A NOVEL
CONDITION ASSESSMENT TECHNIQUE
FOR RAILWAY TRACK SUBSTRUCTURE USING SOFT COMPUTING

SHADI FATHI

Doctor of Philosophy

ASTON UNIVERSITY

June 2022

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Abstract

The railway infrastructure in the UK is one of the oldest transportation systems in the world. Substructure is a key component of railway track, and similar to other surface transportation systems, track substructures are subjected to ageing and deterioration. Additionally, drainage malfunction in railway track substructure causes local soil weakness that, subsequently, can lead to railway failure. Although there are different destructive and non-destructive tests (NDTs) used in railway substructure condition assessment, there is limited knowledge about how to interpret surface deflection data for the purpose of substructure condition assessment. Limited knowledge about the current conditions of substructure layers in the presence of any local structural weakness can lead to the employment of inefficient and time- and cost-consuming maintenance actions. Therefore, this research proposes the use of a novel back-analysis technique to interpret and estimate the stiffness properties of substructure components using a falling weight deflectometer test data (a well-established and widely used NDT in the UK) and to detect any existing local anomalies in the ground layers. The proposed technique is an integration of an artificial neural network (ANN) with metaheuristic optimisation algorithms. In this regard, where the ANN surrogate forward model is trained based on a database generated by the validated finite element (FE) models. The results indicate that the proposed hybrid technique is a reliable approach to estimating substructure's layer moduli, as well as identifying a weakness zone's modulus and its geometrical properties. The corresponding limitations of the proposed technique are then discussed, and further avenues of research are suggested.

Keyword: Back-analysis technique, railway track substructure, ANN-GA, local soil weakness

Dedication

DEDICATED TO MY BELOVED PARENTS, Sholeh & Jamal

Acknowledgements

I would like to acknowledge and express my sincere gratitude to my supervisor, Dr Moura Mehravar for her continuous support, guidance, great inspiration, and encouragement during my PhD studies in the Aston University. The completion of this PhD study would not have been possible without her supervision, wonderful insight and constructive advice.

I would like to thank my second supervisor Prof Mujib Rahman for his great support and encouragements throughout my study. More specifically, I would like to thank Prof Edward Sweeney for his support during the first and second year of my study as a second supervisor.

A special thanks to Dr Yuqing Zhang and Dr Aristides Matopoulos for their valuable comments on my annual reports.

I would like to express my sincere gratitude to Dr Farough Rahimzadeh of the University of Birmingham for his excellent advice and feedback on my thesis. Also, many thanks to my friends and colleagues in MB228 office at Aston University, for all listening, friendship, supporting and helping the time to pass quickly.

Last but not least, I would like to thank my mother and father for their unlimited loves, supports, helps and encouragements during my whole life. Without your love, smiles and support I would never have made it through to the end. Thank you both, Sholeh and Jamal, for your smiles and encouragement, teaching me hard work and believing in myself. I am grateful to them both for being wonderful role models to me in my entire life.

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List of Abbreviations

Non-destructive tests	NDTs
Artificial neural network	ANN
Finite element	FE
California bearing ratio	CBR
Standard penetration test	SPT
Dynamic cone penetration test	DCP
Cone penetration test	CPT
Fast Fourier transformation	FFT
Falling Weight Deflectometer	FWD
Track loading vehicle	TLV
China Academy of Railway Sciences	CARS
Transportation Technology Centre, Inc.	TTCI
Rolling stiffness measurement vehicle	RSMV
University of Nebraska–Lincoln	UNL
Ground penetrating radar	GPR
Electromagnetic	EM
Spectral analysis of surface waves	SASW
Multichannel analysis of surface waves	MASW
Infrared thermography	IRT
Backscatter computed tomography	BCT

Computerised tomography–scanning	CT-scanning
Layered elastic theory	LET
Multi-layered elastic theory	MLET
Two-dimensional	2D
Three-dimensional	3D
Genetic algorithm	GA
Differential evolution	DE
Shuffled complex evolution	SCE
Resilient moduli	M_R
Long-Term Pavement Performance	LTPP
Rail falling weight test	RFWT
Ground falling weight test	GFWT
Moduli of clean ballast layer	E_2
Moduli of contaminated ballast layer	E_3
Moduli of subgrade 1 layer	E_4
Moduli of subgrade 2 layer	E_5
Moduli of subgrade 3 layer	E_6
Deflection at n mm offset from loading point	D_n
Ant colony optimisation	ACO
Ant colony optimisation for continuous domain	ACO_R
Layered elastic analysis forward model	LEAF
Root mean squared	RMS

Downhill multidimensional simplex minimisation	DMSM
Multilayer perceptron	MLP
Root mean square error	RMSE
Levenberg–Marquardt backpropagation	LMBP
Coefficient of correlation	R
Mean squared error	MSE
Pheromone evaporation rate	ξ
Selection pressure	q
Archive size	k
Void angle	V_A
Void width	V_w
Void depth	V_D
Void length	V_L
Location of the void with respect to the loading point	Y_v
Local weakness zone modulus	E_V
Radial basis function	RBF

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Chapter 1

Introduction

1.1 Background and motivation

Most of the railway track infrastructure in the UK was constructed in the 19th century; as such, the infrastructure is considered to be one of the oldest in the world (Gunn et al., 2018; Skempton, 1995). The use of network rails has increased over the past few decades, resulting in the rapid deterioration of railway substructures. This, consequently, has imposed costly maintenance and renewal operations on railway stakeholders. Based on the latest statistics from Network Rail, the total expenditure on the UK's rail network in 2020–2021 has seen a 32% increase on 2019–2020 figures, with maintenance and renewal representing 56% of this expenditure – i.e., £3.1 bn out of £5.7 bn – in 2020–2021 (Davies et al., 2021; The Office of Rail and Road, 2021).

The railway track substructure is also known as the foundation of the railway track, playing a vital role in supporting the railway system; its mechanical properties directly affect the performance of the railway operation (Shaltout et al., 2015). There are two types of substructures/foundations: ballasted and non-ballasted tracks. Of these two, the ballasted track is the conventional and most common used railway track system, seen all around the world. A typical ballasted railway substructure consists of ballast, subballast, and subgrade layers which transfer the loads from the superstructure through the sleepers to the ground, and drainage system which conduct surface and subsurface water out of the railway substructure.

Among the abovementioned ballasted railway track substructure components, the subsurface drainage system has a significant effect on railway track performance. Observations by other research studies indicate that a major part of railway maintenance costs is related to the substructure layers and the inefficient drainage system (Kaewunruen & Remennikov, 2008; Tennakoon et al., 2012). Compared to superstructure-related issues, which can be identified by visual inspection techniques, railway track substructure issues are normally difficult to identify (Duong et al., 2015; Zhuang et al., 2020). Additionally, conventional inspection techniques are not able to provide railway stakeholders with useful information regarding the root cause of a problem. Consequently, due to the expanding railway network, the cost of corrective maintenance operations has increased (Morais et al., 2022).

To reduce the costly maintenance operations and maintain a healthy railway network, frequent railway system condition assessment (and track substructure assessments in particular) are required for the early detection of defects; this is known as proactive management. Proactive management provides the necessary information and sufficient time to asset managers, allowing them to plan and apply effective maintenance actions. This type of effective maintenance approach to railway substructures will significantly reduce annual maintenance costs (Ngo et al., 2019; Sharpe, 2000). In light of the transition from reactive to proactive management, various non-destructive tests (NDTs) for use in condition assessment have been developed over recent years (Artagan et al., 2020). Despite this improvement in the development of NDTs and their introduction to the field, there is still a lack of systematic interpretation techniques that can utilise NDT measurements for railway track substructure condition assessment and detection of local defects in the substructure. One commercially available back-analysis program is BAKFAA, which is widely used for the back-analysis of pavement substructures' layer moduli using deflection data. In this study, the performance of BAKFAA has been critically investigated for railway track applications. The investigation demonstrates that the reliability and robustness of BAKFAA requires improvement and that an alternative back-analysis technique is needed for railway track substructure condition assessment.

On this basis, this study aims to provide an interpretation framework using one of the available NDTs, for the condition assessment of railway substructures. To this effect, a novel hybrid back-analysis technique has been developed for railway track substructure condition assessment and the detection of local weakness zones. This back-analysis technique utilises deflection data from a falling weight deflectometer (FWD) test, which is one of the widely used NDT tests.

In order to develop the back-analysis technique, the responses of the railway substructure under the FWD drop load, was modelled using finite element (FE) method. For this purpose, COMSOL Multiphysics was employed. The FE model of the railway substructure was then validated against experimental data from literature. In addition, an artificial neural network (ANN) tool was employed as an alternative to the FE model to reduce the computation time required by the analysis. Following this, the back-analysis technique, which incorporates the ANN tool and a metaheuristic optimisation algorithms including genetic algorithm (GA) and ant colony optimisation (ACO_R) for coninuous domain, was developed. The developed back-analysis technique was then proposed for use in an inversion analysis of FWD deflection data. This technique was employed to estimate the railway substructure's layer moduli, detect soil weakness zones in the substructure as a result of mulfunction in buried drainage pipe. These applications of the proposed back-analysis technique were illustrated using a number of numerical examples and parametric analyses. The results demonstrate the capability, accuracy,computational time efficiency and cost-effectiveness of the proposed technique for railway substructure condition assessment and detection of local soil weakness in the substructure.

1.2 Aim and objectives

The aim of this study is:

- To develop a back-analysis technique using FE method and machine learning for NDT condition assessment of the railway substructure, based on FWD testing results.

The research objectives (ROs) required to achieve the aim are as follows:

- RO1: to perform a comprehensive literature review that will investigate the available condition assessment methods used to (i) evaluate ground subsurface including both pavement and railway track substructure and (ii) to estimate railway track moduli (i.e., stiffness) and identify any gaps in the knowledge.
- RO2: to assess the performance of the BAKFAA software package for railway track condition assessment.
- RO3: to develop and validate a numerical FE simulation of a railway track substructure section under FWD testing condition.
- RO4: to develop a hybrid back-analysis technique using the developed FE model (in RO3) and machine learning techniques (ANN-GA and ANN-ACO_R).

