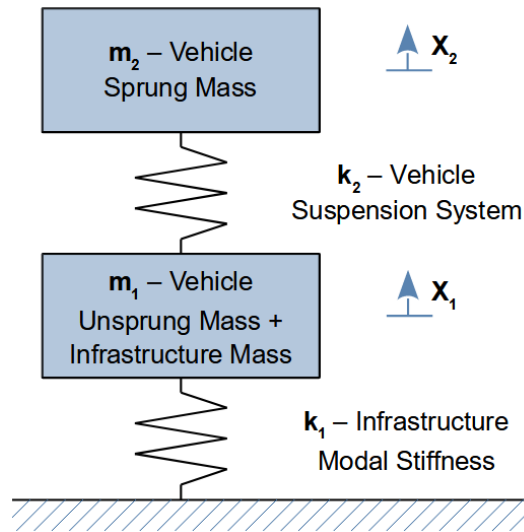


Figure 3.1: Lumped-elements model used in the proposed TMM.

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Mass element 1 represents the unsprung mass of one vehicle axle plus the respective mass of the infrastructure that is dynamically excited by the moving vehicle (m_1). Mass element 2 represents the vehicle's sprung mass that is supported by one vehicle axle (m_2). These mass elements are linked by a spring that represents the vehicle's suspension system (k_2). The other spring element represents the modal vertical stiffness of the railway infrastructure, with a special focus on subgrade stiffness (k_1). The output of this model are two characteristic frequencies (ω_1 and ω_2), which are related with these four modal parameters (Maia and Silva, 1997). Frequency ω_2 corresponds the vertical oscillatory motion of the vehicle's sprung mass, which has typical frequency values between 1 and 5 Hz for most railway vehicles (Zhai, 2020). Meanwhile, frequency ω_1 is mainly influenced by the modal parameters of the railway related elements, where the subgrade related parameters have a very significant influence, thus representing the main frequency of interest for the proposed TMM (Kouroussis et al., 2015).

This 2-DoF model is intended to provide the underlying means to interpret the acquired frequency data in the context of the proposed methodology, enabling the extraction of relevant information regarding track support conditions. Therefore, it does not need to explicitly represent the wheel-rail contact or any railway superstructure elements (e.g., rails, sleepers and ballast layer) with dedicated elements because the influence of these aspects on the natural frequencies under assessment is negligible. The wheel-rail contact, which is usually described by a high stiffness Hertzian spring on other models of this type (Montenegro, 2015; Zhai, 2020), can only create higher value natural frequencies that are significantly separated from the frequency band of interest (Kouroussis et al., 2015). This is also true for the superstructure elements, as was explained in section 2.3.1. This also precludes the need to have exact data, or reliable estimates, for values regarding the equivalent vertical stiffness of these additional elements. Therefore, in this specific context, these elements can be disregarded, thus enabling the presented model. The validity of this 2-DoF model to represent the natural frequency of interest, and its respective vibration mode (i.e., the rigid body movement of m_1 over the adjoining k_1 and k_2 springs) will be demonstrated in section 4.2.1 using numerical data.

While a more complex lumped-element model could be used for this purpose, which could include additional railway elements, the focus of this model is on the subgrade layer and its proven significant influence on overall track support conditions (Connolly et al., 2015; Kouroussis et al., 2015). Dedicated damping elements are also not included in this model for two reasons: i) for its intended purposes, this type of modal elements do not significantly change the dynamic response of a mechanical system in terms of its natural frequencies values (Maia and Silva, 1997); ii) in the railway context, where obtaining reliable stiffness values for most railway related elements is already a significant challenge, determining accurate damping properties of the subgrade layers is an even more arduous and unfeasible task (Selig and Waters, 1994).

Having established this concept, the theoretical model now required a link between the

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proposed 2-DoF model and reality itself. In other words, additional components were required to provide a concrete solution to convert acquired frequency data into physical parameters familiar to railway managers (e.g., vertical track stiffness or track modulus) or into condition related information on the subgrade layer under assessment. Another important issue that had to be solved at this stage was to find an adequate modelling solution that would enable the representation of this specific problem in a numerical model, which should allow for the direct simulation of the frequency content of interest and not rely on the oversimplified representations of the subgrade layer that are common in this context. The devised solution solved all the previous issues through a combination of additional theoretical models and a dedicated MS specifically developed in this study. Table 3.1 presents all the relevant parameters that are used in the expanded theoretical model.

Table 3.1: Main parameters used in the proposed theoretical model.

Vehicle-Track Parameters	Vehicle-Track Parameters
Layered elements diameter (θ)	Soil layer shear modulus (G)
Subgrade layer height (h_{su})	Soil layer Young's Modulus (E)
Ballast layer height (h_{ba})	Soil layer Poisson's ratio (ν)
Subgrade density (ρ_{su})	Vertical track stiffness (k_{tr})
Ballast density (ρ_{ba})	Subgrade layer vertical stiffness ($k_{i,su}$)
Subgrade layer mass ($m_{i,su}$)	Ballast layer vertical stiffness ($k_{i,ba}$)
Ballast layer mass ($m_{i,ba}$)	Sleeper/fasteners vertical stiffness ($k_{i,sl}$)
Sleeper mass ($m_{i,sl}$)	Chassis body mass ($m_{v,c}$)
Sleeper length ($2a$)	Bogie mass ($m_{v,b}$)
Sleeper width ($2b$)	Axle mass ($m_{v,a}$)
Soil layer natural frequency (f_l)	Primary suspension stiffness ($k_{v,s1}$)
Soil longitudinal wave velocity (c_p)	Secondary suspension stiffness ($k_{v,s2}$)

In early development stages of the TMM, the need to simulate extensive lengths of railway track became evident to adequately supply the required testing data. However, there was also the intent of employing a modelling solution that would not require an inordinate amount of time to perform the entailed simulations. Relevant state-of-the-art solutions were not adequate for this application due to two problems: i) the solutions either relied on the Finite-Elements Method (FEM) or similar methods to provide the means to convert between subgrade stiffness/soil deformation modulus and track modulus or vertical track stiffness, which suffer from inherently high development and computational costs that go against the established goal, ii) or the theoretical models behind the proposed solutions were not compatible with the previously described 2-DoF model since they were developed for different goals (Selig and Waters, 1994; Powrie, 2024).

Considering the previous requirements and concerns, numerical models based on an MBS software were selected as a desirable option, since they are intrinsically well adapted to represent lumped-element models and are generally more computationally efficient than

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FEM models (Zhai, 2020; Fernández-Bobadilla and Martin, 2023; Lamprea-Pineda et al., 2024). This option thus provided the means to naturally integrate the 2-DoF model into the numerical simulation models used during the TMM's development, while also enabling the simulation of considerable track extensions (usually over 1 km) in reasonable conditions due to the lower resource requirements of MBS models. Additionally, this modelling option also provided a solution for the parameter conversion issue between subgrade stiffness and vertical track stiffness of the entire infrastructure. This specific solution was derived from the MBS model formulation through the underlying relationship between the main contributors to overall track stiffness, which corresponds to an association in series of the relevant spring element (Equation 3) (Selig and Li, 1994; Auersch, 2005; Wang et al., 2016). In the present configuration, this entails the stiffness contributions from the subgrade layer ($k_{i.su}$), from the ballast layer ($k_{i.ba}$) and from the superstructure related elements that include the sleepers and their fasteners to the rails ($k_{i.sl}$). This last component is the least important in this arrangement since it represents the higher stiffness contribution in isolation, thus representing the least impact on overall vertical track stiffness (Selig and Li, 1994; Maia and Silva, 1997).

$$\frac{1}{k_{tr}} = \frac{1}{k_{i.su}} + \frac{1}{k_{i.ba}} + \frac{1}{k_{i.sl}} \quad (3)$$

Refinements to this formula with additional elements could certainly be made, but this configuration already provides an acceptable solution to convert between subgrade stiffness and vertical track stiffness and is also aligned with the elements used in the developed MBS models. Sleeper/rail stiffness and ballast stiffness values used here need to be adequately verified to guarantee that the resulting estimates are realistically compatible. This that was achieved by consulting relevant bibliography for common values for these parameters (Gallego et al., 2011; Zhai, 2020) and validated through comparisons between track deformations values at each level of the numerical models and their experimental counterparts (i.e., comparing deformation values at the sleeper level, ballast level and subgrade layer level) (Fernández-Bobadilla and Martin, 2023).

Having solved the parameter conversion issue previously mentioned, the topic of being able to adequately represent the subgrade layer was still not fully solved. This is the reason that justified the additional theoretical models that were added to the overall formulation devised for the proposed TMM and the underlying MS.

While MBS solutions are already amply used to model railway vehicles and the railway superstructure (Kong and Cai, 2017; Lesgidis et al., 2020; Shang et al., 2021), there was no available modelling solution capable of representing the railway substructure in this type of software as a fully independent set of elements with their own complete modal properties. Established modelling solutions that are used to represent the subgrade layer in an MBS model typically oversimplify the subgrade by modelling it with only spring-damper elements, thus inherently coupling its modal properties and dynamic responses to the surrounding elements (Zhai, 2020; Fernández-Bobadilla and Martin, 2023; Lamprea-

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Pineda et al., 2024). A common example of this issue are the solutions where the subgrade stiffness is modelled in the form of a distributed stiffness element, according to Winkler's elastic beam model (Esveld, 2001), which is not compatible with the intended goal of a modelling solution that enables the full representation of the subgrade layer as an independent element and not as an outlying component of the model or just a boundary condition. Therefore, this issue entailed the development of a specific MS in the MBS framework, to enable proper modal analysis on the railway subgrade and the simulation of the uncoupled natural frequencies of this railway component. In other words, this MS was designed to provide a method to assure that the geometry/mass of the subgrade element would result in realistic subgrade related frequencies.

The additional framework required for this dedicated MS consisted of three more equations that were added to the overall theoretical formulation that was previously described. The first additional component is the equation for the natural frequencies of a surface-level soil layer from a natural soil deposit (Esveld, 2001; Kouroussis et al., 2012). The specific form of this equation used here (Equation 4) gives the frequency value of the first vibration mode (f_1), due to a vertical excitation source, based on the soil's characteristic longitudinal wave velocity (c_p) and the soil layer's height (h). This corresponds to the first vertical vibration mode that is dynamically excited by the presence of an excitation source above the soil layer, such as a railway vehicle, which is the relevant situation in this context (Esveld, 2001)].

The second additional component is the equation for the characteristic longitudinal wave velocity of a soil layer (c_p) (Esveld, 2001; Kouroussis et al., 2012). This provides a relationship between relevant mechanical properties of the soil to be simulated (Equation 5), namely, its shear modulus (G), its density (ρ), its Young's modulus (E) and its Poisson's ratio (ν). Equations 6 and 7 present the formulas for the Lamé parameters (λ , μ), which are relevant for Equation 5. The final extra component is an equation that gives an estimate of the vertical stiffness that a platform or foundation would perceive when supported by a single soil layer (k_f). This extra model (Equation 8) defines the soil layer as a homogeneous half-space and is solely based on the in-plane dimensions of the platform (a sleeper in this case) and the mechanical properties of the soil layer (Wolf and Somaini, 1986). This equation is used here to provide an estimate for subgrade layer vertical stiffness ($k_{i.su}$), a concept that has already been used in another railway-related study to analyse vibration propagation from a railway track (Kouroussis et al., 2012).

With these additional equations, the proposed model now contains a deterministic solution for the geometry of the railway's layered elements to be used in an MBS model and provides a formulation to determine expectable frequency values for a subgrade layer in both simulated and non-simulated contexts (Equation 9 that is based on the 2-DoF model). Finally, by selecting a cylindrical shape for the body elements of the railway's layered elements (e.g., a subgrade layer and a ballast layer) and some input parameters related with their mechanical properties, the additional elements that were added to the

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proposed theoretical model result in an equation that gives the diameter of these cylindrical elements (θ), as a function of subgrade layer height (Equation 10). This represents the main output of the proposed MS.

$$f_1 = \frac{c_p}{4h} \quad (4) \quad c_p = \sqrt{\frac{\lambda + 2G}{\rho}} \quad (5)$$

$$\lambda = \frac{\nu E}{(1 + \nu)(1 - 2\nu)} \quad (6) \quad \mu = \frac{E}{2(1 + \nu)} = G \quad (7)$$

$$k_f = \frac{G * b}{(1 - \nu)} \left[3.1 \left(\frac{a}{b} \right)^{0.75} + 1.6 \right] = k_{i.su} \quad (8)$$

$$\omega_1 = \sqrt{\frac{k_2 + k_1}{m_1}} * \frac{1}{2\pi} = \sqrt{\frac{k_{v.sl} + k_{i.su}}{m_{v.a} + m_{i.su} + m_{i.ba} + m_{i.sl}}} * \frac{1}{2\pi} \cong f_{1.su} \quad (9)$$

$$\theta = \sqrt{\frac{\frac{k_{v.sl} + k_{i.su}}{(2\pi * f_1)^2} - (m_{i.sl} + m_{v.a})}{\frac{\pi}{4} (h_{ba} * \rho_{ba} + h_{su} * \rho_{su})}} \quad (10)$$

Having this final formulation, the extended theoretical model now represents a deterministic solution for the geometry of the railway's layered elements to be used in an MBS model. Below is a short list of relevant conditions and considerations related with the proposed MS:

- This formulation works with a vehicle control volume of one axle and the respective share of vehicle sprung mass (e.g., for a vehicle with four axles, the sprung mass to be considered here would be ¼ of the total sprung mass);
- The heights of the railway layered elements to be modelled in the MBS software are imposed by the user. The diameter of the cylinders that are used to represent these elements are then given by Equation 10;
- The density of the railway layered elements is also selected by the user. From a practical point of view, estimates of these values can be obtained based from experimental data or from bibliographic references.
- The stiffness values for the railway layered elements are also imposed by the user. For the ballast layer, this can also be acquired from experimental data or bibliographic references. As for subgrade stiffness, this MS proposes the use of equation 3 to convert between it and vertical track stiffness, which in turn can also be obtained from the previously mentioned sources.

3.3 Proof-of-concept test 1: GroutRail data

As a preliminary attempt to validate the concepts behind the proposed methodology, an

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experimental test was designed and performed in the early stages of this study. Its main objective was to verify if a single dominant characteristic frequency of a railway infrastructure could be identified in data collected with adequate instrumentation, through the application of time-frequency tools. In other words, if a dominant frequency could be obtained from a track model that was mainly related with the subgrade layer, and from that check if that frequency could provide information on the overall track support conditions. The experimental model tested in this campaign corresponded to the final configuration of a full-scale physical model used in the context of a project carried out in LNEC, named GroutRail. This project aimed to develop a new railway subgrade reinforcement method, which consisted in injecting short columns of grout soil-binder into the subgrade by drilling through the ballast layer. The subgrade layer of old railway tracks often exhibits poor geotechnical behaviour, particularly the soil on which the ballast layer rests. Such poor behaviour usually implies significant maintenance costs and interruptions on regular operations of the affected track. The reinforcement of subgrade soils by injection of binders can mitigate these issues, but previous studies on the subject showed some limitations, and the quality of the results depends on many factors (Francisco et al., 2018; Fortunato et al., 2021). The method developed in this research aimed at solving these issues, while providing a solution that could be economically efficient to deploy and minimized the impact on railway operations.

When the GroutRail project was concluded, the final state of this model consisted of four railway track modules (M1, M2, M3, M4) with different track configurations due to the reinforcement solutions that were tested (Figure 3.2). Each module was about 2.0 m wide, 2.8 m deep and 2.7 m long, and consisted of a section of railway track with two rails mounted on a set of sleepers. Beneath the sleepers was placed a ballast layer with a depth of 0.3 m, and below that was a subgrade layer. This subgrade layer was poorly compacted on purpose to simulate a degraded railway track in need of maintenance. The values of relative compactness ranged between 75% to 92% of the maximum dry density of the modified Proctor test for each layer of material used in the construction of the modules.

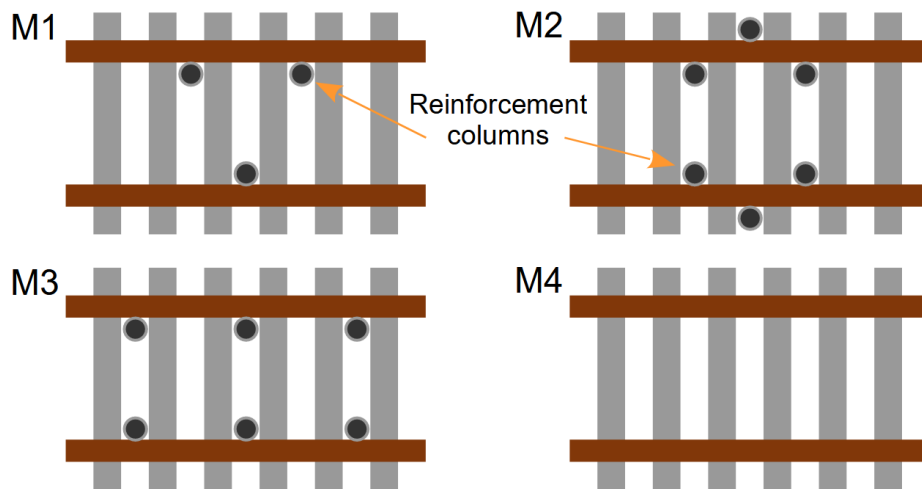


Figure 3.2: Schematic representation of the four physical modules tested in the GroutRail project.

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During the GroutRail project, two types of subgrades were tested in this model: a clay-based subgrade and then a sand-based subgrade. Only the results regarding the tests with the clay subgrade were presented in the paper by Fortunato et al. (2021). The final model configuration used in the present tests corresponded to the sand subgrade, but the results and conclusions obtained with it were similar in nature to the ones regarding the clay subgrade that can be consulted in the previously mentioned paper. The sand subgrade was characterized in laboratory and revealed a maximum dry density of 17.3 kN/m^3 , using the modified Proctor test, and an optimum moisture content of 11.4%.

After the initial construction of the entire physical model, modules M1 through M3 were reinforced with different reinforcement configurations, while M4 remained unchanged to serve as the reference for the initial conditions. Each module was subjected to a series of loading cycles, to assess track settlement over time. In the previously mentioned paper, estimates of track stiffness for the clay-based model are presented, which were obtained through dedicated loading tests (i.e., by applying a load and measuring the resulting track deflection). The obtained values were 10% to 20% higher than the track stiffness value of M4, depending on the amount of reinforcement columns applied to each module. Thus, this sand-based physical model with four different railway configurations had the potential to be useful in the context of these tests, since these modules could present distinguishable resonance frequency values related with the characteristic frequencies of the subgrade in each module. The rest of this sub-section describes the experimental setup used to verify if these different characteristic frequencies could be observed, the test plan employed in each module, and the obtained results.

3.3.1 Experimental setup

Figure 3.3 presents an overall view of the experimental setup used in these tests. The general concept of the tests was to first apply a static load to the track module under assessment, with this load being equivalent to the typical weight imposed by a railway vehicle axle, using a hydraulic system dedicated to this task. The value used was around 170 kN. This static load was important to place the infrastructure in loading conditions similar to a real scenario with a railway vehicle, which is necessary due to the non-linear behaviour of the geomaterials that are used in this type of civil engineering structures (i.e., this refers to the loaded vs unloaded issue described in section 2.2). The static load was applied to the track with a load distribution device placed on both rails (black coloured beam in Figure 3.3), between two sleepers. The infrastructure was then excited with a dynamic load, composed by sinusoidal signals within a frequency band between 0 and 100 Hz. Based on the information presented in section 2.3, the subgrade's characteristic frequency of each module should be within this frequency band. Considering the characteristics of the available actuators, this dynamic excitation load was applied with a separate hydraulic system, which had a maximum load capacity of 5 kN. The dynamic load was directly applied to one of the sleepers adjacent to the static load distribution device, to

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avoid wasting the available energy on exciting masses not directly related with the module under assessment.

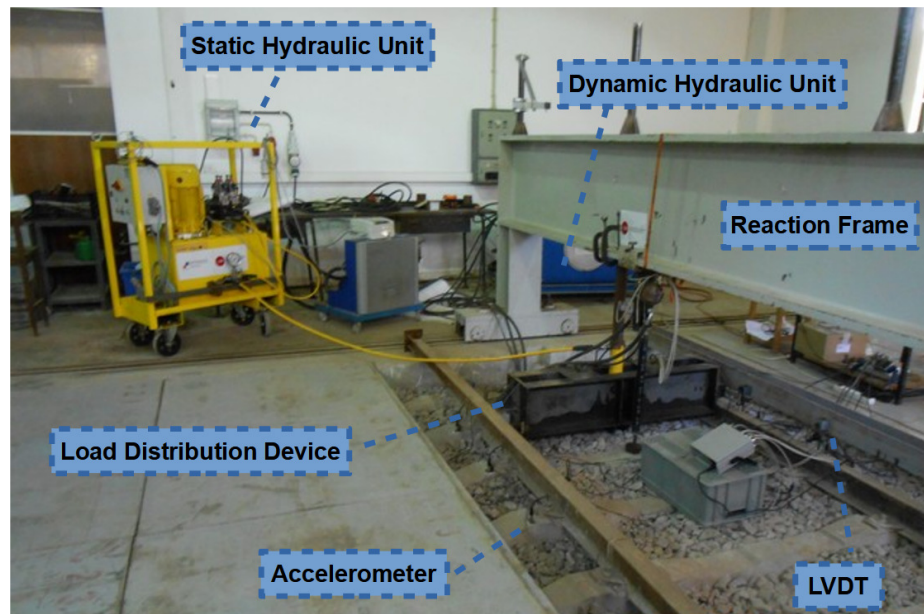


Figure 3.3: Experimental setup used in the laboratory test, including the sensors and both actuators.

Each module was instrumented with the sensor arrangement that can be seen in Figure 3.4: six LVDT displacement transducers measuring the deformation applied to both rails (three in each rail) and six accelerometers measuring the accelerations on the sleepers adjacent to both load application points. Figure 3.4 also presents the naming codes of the LVDT and accelerometers used in these tests, according to their position on the track relatively to the cardinal directions (W – West; E – East; N – North; S – South; C – Central). Additionally, both actuators were equipped with load cells to measure their respective actions on the infrastructure.

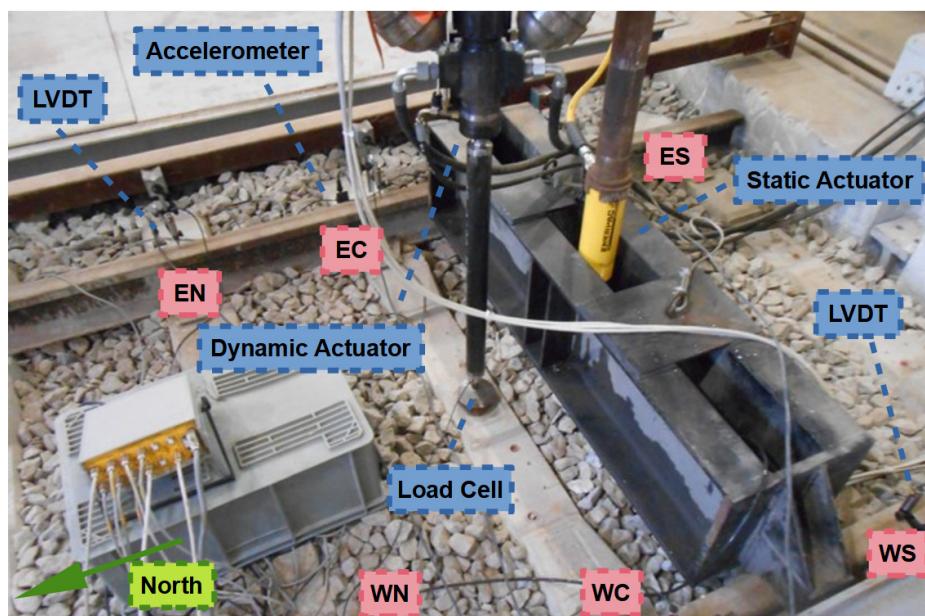


Figure 3.4: Closer view of the experimental setup used in the test. The naming codes of the LVDT and accelerometers is based on their position relative to the cardinal points (pink tags).

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After some preliminary tests, it was verified that the displacement transducers and the accelerometers were not suitable to assess the dynamic response of the system due to insufficient dynamic sensitivity, since the resulting displacements and accelerations caused by the dynamic load were relatively small (0.02 mm of cyclic displacement amplitude and acceleration levels around 0.01 g). On the other hand, both load cells provided output signals with adequate signal-to-noise ratios to assess the system's dynamic response. Therefore, the obtained load signals were selected as the primary data sources in these tests. All data was acquired using a centralized data acquisition system, at a rate of 2048 Hz. The reference signal used in the dynamic actuator was also injected with the same data acquisition system, to guarantee the synchronous acquisition of all input and output signals.

The initial solution used to excite the characteristic frequency of the subgrade was to inject a signal with a broad frequency band in the dynamic actuator, using the entire frequency range of interest (0 to 100 Hz). In these conditions, a resonance frequency was identified between the 60 Hz to 80 Hz. But the energy capacity of the dynamic actuator was too dispersed over this relatively broad frequency band, thus the response amplitudes were too small to provide reliable results using this solution. Therefore, another solution was employed that used excitation signals composed by multiple harmonic waves, each representing a different excitation frequency, limited in the number of waves per signal to avoid the previous issue. The multiple harmonic waves were equally spaced in the frequency bands being used to avoid localized interferences between them. The concept was now to first assess the overall dynamic response of the infrastructure to check if a dominant resonance frequency was present and obtain a rough estimate of its value in the case that it existed. Then, after an initial broad frequency range containing the resonance frequency was identified, that range was then thoroughly analysed with more tests using additional signals with narrower frequency bands. Following this logic, the initial frequency range of interest was divided in two sub-bands (0-50 Hz and 50-100 Hz). Initial broad band tests were performed in each of these frequency band. Then, the frequency band that showed greater amplitude responses was again sub-divided into smaller bands and subjected to further tests.

The final version of the test plan employed to the four modules is presented in Table 3.2. Each test had a duration of one minute. This duration was adequate to monitor the dynamic response of this system, because the reference signals used were periodic and invariant in the time domain and any transient response from the system dissipated after a few seconds. This test plan resulted in an excitation frequency resolution of 5 Hz in the initial frequency band of interest. This was then increased to a combined frequency resolution of 1 Hz in the narrower frequency band around the resonance frequency identified during the preliminary tests. Every test performed used the following loading conditions: an average value of 170 kN on the static load actuator and a maximum cyclic amplitude of 5 kN on the dynamic load actuator.

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Table 3.2: Test parameters of the implemented version of the test plan.

Test name	N° of waves	Frequency range [Hz]	Wave spacing [Hz]
Test1_0-50	10	0 - 50	5
Test1_60-100	10	60 - 100	5
Test2_50-70	5	50 - 70	5
Test2_70-90	5	70 - 90	5
Test2_90-110	5	90 - 110	5
Test3_66-86	5	66 - 86	5
Test3_67-87	5	67 - 87	5
Test3_68-88	5	68 - 88	5
Test3_69-89	5	69 - 89	5

3.3.2 Test results

The individual test results that will be presented here pertain only to module M2, because the results from all modules were sufficiently similar in graphical appearance and frequency values to not justify showing them all. This will be made evident through a final graph with the compiled dynamic response from the four modules. Module M2 corresponds to the reinforcement solution with the highest count of reinforcement columns. Since the acceleration data and the rail deformation data were not used in the search for the resonance frequencies of the system, and were similar between all the tests, only a sample from a single test will be shown here. More specifically, only an example of deformation data is shown in Figure 3.5 regarding Test3_66-86, and no example will be provided regarding acceleration data because it did not provide any usable information (i.e., this data only shown very small oscillations due to the low sensitivity of the accelerometers). In this figure it is possible to observe the deformation applied by the static load, corresponding to the different average values of each LVDT, and the deformation imposed by the dynamic load, which is the oscillatory values around each average value (i.e., the high frequency deformation cycles applied by the dynamic excitation). The dynamic induced deformation is relatively small when compared with the static component, due to the comparatively low value of the dynamic load that was used. In this figure it is also possible to verify that the deformation is higher on the two sleepers adjacent to the static load actuator (Central and South sleepers in this module), as expected.