- RO5: to investigate the application of the developed back-analysis technique and its ability to identify a local anomaly around a drainage pipe in the railway track substructure.

1.3 Layout of the thesis

This thesis consists of six chapters. A brief description of the contents of each chapter is presented in the following paragraphs.

Chapter 2 provides an extensive literature review that identifies the gaps in the knowledge on this subject and puts the current study into perspective. This chapter shows the importance of the effect of substructure condition on railway track system performance, and demonstrates the importance of track modulus (i.e., stiffness) and its role as a key parameter in railway track substructure condition assessment. In addition, this chapter provides a review of the available NDT methods for track modulus measurement, and various back-analysis techniques used to interpret the FWD test data for pavement and railway track applications to date are critically reviewed. As a result of the critical literature review provided in this chapter, the importance of the current study and the existing gap in the knowledge on this topic are identified.

Chapter 3 presents the development of a FE model of a section of railway track structure, using COMSOL Multiphysics to calculate track surface deflection under the FWD loading condition. In addition, the effect of various substructures' layer moduli on surface deflection is investigated through a parametric study.

Since there is yet no commercial tool that has been developed for the back-analysis of railway track substructures, Chapter 4 investigates how the BAKFAA program, which was originally a linear elastic theory–based back-analysis program used to analyse pavement structures, can be applied to railway tracks. In this chapter, to assess the performance of the BAKFAA software when it is applied to railway tracks, a virtual experimental database is generated using the FE model of the track section developed in Chapter 3. A virtual experimental database was generated using FE model because of the limited available experimental FWD data for railway.

In Chapter 5, a framework for the back-analysis of FWD test data for railway track applications is developed. The proposed novel technique is a hybrid of an ANN and metaheuristic optimisation algorithms.

In Chapter 6, the performance of the developed back-analysis technique for identifying a soil weakness /local anomaly in railway substructure layers is investigated via numerical examples and parametric analyses. Finally, Chapter 7 presents the key findings and offers the main conclusions, providing recommendations for future research.

Chapter 2

Literature review

2.1 Introduction

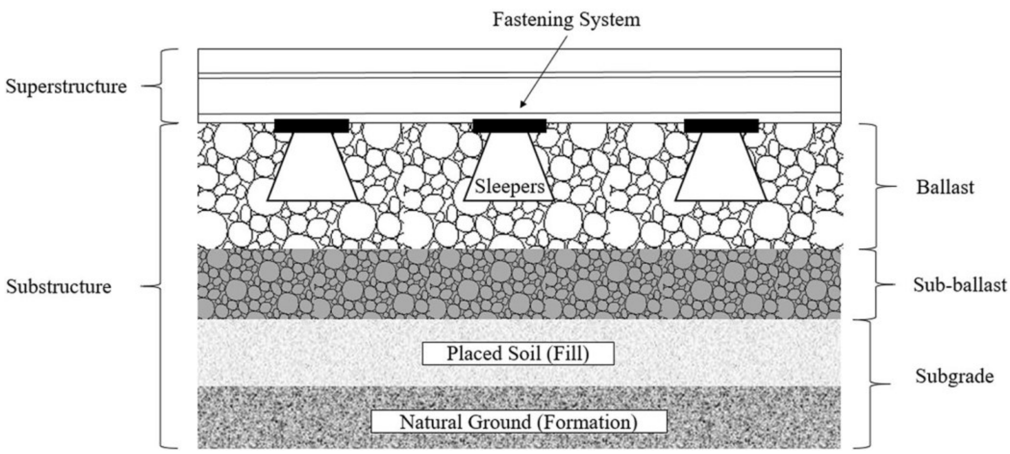
This chapter first reviews the components of a ballasted railway track substructure and then investigates how the impact of the substructure layers and subsurface drainage network on the performance of the railway track is portrayed in the literature. In this review, the importance of track modulus to railway track substructure condition assessment is clarified, and various destructive and non-destructive (NDT) methods of measuring railway track moduli are reviewed. In addition, a review of the literature on the currently available NDTs for subsurface exploration and their advantages and disadvantages is carried out. Among the reviewed methods, the emphasis is on the FWD test, which is a well-established NDT. A comprehensive review of the interpretation techniques used with the FWD deflection data (i.e., back-analysis techniques or inversion frameworks) is also carried out for railway track substructure condition assessment and the detection of local structurally weakened zones around a buried drainage pipe.

In addition to the above, back-analysis techniques and available programs that can interpret the FWD test data for pavement substructure condition assessment were critically reviewed, as these have mutual principal aspects with railway track substructures.

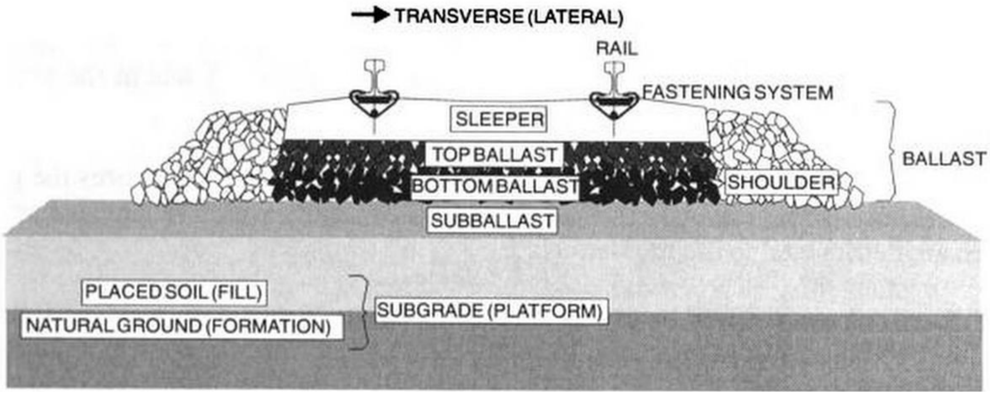
The key findings in this literature, described in the final section of this chapter, highlight the limitations of the current back-analysis techniques in terms of their ability to interpret FWD test deflection data for the purpose of railway track condition assessment. Furthermore, this review illustrates the untapped potential of the FWD test, which (with the aid of advanced data interpretation techniques) can offer fast and frequent railway track substructure condition assessment and detect local anomalies occurring due to malfunctions in the drainage network.

2.2 Railway structure

The two main types of railway track infrastructure are the conventional ballasted track and ballastless track (slab track). The focus of this thesis is on the conventional ballasted railway track, which is the most common type of railway track infrastructure found all around the world (Michas, 2012; Sol-Sánchez & D'Angelo, 2017). A conventional ballasted railway track is defined as a multilayer structure consisting of two main components: superstructure and substructure. Both the superstructure and substructure include various components that are based on their functional purposes (Araújo, 2011). The superstructure is comprised of the rail, rail pads, fastening systems and sleepers, while the ballast, subballast, sub-grade and subsurface drainage network are the main components of a railway track substructure (Li et al., 2015; Li & Wilk, 2021). This categorisation may differ between various studies on this topic in the literature. The ballast layer may be identified as part of the superstructure (Kondratov et al., 2017) or substructure (Ferrante et al., 2021; Indraratna et al., 2016). This study considers the configuration reported by Indraratna et al. (2016) for the ballasted railway structure. Based on Indraratna et al. (2016), ballast and subballast were considered to be the substructure components, while the superstructure consists of the rail, rail pads, fastening systems and sleepers. Figure 2.1a–b shows both a side view and a cross-sectional view of a conventional ballasted railway track structure.



(a) Side view



(b) Cross-section

Figure 2.1: (a) Side view of ballasted track structure components (Ferrante et al., 2021); (b) Cross-section of ballasted track structure components (Rezaei Tafti (2018))

In comparison to the superstructure, the characteristics and condition of previously laid substructure components are not completely known, as they are embedded into the ground. The substructure is mostly constructed from natural materials with highly uncertain behaviours (Rezaei Tafti, 2018).

As the focus of this research is on railway track substructures, descriptions of each substructure component and their characteristics and specific roles are presented in the following sections (see Figure 2.1a).

2.2.1 Ballast

Generally, the ballast layer is a 250 to 300 mm layer of granular material (medium to coarse gravel material) positioned under the sleeper (see Figure 2.1b) (Esveld, 2001). The main functions of the ballast layer are preventing sleeper and rail movements, providing adequate and fast drainage to the track and distributing the load transmitted from the sleeper.

2.2.2 Subballast

As shown in Figure 2.1a–b, the subballast layer is located between the ballast and subgrade layers. The subballast layer material consists of a broadly graded sand mixture. The main functions of the subballast layer are providing proper drainage and preventing the penetration of fine subgrade materials into the ballast layer and of coarse-grained materials from the ballast into the subgrade layer. The subballast also reduces the stress level at the bottom of the ballast layer and at the top of the subgrade; it does so by redistributing the stress to a sider area and partially damping the loading energy (Ahmadkhani, 2021; Indraratna & Salim, 2005; Kaewunruen & Remennikov, 2008; Rezaei Tafti, 2018).

2.2.3 Subsurface drainage

Subsurface drainage systems are used at railway track sites where there is inadequate surface drainage. This type of drainage consists of pipes, joints, and sumps. Subsurface drainage should be able to remove surface water runoff, groundwater and water collected from other networks that are connected to the new network. The minimum required pipe diameter for subsurface drainage is 225 mm (Chudley & Greeno, 2005; Spink et al., 2014).

2.2.4 Subgrade

This layer is located exactly under the ballast and subballast layers and is referred to as the railway track foundation (see Figure 2.1a–b). The subgrade layer material can be either natural ground or filled material. This layer is ultimately carrying the whole weight of the railway track structure. In a proper and optimum railway track–bed design, to prevent the subgrade's failure both the ballast and subballast layers and the drainage network should be designed to provide efficient protection from extreme stresses and environmental conditions. As such, the main role and function of this layer is to provide a stable foundation for the track infrastructure, sufficient drainage for the upper layers and sufficient bearing capacity (Ahmadkhani, 2021; Kaewunruen & Remennikov, 2008; Lim, 2004).

2.3 Railway track substructure condition assessment methods

A railway track's condition and performance can be described and assessed using two measurements known as functional and structural measurements of track structure. The functional measurement is referred to the performance of the track from the user's point of view, concerning such matters as ride comfort and track geometry. In comparison, the structural measurements are concerned with the track's ability to support applied loads and involves the structural properties of the track and its substructure, such as their strength and stiffness (Ebersöhn & Selig, 1994a). It is worth mentioning that, unlike the functional measures (i.e., the track geometry measures), which offer an overall insight into track structure problems (such as geometry deterioration), structural measures (i.e., measures of the strength and stiffness or the track deflection and settlement) provide information regarding the structural integrity of a track and its ability to perform satisfactorily for a long time (Ebersöhn & Selig, 1994b; Wehbi, 2016). The quality of the track geometry is a criterion in railway track performance. However, the geometrical irregularities of the track do not consider the condition of the substructural components. In addition, an investigation of the root reason behind a railway track substructure's malfunctioning cannot be based only on geometric data (Do, 2020). Thus, a measurement of track modulus data is necessary when investigating the condition of substructure layers and detecting the root cause of railway track substructure–related issues.

The condition of railway track substructures has an extensive effect on the performance of the whole track. In fact, a railway track substructure in poor condition will result in progressive track deterioration and eventually lead to track failure. To this effect, the acquisition of accurate information regarding the current condition of a railway track substructure is crucially important to providing effective maintenance actions and preventing track failure (Artagan et al., 2020). However, the process of a substructure section condition assessment is generally more challenging than a superstructure assessment, due to the complexity involved in the identification of the geotechnical properties of the buried substructural layers (Berggren, 2009). For this reason, more attention has historically been paid to railway track superstructure condition assessment.

Track modulus is a key parameter that can be used to determine the structural condition of a railway track substructure (Ebersöhn & Selig, 1994a; Rezaei Tafti, 2018; Rogers et al., 2012; Wehbi, 2016). Track modulus is a basic stiffness characteristic of a railway track and an indication of the vertical stiffness of the track foundation (Selig & Li, 1994). This parameter is a function of the elasticity modulus of individual railway substructural layers (Wehbi, 2016). A common definition of track modulus is the correlation between the load applied to the railway track structure and the displacement reflection of the track. Esveld (2001) introduced the track modulus as a useful property for identifying structural deterioration in the railway track substructure that requires maintenance. Esveld (2001) concluded that a discrete variation in the track moduli along a track shows the possibility of a deterioration in the substructure. Several other studies have also reported on the importance of track moduli to railway track substructure condition assessment and track maintenance (Artagan et al., 2020; Do, 2020; Mehrali et al., 2020; Morais et al., 2022). These studies note that the frequent measurement and analysis of the vertical track modulus is crucial to assessing the quality of the track substructure and the performance of the individual track components, as well as to detecting any local anomalies in the track and planning time- and cost-effective maintenance actions.

Over the years, several tests to measure the track modulus of railway substructures have been designed and developed by organisations and institutions all around the world. These include the California bearing ratio (CBR), triaxial testing and repeated load triaxial test (i.e., cyclic triaxial) (McHenry & Rose, 2012; Paulsson et al., 2017). While some of these conventional laboratory tests can be useful to railway track applications, from a practical point of view in-situ tests are more informative and efficient for the railway sector. Furthermore, laboratory tests require sampling, which is commonly associated with destructive testing, while in-situ tests can be non-destructive and more time-efficient, as they provide immediate information about the condition of the railway track being tested. Destructive and non-destructive testing methods are discussed in the following section.

2.4 Destructive tests

Destructive in-situ tests such as the standard penetration test (SPT), cone penetration test (CPT) and dynamic cone penetration test (DCP) are methods by which the elastic modulus (i.e., stiffness) of railway track substructures can be tested. These methods only provide information about the specific location being tested; they are not representative of the track condition overall. Furthermore, they require boring and sampling, which cause the damage of the railway track structure and are both labour intensive and time consuming. In addition, the destructive in-situ testing methods cannot provide continuous inspection, instead only providing discrete information about the railway track (McHenry & Rose, 2012).

2.5 Non-destructive tests

In order to overcome the above-mentioned shortcomings in the conventional destructive methods, over the years various NDTs to identify track moduli have been developed. These methods are categorised in three groups: standstill; rolling (vehicle-based); and trackside-based methods. In the following sections, the important in-situ NDTs for track moduli are explained in detail.

2.5.1 Standstill methods

Standstill track modulus measurement methods were developed mostly for research purposes and currently are commonly used techniques that measure track modulus at discrete points (Burrow et al., 2009; Hua et al., 2022). Various standstill methods are explained as follow.

2.5.1.1 Traditional hydraulic jack loading method

This method was developed in 1918 by the Talbot community; Figure 2.2 shows the schematics for this method. Here, the load-deflection curve of the track is obtained by applying a load to the track through a loaded flatbed trailer and recording the deflection of the rail via a displacement meter or a dial indicator. The loaded flatbed trailer in this method is mounted on the track, so is able to move along the track and perform multiple successive measurements. The stiffness of the track is then calculated based on the gradient of the load-deflection curve thereby obtained (Kerr, 2000; Wang et al., 2016).

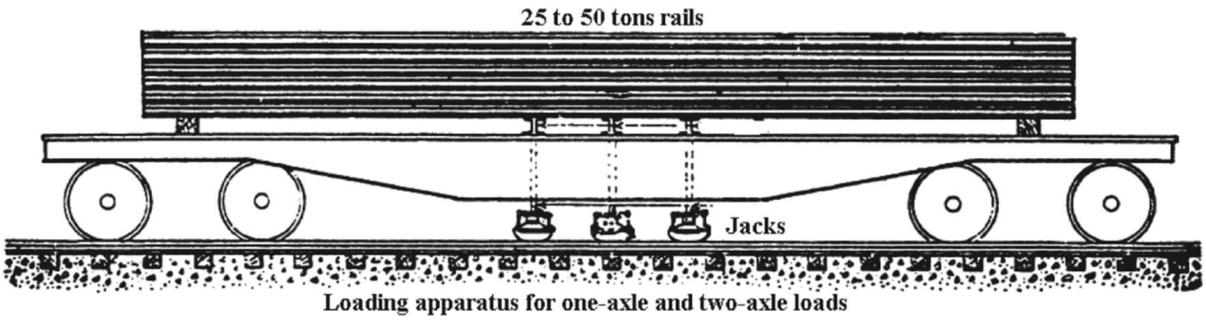


Figure 2 2: Talbot measurement equipment

2.5.1.2 Impact hammer method

The impact hammer method is one of the most commonly used approaches to modal analysis in which the impulse load is applied to the rail or to the sleeper via an impact hammer. Here, the applied impulse load is measured by a force transducer that is installed on the hammer head. The track deflections caused by the hammer's impact are recorded by a velocity transducer (i.e., geophone) and a displacement transducer. The recorded deflection in this test is then converted from the time-deflection domain to a frequency-amplitude domain using the fast Fourier transformation (FFT) technique. The geophone employed by this method has a low recording frequency and can capture those vibrations (i.e., dynamic track deflections) that have a frequency of less than 100Hz; in comparison, the displacement transducer records higher-frequency vibrations. Typically, the impact hammer method can cover a frequency interval of 50 to 1,500 Hz, depending on the material out of which the hammer head is made. Even though the impact hammer is an effective method for analysing noise and environmental vibration applied to the rail track, it is not reliable enough for the inspection of railway tracks and detection of track deterioration (Gopalakrishnan et al., 2006; Kaewunruen & Remennikov, 2005). Furthermore, the impact hammer method is unreliable when the impact load has a frequency of less than 50 Hz (i.e., requires a high-energy impact and high-frequency vibrations in the track to produce reliable results).

2.5.1.3 Falling weight deflectometer

The original concept of the FWD was first developed during the 1960s (De Bold, 2011; Tawfiq, 2003). This device consists of a falling weight that applies a mass load to a circular plate. The circular plate is located on the test surface (e.g., pavement or railway track) with a rubber cushion between the pavement surface and the load plate to decrease the effect of the load on the surface. There is a load cell at the centre of the FWD load plate that measures the magnitude of the dropping load and a number of geophones that measure surface velocity (which information, when integrated with respect to time, gives the surface deflection data)

(Burrow et al., 2007). The structural properties of the test material, e.g., the elastic modulus of the pavement, can then be inferred through the back-analysis of the recorded deflections. Since the 1960s, however, the FWD system has undergone various improvements in terms of its loading magnitude, calibration process, loading pads, the system used to obtain data and the software that produces a back-analysis of the data.

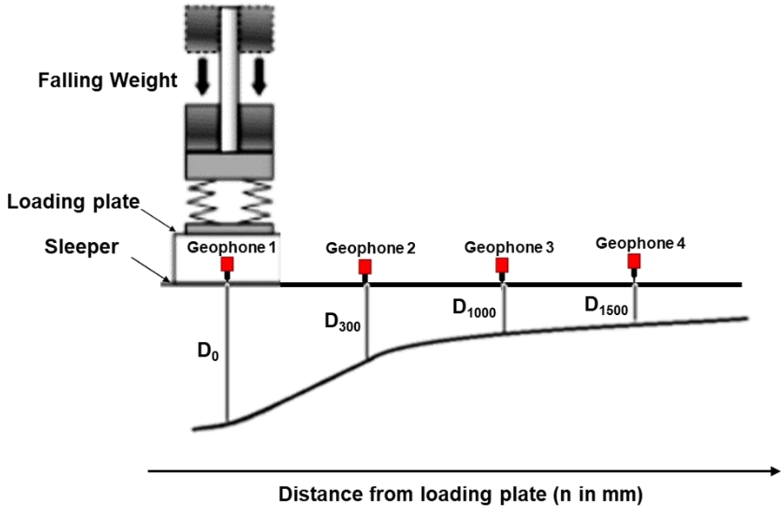


Figure 2.3: The arrangement of geophones in an FWD test applied to railway tracks (Burrow et al., 2007)

The FWD test was originally developed as a pavement condition assessment technique, before being adapted by Sharpe (2000) for the railway industry through a minor change in the geophones' configuration and the loading conditions. In the FWD test employed in railways, load is typically applied through a 1.1 m loading beam that applies a 125 kN load to both ends of a railway sleeper. This load is approximately equal to that of a single-axle train passing at high speed (Burrow et al., 2007). The magnitude of the applied load is measured at the centre of the loading beam.