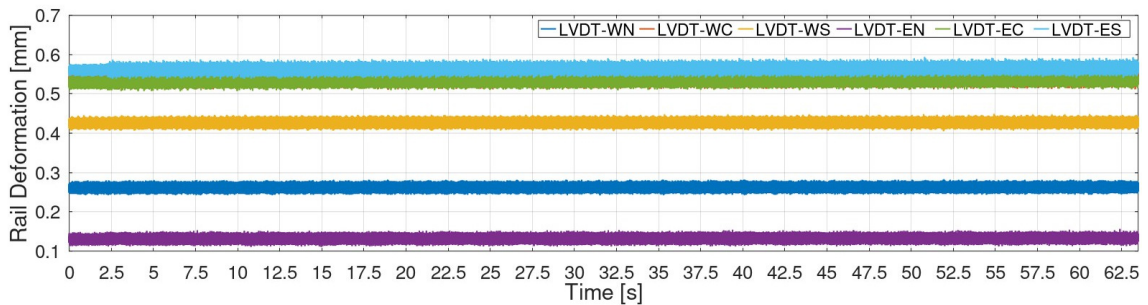


Figure 3.5: Displacement data from Test3_66-86, module M2.

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Following a similar logic, only one example of load data will be shown because the obtained curves are also similar between each test, when looked at in the time domain. Figure 3.6 presents the obtained load data for Test3_66-86. In this figure it is possible to observe the time history of the dynamic actuator on the first graph and of the static actuator on the second graph. The third graph in this figure presents a zoomed view on the time history of both actuators focused on the start of the dynamic actuation. This third graph is relevant to visualise the effect that the dynamic load had on the static load, where the total load on the reaction frame remained constant, but the application of the dynamic load implied a reduction on the static load observed by the respective load cell (i.e., when the dynamic load was applied, there was a small reduction in the oil pressure in the static actuator due to the volume change). This phenomenon is just a consequence of the experimental setup being used. Overall, the load data in the time domain was mainly used to verify that each test occurred at the intended loading conditions.

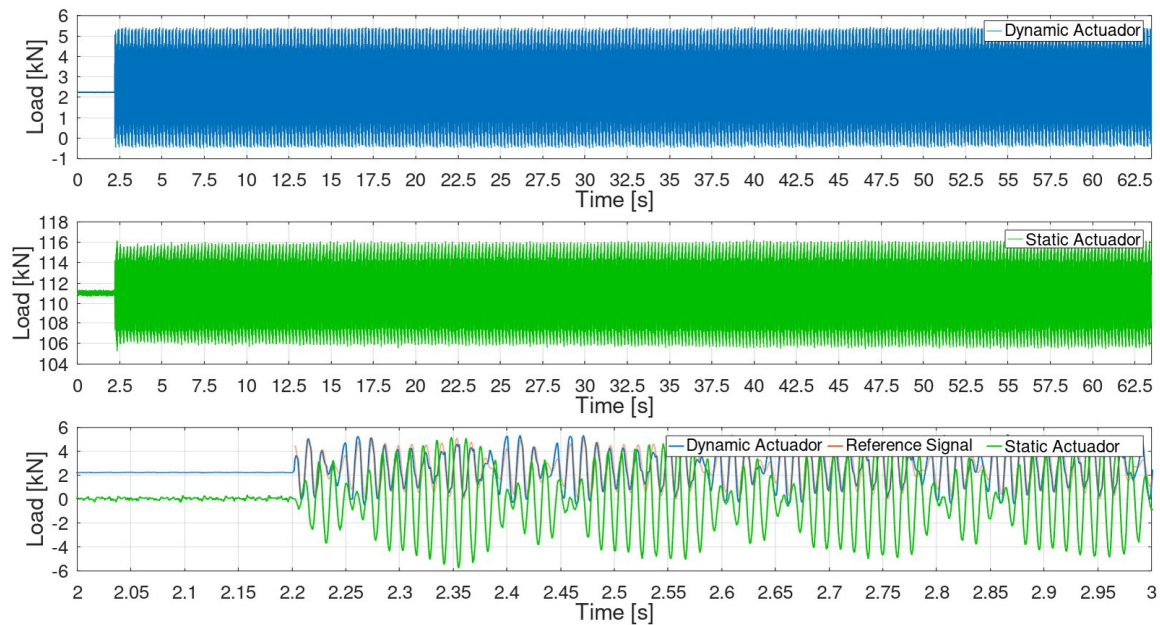


Figure 3.6: Loading data (static and dynamic components) from Test3_66-86, module M2.

Since the reference signals used here for the dynamic actuation were periodic and invariant in the time domain, the use of the spectrogram to represent the results in the time-frequency domain was not necessary in this case. Thus, the frequency results from each test will be presented in the form of separate spectrums, calculated through the application of a FFT to the relevant load data from each source. In the following graphs displaying these results, the blue curves represent the spectrums calculated with data from the dynamic actuator, the green curves refer to data from the static actuator, and the red curves were calculated from the reference signal used in each test. Figure 3.7 shows the calculated spectrums from Test3_66-86. Since no major conclusions could be extracted from the results obtained from the individual tests, except that there was evidence of a resonance frequency present in the system, the results from every test were compared to obtain a better estimate of the real value of this resonance frequency.

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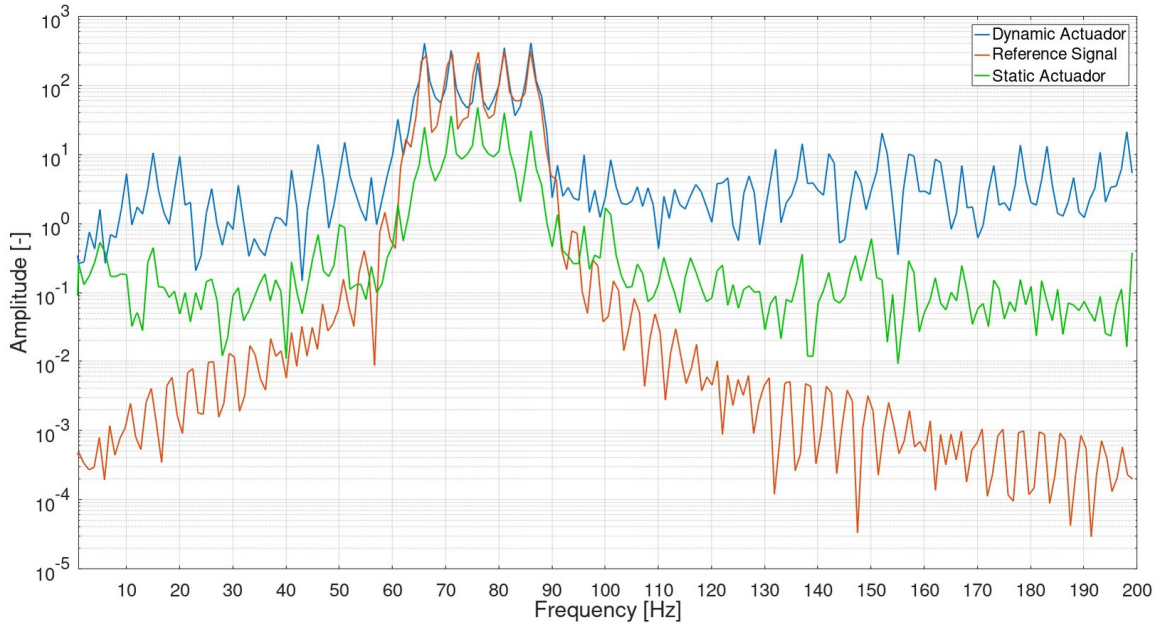
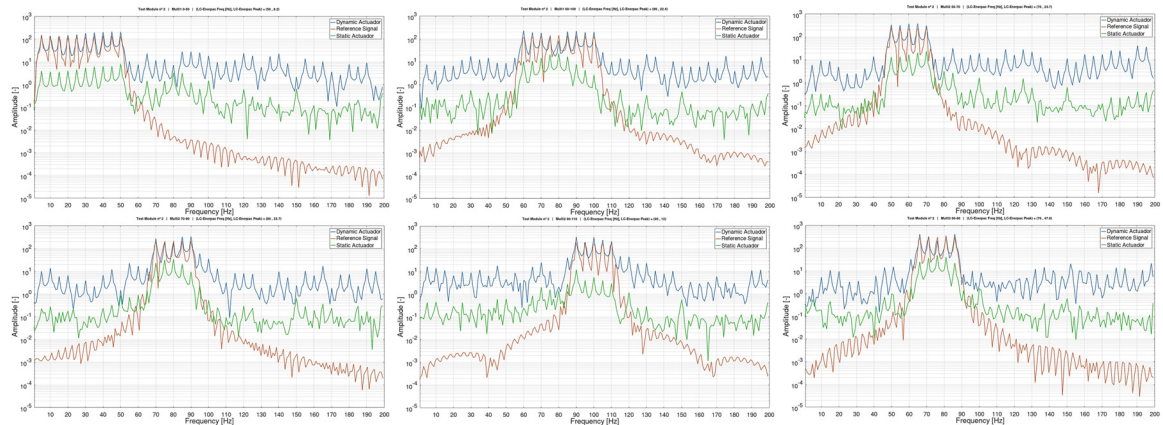


Figure 3.7: Obtained frequency spectra from Test3_66-86, module M2.

Figure 3.8 shows the spectra obtained from every test on M2, following the order presented in Table 3.2. From these curves, the dominant frequency output in each test was identified based on the frequency with the highest amplitude response, which corresponded to the excited frequency closest to the resonance frequency of the system. While the maximum amplitude values of the system's response observed with the dynamic load cell were greater than those obtained with static load cell, the detection of the dominant frequencies was more reliable when using the spectra calculated with the static actuator data. This was due to an effect that the identified resonance phenomenon had on the observable system response, where the response amplitude at the resonance frequency actually diminished in the dynamic load data when compared with that of surrounding frequencies. This phenomenon is very likely related with the previously identified load transfer effect that occurred between both actuators. On the other hand, the response of the system when looked at in the data from the static actuator behaved as expected, since the response amplitude increased when the system was excited at the resonance frequency and in the frequency band around it. The spectra obtained with the reference signal was just used to validate each test, by comparing the input with the outputs.



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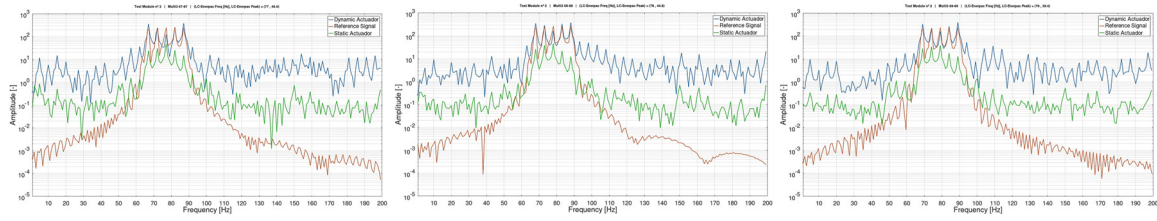


Figure 3.8: Obtained spectra from the tests performed on M2. The sequence of the graphs follows the order presented in Table 3.2 (from left to right, top to bottom).

From the multiple spectrums presented in Figure 3.8 it was possible to obtain the final estimate of the dominant resonance frequency detected in this module, with the value of 76 Hz. Due to the frequency resolution used here, obtained by combining the spectra from all the tests, the actual resonance frequency value is likely to lie in the range of 75.5 Hz to 76.5 Hz. But for the present purpose, this estimate is adequate. To better visualize these results, the spectra from the static load cell were compiled into a single spectrum by picking the maximum response amplitude at each frequency point. Figure 3.9 shows the resulting combined spectrum for M2, where the obtained higher resolution in the frequency band from 65 Hz to 90 Hz is perceivable when compared with the rest of the frequency band of interest. This spectrum represents an estimate of the sensitivity of this system to excitation inputs in the tested frequency band, in terms of its response amplitude. In other words, it corresponds to a rough estimate of the system's Frequency Response Function (FRF). Naturally, this system has other natural frequencies, especially in the frequency range above 100 Hz (e.g., the natural frequencies of the railway superstructure elements). However, those were not the focus of these tests and cannot be properly identified here, because the obtained results above 100 Hz are unreliable for this purpose.

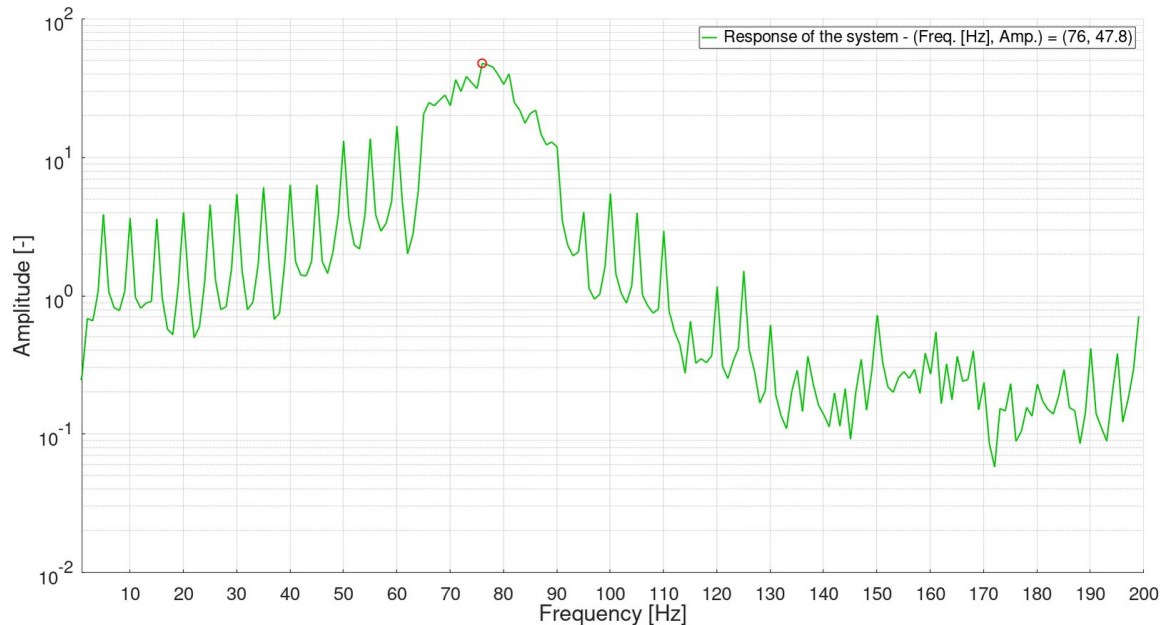


Figure 3.9: Combined spectrum from the tests performed on M2. The red circle indicates the identified resonance frequency at 76 Hz.

In order to verify if the four modules exhibited different dynamic responses in terms of the dominant resonance frequency value and the FRF estimates, the combined spectrums

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from each module were represented in the same graph (Figure 3.10). From this graph, the immediate conclusion is that the dynamic responses from the four modules are practically equal in terms of the dominant resonance frequency values and the overall shapes of the FRF in the tested frequency band. There are only some small amplitude differences on the resonance responses from each module. These amplitude discrepancies appear to be directly related with the number of reinforcement columns from each module, in that a module with higher number of columns showed a dynamic response with more amplitude. This is possibly related with a change on the infrastructure's damping properties imposed by the addition of the reinforcement columns. Regarding the similar dominant resonance frequency values from the four modules, the reinforcements appear to not significantly change their dynamic responses in this regard, contrarily to what was anticipated. Since track stiffness values were not determined for these modules during the GroutRail project, there was no prior data to validate these final results. However, according to some estimates of track stiffness calculated with the displacement data collected in these tests and the static load values used, all four modules showed vertical stiffness values around 220 kN/mm. According to the concept under assessment here, these track stiffness estimates are compatible with the obtained resonance frequency values of the four modules. But this overall result just proves that the experimental setup allowed for the observation of a dominant resonance frequency present in the mechanical system. Now it was necessary to prove that these resonance frequencies were indeed related with the railway subgrade and not with another element of the mechanical system, to fulfil the main objective established for these tests.

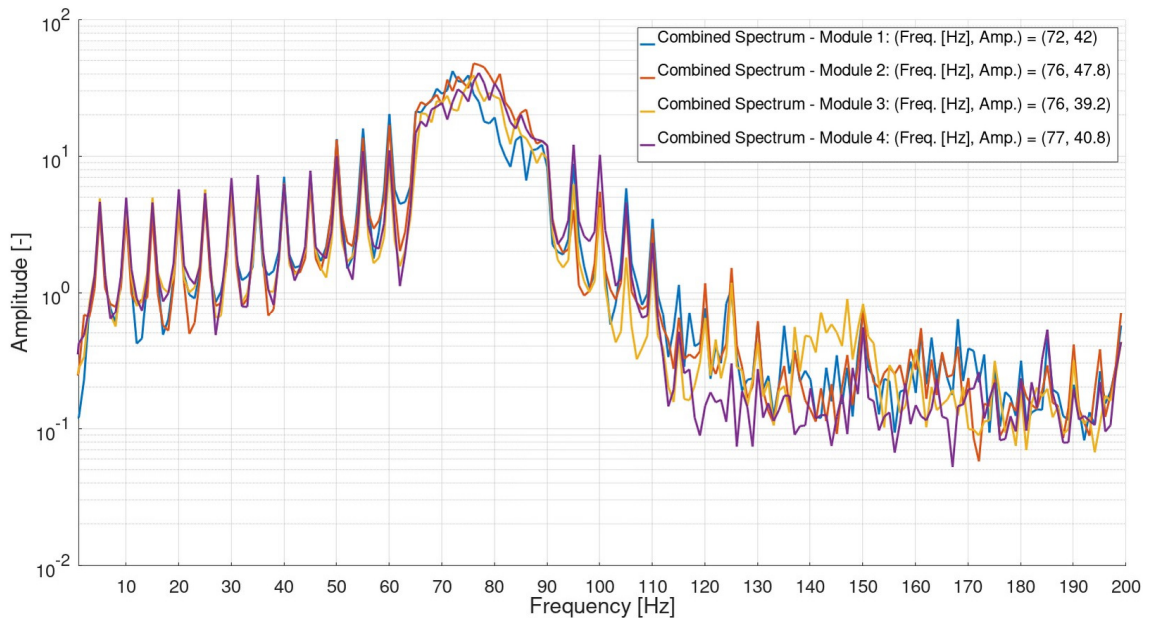


Figure 3.10: Combined spectra for the four tested modules.

3.3.3 Results' validation

The only candidate that could have a relevant resonance frequency in the range of interest is the reaction frame used in these tests (Figure 3.3). It has the appropriate mass

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and stiffness, in terms of orders of magnitude, for this situation to be possible. Thus, an estimate of the reaction frame's natural frequency value for the first mode of vibration was calculated. While not totally exact, this calculation was performed based on a loading scenario that consisted only of the upper beam of the reaction frame with a perpendicular load applied to the central span. This modelled beam was considered fixed in both ends, in order to simulate the presence of the two smaller vertical beams of the reaction frame. This scenario corresponds to the formula presented in Equation 2, which was used to calculate this estimate (Young and Budynas, 2002). The parameters in this equation are as follows: E is the Modulus of Elasticity of the beam; I is its Area Moment of Inertia; g is the gravitational acceleration; w is the uniform load per unit length applied to the beam; and L is its length.

$$f_1 = \frac{22.4}{2\pi} \sqrt{\frac{EIg}{wL^4}} \quad (2)$$

The reaction frame's natural frequency estimated by this equation was 188.9 Hz. Even if this estimate is not the real value of the reaction frame's first mode of vibration, it is still a useful estimate because the constraints applied to the upper beam of the reaction frame are similar to the boundary conditions considered in this formula. Since this value is significantly higher than the dominant resonance frequencies identified in the test results, and there appears to be no more candidates that could present natural frequencies in the frequency band of interest, then the identified dominant resonance frequencies are very likely related with the subgrade layer of the tested modules.

With this result, the main objective of these tests was achieved, which was to verify if a clear characteristic frequency of a railway infrastructure could be identified in data collected with adequate instrumentation in an experimental setup. The results show a dominant resonance frequency in each module, which appears to be related with the railway subgrade and is in accordance with the respective estimated values of track stiffness. In the end, the goal of these tests was to provide some practical insights into the difficulties in monitoring subgrade related frequencies from an external observation point and provide some preliminary validation results on the main concept behind the proposed methodology.

3.4 Proof-of-concept test 2: COURSE data

The initial development steps of the proposed TMM were based on experimental data collected in the context of a LNEC research project called COURSE, which was developed between 2016 and 2018. This railway track monitoring project aimed to create and demonstrate the applicability of an integrated vehicle-based solution, capable of continuously assessing railway functional and structural parameters taking into account aspects related to the structural response of the dynamic interactions of the vehicle and railway system (Morais et al., 2019a; Morais et al., 2019b). The data obtained in this project was fundamental during this stage to gain preliminary insights into the viability of the

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proposed solution and perform some implementation tests. As a side note, additional experimental data sets were also analysed and tested upon during the present thesis. However, every single one of them was eventually discarded, due to specific individual reasons, with only the exception of the data set that was used in a validation test on the last iteration of the TMM. The results from this specific test are described in chapter 6.

Under the COURSE project, a system prototype was developed and embedded into a self-propelled vehicle, model DD 450B, manufactured by SVI (Figure 3.11). From the complex instrumentation setup that was installed in this vehicle, the sensors that provided the data used in the early development of the TMM were two high-sensitivity ± 4 g triaxial accelerometers, installed symmetrically inside each of the vehicle's cabins. The prototype also includes two velocity sensors, installed on each axle, which together with a GPS system, were used to obtain the position of the vehicle along the rail track. A data acquisition system collected data at a sampling frequency of 1000 Hz. For additional information on the COURSE prototype system, refer to Santos et al. (2018).



Figure 3.11: Monitoring vehicle used to validate the COURSE system prototype.

The data set that was obtained in the single campaign performed with this prototype was extensively analysed in the early stages of this study. Despite the beneficial impact that it had at the time, the usefulness of this data set was eventually exhausted because only a single experimental campaign was performed. This restriction meant that important tests such as results repeatability were not possible to be implemented. Thus, the developed numerical models eventually became the main source of data used in the development and testing of the TMM. The cabin accelerometers were in prime positions for the intended purpose of the current study due to the following reasons:

i) Their position above the wheel axles of the vehicle meant that they could adequately observe the vertical movements and vibrations of the vehicle and the interactions between the vehicle and the railway infrastructure. This also meant that there shouldn't be any major contributions from phenomena that are not relevant to this study, such as the vibration modes of the vehicle due to flexural deformations.

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ii) The fact that these accelerometers were on the chassis meant that they were less susceptible to mechanical noise and unwanted interferences due to the filtering provided by the vehicle's suspension system. Railway vehicle suspension systems are designed to attenuate the higher frequencies bands, to provide adequate passenger comfort levels and better vehicle running conditions (Iwnicki et al., 2019; Zhai, 2020). This means that acceleration data measured at this level usually has an intrinsic low level of mechanical noise, thus removing the need to apply digital filters during the data processing phase to mitigate any negative effects. Additionally, the frequency content of interest should be within the range that is observable in the vehicle cabin (i.e., below 200 Hz) (Zhai, 2020), based on expected values for the subgrade related frequencies. Accelerometers mounted below the suspension system (e.g., on the axle box) of a railway vehicle are better suited to monitor phenomena related with the railway superstructure, including the detection of rail and sleeper defects (Iwnicki et al., 2019; Zhai, 2020).

iii) The comparison of data obtained from the two cabin accelerometers, which for the intended purpose were subjected to practically the same inputs from the railway-vehicle interactions, allowed for preliminary verifications regarding issues such as the stability of the obtained acceleration values and frequency content obtained from multiple sources. Since both accelerometers were measuring the same response from the system under observation, the proposed methodology was applied to both independently, and then the results were compared to assess these topics.

The rest of this section describes the proof-of-concept test that was performed based on the data collected during the COURSE project, which was also the focus of a publication in the context of this thesis (Morais et al, 2021). The specific case study presented here was selected for this purpose since it was already studied in detail in the context of another LNEC research study (Paixão et al., 2015; Ribeiro et al., 2015) (henceforth referred as on-site study).

3.4.1 Case study description

The COURSE experimental campaign using the vehicle prototype was performed on a stretch of the *Linha do Sul* from the Portuguese railway network, located between *Ermidas do Sado* and *Poceirão*, on the *Alcácer* bypass. From the data collected in this campaign, two specific locations were selected and analysed as a single case study with the intent of performing a preliminary application test of an early version of the proposed TMM. These locations correspond to transition zones for two very similar underpasses of this railway track, composed by reinforced concrete closed frames (UP1 and UP2). The two structures are located at marks 62.940 km and 81.187 km of this track and the main difference between them is that 44 sleepers at UP1 were equipped with under sleeper pads (USP) during the track's construction, while UP2 contains sleepers without USP. The main features of each transition zone are presented in Figure 3.12.

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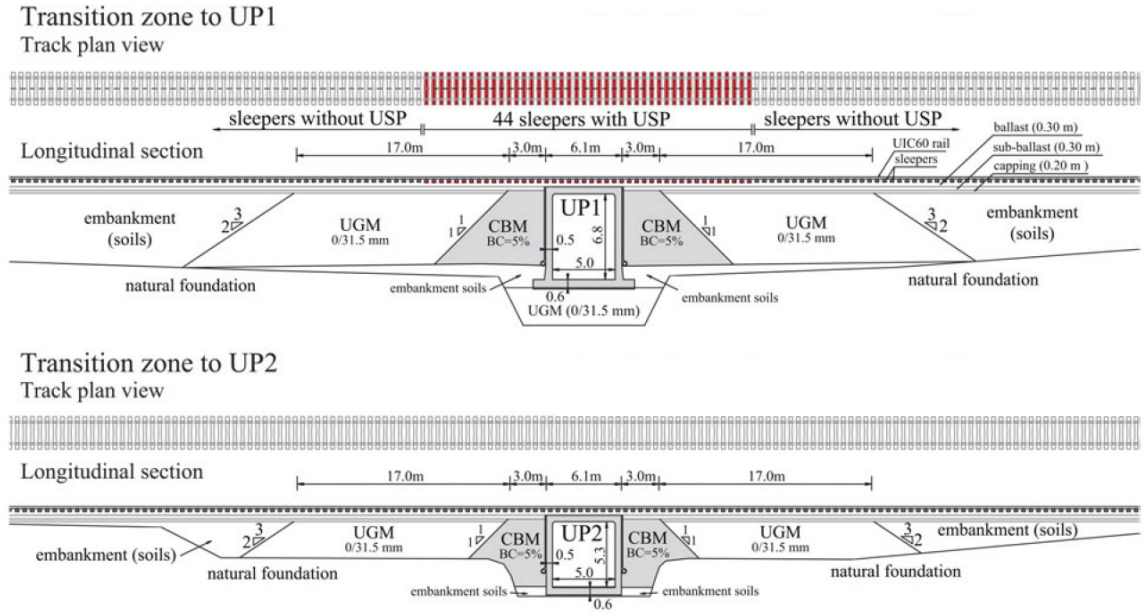


Figure 3.12: Longitudinal profile of underpasses UP1 and UP2 (adapted from Paixão et al., 2015).

Both underpasses possess wedge-shaped backfills, which are intended to control the long-term deformations that usually occur near these concrete structures, as well as enable a smooth transition of the track's vertical stiffness over these areas. The layers of the backfills are constructed with Cement Bound Mixture (CBM) or Unbound Granular Materials (UGM), which were compacted with an average degree of compaction of 99% regarding the modified proctor compaction test (UIC, 2020). The natural foundation of both transition zones is comprised of monogranular fine-grained sands, providing adequate foundation conditions.

3.4.2 Application of the methodology

At this stage, the data processing procedure of the TMM only included the application of a FFT routine to obtain spectrograms of the collected acceleration data. These results were then analysed by selecting the relevant frequency curves present in the spectrogram to then identify the more likely candidate that could correspond to a characteristic frequency of the subgrade layer. This selection process was mostly based on the information provided in section 2.3.1 regarding the expected ranges of subgrade related natural frequencies and their behaviour.

UP2 underpass results

Starting with the UP2 underpass, Figure 3.13 shows the raw acceleration data obtained with the front cabin accelerometer and the speed profile of the vehicle (orange curve), which were acquired during a time window that included the passage over this underpass. This time window corresponds to 100 seconds and a total of 828 m of distance travelled by the vehicle.

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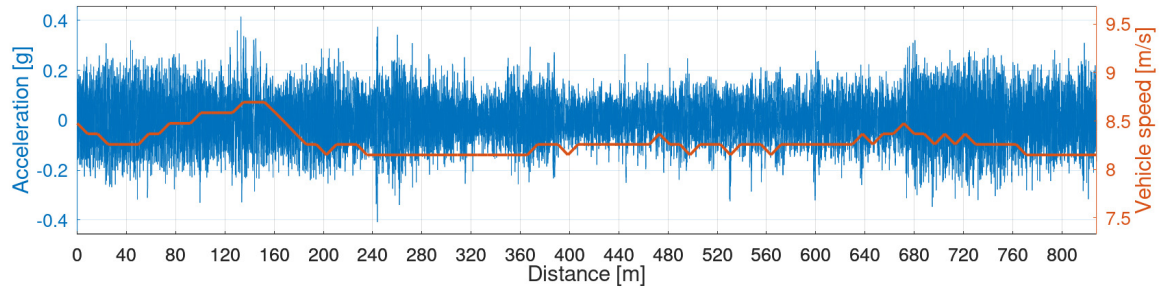


Figure 3.13: Acceleration data and vehicle speed data collected around the UP2 underpass.

Using this data, the proposed methodology was applied to obtain the spectrogram in Figure 3.14, which is set to the frequency range between 0 to 150 Hz because no relevant information was found above this threshold. This is due to the position of the accelerometer in the vehicle's cabin and to the fact that the accelerometer's bandwidth is limited to 200 Hz. For improved readability, the amplitude data displayed in the following spectrograms is represented using a logarithmic scale. In this spectrogram, the two common types of frequency curves can be perceived: frequencies that depend on the vehicle running speed (F_{ds}) and frequencies that are independent of the vehicle running speed (F_{is}). For example, the F_{ds} curve that starts around 14 Hz, and matches the pattern described by the vehicle speed curve in Figure 3.14, corresponds to the frequency excited by the passage of the vehicle over the rail sleepers.

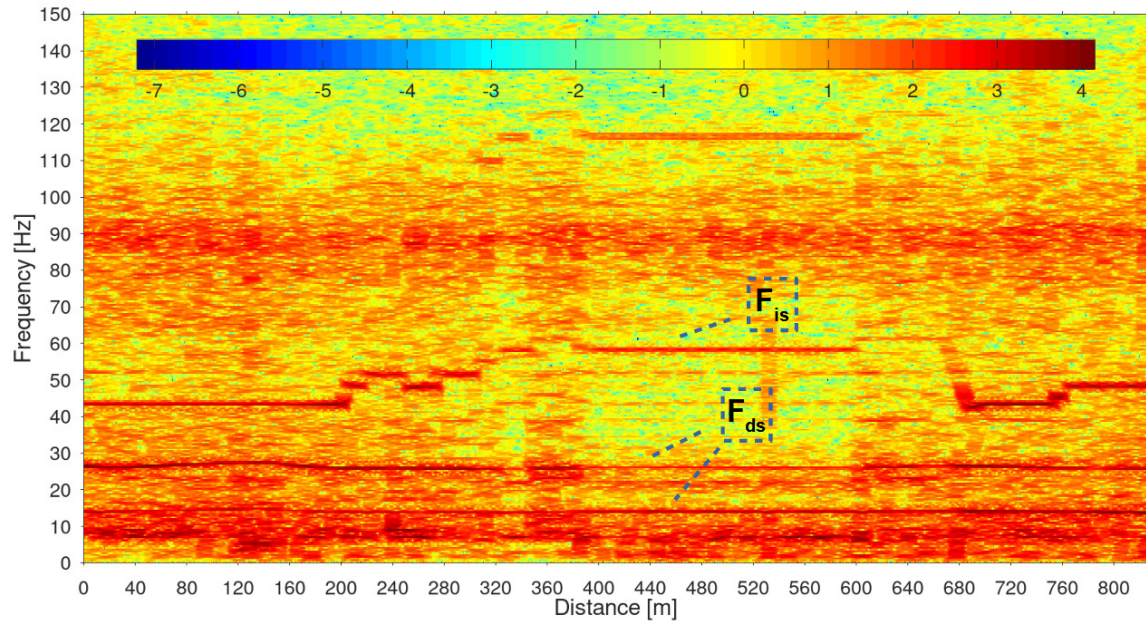


Figure 3.14: UP2 spectrogram, identifying the two types of frequency curves present in the data.

Although the overall interference created by the presence of mechanical noise is insufficient to significantly disrupt this spectrogram, because the frequency curves can still be analysed, it negatively affected the readability of the spectrogram especially in the lower frequency band. In order to improve upon this issue, considering the employed experimental setup, the cross-spectrum of the spectrograms obtained with the two cabin accelerometers was calculated (Figure 3.15a). Overall readability was greatly improved in

3. Proposed theoretical models

this new spectrogram, because the physical aspects related with the deterministic inputs were reinforced by this procedure (in this case, the railway-vehicle interactions), while the influence of the stochastic inputs (e.g., noise) were mitigated (Randall, 1987). The remaining spectrograms presented in this sub-section were all obtained using this process.

According to the proposed theoretical model concept, the marked F_{is} curve in this spectrogram should be related with the subgrade layer (ω_I from the 2-DoF model). This in turn means that the modal stiffness k_I is changing along this railway stretch according to the perceived pattern. Using the GPS data, the central position of the underpass is at the 362 m mark. In the spectrogram, the area around this position has a constant and relatively high frequency value, for an approximate length of 20 m. Using the available information, it is reasonable to assume that this frequency value corresponds to the presence of the CBM section of the technical block around the underpass. This conclusion agrees with the underpass's configuration, showed in Figure 3.12, and the knowledge that these technical blocks have higher structural stiffness than the surrounding railway infrastructure (UIC, 2020). Thus, the presence of the technical block appears to cause a distinguishable variation in the modal stiffness k_I , which corresponds to a variation in track support conditions. This apparent correlation represented an initial validation of the concept behind the proposed TMM.

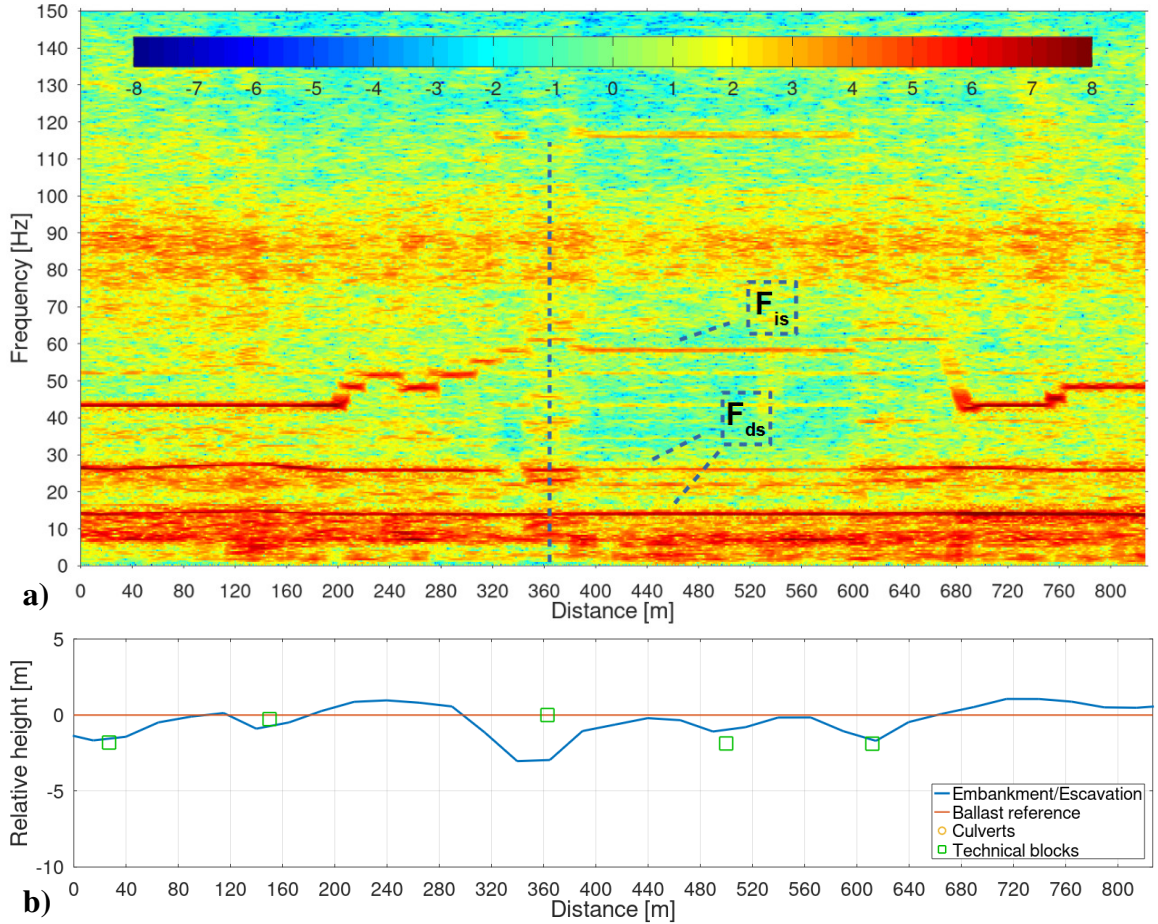


Figure 3.15: (a) UP2 cross-spectrum spectrogram (the dotted vertical line represents the location of the UP2 underpass, at the 362 m mark) and (b) groundworks configuration for the area around it.

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In order to find additional arguments to justify the perceived ω_I frequency pattern, Figure 3.15b presents the longitudinal configuration of this railway stretch in terms of groundworks, since substructure configuration is an aspect that should have a high impact on k_I . This profile gives the configuration of the embankments and excavations present on the line, relative to the vertical position of the railway track. It also contains the position of every technical block and culvert present on the line. There appears to be some correlation between the groundworks' configuration and the ω_I frequency curve/ k_I modal stiffness, especially in the stiffer zones around the technical blocks and the excavation zones. Zones with excavations or embankments appear to present higher ω_I values, when compared with the surrounding areas. This correlation is naturally not completely verified throughout this example, because there are other factors that influence track support conditions which are not being taken into consideration in this analysis.

UP1 underpass results

Figure 3.16 now represents the raw data obtained from UP1 underpass, which contains the 44 sleepers with USP. The time window used also corresponds to 100 seconds, which translated into more than 751 m of distance travelled by the vehicle.

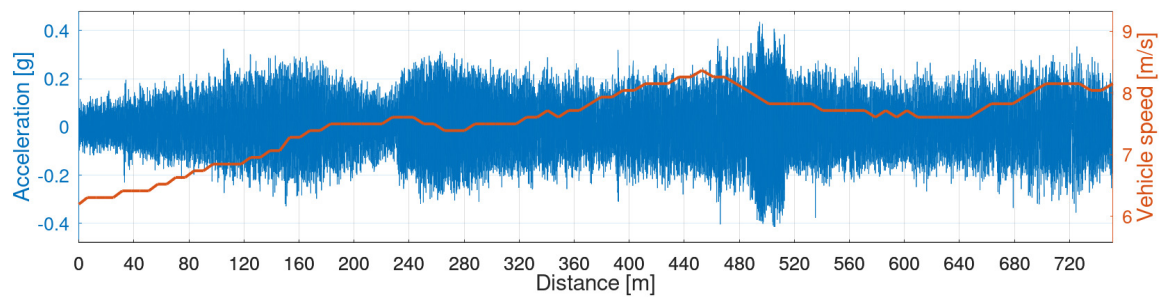


Figure 3.16: Acceleration data and vehicle speed data collected around the UP1 underpass.

Figure 3.17 shows the resulting cross-spectrum spectrogram and the corresponding groundworks' configuration for this railway stretch. Overall, the correlation between the groundworks profile and the ω_I frequency curve stills has some significance here, since the average ω_I value for this area is higher than the average value for the UP2 case, as is the average embankment depth.

The central position of the UP1 underpass is at the 248 m mark. The surrounding area around the position of the underpass, with an approximate length of 26 m, has a new behaviour that can be observed where the ω_I frequency curve is severely mitigated. The most likely cause of this behaviour is the presence of the USP since they are placed along a track length of 26.4 m, which is very similar to the railway length where this frequency curve is mitigated. This gives evidence to the damping provided by these devices which, in this case, appears to mask the frequency values of the subgrade.

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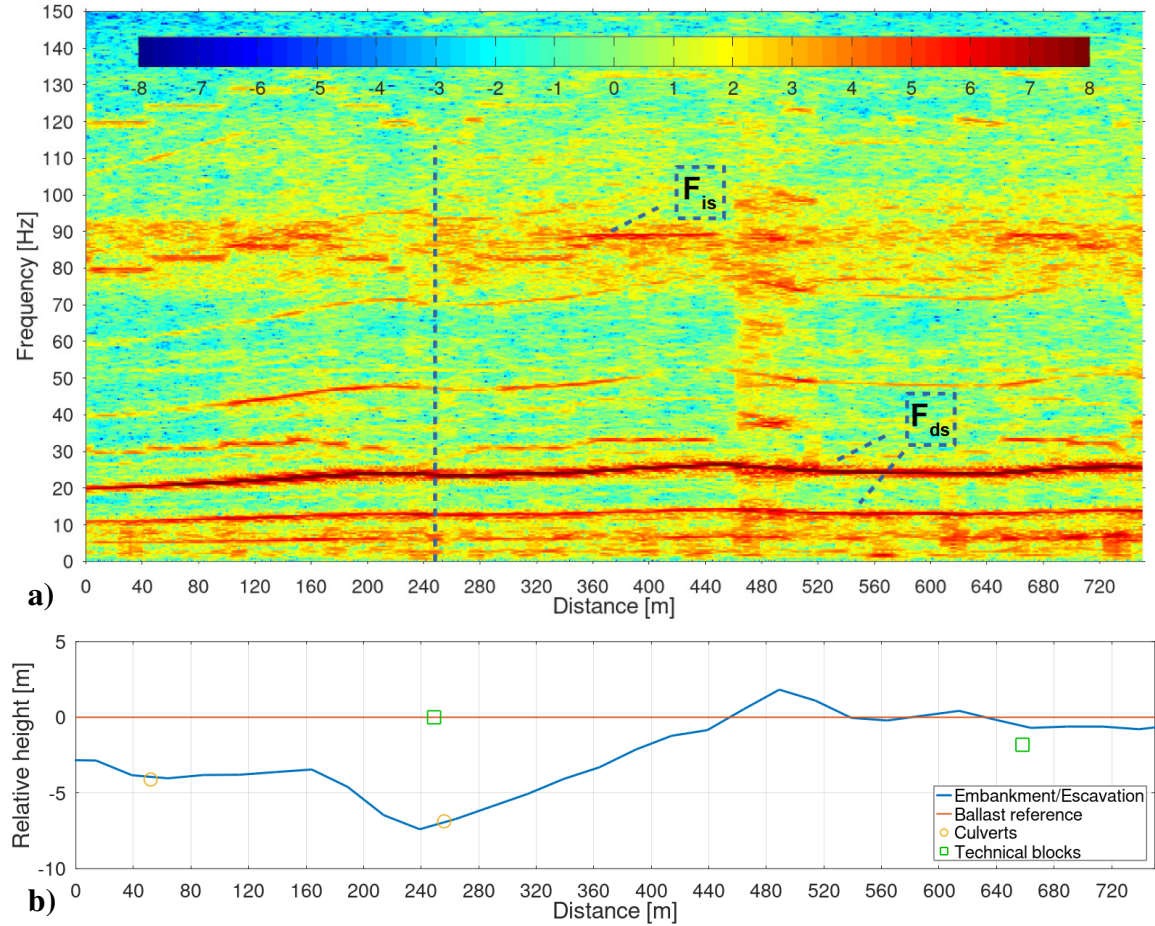


Figure 3.17: (a) UP1 cross-spectrum spectrogram (the dotted vertical line represents the location of the UP1 underpass, at the 248 m mark) and (b) groundworks configuration for the area around it. The more defined frequency curves present are labelled according to their type.

Based on the results from these two case studies, this methodology appears to be able to provide information regarding several aspects related with railway track support conditions. More specifically, qualitative information was extracted regarding the modal stiffness of the railway by evaluating the ω_I frequency curve. One perceived relevant behaviour of the ω_I frequency curves is that they have no correlation with vehicle speed. The longitudinal groundworks' configuration seemed to be a relevant factor in the obtained results, giving evidence to the capabilities of this concept to observe the railway infrastructure as a whole and in depth.

3.5 Chapter final remarks

This chapter presented the foundation that serves as the theoretical framework for the proposed TMM, along with some information on the main steps and decisions that were made along its development. Naturally, a significant part of the information regarding failed experiments or details on the smaller iterative steps on the methodology's development process are not present in this chapter. However, almost every single step made in the context of this study was performed according to the initial goal of developing a track monitoring methodology focussed on assessing subgrade condition and were

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important for the final results that were achieved here.

4 Simpack numerical models

In the context of the present thesis, the MBS software that was selected for the implementation of the numerical models used in the development of the proposed TMM was Simpack[®], version 2021. This software by *Dassault Systèmes* is a complete package dedicated to the development and simulation of high-fidelity multibody system virtual prototypes. Thanks to its capability to model a wide range of mechanical systems, Simpack[®] is a versatile tool that can be employed to solve engineering problems across a wide variety of subjects. Some of these subjects are tackled using dedicated software packages inside Simpack[®] that possess specific tools useful in their respective contexts. Particularly relevant for the present study, Simpack[®] has an extensive package dedicated to the railway context which enables the modelling and analysis of a wide range of rail-guided systems and railway vehicles including high-speed trains, local trains, locomotives, trams and freight vehicles. It can also be used to model common track types, including ballasted track, slab tracks, bridges, turnouts and crossings. However, this package does not have a dedicated solution capable of modelling the railway subgrade as an independent element, with its own natural frequencies and vibration modes. Instead, the influence of this railway component is usually just incorporated into the modelled vertical stiffness of the track. The lack of such a solution in this software, which is something that is also not available in other MBS modelling software, is the main reason that led to the development of the dedicated MS that was introduced in the previous chapter.

Several Simpack[®] numerical models were tested in the present study, to first obtain the required experience in the use of this modelling software and then to progressively increase the models' complexity until the final versions that were used to validate the proposed TMM. Figure 4.1 presents some examples of tested model configurations, which are used here to highlight three specific aspects that are worthy of reference in this context: i) the first is that the infrastructure layered elements were originally only applied to the frontal axle of the modelled railway vehicle (Figure 4.1a). This preliminary configuration was more focused on identifying the appropriate solution to model these elements in Simpack[®], than representing a realistic situation. These elements were eventually added to every axle of the modelled railway vehicle. ii) The second aspect is that multiple subgrade element geometry configurations were tested during this process (Figure 4.1b). The initial configurations lacked any theoretical background and were just practical attempts to model the subgrade in Simpack[®]. These initial solutions were eventually refined with the help of the described MS into the final model configuration described below. iii) The third relevant aspect is that tests were also made with model configurations containing multiple railway

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vehicles (Figure 4.1c). The results obtained in these models were similar to those obtained in the single vehicle configuration in terms of the parameters of interest (i.e., the natural frequencies and vibrations modes related with the layered elements of the railway infrastructure). However, the single vehicle configuration entailed significantly less computational resources for the respective numerical simulations, thus the multiple vehicle options were eventually discarded.

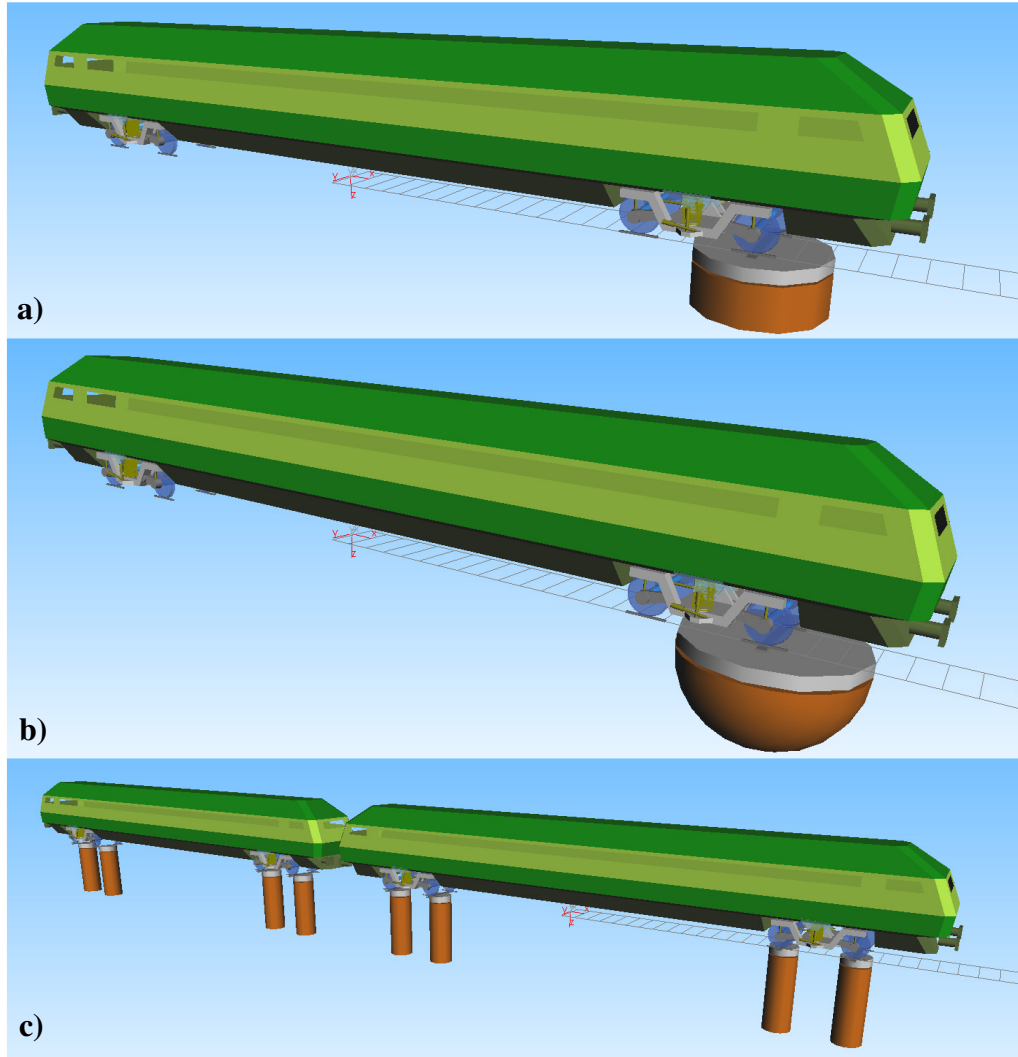


Figure 4.1: Examples of the Simpack® models that were designed and tested during the development of the proposed subgrade modelling solution.

This chapter presents in detail the final numerical model configuration that was developed in this study. Then, two validation tests that were performed during the models' development process are described, each focused on relevant aspects that had to be adequately validated. The topics presented in this chapter have already been included in some of the publications written in the context of this thesis (Morais et al., 2023, 2024a).

4.1 General simulation setup

This section presents the final MBS model (Figure 4.2) that was used to assess the capabilities of the relevant tools and methods developed in this study, along with a

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description on the results obtained from applying the developed TMM to the acquired simulated data. There were three main objectives for this model: the first was to test the proposed MS, in terms of assessing the layered elements modelling solution; the second was to supply the training and testing data to assess the damage detection capabilities of the unsupervised data-driven tool that was developed to apply the TMM; and third to represent a general validation test on the proposed TMM.

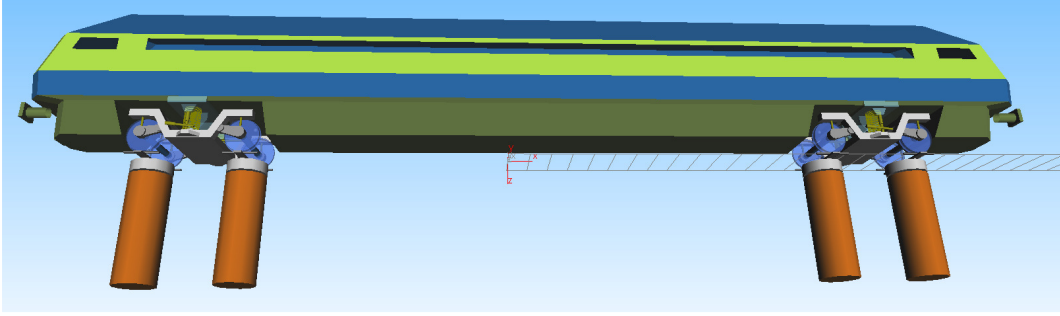


Figure 4.2: Simpack® model containing a railway passenger carriage and railway infrastructure elements, which include a railway track and four cylindrical body sets for the ballast and subgrade.

This Simpack® model contained a generic railway passenger carriage, with two bogies and four wheelsets, and four identical sub-sets of elements placed below each vehicle axle to represent the presence of the railway infrastructure (Figure 4.3). The cartographic profile used in this model was a straight track with a length of 2000 m, since this aspect does not interfere with the focus of this study, as was demonstrated in a previous publication in this context (Morais et al., 2023). An insight into this topic is also shown in section 4.2.1. Virtual accelerometers were placed in nine points along the vehicle (three on the chassis, two on the bogies and one in each wheelset) to provide the required data, with a sampling frequency of 1000 Hz. This arrangement was selected to also test the frequency output of these positions.