Figure 2.3 shows a schematic of the FWD test. In this figure, horizontal distance from the centre of the loading plate is shown by n (n is in mm). D_0 is the deflection at the geophone located at the loading point. D_{300}, D_{1000} and D_{1500} show the deflections at 300 mm, 1000 mm and 1500 mm offset from the centre point. It should be noted that, geophone 1 is located on the sleeper where the rest were located on the ballast surface. These geophones are used to measure movement velocities caused by the drop load. The measurement taken by the first geophone (D_0) is the sleeper velocity and the rest of the geophones measure the ground velocity as the latter geophones are located on the ballast surface. These velocities are then converted into the deflections by integration with respect to time. Figure 2.4 shows the configuration of FWD test loading and geophone arrangements for railway application.

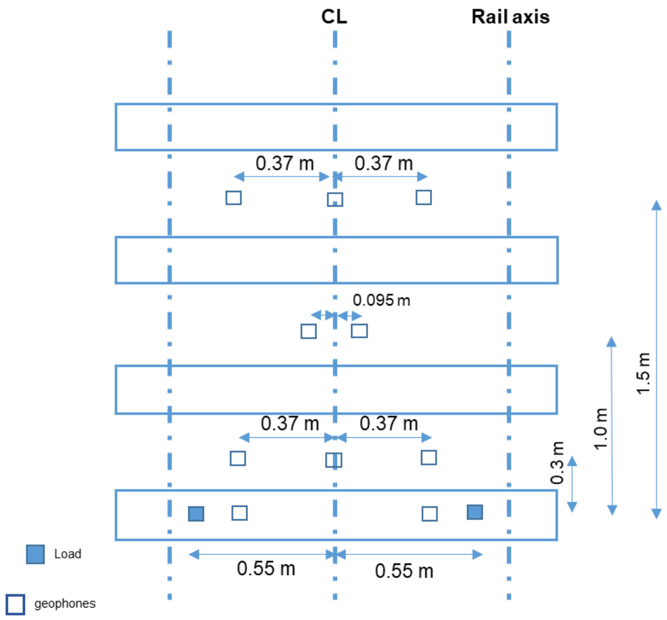


Figure 2.4: FWD Loading and geophone configuration (Burrow et al., 2007)

2.5.1.4 Track loading vehicle

This technique, in principle, is similar to the traditional hydraulic-jack method; however, it can apply a larger amount of vertical load than the traditional hydraulic jack method, and its operation in the field is relatively more time-efficient and requires less expert training. As is shown in Figure 2.5, the load applies to the track through both the hydraulic jack and the track loading vehicle's (TLV's) own weight. The loading condition can be varied based on the equipment; the load is generally applied to the rail head, but the uncoupled sleeper can also be loaded as in the FWD test (Burrow et al., 2009; Wang et al., 2016). However, TLV and its operational process is more time consuming than other approaches such as rolling measurement methods (which are discussed in the next section); this is because it is necessary to close the railway track during the test operation (Hua et al., 2022; Wang et al., 2016).

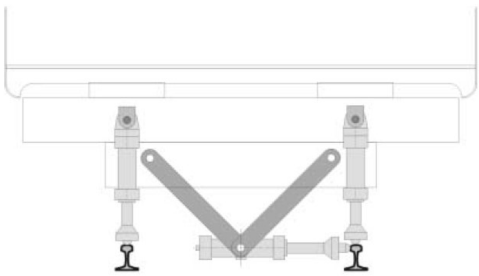


Figure 2.5: Track loading vehicle equipment (Wang et al., 2016)

Standstill methods are generally employed for research purposes. Among these, the FWD test is a tried-and-tested, well-established, commonly used and practical method employed in the UK and around the world.

2.5.2 Rolling measurement methods (vehicle-based methods)

Rolling measurement methods (also known as vehicle-based testing methods) were developed by several research institutes and organisations around two decades ago. The following paragraphs discuss the rolling methods developed by each of these institutions.

2.5.2.1 China Academy of Railway Sciences (CARS)-stiffness equipment

The China Academy of Railway Sciences (CARS) designed and developed a continuous stiffness measurement device that has became one of the main continuous measurement devices used in the field of railway structure testing (Wangqing et al., 1997). As shown in Figure , the test equipment, which is designed to take measurements while moving along the railway track at speeds of up to 60 km/h, consists of two cars equipped with measurement tools: one light-weight car at the back of the vehicle system and a heavy-weight car at the front (Berggren, 2009; Burrow et al., 2009; Wang et al., 2016). The light-weight car body has an axle load of 40 kN, which is heavy enough to eliminate the effect of voided sleepers and voids between the sleeper and the ballast bed. This load reduces the effect of geometrical track irregularities on the stiffness measurement. The heavy car, with a varying axle load of 80 to 250kN, is used to assess the effect of various train axle loads on the track deflections. This system measures the track modulus by combining the deflection measurements of both the light-weighted and the heavy-weight cars.

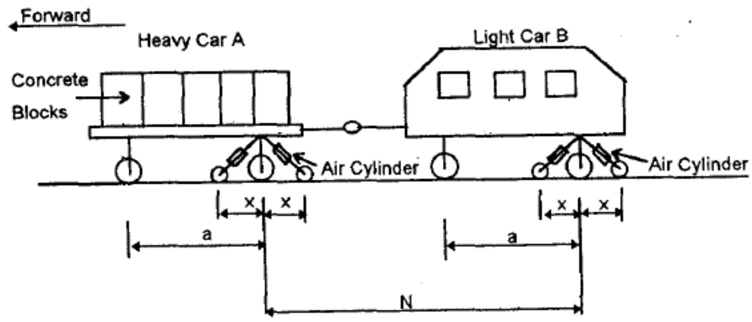


Figure 2.6: China Academy of Railway Sciences equipment measurement system (Do, 2020)

2.5.2.2 Transportation Technology Centre, Inc. (TTCI) equipment

Another continuous track modulus measurement tool that has been developed by the Transportation Technology Centre, Inc. (TTCI) in Pueblo, Colorado, US combines the TLV method with the CARS measurement principle (Section 2.4.2.2.1) to provide an automatic continuous measurement of the elastic modulus of the railway track based on the track deflections under the moving vehicle (Li et al., 2004). Figure 2.7 shows a photo of the TTCI track measurement vehicle. This vehicle consists of a heavy- and light-weight railcar and an empty tank car (Li et al., 2004; Wang et al., 2016). This method uses laser sensors to measure the rail-bending deflection under the applied loads. The corresponding loading range with the heavy car is 4 to 267 kN, which is applied through a hydraulic jack over the railhead. The standard wheel-load employed for this method is 178 kN. To evaluate the track modulus, this test conducts two sets of runs under standard load tests at 178 kN and 44 kN (Fallah Nafari, 2017). The second run, under a 44 kN load, effectively removes the effect of any track gaps and irregularities (Burrow et al., 2009). This equipment measurements are limited to 16 km/h, which makes this method unsuitable for long-distance railway tracks and tests at a network level. Moreover, this method is highly costly in terms of the equipment required and its operational requirements (McVey et al., 2005).

Figure 2.7: TTCI track measurement vehicle (Do, 2020)

2.5.2.3 Bankverket rolling stiffness measurement vehicle

Within the Eurobalt II project (conducted by the Swedish Railways Administration [Bankverket] from 1998 to 2000) a standard prototype was developed that could be employed with Swedish TLV to obtain vertical track modulus measurements at a speed of 30 km/h (Berggren, 2009; McHenry & Rose, 2012). In 2003–2004, after successfully testing the prototype trolley used to measure vertical track modulus, which indicated the potential of this tool, the primary designed vehicle was upgraded by the Banverket and Royal Institute of Technology (KTH) in Sweden. This upgraded vehicle named the Bankverket rolling stiffness measurement vehicle (RSMV), was reconstructed on a two-axle freight wagon. As with the other two-axle load systems, a light axle load is employed to account for track irregularities. As shown in Figure 2.8, this modified vehicle consists of two mass bodies, a force transducer, an accelerometer, a hydraulic system and a battery plate; it can measure dynamic stiffness at various frequencies up to 50 Hz. The maximum static and dynamic axle load that can be applied by this system are 180 kN and 60 kN, respectively. Track modulus measurements can be obtained by measuring the force and the vertical accelerations caused by the force, using a force transducer and accelerometers, respectively.