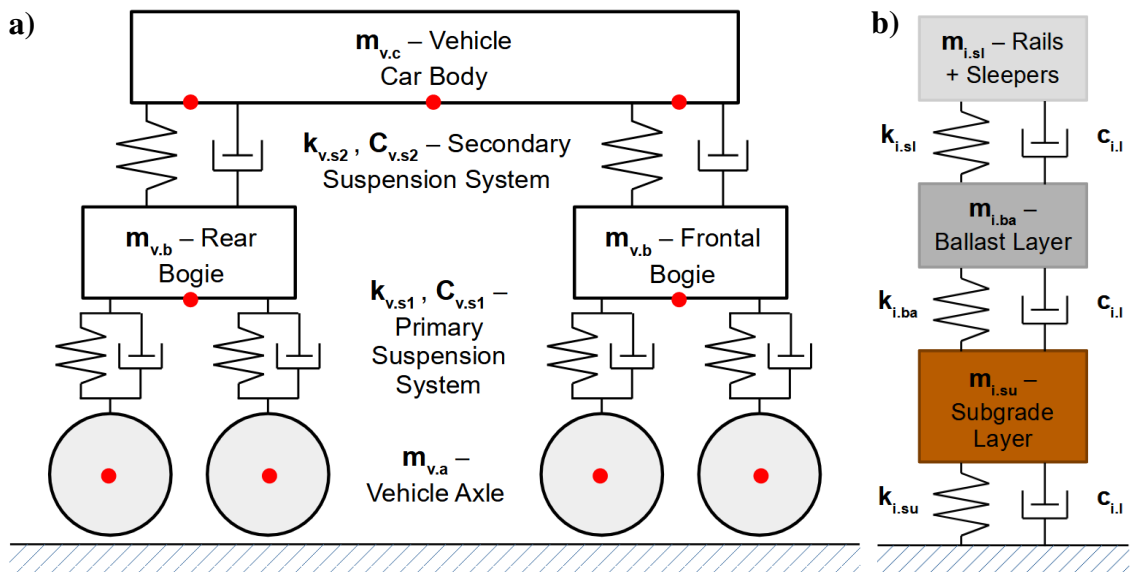


Figure 4.3: Free-body diagrams of the (a) railway vehicle and (b) of one infrastructure sub-set. The red dots represent the positions of the virtual accelerometers.

4. Simpack numerical models

The generic vehicle model used in these simulations included springs and dampers to represent two levels of suspension systems, and mass elements to represent both the sprung and unsprung mass components of the railway vehicle. Table 4.1 presents the nominal values used for the main modal parameters of the vehicle model. These parameter values are in accordance with the BNN carriage from the Portuguese *Alfa Pendular*, which is a common passenger vehicle used in Portuguese lines.

Table 4.1: Main parameters used in the Simpack® vehicle model.

Vehicle parameters	Value
Chassis body mass, with no passengers on-board ($m_{v,c}$)	35,640 kg
Bogie mass ($m_{v,b}$)	5204 kg
Axle mass ($m_{v,a}$)	1538 kg
Primary suspension stiffness, per axle ($k_{v,s1}$)	0.564 kN/mm
Secondary suspension stiffness, per bogie ($k_{v,s2}$)	0.256 kN/mm
Primary suspension damping, per axle ($C_{v,s1}$)	18,000 Ns/m
Secondary suspension damping, per bogie ($C_{v,s2}$)	35,000 Ns/m

Following the proposed MS, the railway infrastructure was described by four identical sets of body elements, each including two rail elements, one sleeper, and two cylinders stacked on top of each other. These cylinders were used to represent the ballast layer (grey cylinder) and the subgrade layer (brown cylinder). This part of the model also contained spring-damper elements to simulate the equivalent vertical stiffness behaviour from each of these components. The diameter of the layered elements was calculated with Equation 10, based on pre-selected height values for the subgrade layer and the ballast layer. For the model described in this section, subgrade layer height was set at the common and reasonable value of 3 m with the intent of representing a generic soil layer. These body elements sets follow their corresponding vehicle axle as the vehicle moves along the cartographic profile of the track, thus enforcing the vehicle-track behaviour of interest in the model. Table 4.2 presents the values used for the modal parameters of the infrastructure elements sets. The implemented stiffness, specific mass and damping values used here are in accordance with common values used in other studies (Milne et al., 2019).

As will be explained in the following chapter, unsupervised data-driven tools require extensive and adequate amounts of training and testing data for a proper assessment of their capabilities. In an SHM context, this is typically done by first establishing a data batch that represents the subject under analysis in the nominal conditions (i.e., in this case, this data batch should represent a railway track with adequate track support conditions in terms of the underlying subgrade condition), which is normally referred as the baseline. This baseline is then supplemented with an additional data batch that should represent several configurations of the test subject with examples of relevant damaged cases to be identified by the data-driven tool, together with other types of damage or anomalies that should be discarded by the tool.

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Table 4.2: Main parameters used in the Simpack® infrastructure model.

Infrastructure Parameters	Value
Layered elements diameter (θ)	1.070 m
Subgrade layer height (h_{su})	3 m
Ballast layer height (h_{ba})	0.3 m
Subgrade specific mass (ρ_{su})	2000 kg/m ³
Ballast specific mass (ρ_{ba})	1500 kg/m ³
Subgrade layer mass ($m_{i.su}$)	5152.9 kg
Ballast layer mass ($m_{i.ba}$)	386.5 kg
Sleeper mass ($m_{i.sl}$)	330 kg
Sleeper spacing (L_{sl})	0.5 m
Subgrade layer spring element stiffness ($k_{i.su}$)	225 kN/mm
Ballast layer spring element stiffness ($k_{i.ba}$)	450 kN/mm
Sleeper spring element stiffness ($k_{i.sl}$)	1800 kN/mm
Layered elements damping ($C_{i,l}$)	37,600 Ns/m

In the present context, an initial batch of simulations with adequate subgrade conditions was performed using this model to define the baseline, based on a nominal subgrade stiffness profile. Afterwards, additional simulations batches were performed, also based on this model, where a damaged track section was introduced on a specific location. The goal was to test if the data-driven tool could reliably identify the baseline cases as undamaged (i.e., negative damage classification) and detect the presence of damage in the damaged track cases (i.e., positive damage classification). The description of this specific simulation setup is included in the following chapter.

4.2 Validation of the employed modelling solutions

The first validation test that is described in this section refers to a preliminary assessment on relevant concepts of the proposed theoretical formulation that supports the TMM. The second test refers to a sensitivity analysis that was performed to assess the application range of the proposed MS, with a focus on evaluating the effects that each variable from Equation 10 has on the resulting layered railway elements' diameter.

4.2.1 General model validation test

An important aspect of the proposed TMM that needed to be validated was the concept the assessing track support conditions of a railway infrastructure through its natural frequencies. More specifically, the aspect that was assessed here was if it is possible to observe a dominant resonance frequency related with the railway subgrade layer under assessment, and if this frequency is adequate to provide useful information on overall track support conditions. This statement represents one of the main pillars supporting this methodology. Since the proposed 2-DoF model is naturally dependent on the modal

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characteristics of the instrumented vehicle, a concern that was also tested here was whether there would be the need to adapt this model based on the number of suspension levels of the instrumented railway vehicle being used (Zhai, 2020). The 2-DoF model is clearly more suitable for vehicles with only one suspension level, since it only has one spring element assigned to this aspect. Thus, the following hypotheses were assessed in this test:

- **H1:** if a single dominant resonance frequency related with the dynamic response of an entire railway infrastructure section exists and is observable in data collected with an instrumented railway vehicle moving over the railway track.
- **H2:** if the proposed theoretical model is compatible with instrumented railway vehicles with one or two suspension levels.

Simulations' models

Two model variants (M1 and M2) were implemented here to assess the previous hypotheses, based on a Simpack® model configuration like the one previously shown. Both variants used the same model parameters and conditions, with only the following differences. In model variant M1, which represented the first step in the test plan, the secondary suspension level of the vehicle was effectively suppressed by increasing its stiffness value by six orders of magnitude, to simulate a vehicle with only one suspension level. This model variant used the original two suspension level vehicle with the described modification, instead of using a different vehicle model with only one suspension level, to allow for more direct comparisons between results from the two model variants. On the other hand, in model variant M2 the secondary suspension level was re-established to the original stiffness values.

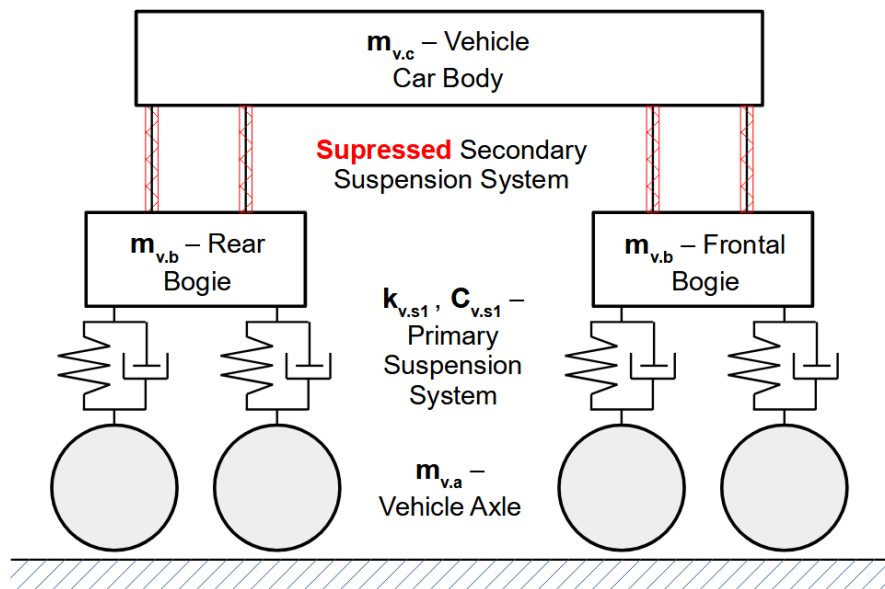


Figure 4.4: Free-body diagram of the railway vehicle used in model variant M1.

Each models' simulations were conducted using a data sampling frequency of 1000 Hz and a run-time of 160 s. The integration method used was the SODASRT 2 with an

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automatic time-step size, with a maximum of 0.5 s. Each model had a virtual accelerometer placed in the frontmost axle of the vehicle, another on the frontal bogie, and a third on the chassis directly above the instrumented bogie. The first 100 m of both simulations were cut from the following graphical representations to remove the transient corresponding to the simulation's start. Acceleration data collected with the bogie sensor was only relevant to verify the suppression of the secondary suspension system in simulation M1, since frequency results obtained from this sensor did not present any additional useful information when compared with the results from the other two sensors.

Simulation M1

Figure 4.5 presents the raw acceleration data obtained from this simulation, along with the implemented vehicle running speed profile. As expected, the acceleration data from the axle sensor had significantly higher amplitude values than the data from the other two sensors (Zhai, 2020), due to the damping effect provided by the suspension system of the vehicle. This difference is also present in the respective frequency spectrums. In this model, the acceleration data from the bogie and the chassis sensors are equal due to the suppression of the secondary suspension system, as expected.

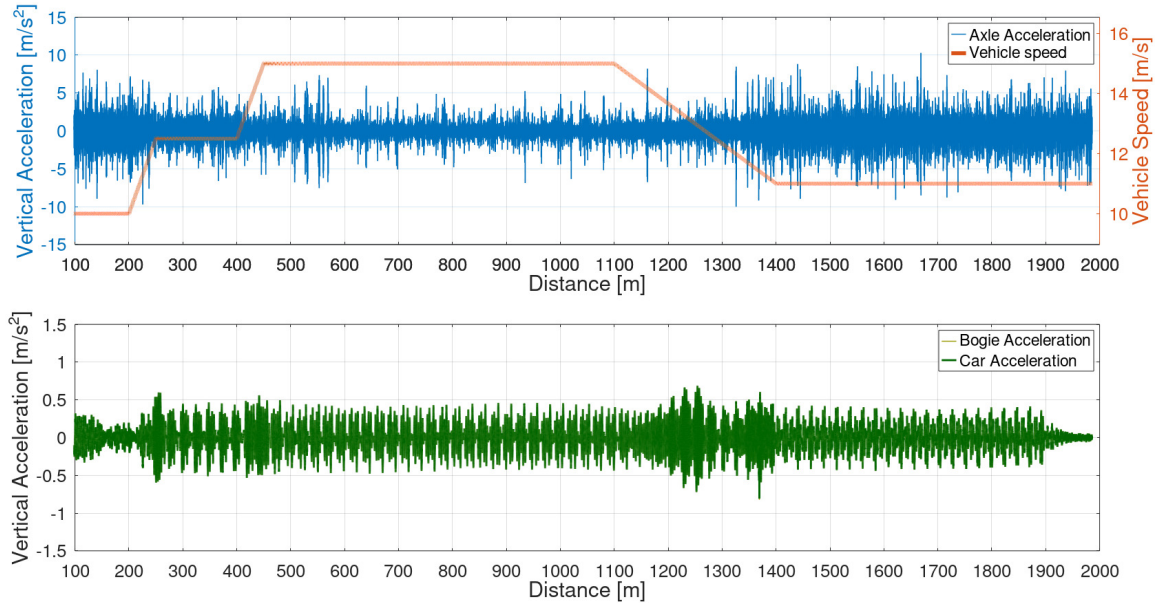


Figure 4.5: Raw data from simulation M1 (acceleration data and vehicle running speed).

Figure 4.6 presents the spectrograms obtained from the axle (Figure 4.6a) and the chassis (Figure 4.6b) acceleration data, and the vertical track stiffness profiles used on the spring elements associated with the two layered elements of the infrastructure (Figure 4.6c). The track stiffness profiles that were employed at this time were completely synthesised, since the theoretical model described in chapter 3 was still not fully developed. However, precautions were taken to guarantee that the employed stiffness values were not unrealistic, even if the shape of the profiles was more focused on facilitating results analysis than on being an accurate depiction of a real situation. Data analysis in this test was still being carried out by visual inspection of the obtained spectrograms.

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Both spectrograms present mostly the same observable frequency curves, except for two relevant differences. One difference is that spectrogram (a) does not present any significant frequency content below 10 Hz, while spectrogram (b) presents frequency curves in this area that correspond to natural frequencies of the chassis (Zhai, 2020). These frequencies do not appear in the axle sensor because of the suspension system. The second relevant difference is that some of the frequency content that appears on spectrogram (a) is significantly mitigated in spectrogram (b), especially the higher frequency content, again because of the suspension system.

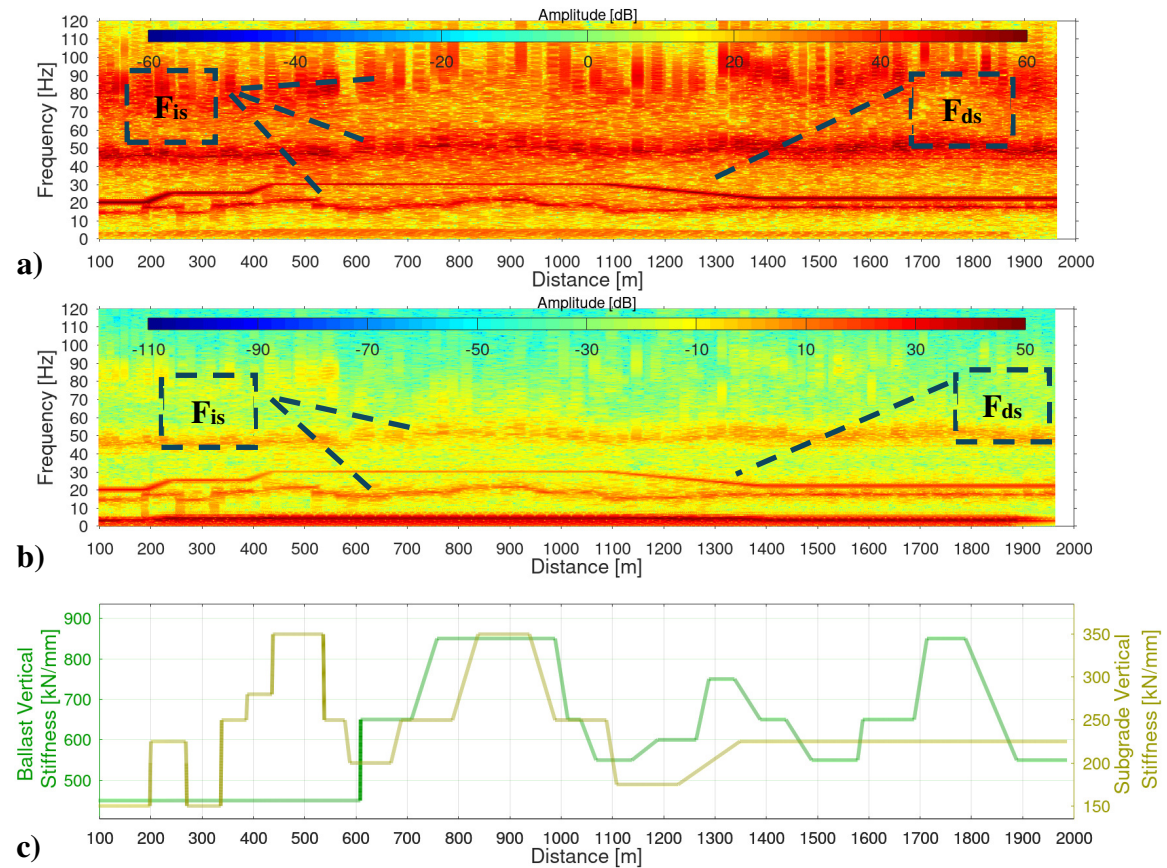


Figure 4.6: Obtained spectrograms and applied track stiffness profiles from simulation M1.

The frequency content of interest was then extracted from the spectrograms, by discarding the irrelevant frequency curves. During this analysis, the important distinction between frequencies that depend on the vehicle's running speed (F_{ds}) from those that are independent from it (F_{is}) was also used in this task. As previously explained, the characteristic frequencies of this combined mechanical system, which include the frequencies of interest, are not dependant on the vehicle's speed. Thus, frequencies that can be correlated with the vehicle's speed profile (Figure 4.5) can be discarded. In these spectrograms there is only one F_{ds} curve, which corresponds to the parametric frequency created by the interaction of the vehicle's wheels with the spacing between the sleepers. Additionally, the F_{is} curves present in spectrogram (b) below the 10 Hz mark can also be discarded because these correspond to natural frequencies of the sprung mass of the vehicle (Zhai, 2020).

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Having discarded some frequency content, there were still three observable F_{is} curves to analyse, which are identified in Figure 4.6. Due to the damping effect of the suspension system, the identified F_{is} curve with the higher frequency values that is observable in spectrogram a) is barely visible in spectrogram b). However, the other two frequency curves are clearly visible in both spectrograms. Using a dedicated Simpack® tool that calculates and represents the kinematics of each natural frequency present on a simulated model, using its initial conditions, these frequencies were identified as three different modes of vibration from the infrastructure elements coupled with the unsprung mass of the vehicle. According to this modal analysis tool, these two groups of elements form a sub-system that is dynamically excited during the simulation and exhibits resonance frequencies that can be associated with the railway infrastructure. Figure 4.7 presents the values given by Simpack® for these three resonance frequencies, which match the values shown in the spectrograms on the initial track stiffness values, along with a representation of their mode shapes based on the three main body elements of this sub-system.

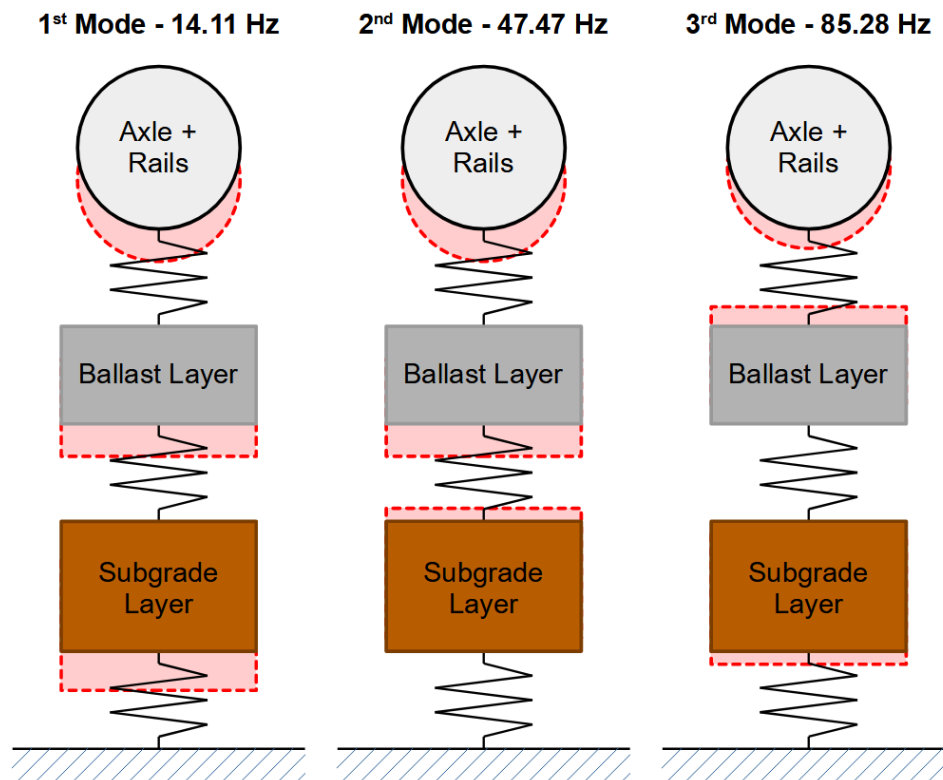


Figure 4.7: Representation of the three main infrastructure related vibration modes from the tested model.

The first mode represents the full body oscillation of this sub-system over the adjoining springs, while the two remaining modes represent higher order vibration modes from this three element sub-system. The patterns of these three frequency curves, visible on the spectrograms, resemble the vertical track stiffness profiles applied to the layered infrastructure elements, which further supports the statement that these resonance frequencies are related to them. More specifically, the first mode appears to be heavily influenced by the subgrade track stiffness profile, which matches the mode shape description that this vibration mode corresponds to the oscillation of the entire mass of the

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infrastructure, plus the axle of the vehicle, over the subgrade spring element. The second mode's frequency curve on the spectrograms resembles the ballast track stiffness profile, which also agrees with the shape mode's representation in Figure 4.7 where it is reasonable that the ballast spring element should be the main influencer. The third mode's curve seems to be a combination of influences from the two track stiffness profiles, which again also matches its shape mode representation in Figure 4.7.

Taking these results into account, the first mode of vibration described in Figure 4.7 could potentially be used to provide information on the track's support conditions of the railway infrastructure model under assessment due to its direct relationship with the subgrade stiffness profile. Furthermore, this first vibration mode appears to correspond to the postulated behaviour of the dominant resonance frequency entailed in hypothesis H1. This resonance frequency exhibits the highest average amplitude values between them and is highly sensitive to the track stiffness of the subgrade layer. Thus, from the previous results, hypothesis H1 was validated for model M1 by selecting this vibration mode as the dominant resonance frequency of interest.

Simulation M2

Figure 4.8 presents the raw data obtained for this simulation. Since this model now has two working suspension levels, the acceleration data from the bogie sensor is now observably different from the data obtained with the chassis sensor. The bumps in the acceleration data from these two sensors, at around the 500 m and 1450 m marks, correspond to the presence of two vertical slopes used in the cartographic profile of this model. As will be shown, these do not interfere with the frequencies of interest.

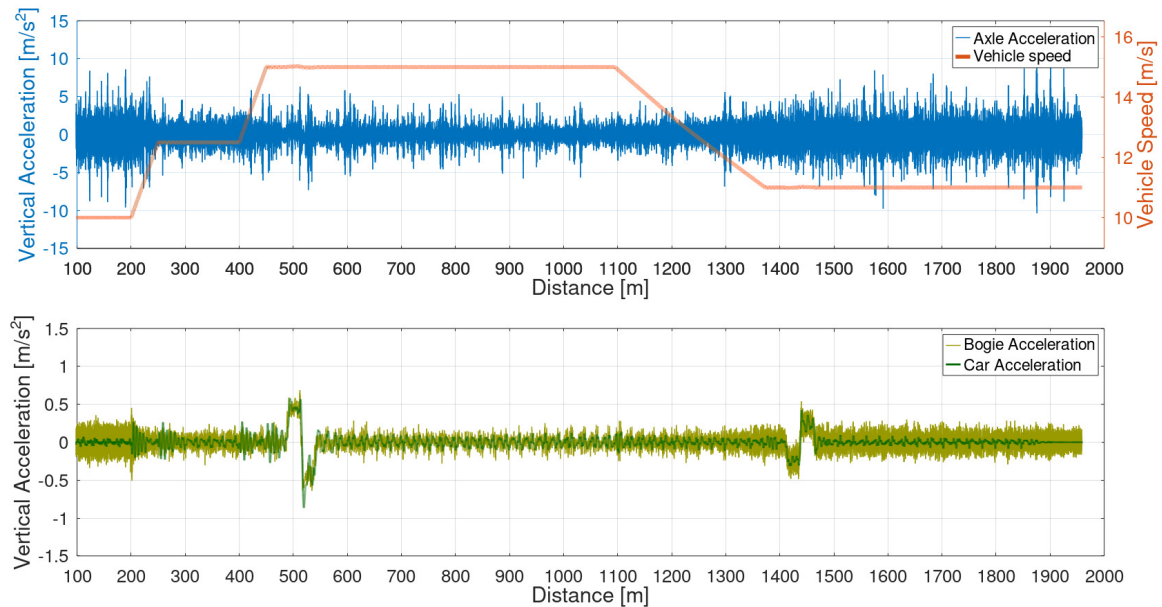


Figure 4.8: Raw data from simulation M2 (acceleration data and vehicle running speed).

Figure 4.9 presents the obtained spectrograms from the axle and chassis sensors, and the vertical track stiffness profiles used on the spring elements associated with the layered elements of the infrastructure in this model. These track stiffness profiles are the same as

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the ones used in M1. Both spectrograms also present similar frequency contents between them, just like the M1 results. This includes the same two differences in frequency content that were described for M1. Upon further inspection, these two spectrograms are indeed very similar to the ones from simulation M1. They include the same frequency curves that were eventually discarded, and the three observable F_{is} curves of interest identified in the spectrograms from Figure 4.6. The frequency values of each of these frequencies are also practically the same as the respective values obtained in M1. From these results, hypothesis H1 was also validated in simulation M2 since every consideration made for M1 was also valid here. Thus, H1 was validated in the present simulated environment. Expanding the validation scope of this hypothesis, regarding the existence of an observable resonance frequency related with the conditions of the railway subgrade is something that was progressively addressed over the course of this study. As will be shown in the following chapters, the validation of this concept was achieved to an adequate degree, considering the available resources.