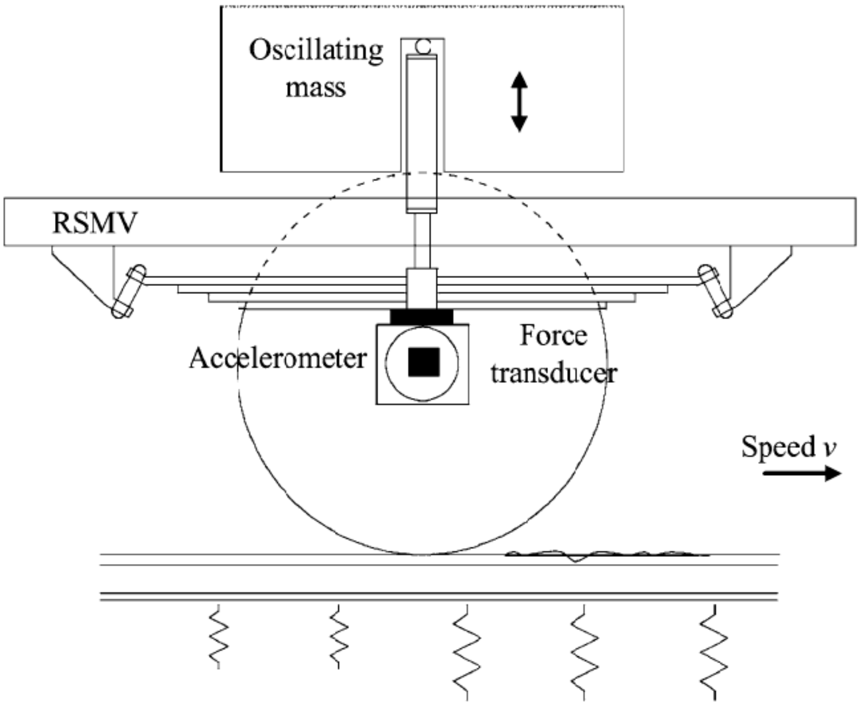


Figure 2.8: Rolling stiffness measurement vehicle equipment (Wang et al., 2016)

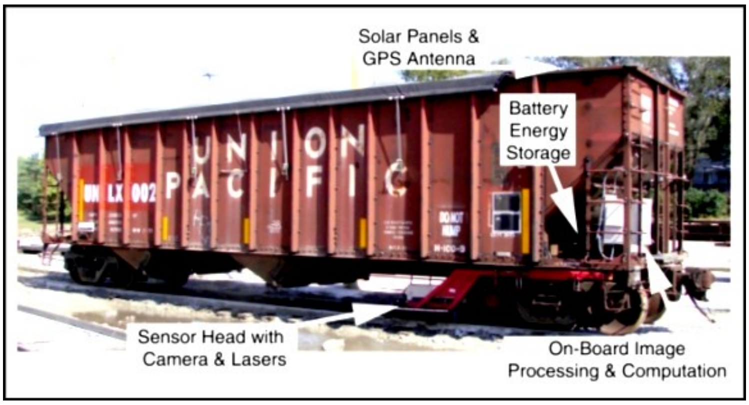
2.5.2.4 Portancemètre

The Portancemètre, designed by the CETE Normandie Centre, is another piece of equipment used to continuously measure overall track modulus. Figure 2.9 shows the on-site Portancemètre equipment in France. Its measurement approach is similar to the RSMV, in that a dynamic load is applied via a vibrating wheel suspended by a spring and a damper (Berggren, 2009; Do, 2020). The Portancemètre's static load may vary between 70 and 120 kN, while its maximum dynamic load amplitude can go up to 70 kN. The Portancemètre can also measure stiffness by exciting the track at a frequency of up to 35 Hz (Innotrack, 2006). Figure 2.9 shows the on-site Portancemètre track modulus measurement equipment. This equipment, as a part of the INNOTRACK project, was originally designed for road applications, but has now been adopted for railway track applications (Hosseingholian et al., 2006). However, in comparison to the frequency of its use with road beds, this method is not often used to measure railway tracks (Berggren et al., 2014; Hosseingholian et al., 2006).

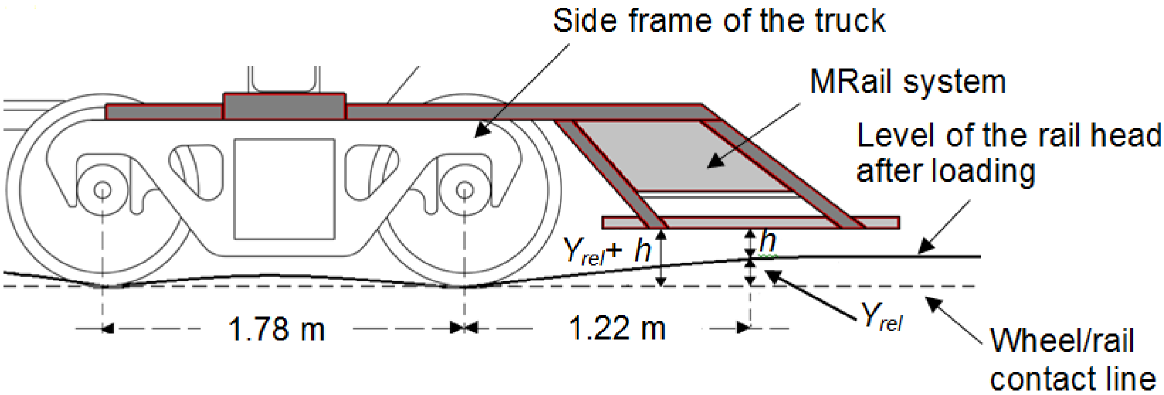
Figure 2.9: On-site measurement using the Portancemètre in Rouen, France (Do, 2020)

2.5.2.5 Nebraska University

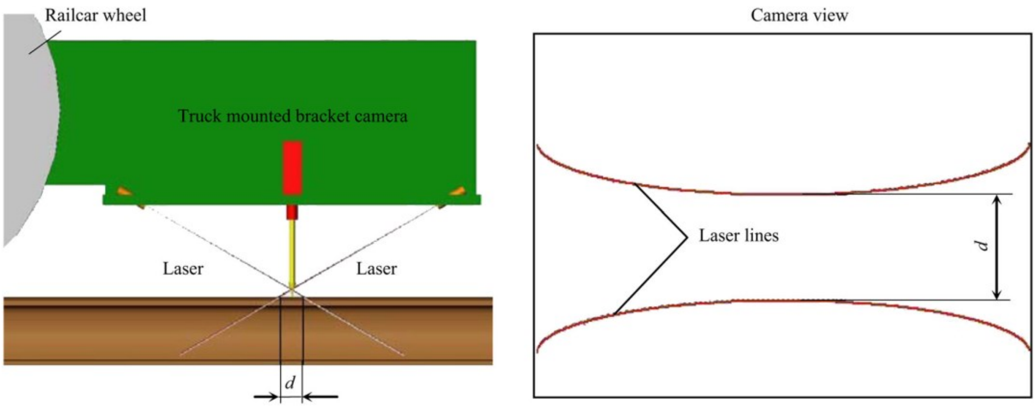
Another system, developed by researchers at the University of Nebraska–Lincoln (UNL), was commercialised by MRAIL Inc in the US. It is a non-contact and laser-based measurement method used to define track moduli that can take measurements at a speed of up to 65 km/h. Two lasers are used in this measurement vehicle to measure the relative deflection of the rail and then estimate the track modulus (which corresponds to the deflections via a mathematical model). The laser measurement system employed by this system is used to increase the measurements' accuracy. Figure 2.10a–d shows the measurement system used by this test. Here, d is the distance between two laser curves (which is measured according to the camera-view analysis), Y_r represents the track deflections under load, and L_1, L_2, h_1, h_2 and H are all known values related to the equipment specifications. Finally, Winkler's foundation model is used to relate the measured values of Y_r to the track modulus (Berggren, 2009; Burrow et al., 2009; Wang et al., 2016).



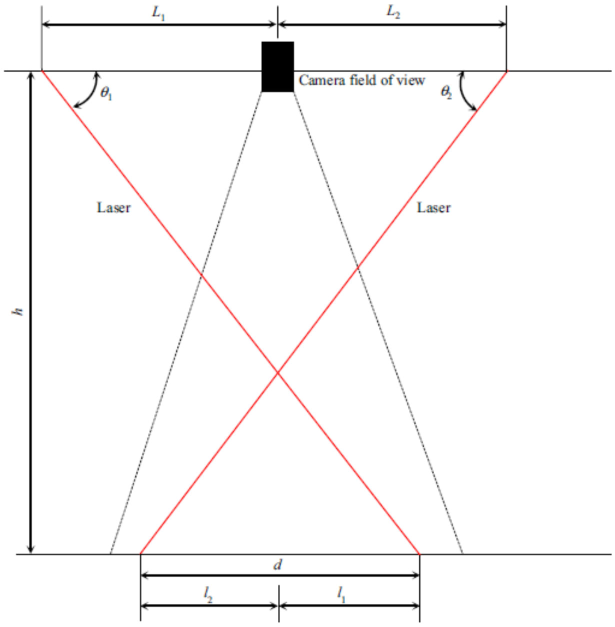
(a) System instrumentation



(b) Diagram of the measurement principle



(c) Camera/laser system



(d) Sensor arrangement in the University of Nebraska–Lincoln test

Figure 2.10 : (a) System instrumentation; (b) Diagram of the measurement principle; (c) Camera/laser system; (d) Sensor arrangement in the Nebraska–Lincoln University equipment (Fallah Nafari, 2017; Wang et al., 2016)

Despite all the above-mentioned improvements in the vehicle-based track modulus measurement methods, several main shortcomings associated with these methods have been noted (Berggren et al., 2011; Do, 2020; Fallah Nafari, 2017). Some of these shortcomings can be summarised as follows. First, these methods result in various modulus values due to operational conditions such as loading values, frequency, the vehicle's speed during its operation, and track modulus resolution. In addition, railway-related organisations and research institutes all around the world have designed and developed their own rolling measurement systems, which are not accessible worldwide. This has meant that their accessibility and usability by others is limited, consequently limiting the available experimental data for comprehensive performance analyses. In addition, interpreting data acquired from vehicle-based track modulus measurement methods is still challenging and requires further study.

2.5.3 Trackside-based measurements

Over recent decades, various trackside-based tests for track modulus measurement have been developed for railway applications. Trackside measurement methods either take a direct approach (measuring the track displacement and calculating the track modulus via the applied load) or an indirect approach (measuring velocities or accelerations and then integrating these data to determine displacement) to define the track modulus via an applied load (Gallou, 2018).

From another point of view, the various trackside techniques can be categorised into three main groups based on what they measure: namely, vertical displacement, vertical velocity, and the acceleration of the track response. Laser deflectometers, video recording, geophones and accelerometers are all measurement sensors used in trackside-based methods. For example, laser deflectometers and video recordings are related to the vertical displacement group, while geophones and accelerometers belong to the vertical velocity and acceleration groups, respectively.