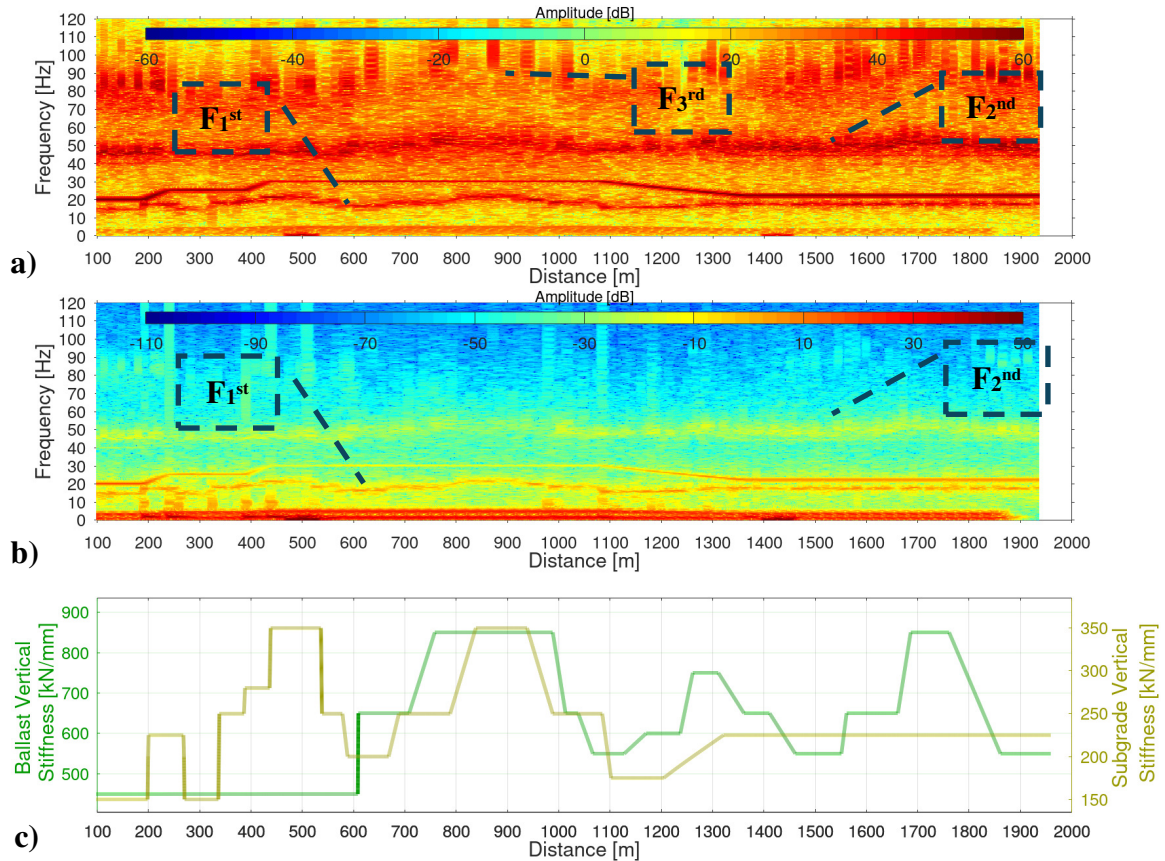


Figure 4.9: Obtained spectrograms and applied track stiffness profiles from simulation M2.

The results provided by this test also showed that the value of this dominant resonance frequency does not depend on the number of suspension levels of the instrumented railway vehicle being used to monitor the railway infrastructure under assessment, thus validating hypothesis H2 in the present conditions. The validity of this statement was progressively reinforced as the complexity of the employed numerical models evolved over time.

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4.2.2 Subgrade modelling solution validation

As presented in the previous sub-section, the subgrade vibration mode of interest for the TMM observable from an MBS model with the proposed MS corresponds to the full-body oscillation of all infrastructure elements, coupled with the unsprung mass of the vehicle, over the adjoining spring elements. This sub-section describes a test that was performed with numerical data to assess the validity of the proposed MS, focused on this resonance frequency of interest. This was performed by comparing the subgrade's theoretical natural frequency values given by the proposed theoretical model with the respective resonance frequency values obtained from a Simpack® model built with the proposed MS. In other words, assuming the intrinsic validity of Equation 4 that gives the natural frequency of a soil layer, the objective was to verify if the relevant resonance frequency values obtained from a Simpack® model using the proposed MS (Equation 10) would represent an acceptable estimate of this natural frequency. The resonance frequency values were extracted from Simpack® using the previously mentioned modal analysis tool, thus there was no need to perform any running simulations for this test. The numerical model employed here will not be fully detailed since it was similar to the one previously described.

An initial comparison was performed based on the nominal values selected for the modal parameters of this model (Table 4.1 and Table 4.2 from the previous sub-section). The obtained frequency value was suitably close to the theoretical model's estimate for the test to continue, with a difference under 5%. Therefore, a sensitivity analysis was performed to check the influence that several relevant parameters could have on the quality of this estimate; that is, to check if the obtainable error margin was still acceptable in a broader range of the relevant model parameters, thus assessing the MS's application range. The parameters that can directly influence this estimate are the variables present in the theoretical model (Equations 3 to 10). Additional parameters tested corresponded to variables that could influence the obtainable frequency results but are not specifically present in the theoretical model. The only additional parameter that will be shown here is the car body mass ($m_{v,c}$). Table 4.3 presents the values of the parameters that were used in this sensitivity analysis. While most of the parameter values used were realistically adequate (Milne et al., 2019; Zhai, 2020), the specific ranges were selected with the intent of testing the limits of the MS from a mathematical standpoint and were less focused on trying to replicate any specific situation. The central value of each parameter range was equal to the respective nominal values presented in Table 4.1 and Table 4.2.

The sensitivity analysis was performed by separately changing each of these parameters in each step, while the remaining parameters were kept in the respective nominal values. Additionally, for each parameter combination, the frequency values of interest were determined for multiple subgrade layer heights. The selected height values, which include the nominal subgrade layer height mentioned in Table 4.2, were chosen to further test the capabilities of the proposed MS on an even wider range of scenarios.

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Table 4.3: Parameter values used in the sensitivity analysis on the proposed modelling solution.

Subgrade Layer Stiffness ($k_{i.su}$) [kN/mm]	Subgrade Density (ρ_{su}) [kg/m ³]	Ballast Density (ρ_{ba}) [kg/m ³]	Suspension Stiffness ($k_{v.s1}$) [kN/mm]	Car Body Mass ($m_{v.c}$) [kg]
226	1000	500	0.9	33,000
257	1500	1000	1.8	38,000
300	2000	1500	3.6	43,000
365	2500	2000	5.4	48,000
473	3000	2500	7.2	53,000

The following graphs present the results obtained from the sensitivity analysis. The results are presented in two graphs per tested parameter. The first graph relates the imposed subgrade layer heights with the layered element's diameter obtained from Equation 10. This group of graphs provides information on whether and how the tested parameters affect this relationship. The second graph presents the ratio between the subgrade layer natural frequency value obtained from Equation 4 and the respective frequency value obtained from Simpack® (f_1/f_{sim}), for each subgrade layer height. From this second group of graphs, data regarding the validity of the proposed MS is extracted, since it presents the difference margin in the estimation of the simulated resonance frequency of interest for each tested configuration. Figure 4.10 to Figure 4.14 present these results, following the parameter order used in Table 4.3.

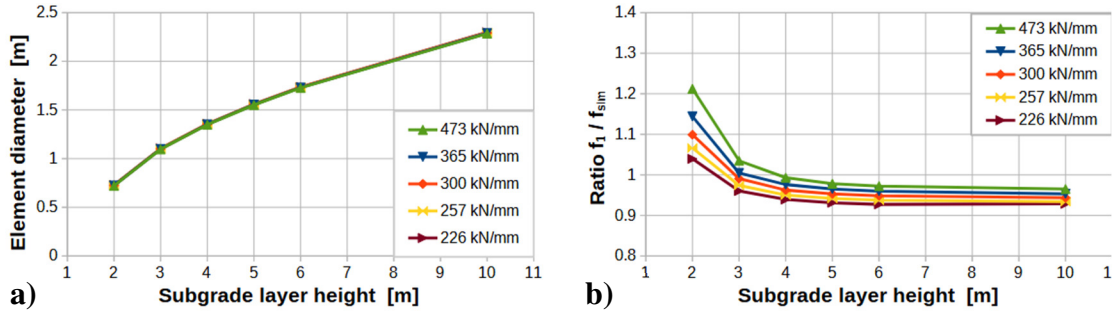


Figure 4.10: Sensitivity analysis results in relation to subgrade stiffness ($k_{i.su}$): (a) subgrade layer height vs cylindrical element diameter; (b) subgrade layer height vs obtained frequency ratio.

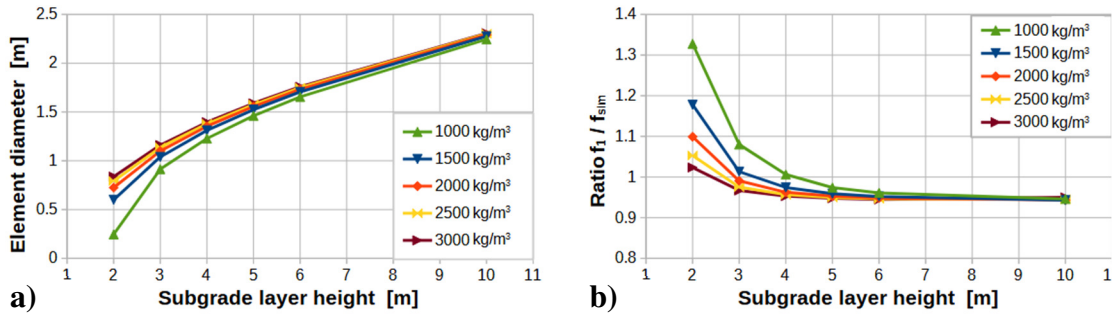


Figure 4.11: Sensitivity analysis results in relation to subgrade density (ρ_{su}).

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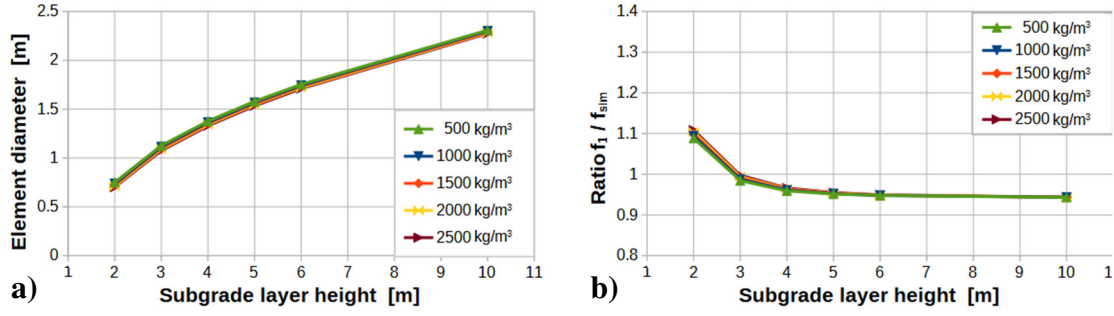


Figure 4.12: Sensitivity analysis results in relation to ballast density (ρ_{ba}).

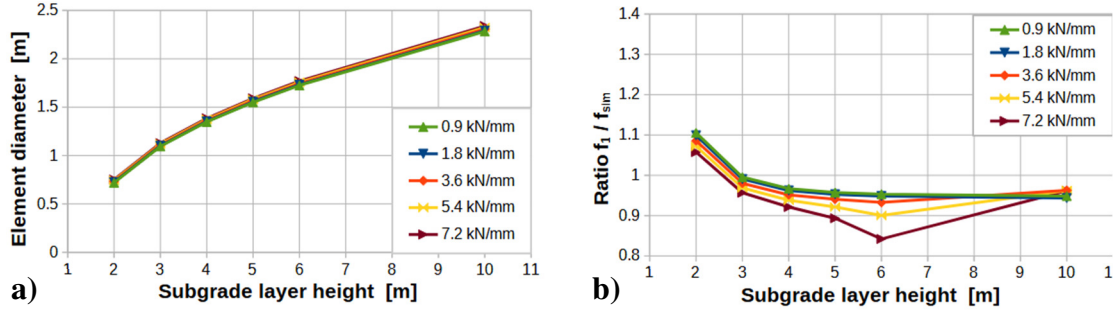


Figure 4.13: Sensitivity analysis results in relation to vehicle primary suspension stiffness (k_{1s1}).

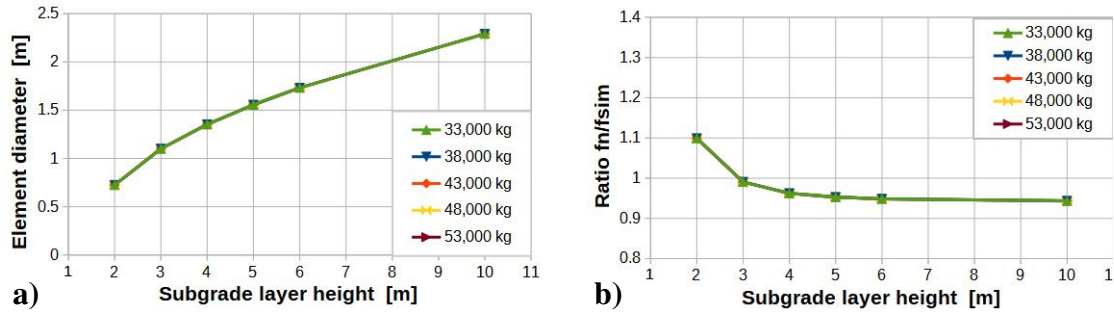


Figure 4.14: Sensitivity analysis results in relation to car body mass (m_{c}).

Apart from a small discrepancy due to two points in Figure 4.13b (i.e., the two points with subgrade height of 6 m, from the brown and yellow curves), the curve patterns observable in each graph type are very similar between them. These deviated points are the result of an unexpected dynamic interaction between the specific suspension stiffness values used in those cases and one vibration mode from the subgrade element (i.e., a local resonance effect due to two overlapping natural frequencies). Although some attention should be paid to these types of situations when running modal analysis on multi-DoF systems such as this, this phenomenon does not significantly influence the validity assessment of the proposed MS, since the resulting estimate errors are still reasonable and it was an isolated occurrence.

The first graph type clearly shows that the relationship between the layered elements' diameter and subgrade layer height is not significantly influenced by the tested parameters, with an almost linear and constant behaviour between these two factors. This behaviour is also evident for the remaining parameters that are used in the theoretical model. These parameters were also tested in this context, but the respective results are just not shown

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here. The only exception to this conclusion is for the subgrade density parameter (Figure 4.11a), where for the smaller subgrade layer heights and lower density values there is a minor shift in the overall pattern. This happens because for smaller subgrade element mass values, the relative importance of this element in the overall dynamic response of the multi-element mechanical system begins to change. This results in a shift in the related vibration modes and in the corresponding resonance frequencies (Maia and Silva, 1997). This is a direct consequence of testing the proposed MS in these severe parameter configurations, where the resulting mass of the subgrade element can become extremely small when compared with the vehicle's mass. For example, in the case with subgrade layer height equal to 2 m and 1000 kg/m³ of subgrade density (green curve from Figure 4.11a) the resulting subgrade layer mass was only 90.7 kg. In such severe cases, it is expected that the proposed MS will provide less adequate results, simply because the premise that frequency ω_1 is an adequate estimate of the subgrade's resonance frequency of interest given by the MBS model is no longer as valid (i.e., the multi-element mechanical system is no longer as adequately approximated by the proposed 2-DoF model).

Now regarding the (b) graphs, the correlation between the frequency ratio and subgrade layer height also follows a pattern that is shared by each of the tested parameters. This behaviour is also true for the remaining parameters that are present in theoretical model. The obtained frequency ratios tend to be higher than 1.0 for the smaller subgrade layer heights, crossing the unity threshold around a subgrade layer height of 3 to 4 m, and then are lower than 1.0 for the rest of the tested range. The steep changes in these ratios on the lower subgrade heights is very likely also due to the changes in the dynamic behaviour of the multi-element mechanical model that can occur in these conditions, which was explained before. This means that the proposed MS can provide less adequate results in the lower subgrade layer height range. However, the frequency estimation error for a subgrade layer height of 2 m is just around 10% for most of the tested parameter configurations, which still represents a decent estimate for many applications. The high dispersion of the presented curves in some of these cases, which is also concentrated in the lower subgrade layer height range, is also a consequence of the changes in the dynamic behaviour of the multi-element mechanical system. These behavioural changes are naturally more influenced by the modal parameters that are directly related with the subgrade element (i.e., subgrade mass and stiffness) or with the vibration mode of interest from the infrastructure (i.e., primary suspension stiffness).

In general, there is an apparent trend for the frequency ratio to converge to a value at around 0.95 for higher layer heights. Therefore, excluding the lower subgrade height cases, this MS represents an MBS based solution that is able to provide a very stable and adequate estimate of the first natural frequency of the upmost railway subgrade layer in a wide range of model parameterizations. The minor difference represented by this 0.95 value between the calculated and simulated frequency values was expected, since the proposed MS stands on an inherent approximation of a complex mechanical system (i.e., the railway

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infrastructure and a railway vehicle) provided by a relatively simple 2-DoF lumped-elements model. It is possible that improvements in the quality of these results could be made by using a more refined theoretical model that further discretized the vehicle–track system (e.g., that separated the subgrade into more layers or included specific elements for more sleepers). However, the proposed MS fulfils the intended goal of representing a robust solution that can provide realistically adequate values for the vertical resonance frequency of the underlying soil layer of a railway infrastructure from an MBS model in a wide range of situations, while still being a relatively simple and efficient tool to implement.

While the validation of the MS presented here was solely based on simulated data, its theoretical validity is supported by the fact that all individual components of the developed theoretical model are thoroughly validated in their respective contexts. Additionally, this MS concept represents a potentially relevant advancement in the relatively specific and unexplored topic of modelling soil layers as independent lumped elements using an MBS software. While in the present application this was used to enable modal analysis on these specific elements, this MS could also represent the means to enable or enhance other research studies.

4.3 Final chapter remarks

This chapter described the framework used to create the numerical models employed in this study to provide the required testing and validation environment for the proposed TMM. Relevant aspects were presented regarding the several model iterations developed in this context, along with a detailed description on the final model setup. According to the presented validation tests, the proposed MS represents a successful attempt at fulfilling the established goals of providing the means to represent the railway subgrade in an MBS model as a fully independent element, which can be used to run extensive simulations in a time efficient manner.

5 Unsupervised data-driven tool

Taking advantage of recent developments in Machine Learning (ML) based technological solutions, the proposed TMM also makes use of ML methods in the data processing phase. During the TMM development, obtained preliminary results demonstrated its potential as an alternative track monitoring method that could assess subgrade conditions. However, attempts to extract reliable results from realistic numerical data or from experimental data were not successful mostly due to difficulties in discerning the frequencies of interest from the remaining frequency content (Figure 5.1). In other words, the issue was that while the subgrade frequencies of interest were present in collected acceleration data, these were easily masked by other phenomena when analysed manually. As previously mentioned, this task was originally performed through visual analysis of the obtained spectrograms.

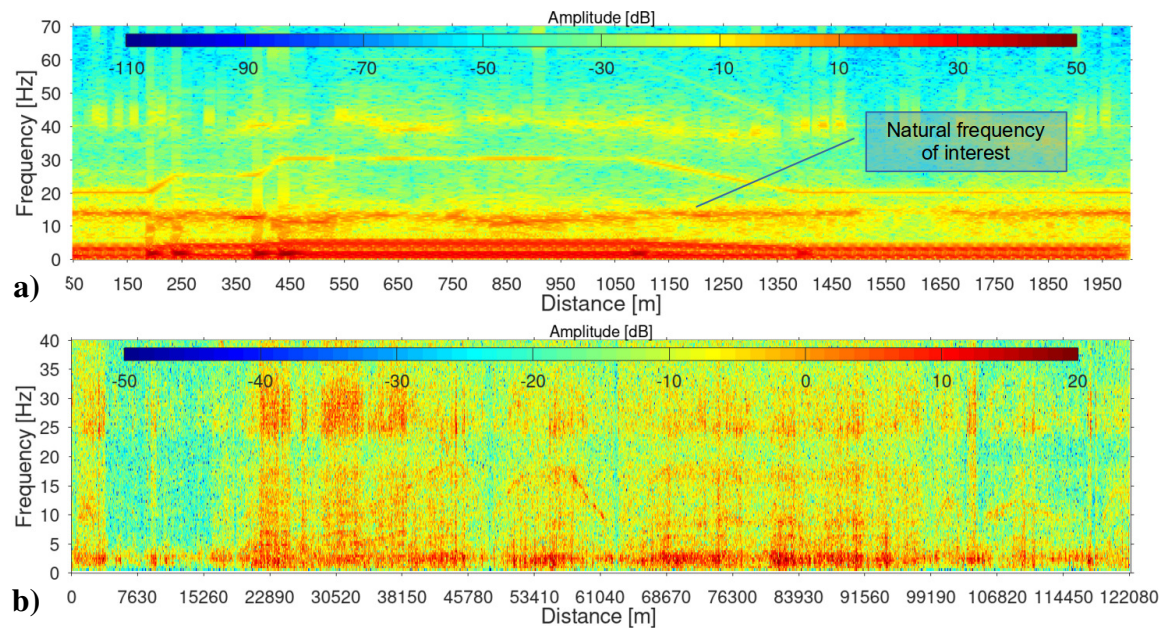


Figure 5.1: Spectrograms obtained from a) simulated data (this data came from a preliminary model used to test the TMM) and b) from experimental data.

To solve this issue and improve upon the overall reliability of the proposed methodology, an Unsupervised Data-Driven Tool (UDDT) was developed to apply it to acquired acceleration data, obtained with an instrumented railway vehicle, and detect the presence of damage on a subgrade layer in an automatic and more efficient way. An unsupervised data-driven solution was selected for this application due to two main reasons: their improved computational efficiency, when compared with supervised methods; and the fact that they only require data on the healthy state of the structure under assessment to parameterize the data processing routines (Farrar and Worden, 2013; Ruifan

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et al., 2022). Additionally, the statistical nature of data-driven methods should also improve the reliability of the proposed tool to provide adequate results when analysing data obtained from the complex mechanical system of interest. These benefits, together with the possibility of being able to automatically parse and discard the environmental and operational effects from collected data, represent some of the relevant benefits that can be gained from the use of ML based tools in the context of railway SHM methods (Farrar and Worden, 2013; Ruifan et al., 2022).

The initial versions of the UDDT were based on the Principal Components Analysis (PCA) and the Mahalanobis Distance (MD) as the major steps in the data processing algorithm. The obtained results were promising but showed space for improvement, since this version of the UDDT had over 95% damage detection accuracy (Morais et al., 2024b) but it showed no capability to discern between different damage intensities or types. Thus, a new set of UDDT versions were developed based on the Auto-encoder (AE) concept as the main component in the data processing algorithm. AE are well known for being a very powerful tool to work with intricate data sets, where their capability to learn patterns and behaviours can be used to extract reliable results even in more complex situations (Farrar and Worden, 2013). The results obtained with this concept showed the adequacy of this tool to provide accurate subgrade condition results, even with data from numerical simulations.

This chapter provides a general description on the several iterations of the UDDT, along with the reasons that led to the developments choices made in this process. Two important versions of this tool are then described in detail, followed by a description of the simulation setup that was used to generate the data required for the training and testing processes of the developed UDDT versions. Then, a description on the validation efforts that were made to assess their capabilities is provided, which were also based on numerical data. The description of some UDDT versions and these assessment test results have already been included in some of the publications written in the context of this thesis (Morais et al., 2024b).

5.1 Tool development process

The UDDT presented here for the automatic application of the proposed TMM aimed at being a robust and generic enough solution to be applied to any type of plain railway infrastructures and compatible with a wide range of railway vehicles. The purpose of this tool is to automatically detect if any given track section contains damage at the subgrade level and to also provide information on the severity of said damage (i.e., to detect and classify subgrade damage on a railway track). Since it is based on traffic-induced dynamic responses (i.e., acceleration data acquired with an instrumented vehicle), it is very important that the tool can account for and discard the effects of the environmental and operational variations (EOV) that are common in experimental data from real structures. In this context, EOV include effects caused by vehicle running speed, rail defects and

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irregularities, temperature changes and other weather-related phenomena. Considering the explanation provided in section 2.3.2. regarding linear mechanical systems, most of the weather-related phenomena should not interfere with the frequencies of interest for the TMM, neither should changes in vehicle running speed. However, it is still recommended to implement generic and self-sufficient EOV mitigation steps in an unsupervised damage detection tool, since such a tool is meant to be an automatic process without direct influence from the user or the consideration of direct measurements of such phenomena (Farrar and Worden, 2013).

In the context of ML based tools used in SHM applications, the process of obtained damage-related data usually involves the monitoring of the mechanical system over time using periodically spaced dynamic response measurements. Damage-sensitive quantities, normally called features in this context, can then be directly extracted from this data or obtained through statistical analysis to determine the current state of the system under assessment. Therefore, feature extraction refers to the process of converting acquired data into alternative forms where damage-related information can be more readily obtained (Farrar and Worden, 2013). Modal-based features are the more commonly used solution for SHM applications (Farrar and Worden, 2013) due to the advantage of them being directly associated with the modal properties of the structure under assessment, which are expected to change in the presence of damage (Maia and Silva, 1997). This is particularly true for modal stiffness, which tends to be more sensitive to the presence of damage in a structure, as was explained in section 2.3.2.

Since the proposed TMM was already based on converting acquired acceleration data from the time domain into the frequency domain to search for frequencies that could be related with the modal properties of the track subgrade, using modal features was a very natural choice as the first solution for the feature extraction step of the UDDT. However, before immediately settling on this option, alternative features were tested and discarded. These alternative features included processing the acceleration data directly in the time domain, to using statistical-based features such the root mean square, the standard deviation, skewness and the kurtosis (Farrar and Worden, 2013). Preliminary tests with these features clearly demonstrated that the only viable solution for the current application were frequency-based features, since every tested alternative lacked sensitivity to subgrade damage. Insights into this topic will be shown in the analysis of the validation results that is presented later in this chapter, where instead of the good quality results obtained with the implemented frequency-based solution, results with some of these alternative features showed poor results in the damage detection task.

Having selected a frequency-based feature class for the UDDT, the acquired acceleration data is firstly converted into the frequency domain using a Fast Fourier Transform (FFT) procedure with overlapping Hanning time windows. From the obtained spectra, the frequency range of 10 to 50 Hz is extracted based on the expected range of the subgrade related frequencies of interest (Connolly et al., 2015). This specific range was further

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verified through a sensitivity analysis on the variability of the frequency of interest based on reasonable values for the relevant parameters in the proposed theoretical formulation. These results are shown in Figure 5.2. With this frequency range, the UDDT is now focused on this specific set of frequency components (i.e., the extracted features) that should contain information related with the subgrade layer. This frequency range was also the focus of a dedicated analysis to ascertain ideal values, based on numerical data. The obtained results showed that increasing or decreasing this frequency range usually resulted in lower damage detection capabilities, either because damage-related frequency content was missing or superfluous damage-unrelated frequency content was added to the data thus potentially interfering with the damage detection task. Using the selected arrangement, the overall concept of the UDDT is that by detecting specific patterns in this frequency range, the presence of damage in a subgrade layer can be identified with the assistance of the remaining data processing steps of this tool, while also discarding other types of damage in the remaining railway infrastructure elements or on the railway vehicle.

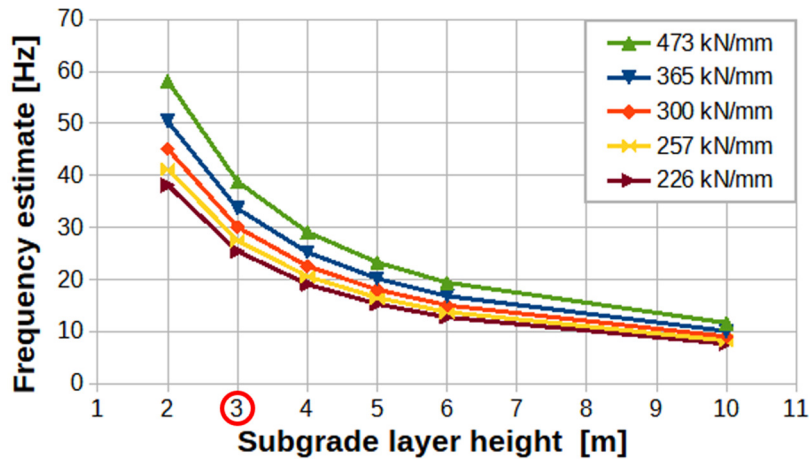


Figure 5.2: Sensitivity analysis results on the variability of the subgrade frequency of interest.