Various research has been caried out on the application of video recording methods such as remote video monitoring (Gallou, 2018). This direct track modulus measurement method is easy to set up and does not require a data logger. However, it requires a large amount of memory when saving the graphical recording and analysis.

Over the years, the use of direct laser-based techniques for track modulus measurement has been investigated, although only for research purposes. Several studies have been carried out that use lasers for track modulus measurement (Hendry et al., 2006; Paixão et al., 2014). The crucial limitation of laser-based methods is the low production and acquisition of data in this method, because, in the current measurement system, only a single laser source and one sleeper are considered during each measurement (Kim, 2016). Due to the low efficiency in data production, and considering the cost of this method, laser-based methods have not found widespread use in industry. The laser-based sensor method is useful for relatively long track sections since the laser-sensing technology is not restricted to high or low train speeds and is reasonably priced. However, the setup and operation of this method are time consuming and require specific expertise, and the instrumentation that can be used in this method is restricted to specific types. Further to these points, this method requires connection along the track to a data logger, which adds complexity to the operational procedures.

The major disadvantage of both video recording and laser-based sensor methods is the effect of ground vibrations on the tripod upon which the sensor is installed, which, consequently, introduces errors into the results. Although the video recording system does not need a data logger and connections along the track, it can only monitor one single point along the railway track and needs too many frames per second (FPS) to be used with high-speed trains, hence the low productivity of this method.

Geophones have been employed as velocity sensors for the indirect measurement of railway track moduli, and a wide range of research has been conducted regarding their application in the railway-testing field (Bowness et al., 2007; Priest & Powrie, 2009). Compared to similar methods, geophones are significantly easier to apply, as they only need to be attached onto the track, or even located under the ground, to measure each layer's displacement (however, the latter would be a destructive testing approach). Generally speaking, low-frequency geophones are used in engineering site investigations. Geophones' output velocity can be integrated to calculate displacement; however, this method is one the most expensive track modulus measurement methods.

There are no restrictions regarding the instrumentation and setup of the geophones in an indirect track modulus measurement method that uses geophones. However, because of their sensitivity limitations relating to low-frequency vibrations, geophones cannot be used in relation to trains that operate at a very low speed. Furthermore, in addition to being an expensive method, geophone-based track modulus measurement (as with the laser-based method) requires the presence of a data logger and connections along the track. Finally, it is worth noting that both the laser-based and geophone methods are single-point measurements.

2.5.4 Local anomaly detection using NDTs

As mentioned earlier in this chapter (Section 2.2.1.3) subsurface drainage is one of the components of a ballasted railway track substructure (Li & Wilk, 2021). Railway subsurface drainage consists of buried pipes, catchpits and manholes; the drainage operates via gravity, with an approach similar to that found in stormwater sewer networks (Wu et al., 2021). Subsurface drain networks are more complicated than surface drain networks. Thus, their design and condition assessment require more detailed geotechnical and hydrological information (Hasnayn, 2016). Despite the above, the current technologies involving railway track drainage systems condition assessment for the purpose of damage and deterioration detection are limited and do not provide sufficient information to come to a conclusive assessment (Wu et al., 2021).

The performance and efficiency of a ballasted railway track substructure is highly dependent on the condition of its drainage system and its ability to drain and remove water from the track substructure. The proper performance of a railway track is achieved by diverting and removing water from the track substructure. At the same time, increasing the axle loads, developing high-speed trains, climate impact and year-on-year ageing, along with poor drainage conditions, will cause the gradual degradation of a track substructure (Bačić & Juzbašić, 2020).

Frequent track substructure damages and failures are associated with water remaining in the lower and upper parts of the track substructure for long periods of time due to a poor drainage system, which leads to unforeseen and costly railway track maintenance requirements (Sañudo et al., 2019). Silting, clogging, blockages with rubbish and malfunctioning are the common phenomena in this regard, resulting in the railway track drainage system's ineffectiveness by causing instability in the track substructure and weakening the material surrounding the drainage pipe (Sañudo et al., 2019). In the UK railway track system, insufficient drainage is one the risk factors that is most likely to cause the failure and deformation of the tracks. The UK has the oldest railway network in the world, classified as an ageing built infrastructure. This classification is also due to the lack of appropriate long-term design guidelines available at the time the drainage systems were constructed (Spink et al., 2014).

One of the biggest challenges facing Network Rail, as the owner of the majority of railway infrastructure in the UK, is a lack of knowledge about the current condition of its drainage networks (Wu et al., 2021). Moreover, it has been mentioned in various studies that inadequate drainage is the primary cause of railway track instability and the root reason behind most railway track malfunctioning–related problems (Li et al., 2015; Sañudo et al., 2019).

It has been shown that subsurface drainage system malfunctioning, including leakage and pipe breaks, results in the emergence of a local structural weakness zone, which is typically followed by the development of a void adjacent to the drainage or water supply pipes (Amran et al., 2021; Chen & Wimsatt, 2010; Wang et al., 2022). A lack of timely detection and the insufficient maintenance of a local structural weakened zone result in a progressive increase in the size of the void, followed by ground collapse and serious damage to a railway track substructure (Wang et al., 2022). Therefore, frequent monitoring and condition assessment of the railway track substructure, as well as the detection of these progressive voids, are of critical importance. Considering the temporal and budgetary limitations present in the railway sector, preventing the loss of support to drainage pipes (caused by the development of voids adjacent to the pipes) can avoid expensive maintenance actions and service disruption following after-collapse maintenance.

Conventional inspection methods of, generally, substructural conditions and, specifically, drainage pipe conditions as a component of a railway track substructure are based on a visual inspection technique (Koch et al., 2015). As such, the inspection and detection of any local structural weakness zone, or void, is a difficult task, considering that it is buried and may, therefore, be hidden from the visual inspection. This is because, in this method, only visible defects are recognisable, and any defect that is invisible to visual sight cannot be identified accurately (or at all). In addition, these methods are not able to provide any information about the size of a local structural weakness zone, nor about the void size. Furthermore, they fail to detect the possibility of void formation adjacent to the drainage pipes (Wang et al., 2022). Over the years, various NDTs have been developed that can assess the condition of a buried infrastructure (i.e., buried subsurface drainage pipes) and investigate and detect local structural weakness zones in roads, pavements, shallow surfaces and urban buried utilities (Costello et al., 2007; Liu & Kleiner, 2014; Xu et al., 2014). As the aim of this research is to develop a technique that can be used to detect local anomalies in a railway track substructure, the following section reviews the use of NDTs to detect soil weakness zones (i.e., soil erosion voids) in the subsurface.

2.5.4.1 Ground penetrating radar

Ground penetrating radar (GPR) is one of the most robust and effective geophysical NDTs, with a proven ability in subsurface investigation. GPR is based on the propagation of short electromagnetic (EM) waves into the substructure and an analysis of reflection waves coming from the ground due to variations in the soil's physical properties, such as electrical conductivity, dielectric permittivity and magnetic permeability.

The development of GPR for the purpose of pavement condition assessment was initiated between the early to mid-1980s; currently, it is a well-established technique used in pavement condition assessment applications (Evans et al., 2008). This method has been effectively employed to locate buried infrastructures such as pipes and cables, as well as to detect local structural weakness zones or erosion voids in pavement structures (Chen & Wimsatt, 2010; Plati & Dérobert, 2015). Over the years, various studies have been conducted regarding the application of GPR technique in pavement substructure condition assessment, as well as in the detection of local anomalies in railway and pavement substructures (Chen & Wimsatt, 2010; Evans et al., 2008; Rasol et al., 2022; Wang et al., 2022). In 1985, this method was adopted for the first time in an investigation of railway track substructures (Ciampoli et al., 2020; Roberts et al., 2007). Several studies of railway track substructure condition assessment have been conducted; these include identifying the substructure thickness, examining the moisture content of ballast layers and evaluating the ballast fouling index (Basye et al., 2020; Li & Wilk, 2021).

One advantage of GPR is that it can evaluate continuous data for high-speed trains (Solla et al., 2021). However, it has been proposed in several studies that GPR data should be supported by data from other NDTs (e.g., FWD, InSAR) or destructive techniques (e.g., coring) to improve the detection of defects in railway track substructures and validate the GPR results (Evans et al., 2008; Ferrante et al., 2021; Tosti et al., 2020). Despite GPR's wide application range, some limitations exist. First, one of the primary shortcomings of the GPR method is that the interpretation of a GPR test results requires considerable knowledge and experience (Evans et al., 2008). Second, the water content of the substructure layers has a significant impact on the penetration depth of the wave pulse and, consequently, on the quality of resultant data (Hunaidi, 1998). A review of the literature shows that the application of GPR to locate buried drainage infrastructure and assess the condition of the soil surrounding a railway drainage pipe has not been sufficiently studied.

2.5.4.2 Seismic wave method

Various and growing use of seismic surface wave methods is demonstrated by increasing number of research papers and practical investigation in the geophysical field engineering, geotechnical site investigation, characterisation of pavements and railways subsurface, anomaly detection (Barta, 2010; Foti et al., 2014; Sussmann Jr et al., 2017; Tamrakar et al., 2017). Seismic wave techniques rely on the analysis of surface wave propagation along the medium, signal processing methods and inversion analysis (Fortunato et al., 2007; Gucunski & Shokouhi, 2004).

Among various seismic methods, spectral analysis of surface saves (SASW) (Nazarian et al., 1983) and multichannel analysis of surface waves (MASW) (Park et al., 1999), are most widely used techniques for civil engineering and transportation infrastructure investigation (Stark et al., 2013).

SASW test equipment includes an active source of surface waves generating, two receivers (i.e., geophones or accelerometers) and a spectrum analysis system (Plati et al., 2020). In this test the dispersion curve (i.e., surface wave velocity variation with frequency) is evaluated using arrivals time delay (i.e., phase shift) at two receivers. Various experimental dispersion curves are estimated at different offsets from receiver positions, and then combined to produce a single dispersion curve for further analysis in the inversion process (Foti et al., 2014; Stark et al., 2013).

MASW is an improved technique for multiple surface wave analysis, employed for near-surface characterisation (Stark et al., 2013).

The main disadvantage of these methods is the interpretation of seismic wave method which is laborious, complicated and dependent on the engineer's judgment and experience. Also, compared to GPR, seismic wave methods are more time consuming (Anbazhagan et al., 2011).

2.5.4.3 Infrared thermography

Infrared thermography (IRT) is another EM technique, similar to GPR, used for subsurface condition assessment. IRT is a relatively new technique developed for railway track substructure inspections, in which there is no need for contact between the IRT equipment and the surface of the track structure under investigation. This method is based on the theory of energy transfer, which states that energy moves from a warmer to a cooler space (Wang, 2017). In this technique, thermal images taken via an infrared camera generate pictures of heat flow and provide thermal information for further analysis (Crouse et al., 2009). This technique is relatively fast and can provide full-field data and real-time condition assessment (Kim, 2019). However, IRT's greatest shortcoming is its dependency on weather conditions, which limits its application considerably (Janků et al., 2019). Another limitation of this method is the need for a clear view between the infrared camera and the target surface (Clark et al., 2004). This technique is useful both for locating and conducting condition assessment of buried infrastructure. When locating buried infrastructure, the IRT measures the temperature difference between the buried infrastructure (such as a buried tank or water and sewerage pipelines) and the surrounding soil. When detecting erosion voids and leakages, this technique measures the temperature difference between the surrounding wet soil and adjacent dry soil to reveal the location of the buried anomaly (Wang, 2017). It is worth mentioning that contrary to its limited application in the UK, IRT has been successfully employed in the field of civil engineering in the USA since 1992. Its limited application in the UK may be due to the cold weather conditions and barometric pressure variations found in the country (Clark et al., 2004). Recent research by Kim (2019) investigated the application of IRT to railway materials and components. This study investigated IRT's ability to analyse deformation and failure probabilities through a temperature analysis of various railway track components. It has been asserted that this study serves as a starting point for railway track applications of IRT, and that further investigation is required for the IRT technique to become well established in the field of railway track measurement. A recent study by Wang et al. (2022) involved a comparative performance evaluation of GPR, backscatter computed tomography (BCT) and IRT. The study looked at the technique's ability to detect erosion voids around an artificially corroded steel pipe and a buried reinforced concrete pipe in a pit at a Queen's University laboratory. However, no study has investigated the ability of IRT to detect an erosion void or a structurally weakened zone around pipes buried in the railway track substructure.

2.5.4.4 Gravity gradient sensors

The novel gravity gradient sensors technique has been employed in various areas such as site investigation, exploration and underwater navigation (Metje et al., 2011). This technique can potentially be employed to detect erosion voids around culverts (Wang, 2017). However, it requires a long measurement time at each data point to acquire sufficiently accurate data. Furthermore, the presence of mass anomalies such as buildings and large structures introduces considerable noise to the data in this technique (Metje et al., 2011).

2.5.4.5 Backscatter computed tomography

Backscatter computed tomography (BCT) is another newly developed technique that uses computerised tomography–scanning (CT-scanning) technology to provide images for the detection of defects and anomalies around a buried culvert in the track subsurface. This method is, in principle, based on the measurement of backscattered radiations from projected gamma rays to the object area (Sheth & Sinfield, 2018). The successful adaption of the BCT method in the inspection of three culverts and the detection of soil erosion voids around these culverts has been reported by a pilot study conducted in the city of Toronto (Anderson & Bowles, 2012).

2.5.4.6 Ultrasonic techniques

Ultrasonic techniques are based on the travel time of acoustic waves that penetrate the ground and the reflection of these waves from the buried pipe wall to the ground surface. In this technique, high-frequency sound waves with a frequency range between 10 and 50 MHz are employed to detect buried anomalies (Sheth & Sinfield, 2018). This technique is useful for detecting cracks, corrosion and voids around pipes. The main disadvantage of this technique, however, is its sensitivity to soil and mud attached to a pipe, which means that the pipe needs to be cleaned before an inspection (Yu et al., 2021).

2.5.5 Advantages of FWD test

Railway track substructure inspections, which include railway substructure layer condition assessment and assessments of buried infrastructures (e.g.,, subsurface drainage pipelines) and the surrounding soil, are intended to detect local structural weakness zones or soil voids in the railway track substructure (Amran, 2020). In Section 2.3, the key role the railway substructure's layer moduli, among the various geotechnical and geophysical properties of the railway substructure soil, play in an assessment of the condition of the substructural layers is explained. Several track modulus measurement methods are then critically reviewed, and it is noted that, of all these methods, the FWD test is the most well-established and commonly used test employed by the railway industry in the UK.

In addition, various NDTs with the general aims of assessing substructure conditions, inspecting subsurface and detecting local anomalies (e.g., soil weakness zone) were reviewed. Each one of these techniques targets one specific physical property of the ground and buried anomalies as key criteria for detection and condition assessment purposes; for example, GPR measures electric impedance, while seismic techniques measure a seismic wave's velocity and its reflection off the buried anomalies. However, it is observed that the elastic modulus of railway substructure layers has not been sufficiently addressed in either railway track condition assessment or the detection of soil voids.

To this end, this research will investigate the potential ability of railway track substructures' layer moduli to represent the condition of a railway track, developing a condition assessment technique based on these moduli via a novel and systematic interpretation of FWD test data. The back-analysis of FWD data is an indirect method of interpreting the surface deflections acquired by this test. In the following section, therefore, the literature on the back-analysis techniques used with FWD test data for various applications, such as quantifying pavement substructures' layer moduli, is reviewed. This is because, while there are various techniques that have been developed to interpret FWD test data, these have mainly been developed for the purpose of calculating the moduli of pavement substructures in highway condition assessment.

2.6 Back-analysis techniques based on the FWD test data

The deflection data acquired from the FWD test need to be analysed and interpreted to produce meaningful information on the condition of the test material (e.g., road, pavement or railway track). Back-analysis (also known as back-calculation or inversion) is a commonly used technique used to analyse FWD data to obtain useful structural information about a buried substructure (Lee, 1988). Generally, a back-analysis technique consists of two main parts: (i) a forward model that is used to calculate surface deflections off a simulated pavement (or railway track) structure under an applied FWD load; and (ii) an optimisation technique used to estimate layer moduli by matching the simulated model with the actual data.

In the following sections, various forward modelling and optimisation techniques for the back-analysis of FWD test data in pavement applications are considered. In addition, a number of relevant studies on FWD's application to railway tracks are critically reviewed.

2.6.1 Current practice in FWD forward modelling

Over the years, various analysis and calculation methods for measuring pavement responses to FWD load have been developed; these are referred to as forward analysis or forward modelling. The basic pavement response model uses the layered elastic theory (LET) which is primarily based on Boussinesq's one-layer linear elastic theory for a one-layer semi-infinite model. This theory provides a closed-form solution that considers a point load applied to a single layer of a semi-infinite, homogeneous, isotropic and linear elastic material (Mohamed Jaafar, 2019). However, this theory is only suitable for one-layer pavements with a thin surface layer; additionally, it assumes static point loading and is not valid for dynamic loading conditions (Cao et al., 2019; Mohamed Jaafar, 2019; Öcal, 2014). To address the limitations of Boussinesq's theory, in the early 1940s Burmister presented a more developed linear elastic analysis method for pavement structures with two and three layers (i.e., surface, base and subbase layers) (Burmister, 1945). Since then, the multi-layered elastic theory (MLET) has been presented by Schiffman (1962) and widely employed in pavement structure analysis. It is worth mentioning that various MLET-based forward analysis programs have been employed embedded in several industrial back-analysis programs such as CHEVRON (Warren & Dieckmann, 1963), (Peutz et al., 1968)BISAR , WESLEA (Van Cauwelaert et al., 1989), ELSYM (Kopperman et al., 1986) and KENLAYER (Bush & Baladi, 1989; Huang, 1993; Kim & Im, 2005).. BISAR is another common and widely used MLET-based programs which was developed by Shell to calculate pavement-response characteristics, including displacement, strain and stress (Hicks, 1982; Peutz et al., 1968). One limitation of the BISAR program is the limited number of pavement layers it can model (a maximum of ten). Moreover, the nonlinear behaviour of the base and subgrade materials cannot be taken into consideration. ELSYM is a pavement analysis model that was developed at the University of California; it can be used to analyse up to five-layer pavement structures (Kopperman et al., 1986).

In 1989, the WESLEA forward analysis program was developed by Van Cauwelaert et al. (1989). This program can be used to compute displacements, strains and stresses for five-layer pavement structures. KENLAYER is reported to be the most robust pavement analysis program among the MLET-based programs, due to its ability to consider nonlinear and viscoelastic material models in its analysis (Huang, 1993).

The MLET is based on the bellow assumptions (Ioannides & Khazanovich, 1998; Öcal, 2014):

- All the pavement substructure layers are homogeneous and isotropic, use linear elastic materials and consider Hooke's law as the constitutive material model.
- Each layer is identified by two mechanical properties, such as layer modulus (elastic modulus) and Poisson's ratio.
- Each layer of the pavement substructure is infinite in a horizontal direction (Burmister's theory assumption).
- All the layers have a finite thickness, except the bottom layer, which is assumed to be a semi-infinite layer (Boussinesq's half-space theory assumption).
- The FWD load is assumed to be a static load that is uniformly distributed over a circular area (Burmister's theory assumption).