Based on the framework described here, multiple iterations of the UDDT were designed, tested and eventually improved upon to reach the final version proposed in this study. Two specific UDDT versions are worthy of additional information. These represented significant marks in the UDDT's development process, but do not embody the only data processing tool configurations that were tested in this context. The first configuration of note corresponds to the final iteration of the UDDT version that relied on using the PCA and the MD as the main elements in the data processing algorithm. The second remarkable configuration is the final version of the AE based version of the UDDT, which corresponds to the last iteration of its development process. These configurations are now described in detail in the following sub-sections.

5.1.1 Principal Components Analysis configuration

The version of the UDDT based on PCA and the MD methods entails the four steps shown in Figure 5.3: (i) a feature extraction step applied to the acquired acceleration data

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to calculate damage-sensitive features, (ii) a feature modelling step to remove EOV, (iii) a data fusion step to merge the features obtained from each sensor and then merge them again to improve the sensitivity to the damage cases, and (iv) a feature discrimination step to automatically determine if the extracted merged features correspond to a healthy or damaged track section. As previously explained, the feature extraction step used here was based on modal features. More specifically, the extracted features correspond to the frequency components obtained between the frequency range from 10 to 50 Hz through a FFT based routine.

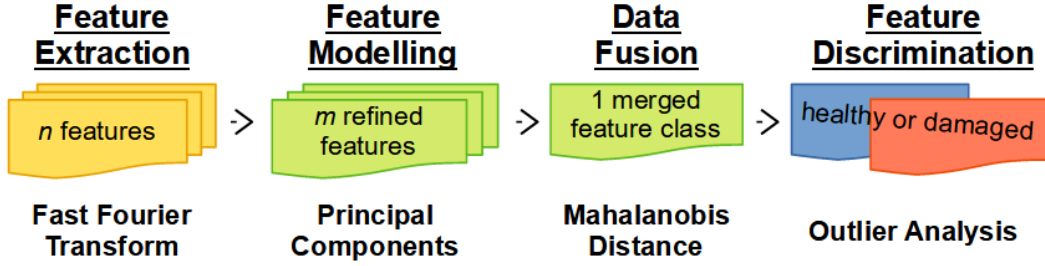


Figure 5.3: Data processing steps of the PCA version of the proposed unsupervised data-driven tool.

Effective damage detection methods must always contend with the issue of separating between measurable changes in the structure under analysis caused by EOV from those triggered by the presence or propagation of damage in said structure. To accomplish this, current ML damage detection methods used in SHM tend to resort to feature modelling tools to solve this issue (Farrar and Worden, 2013). This step is crucial in the railway context to prevent false positive results since environmental effects (e.g., temperature variations) or operational changes (e.g., different vehicle running speeds) may impose greater variations in the collected data than those caused by damage, thus potentially triggering false positive results if countermeasures are not applied to mitigate these EOV. This version of the UDDT applied PCA in this step, which represents a statistical solution to remove the effects of most EOV from the collected data. In the feature modelling context, the concept behind this tool is that from a statistical standpoint most of the energy content from a signal is associated with effects caused by EOV (Farrar and Worden, 2013). Thus, if the signal is discretised into several components based on their respective energy contributions, the main contributors can be identified, and their effects mitigated in the original signal. The signal can then be reconstructed with the effects caused by the EOV properly mitigated. Additionally, this procedure can also potentially highlight some effects caused by the presence of damage in the structure under analysis (Farrar and Worden, 2013).

The purpose of a data fusion step is to reduce data volume and to improve the sensitivity of the resulting features to the presence of damage, while avoiding any significant loss of relevant information on the subject under analysis (Farrar and Worden, 2013; Ruifan et al., 2022). Data fusion procedures can be used to combine features obtained from a single sensor or from multiple sensors referencing the same subject. The MD method is one of the

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more common solutions used in the SHM context for this application due to its capacity to describe the variability in multivariate data sets (Farrar and Worden, 2013). This method calculates the statistical distance between the feature sets to be merged, amplifying the obtained values if any of the pre-merged features are significantly different from a pre-established reference. If a healthy state scenario of the structure under analysis is established as this reference (i.e., a baseline for a healthy structure), then every set of features to be analysed can be compared against this baseline during this step. Any disturbances present in the pre-merged data are thus magnified, which enhances the capabilities of the damage detection tool to isolate the presence of any anomaly. If EOVs are properly removed, then any detected anomaly is likely the result of damage in said structure. This version of the UDDT first calculates the MD with the data from each sensor, thus merging the original frequency-based features into a single more sensitive feature per data point. Then it merges the features from each sensor into a final form that represents a class of features that is even more sensitive to damage in a track.

In the SHM context, the feature discrimination step's purpose is to determine if each batch of features calculated from the acquired data represents a healthy or a damaged situation. The available methods in this category can be divided into supervised and unsupervised learning algorithms (Farrar and Worden, 2013; Ruifan et al., 2022). In situations where data is available from both undamaged and damaged states of a structure, supervised learning algorithms should be used since they tend to provide more reliable classification results. But the inherent need to have data on both damaged and undamaged states of the structure under analysis usually prevents the application of this class of solutions to several real cases where obtaining such data can be simply unfeasible. These situations, just like the present case, justify the use of unsupervised learning solutions, which do not require prior data on the damage scenarios. Due to its simplicity and effectiveness, Outlier Analysis (OA) was the chosen method for the feature discrimination step in this version of the UDDT. This method consists of fitting a probability distribution to the baseline condition data of the structure under assessment and then testing whether the acquired data conforms with that distribution. In other words, this tool calculates a damage threshold value based on the processed features from the baseline data and a confidence level value selected for the distribution being used, which is then used to check the data being analysed. The cases where the processed features fall below the damage threshold value are classified as a healthy structure, while the cases placed are classified as a damaged structure. This classification assumes that divergences from the statistical fit to the selected distribution, based on the confidence level being used, have a high probability to correspond to a damage situation. The current version of the UDDT uses the standard Gaussian distribution in this step, which is the more commonly used distribution (Farrar and Worden, 2013).

The final version of the UDDT using this concept was able to detect damage, with an accuracy of around 95 % using simulated data (an example of this is shown in section 5.3).

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However, this version of the UDDT could not distinguish between the identified damage cases based on their severity or type. Thus, new iterations were developed and tested using an alternative concept in the feature modelling step.

5.1.2 Auto-Encoder configuration

Main damage detection branch

The final AE based version of the UDDT also entails the four steps commonly implemented in this type of tools (Figure 5.4): i) a feature extraction step applied to the acquired acceleration data to compute a relevant set of features, ii) a feature modelling step to refine the extracted features with enhanced damage sensitivity, iii) a data fusion step to merge the refined features, further improving damage sensitivity, and iv) a feature discrimination step to automatically classify the merged features from each data batch into a healthy or damaged track section. Like the previous UDDT version, the feature extraction step used here is also based on the frequency components extracted from the range between 10 to 50 Hz using a FFT procedure.

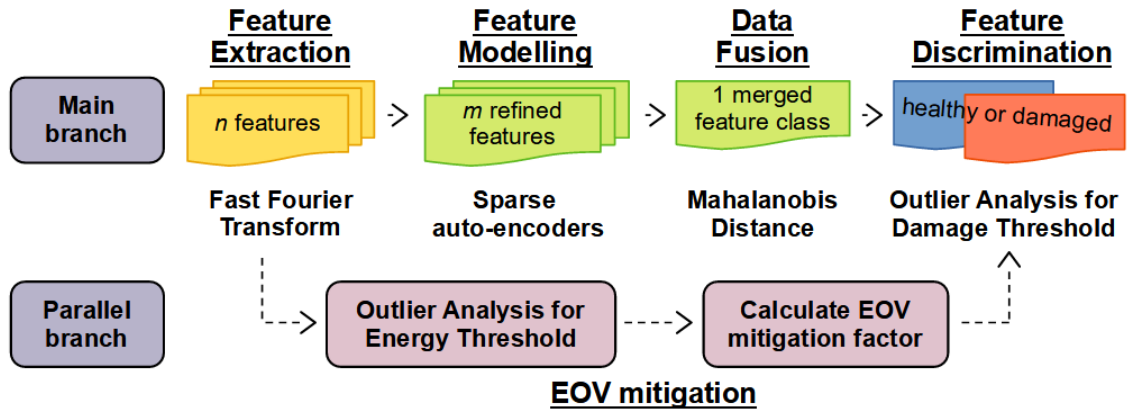


Figure 5.4: Data processing steps of the AE version of the proposed unsupervised data-driven tool.

Instead of relying on PCA for the feature modelling step, this version employed AE to perform this task, which represent a wide class of Neural Networks (NN) that are currently being employed in several applications, including in SHM solutions (Farrar and Worden, 2013; Nelay and Turgeon, 2024). In general terms, an AE represents a data processing tool (Figure 5.5) that takes input data through a series of steps (i.e., the NN layers), rendering it into the underlying patterns present on the data that have been previously imprinted or learnt by the AE during a prior training step based on a carefully selected baseline (Farrar and Worden, 2013; Nelay and Turgeon, 2024). The distilled information can then be re-built into the original form using additional NN layers. This process can result in a re-construction error that can be used to assess the quality of the AE training. Alternatively, this re-construction error can also be used to ascertain how related the input data is with the imprinted patterns, which corresponds to one of the AE architectures that is typically used in SHM applications (Farrar and Worden, 2013; Nelay and Turgeon, 2024). However, there are multiple issues that must be considered when using AE based tools due to this pattern

5. Unsupervised data-driven tool

imprinting process (i.e., the AE training step), due to its very significant relevance in the quality of the obtainable results (Farrar and Worden, 2013). These issues include the proper selection of the AE type for the specific application under consideration, the adequate selection of the training and testing data, and the adjustment of the hyper-parameters that regulate how an AE works.

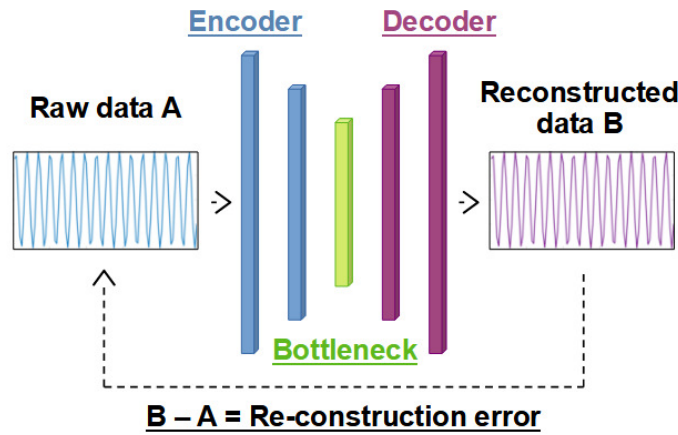


Figure 5.5: Generic representation of the auto-encoder concept applied in the context of SHM.

Overall, the concept of using AE in an unsupervised data-driven application is to train the AE with data from undamaged states of the structure under analysis (i.e., a baseline data set for the healthy structure), thus imprinting the healthy state patterns into the AE. Then, newly collected data can be tested against these patterns by passing the data through the AE and then re-constructing it at the end of the process. If the data represents a healthy structure, the re-construction error will be low because the AE was able to re-create most of the patterns in the data since they were similar with the ones imprinted on the AE during training. On the other hand, if the re-construction error is significant, then there is a strong possibility that the data represents a damage case since some of the underlying patterns were not present in the imprinted baseline. This concept is not infallible, since for example the detected anomaly could just refer to an EOV effect that was not properly represented in the baseline and thus was not adequately imprinted into the AE. However, it has the major benefit versus supervised methods of not requiring prior data on every relevant damage case from the structure under analysis that must be supplied to the AE during the training step. Supervised data-driven methods are well suited for applications where such data is available (e.g., image recognition applications where the possible results are well known) but fall in favour of unsupervised data-driven methods for applications such as the current case where the complexity of the mechanical system under analysis makes any attempt at characterizing every possible damage situation an unfeasible task (Farrar and Worden, 2013; Neloy and Turgeon, 2024).

During the development of the AE based version of the UDDT, several types and configurations of AE were tested, including commonly used solutions such as Convolutional Auto-encoders and the concept of Stacking Auto-encoders. However, the class of AE that consistently provided better results were Sparse Auto-encoders (SAE). The

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overall logic behind this family of AE is that by forcing a dimension reduction in the input features being fed into the AE in the encoding layers (i.e., imposing a bottleneck layer), this forces the AE to focus on the main patterns underlying the supplied data and discarding less relevant information. If properly used, this behaviour has natural benefits for this type of application, as reported in available literature (Farrar and Worden, 2013; Neloy and Turgeon, 2024), since it enables the AE to more reliably learn the important patterns in the data and thus be more capable of detecting any relevant divergence from said patterns. These enhanced pattern recognition capabilities can also be used to mitigate the effects of EOv and other undesirable phenomena from disrupting the damage detection results, especially if complemented with a prior normalization procedure applied before the AE (Farrar and Worden, 2013).

However, the tested SAE solutions could not adequately accomplish the EOv mitigation task without creating situations where the resulting trained AE lost all damage detection capabilities. Considering that solely relying on the AE concept to accomplish EOv mitigation was not achieving the intended results, an additional parallel branch was added to the overall data processing procedure to perform the EOv mitigation task. Thus, in this new arrangement (Figure 5.4), the feature extraction step is accomplished by a shallow SAE configuration (i.e., only one encoder and one decoder layers) that presented adequate damage detection capabilities but negligible EOv mitigation, while EOv mitigation is performed by this additional dedicated procedure. The selected shallow SAE arrangement already showed adequate damage detection capabilities, thus representing a more computationally efficient solution than deeper NN configurations. These more complex SAE arrangements did not show significantly better damage detection capabilities and did not solve the reported EOv mitigation issue.

Resuming the main branch description, this version of the UDDT takes the previously calculated SAE re-construction errors obtained from each sensor being used and merges those features into a single feature class that is even more sensitive to the presence of subgrade damage in a track. This represents its data fusion step. Like the previous iteration, this version of the UDDT also uses the OA method with the standard Gaussian distribution in the feature discrimination step.

Parallel EOv mitigation branch

Based on preliminary tests performed during the development of the SAE based UDDT, the trained AE either had acceptable damage detection capabilities but limited EOv mitigation, thus suffering from a high false positive damage detection rate, or had adequate EOv mitigation capabilities at the cost of losing almost all damage detection capabilities. Definitive explanations for this behaviour were not found, but the high complexity of the mechanical system under analysis, and the relatively low amplitude of the frequencies of interests when compared with the overall frequency spectrum, represent the more probable reasons that lead to this scenario. This eventually led to the development and

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implementation of a dedicated EOVS mitigation branch that works in parallel with the described damage detection branch of the overall data processing procedure. This parallel branch starts by calculating the average energy value (E_m) for each data batch used in the baseline. This is done by calculating the mean value of the squared amplitude of each frequency component (A_i) from the obtained spectrums (Equation 11) (Maia and Silva, 1997). Then, also employing the OA method, this procedure determines an energy threshold based on the calculated E_m values from a pre-selected subset of the baseline data batches where EOVS effects are negligible. This is not to say that an adequate baseline should not contain data batches with EOVS effects, since these cases are important to be present so that the AE can still incorporate some of their effects into the imprinted patterns for the damage identification task. However, based on acquired experience with this solution, a data subset adequate for this task should only include cases where EOVS related parameters were at or below their standard or recommended values (e.g., in terms of vehicle running speed, an adequate set of data should only include cases where vehicle speed went up to the nominal operational values of the instrumented vehicle). The overall logic behind this step is to define a threshold, based on a physical quantity, that can autonomously be used to identify the cases where EOVS mitigation is required. Having this energy threshold, for each new data batch, the proposed procedure calculates its E_m value and compares it against the calculated energy threshold. If E_m is lower than this threshold, then there is a high probability that there is no need to mitigate EOVS effects in this case. Otherwise, if the calculated E_m is higher than the energy threshold, the resulting EOVS mitigation factor to be applied to the merged features, obtained from the data fusion step in the main branch, is the direct proportion between the calculated E_m value and the threshold value. For example, in a case where the E_m value of a new data batch is double of the energy threshold, this parallel EOVS mitigation process would just halve the final feature values for this case. Those values would then be compared against the damage threshold from the main branch and then the final classification of healthy or damaged structure would be issued.

$$E_m = \left(\sum_{i=1}^n A_i^2 \right) / n \quad (11)$$

5.1.3 Data processing workflow

Having described the main data processing steps from these two UDDT versions in some detail, including the parallel EOVS mitigation procedure of the final version, here is a general description on the standard application procedure of the proposed UDDT. It starts by first acquiring a baseline data batch for the track under assessment. In cases where good condition data of the track under assessment is not available, the track's current condition can be used to define the baseline. Then, the following monitoring data can be processed and compared against the established baseline to check for the appearance of damage at any point along the track or check for the deterioration of a previously detected damaged track section.

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As will be demonstrated next, thorough validation tests on this UDDT and the proposed TMM have only been performed with simulated data. This is due to a lack of access to adequate experimental validation data, which is a well reported issue for subgrade related studies since obtaining such data usually requires extensive experimental campaigns that are very labour intensive and costly to implement (Powrie, 2024). Obtaining suitable amounts of adequate experimental data is something that was not possible to accomplish in the present study, considering the available resources. However, enough experimental data was still procured to perform one test on the proposed concepts. This test refers to the case study described in chapter 6 that represents an interesting demonstration of the UDDT's damage detection capabilities.

One of the main reasons that lead to the development of the proposed TMM is exactly this lack of experimental data regarding subgrade condition and the absence of an efficient method to assess this important railway element. The potential of the proposed concepts to mitigate this issue represents one of the main contributions of this study.

5.2 Tool assessment setup

This section described the numerical simulation setup that was used to run the simulations required to create the baseline case (BC) and the damaged cases (DC) that were used during the assessment and validation tests of the UDDT versions. In this context, a specific set of parameters from the previously described Simpack® numerical model (section 4.1) were selected and tuned to create adequate simulation conditions to fulfil these goals. Naturally, the main parameter of interest in this process was the vertical track stiffness of the subgrade elements ($k_{i,su}$). This was the parameter used to define the healthy track conditions for the BC and the damaged scenarios for the DC. Three parameters were additionally selected to create changing EOVS effects, in both BC and DC simulations, to create a wide range of testing conditions to further increase the validity of these tests. The three selected parameters were vehicle running speed, vehicle sprung mass and track geometry in terms of longitudinal level.

The input data for the three EOVS related parameters came from different sources, all related with experimental campaigns conducted on Portuguese tracks. The running speed profiles used in these simulations were all based on a single speed profile acquired from an *Alfa Pendular* train, with just overall amplitude changes to create additional EOVS conditions. The first speed profile used had an average value of 10 m/s and the last speed profile had an average value of 50 m/s. The vehicle sprung mass values used were all based on different passenger occupation levels of an BNN *Alfa Pendular* carriage, employing an average weight value per occupant on the calculations. The longitudinal level profiles used were also based on data collected on a Portuguese track, with just amplitude changes to simulate progressively worse track geometry conditions. The worse geometry profiles used here were designed to go slightly over the warning level values indicated by the norm EN 13848-5 (CEN, 2017), to create situations with less than adequate superstructure

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conditions. This setup was implemented to test if the UDDT could adequately discard this type of damage via the EOv mitigation solutions, since it is not the focus of this tool.

Combinations of the several profiles designed with the previous parameters resulted in the simulations batches that were run for the BC and the DC, as shows in Figure 5.6. The implemented configurations resulted in 100 different simulations for the BC and 144 simulations for the DC (18 simulations for 8 DC groups). The BC simulations all shared the same base subgrade track stiffness profile, and each batch of the 8 DC groups shared their own version of a damaged subgrade track stiffness profile. The data used to create the subgrade track stiffness variation profiles was also collected in an experimental campaign on a Portuguese track, using the *Portancemetre* method (Hosseingholian et al., 2011) that was mentioned in section 2.2.3. This method can measure local vertical stiffness values on a track or road, but only to very shallow depths. Data regarding a specific track section was selected and then slightly adjusted to be within an admissible track stiffness range, based on consulted bibliography (Shi et al., 2023). This profile was then converted into subgrade vertical stiffness and introduced into the numerical model through the described theoretical formulation.

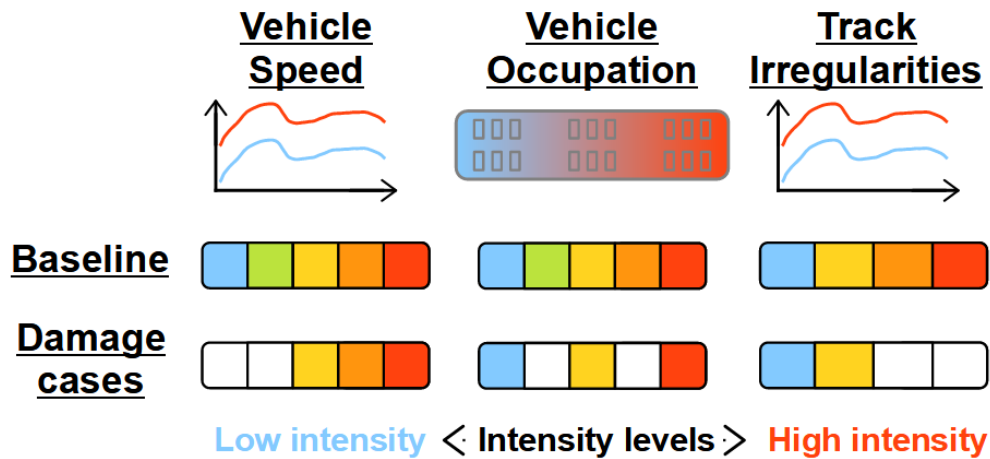


Figure 5.6: Parameter intensity levels used to generate the baseline cases and the damaged cases.

The admissible track stiffness range considered here was 100 to 180 kN/mm, per vehicle axle. The calculated equivalent admissible subgrade stiffness range was then 150 to 375 kN/mm, based on the nominal stiffness values presented in Table 4.2 for the remaining parameters. The resulting modified stiffness profile was used for the BC. The reason behind having to use this procedure was to offset the previously mentioned lack of experimental data regarding subgrade stiffness (Powrie, 2024). However, this converted subgrade stiffness profile was at least based on collected track stiffness data, thus contained somewhat realistic track stiffness variations.

The damaged subgrade sections implemented on the 8 DC were designed so that the imposed subgrade stiffness changes went outside the mentioned admissible range. Figure 5.7 shows the subgrade stiffness profiles used in the BC (blue curve) and in the 8 DC groups. The main design logic for half of the DC groups was to have an increase in stiffness

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above the admissible range (cases 1 to 4) and the other half was designed to contain a decrease in stiffness below the admissible range (cases 5 to 8). Additionally, there was also the intent of analysing if the UDDT could distinguish if these stiffness changes occurred more abruptly (cases 3, 4, 7, 8) or more gradually (cases 1, 2, 5, 6). Finally, in each combination of these two aspects, two damage intensity levels were simulated, where the first level represented a damage case just 10% over the admissible stiffness limit and the second corresponded to a more severe damage situation of around 30% over the respective limit. The DC were created just by manipulating the base subgrade stiffness profile in the selected track section, by respectively increasing or decreasing the local stiffness values, thus maintaining the realistic behaviour of the base profile.

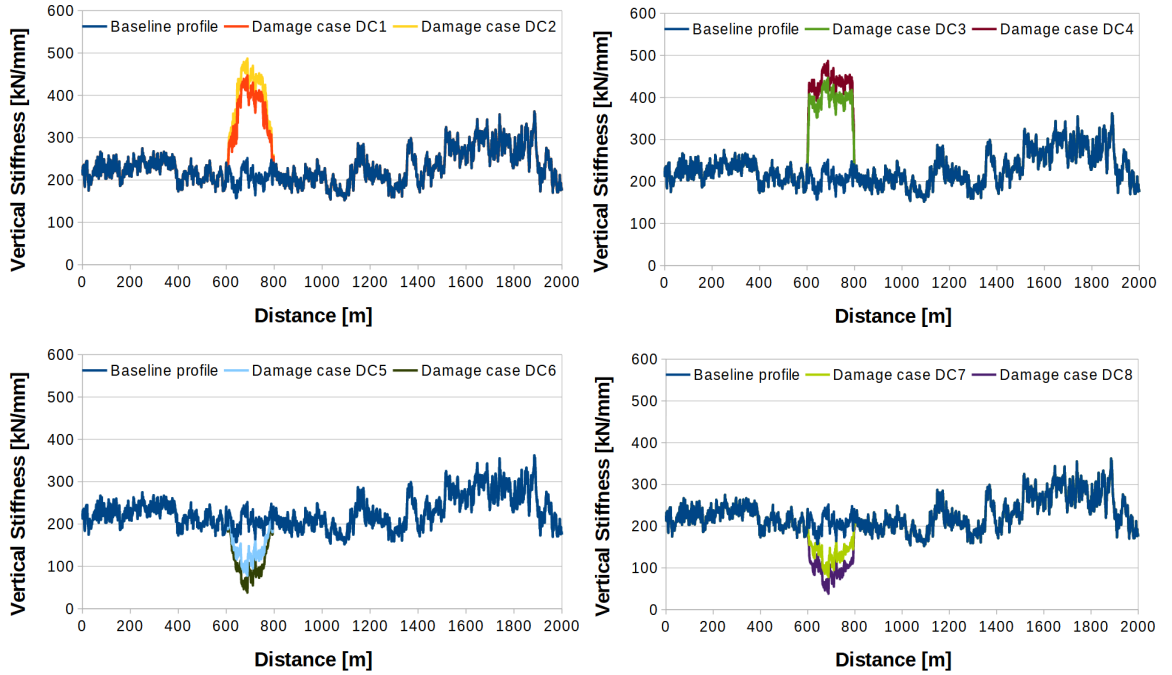


Figure 5.7: Subgrade stiffness profiles used in the BC and DC simulation groups.

5.3 Tool assessment results

This section presents the results obtained in the context of UDDT assessments tests performed on the two versions described in section 5.1. With the previously described simulated data, the developed routines start by processing the BC simulations to establish the baseline reference values that will be used during the entire process. After this step, the entire batch of 244 simulations (BC and DC) was processed by the UDDT to assess its damage detection capabilities. When applicable in the following figures, the 244 simulations are arranged so that the first 100 simulations correspond to the BC and the remaining 144 correspond to the DC (damage groups 1 through 8, in sequential order). The PCA based versions of the UDDT were implemented in OCTAVE[®] programming software, mostly due to the advantages of using a freeware solution. However, the AE based versions had to be developed in MATLAB[®] since this programming software has better libraries for the development of AE based tools. The hyperparameters used to implement the described

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shallow SAE configuration are shown in Table 5.1, which were established according to the available function package from MATLAB®.

Table 5.1: Hyperparameter values used in the training phase of the SAE based UDDT.

Autoencoder hyperparameters	Value
Hidden layer size	30
Maximum training iterations	1500
L_2 Weight Regularization	0.005
Sparsity Regularization	0.5
Sparsity Proportion	0.005

5.3.1 Principal Components Analysis based tool

Figure 5.8 presents two spectrograms obtained from data collected with the frontal chassis sensor, the first from simulation 11 (BC) and the second from simulation 101 (DC). The missing track length at the start of each spectrogram corresponds to data that was discarded to remove the transient period from the simulation's start, where the system is abruptly adapting to the imposed simulation conditions. This data has no physical significance and thus it was just removed. These simulations used the same EOv parameter profiles. Therefore, the only distinction between them is the presence of the damaged track section. This pair of simulation results is shown here to again showcase the previously mentioned issue of applying the TMM based on manual spectrogram analysis. As evidenced by this example, the effects of the damaged track section are practically imperceptible when compared against the rest of the spectrograms, even with knowledge about the actual location of the damage (600 to 800 m range). This result does not mean that the damage has no effect on the frequency data, as will be shown next, it just demonstrates that its effects are masked by the complex dynamic response of this mechanical system.

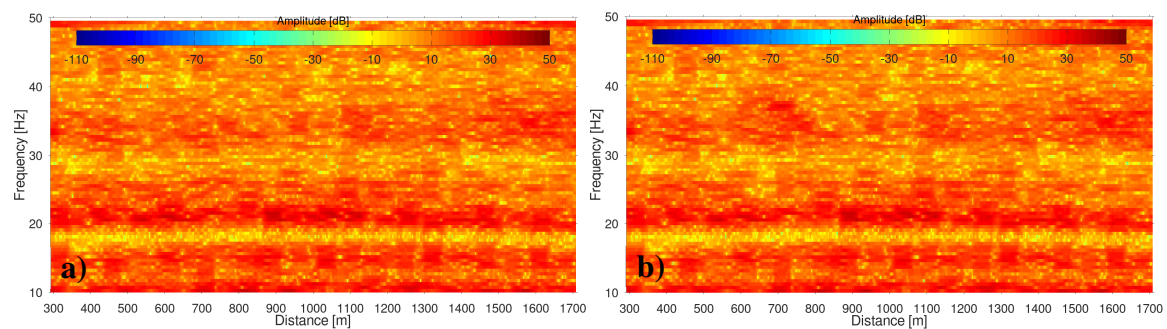


Figure 5.8: Spectrograms from a) simulation 11 and b) simulation 101.

Figure 5.9 shows the results obtained from applying this UDDT version to the previous examples. These curves represent the damage classification result of each individual FFT from each simulation, where the acceleration data from each sensor has already been processed and merged into a single feature per calculated FFT along the track. The

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capability of this UDDT to accurately identify the presence of the damaged track section is showcased here, overcoming the previously observed difficulties, where FFT points pertaining to the damaged track section in simulation 101 are accurately classified as damage because they are above the calculated damage threshold (i.e., the statistical threshold determined by the OA in the feature discrimination step). The rest of the FFT points from both simulations are accurately classified as undamaged because the corresponding results are below the damage threshold.

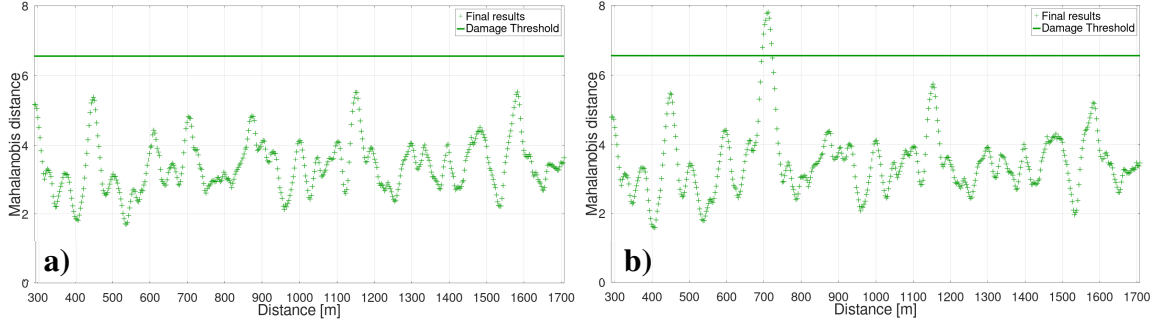


Figure 5.9: Damage identification results from a) simulation 11 and b) simulation 101.

Figure 5.10 now presents the results obtained from a partial application of this UDDT to the data from the 244 simulations, where the data fusion step as just been applied to the data collected from each individual sensor (chassis sensors [1-3], then bogie [4-5] and then wheelset [6-9]). This colour map is just a compact way to graphically represent the obtained results, to check upon the accuracy of the UDDT in the damage identification task. Each cell in the colour map that is coloured in green represents a negative damage identification and a yellow cell represents a positive damage identification. These classification results are the output of the OA step, with a confidence level of 0.99, to the features calculated from each sensor. These results demonstrate that even at this intermediate step of the UDDT, this version already provided adequate damage detection results since the BC were all correctly classified as undamaged cases and only a few DC were incorrectly classified as undamaged (i.e., only six false negative results in total).

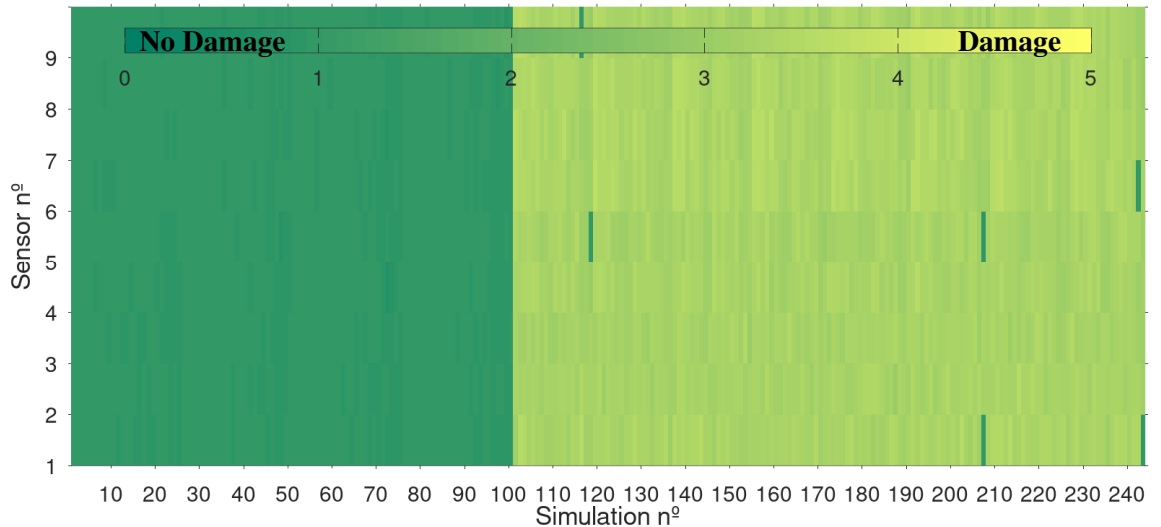


Figure 5.10: Damage identification results from each sensor used in the simulated railway vehicle.

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Following the previous results, Figure 5.11 presents the final output of the UDDT from the data collected in the aforementioned 244 simulations, having merged the features from each sensor into their final form. The horizontal line represents the threshold value given by the OA, thus any points below this line represent a negative damage classification and points above the line represent a positive damage classification by the UDDT. Here the results were even better than those shown in Figure 5.10, since there are still no false negative results and only 2 false positive results in the BC. This represents an accuracy of 99.18 % in the damage identification task. While these results are just from a single case study with simulated data, they still demonstrate the significant potential of the developed UDDT in solving the complex issue of correctly identifying cases where there is damage on a subgrade layer, only based on acceleration data collected with a moving instrumented railway vehicle.

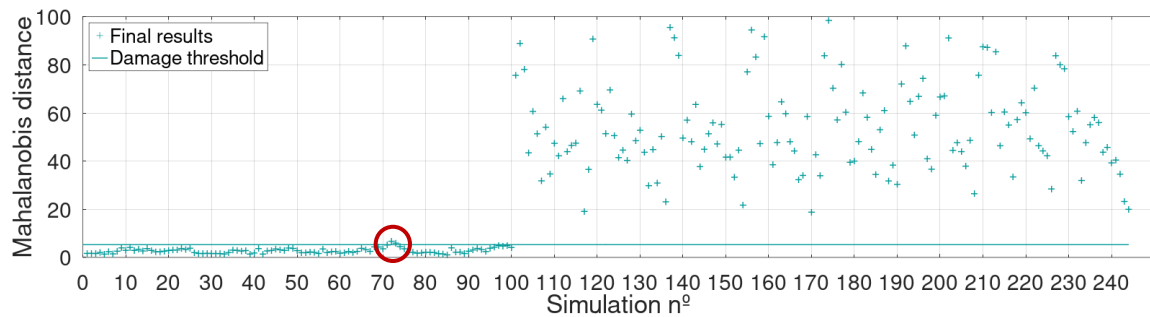


Figure 5.11: Final damage identification results with the PCA based version, after combining the features obtained from every sensor. The red circle indicates the only false damage identification results.

These results demonstrate the adequacy of this UDDT version in the damage detection task, which is the main goal of this tool, since it solves the aforementioned difficulties of extracting reliable results from realistic data. However, the dispersed cloud of points from the DC demonstrates the inability of this version to provide any meaningful information on the types and/or intensity of the damage cases that were detected (i.e., this version is not capable of classifying the DC). This illustrated the main reason that led to the development of the AE based versions of the UDDT.

5.3.2 Auto-Encoder based tool

Figure 5.12 presents the results obtained from applying the SAE UDDT version to the data from a single damage simulation (group DC1, simulation 103). The first graph represents the spectrogram calculated with acceleration data, using the FFT procedure, that was acquired with one of the chassis sensors. The second graph shows the re-constructed spectrogram that results from passing this data through the SAE that was specifically trained for this sensor. Overall re-construction accuracy is not perfect, but it is adequate for the current purpose, as will be demonstrated next. This example also demonstrates that effects due to the damaged track section cannot be reliably detected by manual inspection of the obtainable spectrograms, even with knowledge on the actual location of the damage (600-800 m). Finally, the third graph from Figure 5.12 presents the damage detection

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results obtained from applying the UDDT to this data batch, where each calculated FFT is classified as corresponding to either a healthy or damaged subgrade. The UDDT accurately identifies the presence of a damaged subgrade in the correct track section, marked by the FFT points that are above the damage threshold between the 600 and 800 m range. The rest of the railway track is also correctly classified as having no damaged subgrade layer, because the remaining FFT points are below the damage threshold.

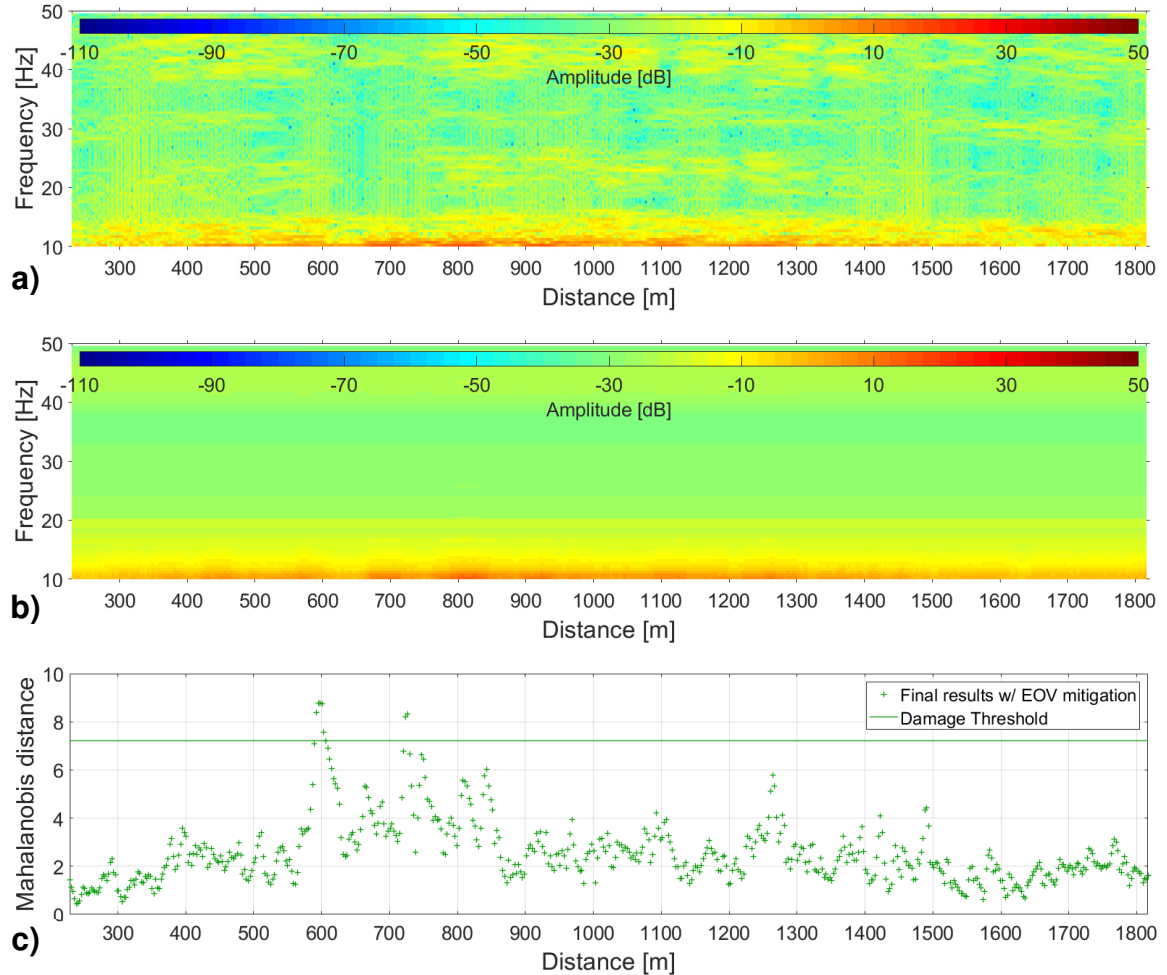


Figure 5.12: Results obtained from simulation 103 – DC1: (a) spectrogram obtained from the acquired data, (b) re-constructed spectrogram from SAE application, and (c) damage detection results obtained from the UDDT.

Figure 5.13 presents the final damage classification results for all 244 simulations, after the results from each simulation are condensed into a single value to facilitate results analysis. The main objective of this figure, before discussing overall damage classification accuracy of this UDDT version, is to demonstrate the EOV mitigation capabilities of the implemented solution. By comparing the obtained results with and without EOV mitigation, it becomes evident that such a solution was fundamental for the proper mitigation of EOV effects in this application, since the amount of false positive results in the BC would be inadequately high. In this specific example, the 20 misclassifications obtained in the BC due to non-mitigated EOV effects are reduced to just 2 by the proposed method, while not interfering with the proper identification of all DC. The robustness of

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this EOv mitigation method was thoroughly evaluated through several additional tests, especially regarding its potential to cause false negative results in damage scenarios by an over-mitigation of the EOv effects. The obtained results reinforced the previous conclusion in that no false negative results were created due to the application of the EOv mitigation procedure.

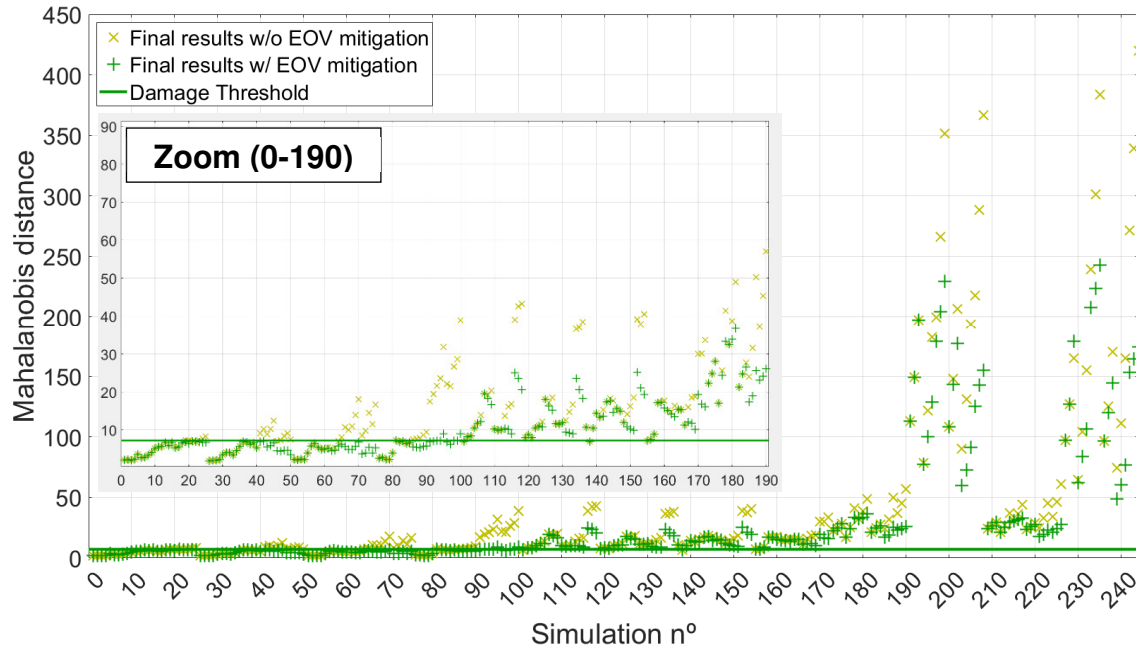


Figure 5.13: Final damage classification results for all 244 simulations, focusing on EOv mitigation. The differences between the green and yellow point sets indicate the cases that required mitigation.

Finally, Figure 5.14 presents again the classification results for all 244 simulations, but now each simulation group is separated with different colours for better graphical readability. These results represent an overall accuracy of 97.95 % in the damage identification task of this UDDT version, with only 2 false positive results in the BC and 3 false negative results in DC 1 to 4. Like the previous UDDT version, these results demonstrate the substantial potential of the developed UDDT to solve the complex issue of correctly detecting the presence of damage on a subgrade layer, solely based on data collected with an instrumented railway vehicle. Additionally, these results also show that the current UDDT version is somewhat capable of distinguishing between different DC types. From this graph, the UDDT appears to be capable of separating the cases where subgrade stiffness went above the admissible range (simulations 101 to 172 – DC1 to DC4) from the groups where subgrade stiffness went below the admissible range (simulations 172 to 244 – DC5 to DC8). It is also evident the separation in results between the 2 intensity levels in the DC 5 to DC 8 groups, where the DC with higher damage intensities showed higher damage scores in the results. However, this aspect is not evident in the DC 1 to DC 4 groups. Overall, these specific results show that the final UDDT version also has some damage classification capabilities, in contrast with the capabilities of the previous UDDT version based on the PCA concept.

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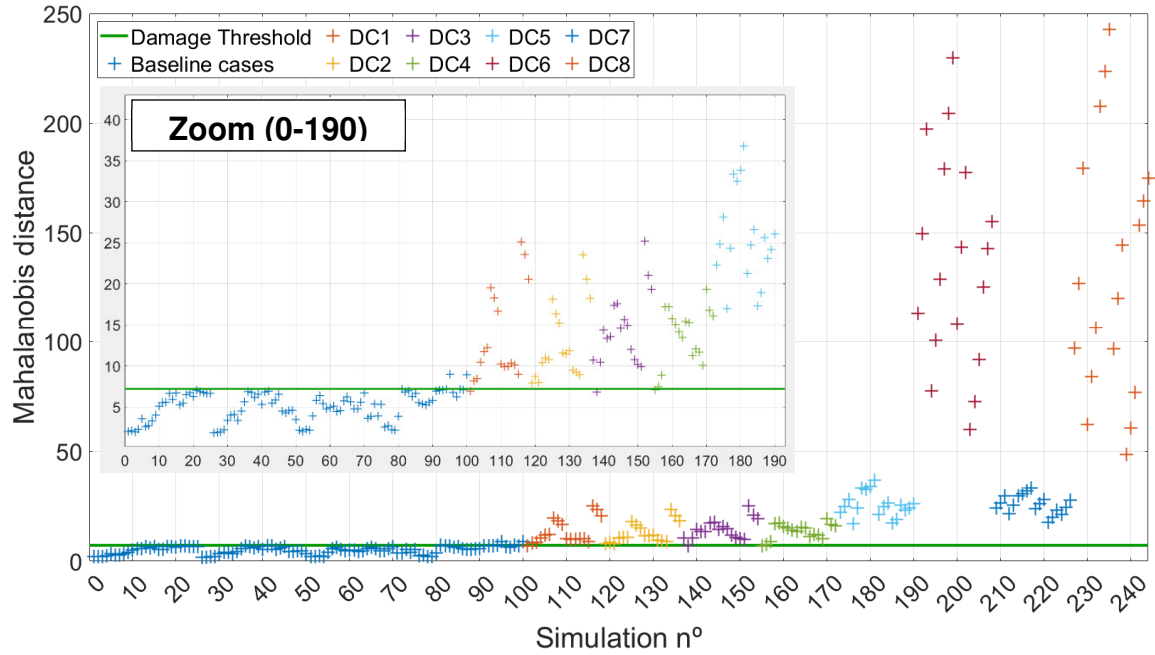


Figure 5.14: Final damage classification results for all 244 simulations, where each relevant group of simulations is identified by a different colour. The first group corresponds to the Baseline cases, and the remaining groups correspond to the 8 Damage cases that were tested in these simulations.

5.3.3 Additional robustness tests

After developing the final AE based UDDT version and considering the overall satisfactory results that were obtained with the simulation setup described in section 5, robustness tests were performed on this tool with new simulated data to further test its capabilities. The more relevant result that was obtained from these tests was that the proposed UDDT appears to have a minimum vehicle speed, where below that speed the tool ceases to be able to detect any subgrade related damage. Figure 5.15 and Figure 5.16 present an example that demonstrates this phenomenon, where one of the damage scenarios previously used was assessed with the instrumented vehicle running with an average speed of 8.7 m/s (Figure 5.16, using the blue speed level from Figure 5.6) and then with an average speed of 26.1 m/s (Figure 5.16, using the yellow speed level from Figure 5.6). This example clearly shows that with the higher vehicle speed the damaged track section is clearly identified, while the damage detection results obtained with the lower vehicle speed are mostly unresponsive to any disturbance in track conditions. Upon further tests on this phenomenon, this speed threshold was determined to be around 20 m/s. This UDDT behaviour is physically reasonable since vehicle speed is directly related with the excitation source that is being used in this system to assess the frequency content of interest. Thus, if the excitation energy levels drop below a certain threshold, it is reasonable that the vehicle should then be unable to dynamically excite the subgrade related elements of the numerical model. The ensuing lack of relevant frequency content to be processed by the UDDT appears to result in its inability to work properly in these specific conditions, thus indicating one possible aspect of the UDDT's working requirements.

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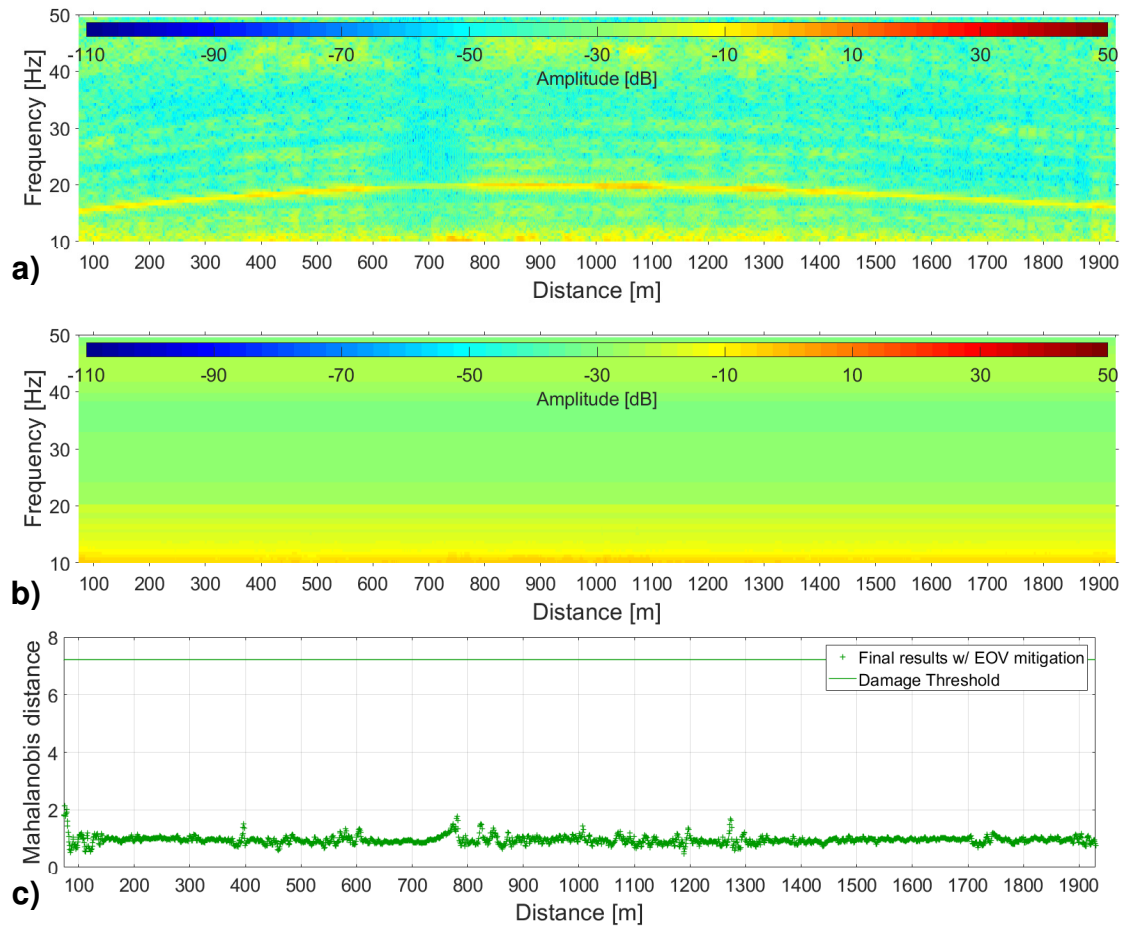


Figure 5.15: Robustness test results obtained from a damage simulation with the first vehicle speed profile: (a) spectrogram obtained from the acquired data, (b) re-constructed spectrogram from SAE application, and (c) final damage detection results obtained from applying the UDDT to this case.

5.4 Final chapter remarks

This chapter described the development process of the proposed UDDT in general terms and then went into detail regarding the two specific versions of this tool that marked relevant moments in its development process. Overall, the final version of the UDDT achieved all the proposed goals. This includes the solution to the issue of extracting reliable results with the proposed TMM when working with realistic data, which this tool fully enables when compared with the previous method of visually analysing the obtained spectrograms. In terms of the position of the accelerometers in the vehicle, the final version of the UDDT showed that sensors placed at the three different position types (i.e., wheelsets, bogie and chassi) were important to increase the capabilities of the tool in the damage detection and damage classification task.

Considering the robustness tests performed on the UDDT, this tool appears to represent an adequate method for the application of the TMM in a wide range of track and EOv conditions. However, a through validation of the proposed track monitoring solution should include the use of experimental data, which due to the already mentioned general unavailability, is something that was not fully achieved in this study. The next chapter

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represents the efforts that were made in this regard, considering the available resources.

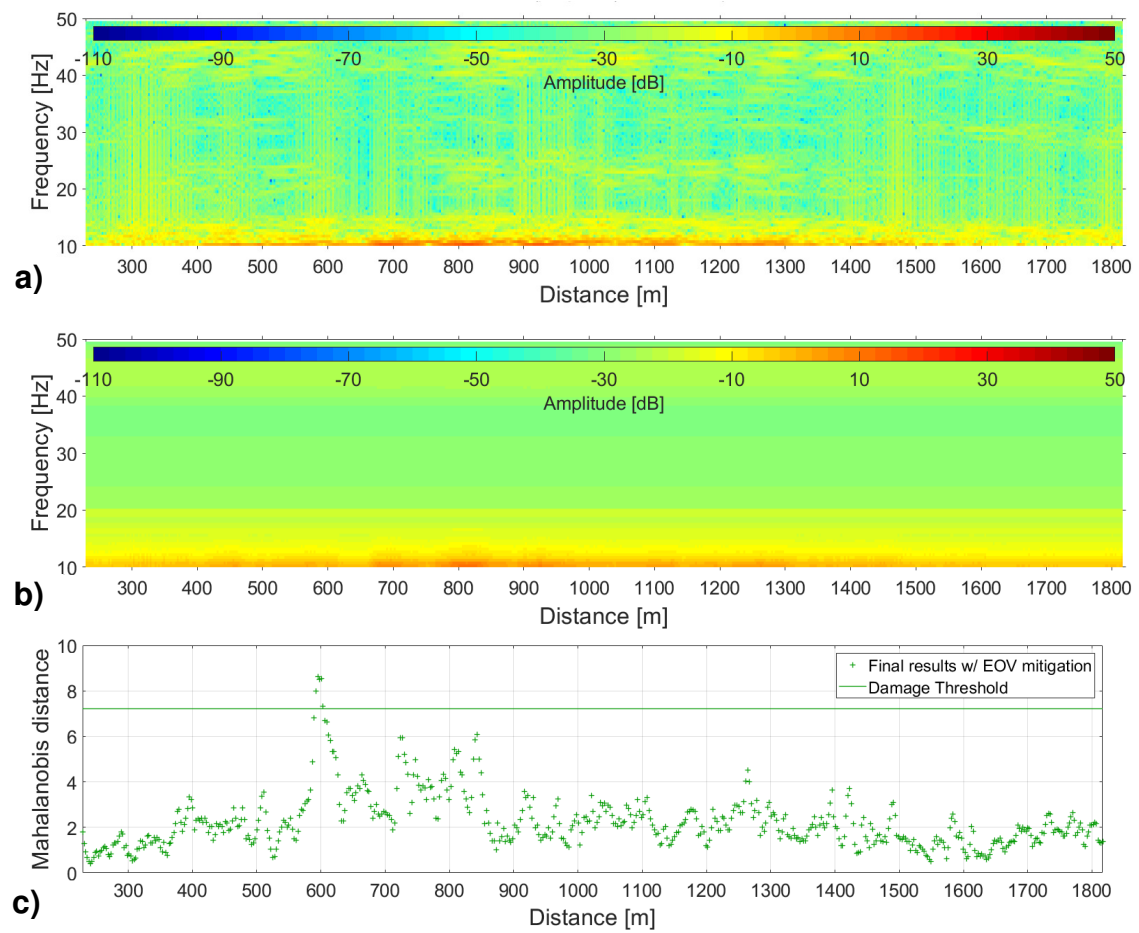


Figure 5.16: Robustness test results obtained from a damage simulation with nominal vehicle speed: (a) spectrogram obtained from the acquired data, (b) re-constructed spectrogram from SAE application, and (c) final damage detection results obtained from applying the UDDT to this case.

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6 Case study: Linha do Norte

This chapter describes the validation test that was performed on the final version of the UDDT and on the overall TMM concept using a set of experimental data that was procured for this specific purpose. This experimental data refers to a section of the *Linha do Norte* from the Portuguese railway network with a length of over 124 km, acquired between *Porto* and *Coimbra* in the context of another research study developed in FEUP (Silva et al., 2023). This track constitutes the backbone of the Portuguese railway system of freight and passenger services, with approximately 720 trains rides each day. The results described here have also been reported in one of the papers written in the present context (Morais et al., 2026).

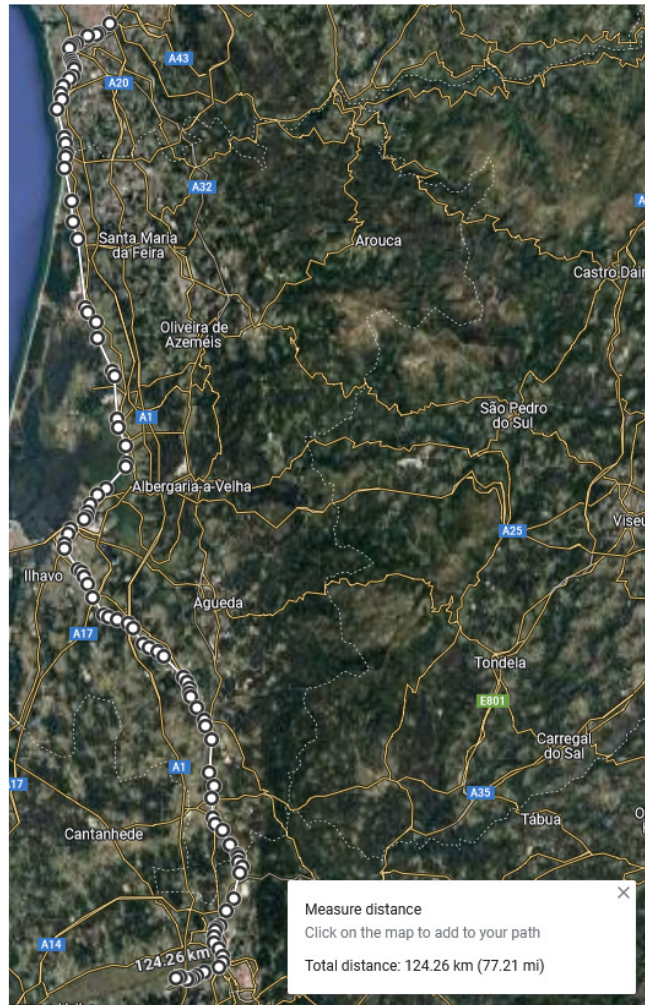


Figure 6.1: Map of the monitored track section (obtained from Google Maps).

In this research study, an *Alfa Pendular* passenger vehicle was instrumented with one accelerometer and a GPS unit. Originally, this data was used to assess passenger comfort

6. Case study: Linha do Norte

levels during the recorded train rides. Here, this data is being used to assess the proposed TMM concept with a real case study. Figure 6.2 shows some of the results obtained with this data, where the first graph contains the raw acceleration data and the vehicle speed, and the second graph contains the obtained spectrogram. This example clearly demonstrated the richness in frequency content that a real situation contains and the inherent difficulty in discerning the frequency content of interest in these conditions.

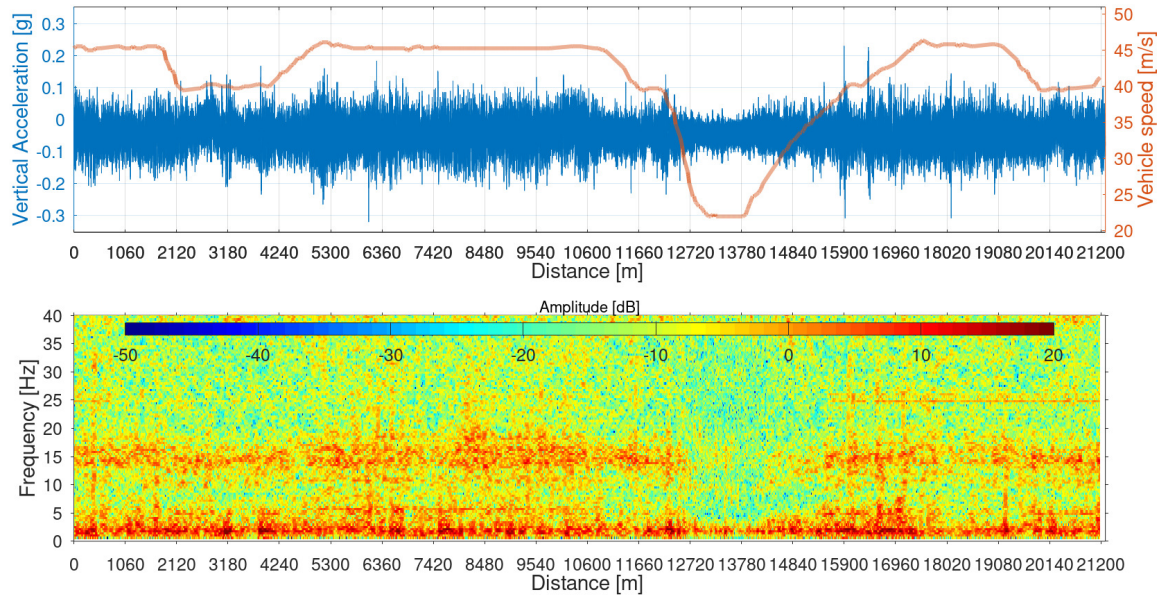


Figure 6.2: Example of the obtained experimental data and the resulting spectrogram.

After the UDDT development process, this data was used as a complementary assessment test on its damage detection capabilities. Due to a lack of supplementary and extensive validation data (e.g., reliable information on subgrade condition on the entire monitored track), the damage detection capabilities of the UDDT could not be fully validated here. However, an initial assessment on this topic was still performed together with important tests on relevant aspects of the UDDT, such as results' repeatability obtained from data acquired in different train voyages and the overall aptitude of the UDDT to work with experimental data. Figure 6.3 presents the original spectrograms and final damage results obtained with the data pertaining to the entire section of monitored railway track, acquired with the instrumented *Alfa Pendular* vehicle. The two sets of graphs correspond to the two trips that this vehicle performed while acquiring data, which were only five days apart.

Due to the lack of reliable data that could be used to establish the required baseline to train one new SAE based only on experimental data, the following adaptation was developed and implemented. One of the chassis level SAE trained with the previous simulated data, which also pertained to acceleration data acquired on a modelled Alfa Pendular carriage, was re-trained based on a sub-section of the available experimental data where observed EOV effects were minimal. This procedure, which only required 10 AE training iterations, allowed for the encoder to learn the new patterns in the experimental data and potentially keep the imprinted capability to detect the presence of a damaged

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subgrade layer. This procedure only required a low count of training iterations because the underlying frequency patterns from both data sets were relatively similar, since they both pertained to an *Alfa Pendular* vehicle. However, this procedure was fundamental to adjust the selected SAE to the specific conditions and patterns of the experimental data.

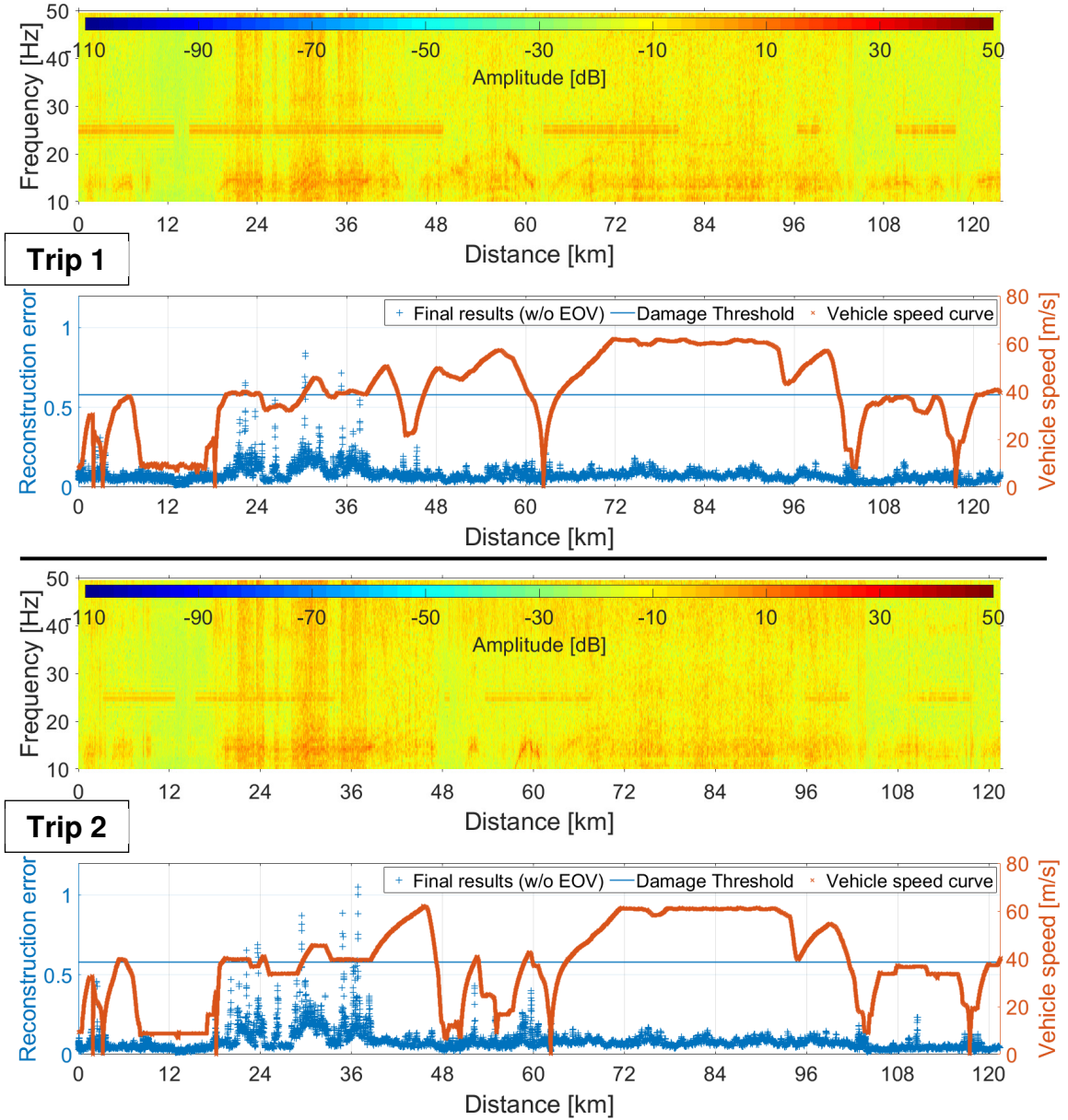


Figure 6.3: Spectrograms and final damage detection results obtained with the experimental data.

From these results, some interesting observations were made regarding aspects related with the application of the UDDT. Result stability or repeatability appears to be adequate for this type of application, since there is a very good match between the results from both trips. This was the desirable outcome since the elapsed time of five days is not enough to warrant any significant changes on the railway infrastructure, under normal circumstances. Another relevant observation that was extracted from these results was on the identified damaged points on the track. All positive damage detection points are concentrated around a single section of this track, which corresponds to a length of over 20 km. The anomalous

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behaviour of this specific track section can also be perceived in the original spectrograms with the higher frequency amplitude values in this region, which is a pattern that can correspond to a defective superstructure (Esveld, 2001; Zhai, 2020). Therefore, this result could be an indication of a damaged subgrade layer that over time also negatively impacted the overlying superstructure, most likely by affecting aspects of its track geometry (Esveld, 2001; Zhai, 2020). Additionally, this damage detection result is not just a misclassification by the UDDT due to the presence of the higher frequency amplitude values, since the other sections of this track that also exhibited this behaviour were not classified as having subgrade damage. Using this logic, this damage identification result is also not related with the local vehicle running speed values, since they also appear in other track sections. While these results provide interesting insights into the potential of the proposed TMM and the associated UDDT, they do not represent concrete evidence into their validity.

6.1 The *Ovar-Espinho* track section

Fortunately, IP was able to provide some supplementary information that was used to further extend the scope of these results. According to this information from IP, the identified track section matches a specific zone of the monitored line that is marked as having moderate foundation issues and is currently under consideration for rehabilitation works (the track section between *Ovar* and *Espinho*) (Figure 6.4). These observations give additional credit to the hypothesis that the presented results are valid and accurate.



Figure 6.4: The *Ovar-Espinho* track section: (a) map view of the monitored track section and (b) picture illustrating the features of this track section (both images were obtained from Google Maps).

In addition to this general conclusion, IP was able to supply specific geotechnical data on this section, acquired in the context of the rehabilitation works project, which was used

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to further assess the validity of these damage detection results. However, this geotechnical data provided by IP was not available for the entire line, thus the ensuing conclusions had to be taken while keeping this fact in consideration. Figure 6.5 presents the attempt to relate the obtained damage detection results from this specific track section with the provided geotechnical data that was obtained from railway characterisation campaigns. Three geotechnical parameters were compared against the damage detection results, namely: percentage of soil particles smaller than 0.074 mm (soil fine content); moisture content of in-situ soil samples; and deformation modulus from the second cycle of a static plate load test (EV_2) (UIC, 2020). These parameters are typically used to obtain an insight into a soil's bearing capacity and overall support conditions for the overlying track structure (Selig and Waters, 1994).

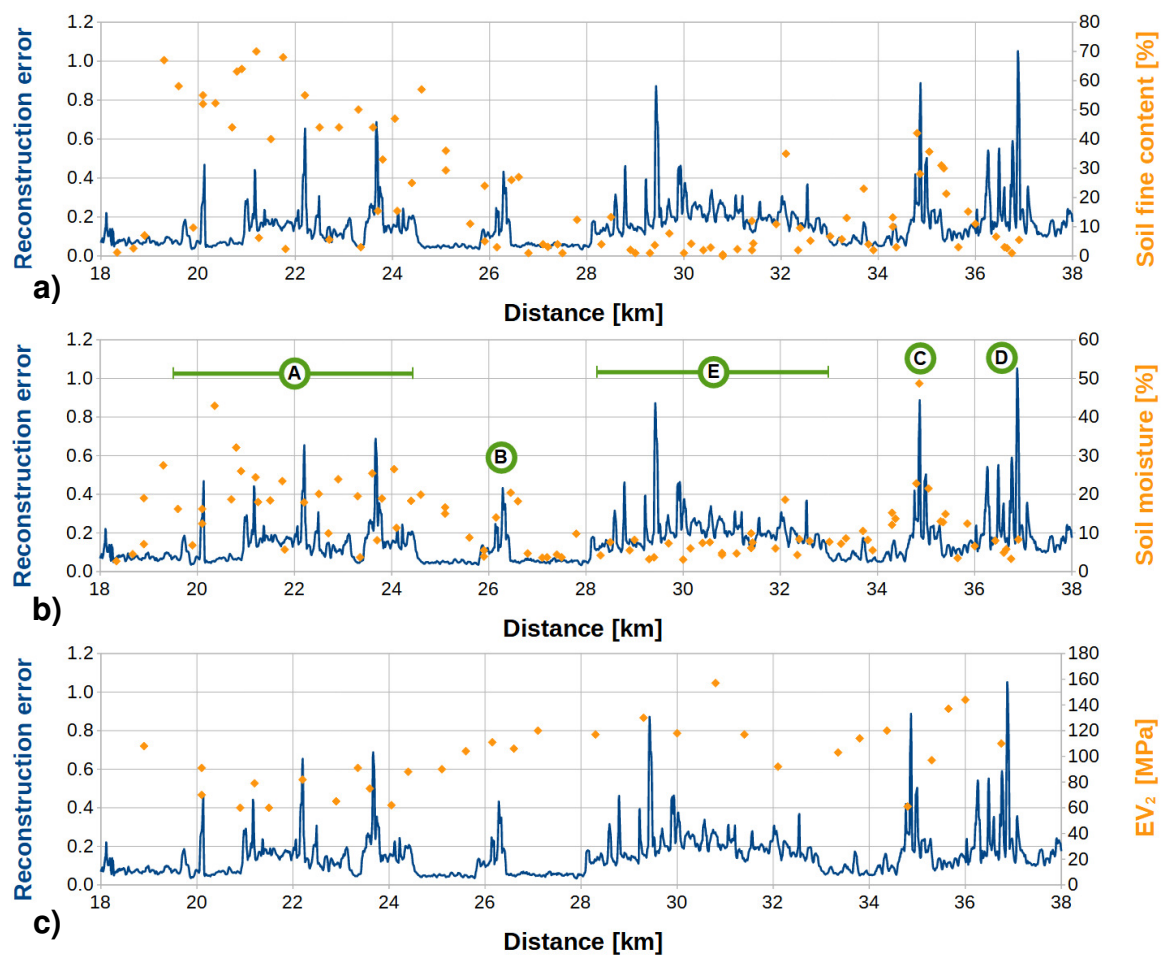


Figure 6.5: Comparisons between subgrade damage results and geotechnical characteristics of the subgrade layer: (a) soil fine content ($d < 0.074$ mm); (b) soil moisture; (c) deformation modulus EV_2 .

From the geotechnical point of view, the performance of a railway in terms of vehicle-track dynamic interaction depends on bearing capacity, which in turn is influenced by the vertical stiffness of the underlying subgrade (Fröhling, 1997; Berggren, 2009; Gallego et al., 2011). This stiffness is greatly influenced by the geotechnical characteristics of the soils that comprise the subgrade layers, namely grain size and moisture content (Selig and Waters, 1994, Fortunato, 2005). Soils that exhibit a higher percentage of fine material (i.e.,

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particle sizes less than 0.074 mm, normally corresponding to silts and clays) tend to be more deformable and to present greater plastic deformations when subjected to loading, particularly when they have relatively high moisture content values (Selig and Li, 1994). By analysing the information presented in Figure 6.5, and considering the previously mentioned geotechnical considerations, the following conclusions were extracted:

- In the areas A, B and C, where subgrade damage was detected by the proposed TMM, the subgrade is predominantly made up of soils with poor geotechnical characteristics, with relatively high percentage of fines (Figure 6.5a) and relatively high soil moisture (Figure 6.5b). These specific track sections have also been identified as prone to floods during the rainy season, which justify the reported lower EV_2 values. Additionally in zone A, problems with the geometric quality of the track have also been reported, especially regarding longitudinal level.
- In the areas D and E, despite the obtained better geotechnical results, there are still reports of geometric quality problems in these sections. These specific areas are also flood-prone locations during the rainy season.

6.2 Final chapter remarks

Overall, these results showcase the potential of the proposed TMM to work as intended, solving the complex issue of monitoring subgrade support conditions from the point of view of an instrumented railway vehicle. A noteworthy aspect of these damage detection results is that they were obtained without requiring any prior data or specific information on the track under assessment. This represents a considerable benefit in the railway monitoring context, since it removes the need to acquire the significant amounts of supplementary data that other methods can require to achieve the same overall goal.

If fully validated, this TMM could represent an important complement to railway maintenance efforts since it would allow for considerably more efficient assessment of subgrade support conditions when compared with the available method of localized inspection campaigns, which usually involve prospection holes or similar methods. Monitoring subgrade support conditions is something that is usually not even considered, due to the lack of reliable methods, but has a known importance in railway structural health (Fröhling, 1997; Berggren, 2009; Gallego et al., 2011). This would also result in the ability to collect valuable information relevant for track maintenance planning decisions, without the need to suspend railway traffic. The lack of extensive experimental data to validate these results and conclusions, such as specific information on subgrade condition on an entire railway line, is the main obstacle on the continuation of these validation efforts.

7 Conclusions and future works

7.1 Main conclusions

In the context of railway Structural Health Monitoring development efforts, a new track support condition monitoring methodology was developed in this thesis that is focused on assessing subgrade layer condition, due to its importance in the overall railway dynamic response. This methodology claims that by monitoring the natural frequencies of the subgrade layer it is possible to infer information on the overall track support conditions. During the development of this methodology, the need for a dedicated numerical modelling solution became apparent to provide the required testing environment for the methodology under development. Additionally, this study also entailed the development of an enhanced data processing method, due to the difficulties encountered when using more common data analysis methods. After considering and testing several options, an unsupervised data-driven tool was designed in this context, which represents an adequate method to implement the developed methodology and achieve the intended goals regarding the tool's capabilities.

This document presents a complete description on the proposed track monitoring methodology, including the theoretical models that are behind it, along with an overall discussion on the state-of-the-art in this area and some considerations on relevant topics. This is followed by a chapter describing the numerical models that were used to test the proposed track monitoring methodology and assess the damage detection capabilities of the developed data processing tool. Then a full description of the data processing tool is provided, including a general reference to the multiple iterations that were tested to reach the final solution. Finally, the results obtained from the assessment tests made on the proposed concepts are presented and discussed, which were performed with simulated data and experimental data. The obtained results with the numerical data demonstrate that this UDDT can indeed adequately be used to apply the developed methodology, by providing accurate results in the damage detection task. Despite the lack of adequate and extensive experimental validation data for the complete validation of the proposed methodology, the obtained results in the experimental context also demonstrate the potential viability of this concept in fulfilling the intended goals.

In terms of applicability of the proposed methodology, some considerations can be made at this point. The methodology can be deployed on a wide range of railway vehicles, including vehicles with two or just one suspension levels. This was verified with numerical data and tested with the available experimental data. Another relevant topic is that there

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appears to be a minimum vehicle speed of around 20 m/s where below it the proposed UDDT starts to lose its damage detection capabilities. This is a reasonable result since the vehicle is the excitation source being used, thus if the vehicle is travelling slowly there is not enough energy to sufficiently excite the resonance frequencies of interest for them to be picked up by the embarked instrumentation. Regarding data acquisition requirements, no special precautions appear to be necessary besides attending to the Nyquist-Shannon sampling theorem (Maia and Silva, 1997) to establish a limit for the minimum sampling frequency to be used, taking into consideration the frequency range of interest. For instance, the experimental data shown in Figure 6.3 was collected with 200 Hz, which appears to provide adequate results.

The proposed modelling solution that enables the representation of the subgrade layer in an MBS model was created to allow the generation of significant amounts of data to test the TMM and the UDDT. However, the option of using MBS models has some drawbacks that should be taken into consideration when employing the proposed solution: i) they are not capable of representing the vibration propagation on the soil layers due to the passage of the train; ii) they cannot take into consideration some of the more complex non-linearities that the vehicle-track system contains; and iii) they are not adequate to enable the study of stress distributions on the track. These drawbacks were not sufficiently relevant for this application to prohibit the use of MBS models, mainly due to the focus on modal analysis of the system of interest, although they can be important to consider in other studies.

7.2 Future works

While the full validation of the proposed methodology is still not complete, the obtained experimental results can be used as the framework for future campaigns by allowing to more adequately define the characteristics of the required experimental data. Thus, the next major step in this study would be to devise and implement an experimental campaign to acquire a new batch of data. In ideal conditions, this new data batch would fulfil the following requirements to enable the proper assessment of the proposed TMM:

- Acceleration data collected with one or more instrumented vehicles over the same railway line. The monitored track should be extensive enough to increase the likelihood of catching multiple damaged subgrade sections.
- The acceleration data should be acquired on several occasions throughout an extensive period to enable the monitoring of subgrade condition over time. If a track could be monitored over multiple years, the influence of aspects such as the weather and the seasons could be assessed and then discarded.
- Extensive geotechnical data on the monitored track, which should include information on the soil layer configuration to a depth of a few meters and any reports on recurring track support condition issues.

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Such an extensive experimental campaign would require the collaboration of a railway manager and a considerable amount of resources. However, the obtained preliminary results can be used as the starting point of such a process. With this data, the overall reliability of this methodology in identifying damaged subgrade sections could be properly assessed.

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