Even though the MLET has been widely used in pavement analysis, there are some limitations associated with this approach that cause errors and uncertainties in back-analysis results. These shortcomings are mainly related to the above-mentioned assumptions. The difference between the simplifying assumption of the linear elastic material model and the real behaviour of the soil material in each pavement layer can cause a modelling discrepancy within the actual test. For instance, the asphalt concrete may show viscoelastic behaviour as a time- and temperature-dependent parameter, or the subgrade material may typically show nonlinear behaviour under loading. In addition, the assumed static loading neglects the dynamic nature of FWD test loading (Cao et al., 2019). However, to be able to solve the governing equations in the forward model, these assumptions are unavoidable. To address this issue, numerical modelling methods have been proposed that offer a more representative simulation of the FWD test and its results. For example, finite element–based (FE-based) forward models can address the limitations of MLET, improve the accuracy of the modelling and, consequently, produce more realistic data (Cao et al., 2019; Hamim et al., 2018).

Over the years, various studies have been conducted that investigate the application of FE models as forward models in back-analysis program packages (Al-Qadi et al., 2010; Ceylan et al., 2005; Jiang et al., 2022; Loizos & Scarpas¶, 2005; Rezaei-Tarahomi et al., 2017). ILLI-PAVE is a two-dimensional (2D) axisymmetric FE–based analysis model developed at the University of Illinois that is used to measure highway and conventional flexible pavement layers (Raad & Figueroa, 1980; Thompson, 1992). A limitation of this program is the large memory space required for ILLI-PAVE analysis.

MICHPAVE is another nonlinear FE model, developed by Harichandran et al. (1990), that can be used to analyse and design flexible pavement structures. MICHPAVE is a user-friendly computer program that can be used on personal computers. Another unique feature of this program is its lower memory requirement and computational time for analysis; this has been achieved by implementing the shallow FE mesh on a flexible boundary (Harichandran & Yeh, 1988). Moreover, both ILLI-PAVE and MICHPAVE have the ability to incorporate any stress-dependent properties and consider the resilient modulus of granular and fine-grained soil materials in the pavement structure (Chen et al., 1995). However, both programs are limited by the simplified loading conditions that they impose. That is, in these programs, only a single circular uniform loading area can be modelled, while dual-wheel loading cannot be modelled.

General FE model–based software such as ABAQUS and ANSYS became useful for pavement structure analysis. These software programs, in comparison to previously developed 2D axisymmetric FE-based programs such as ILLI-PAVE, allow users to simulate a complete three-dimensional (3D) model of a pavement structure. A comparison study was conducted by Chen et al. (1995) that investigated the performance of ILLI-PAVE, MICHPAVE and ABAQUS as FE model–based programs and DAMA and KENLAYER as MLET-based programs; the goal was to identify the most reliable software for flexible pavement structure analysis. The researchers concluded that the 3D FE model, ABAQUS, has a close agreement with the 2D FE model, MICHPAVE. However, ABAQUS's required computation time was reported to be around one to two hours, which was higher than that of the other programs and would not be useful in frequent pavement structure analyses.

Zaghloul and White (1993) conducted research on a section of a conventional flexible pavement structure, consisting of surface, base and subbase layers, using viscoelastic and elastoplastic materials under a moving load. The response of the pavement structure was calculated through 3D dynamic FE modelling in the ABAQUS program. The calculated pavement responses were validated against BISAR, a MLET–based program and show a high linear correlation.

Steven et al. (2007) have presented the results of an analysis of a flexible pavement, located in New Zealand, under varying FWD loading using the ABAQUS program. In this study, a user-defined nonlinear elastic material model was adopted for use with a granular base and subgrade layers. The study's results show that the FE model could successfully simulate and analyse the pavement structure and its surface responses to the applied FWD load.

Another study, conducted by Li et al. (2017), employed a 2D axisymmetric FE model, using ABAQUS to analyse and capture the complex material characteristics, layer interfaces and boundary condition effects of a pavement section under FWD testing conditions. After validating the results against in-field FWD experimental data, this research determined that the ABAQUS simulation employed in the study was able to analyse various constitutive material models, noting the interaction between the layers and taking the temperature effect and dynamic loading effect into account.

In terms of railway track applications, a study has been caried out by Burrow et al. (2007) that employed ABAQUS software to analyse a railway track substructure under the FWD test condition. In this study, a 3D model for a railway track section located near Leominster station, UK was simulated under standard FWD test conditions. Although the FE-based forward models overcome the previously mentioned limitations of the MLET-based forward analysis, they are computationally costly, which makes them inefficient and therefore unsuitable for problems with complex geometries and consequently computationally costly back-analysis techniques (Haji Abdulrazagh et al., 2019; Loizos & Scarpas, 2005; Matsui et al., 2006; Saltan & Terzi, 2004). To overcome the above-mentioned problems, an ANN (as an artificial intelligence [AI]) technique) was introduced as a replacement to the FE-based forward models. For the first time, Meier (1995) used an ANN to estimate a pavement's layers moduli, based on FWD deflection data. Ceylan et al. (2005) later developed an ANN-based forward model (i.e., an ANN surrogate forward model) to calculate pavement surface deflections under FWD loading. In this study, ILLI-PAVE 2000 was employed to generate a database for ANN training. The results of these studies show that ANN forward analysis can calculate the surface basin deflection under FWD loading in a significantly shorter period of time compared to FE-based methods, while maintaining the nonlinearity of the problem. Rakesh et al. (2006) developed an ANN surrogate forward model that incorporated a previously developed back-analysis model (BACKGA) and evaluated the ANN's performance in terms of the back-analysis time. The comparison showed that, compared to BACKGA back-analysis, the computational back-analysis time achieved by ANN–BACKGA was decreased by 97%. This result indicates the fast calculation ability and computational efficiency of the ANN model.

A study conducted by Beltran and Romo (2014) investigated the ability of an ANN to act as an nonconventional approximation method that could predict the pavement surface deflections of a four-layer system and then estimate a pavement's layer moduli based on experimental FWD test data. The assessment of the ANN results demonstrated the robustness and reliability of this method of modelling the correlation between the applied FWD load and its resulting deflections, as well as its ability to calculate surface deflections within an efficient computational time.

Other, similar studies have shown the efficiency of ANN when modelling deflections under FWD loading. For example, Kargah-Ostadi and Stoffels (2015) developed a novel back-analysis technique based on an ANN surrogate forward model and a restart covariance matrix. In this study, a three-layer flexible pavement structure was simulated in EverStressFE software, and 7,778 sets of data were generated for ANN training. ANN replaced a 3D FE-based model, speeding up the back-analysis process while maintaining the accuracy of the calculations.

2.6.2 Available approaches to the back-analysis based on the FWD test data

An inversion analysis of FWD test deflections involves an algorithm that incorporates a forward model of the FWD test (e.g., the FE model or an ANN) and uses a search technique to estimate the moduli of pavement layers by matching the deflections in the forward model with actual FWD deflections (Kargah Ostadi, 2013; Öcal, 2014). In each iteration of the inversion analysis, the search algorithm adjusts the parameters of the forward model so that the calculated deflections in the forward model become closer to the actual measured FWD deflections. This iterative inversion analysis produces a forward model with layer modulus values that are close to the actual test site. Inversion analysis can be categorised into two main groups: classic and soft computing methods. The following sections discuss these two categories in detail.

2.6.2.1 Classic methods

2.6.2.1.1 Iterative back-analysis method

This method is based on the gradient matrices idea, which starts with a set of assumed layer moduli (i.e., seed moduli) and repeatedly adjusts the layer modulus values until a match between the calculated basin deflection and the measured basin deflections (i.e., the minimum difference between the measured and the calculated basin deflections) is achieved (Alkasawneh, 2007; Harichandran et al., 1993; Kutay et al., 2011). To date, several back-analysis programs based on this method have been developed for pavement applications; these include BISDEF, CHEVDEF, ELSDEF, BAKFAA, ELMOD, WESDEF and MICHBACK. These programs are based on the various MLET forward analyses that were explained in the previous section. For example, BISDEF is based on a BISAR forward analysis subroutine, while CHEVDEF and MICHBACK use CHEVRON as the forward analysis subroutine. The first limitation of iterative back-analysis methods is their dependency on seed modulus values at the start. In these methods, the user is required to enter seed modulus values. This dependency can increase the possibility of trapping the analysis in the local minima; that is, providing a local solution to the problem. As such, the quality of the results and the convergence to the predefined range of values are both dependent on the seed values. Secondly, these methods suffer from limitations in terms of the number of pavement layers that they can analyse (they can go up to five layers, except for BAKFAA, which can be applied to 10 pavement layers). Furthermore, increasing the number of pavement substructure layers makes these methods time consuming (Alkasawneh, 2007). Finally, these methods only use a static load for their analyses, and the dynamic nature of FWD loading is neglected (Li, 2017).

2.6.2.1.2 Database back-analysis method

This method was originally developed by Uzan et al. (1988). In this method, a database that includes several generated basin deflections and their corresponding layer moduli is used for the back-analysis. During the back-analysis process, the generated database is searched to find a given basin deflection; the goal is to find the best fit for the basin deflection and the corresponding set of layer moduli. This method is faster than iterative back-analysis methods because it does not include multiple solutions from the forward model (as is the case in iterative analysis). MODULUS, a back-analysis program based on this method, uses a pattern searching algorithm and the Lagrange interpolation technique to estimate layer modulus values in such a way that minimises the error between the calculated and measured basin deflections. This method's limitation is the possibility of converging to the local minima, as the global minima might not be included in the database under consideration (Chou & Lytton, 1991).

2.6.2.2 Soft computing methods

Over the years, various metaheuristic optimisation methods (also known as soft computing techniques) have been employed as search algorithms in as inversion analysis. For example, the GA is a metaheuristic optimisation algorithm that is reported to be a robust tool for back-analysing pavement layer moduli based on FWD deflection data. NUS-GABACK was developed and introduced by Fwa et al. (1997) as the first GA-based back-analysis technique. The BACKGA program was another GA-based model developed for the back-analysis of flexible pavement layer moduli using FWD experimental data (Reddy et al., 2002). ELYAR was employed as the forward analysis model in the BACKGA program. In addition, several research studies have been conducted that investigate the accuracy and efficiency of GA-based back-analysis techniques (Pan et al., 2012; Park et al., 2010). In addition, other metaheuristic optimisation algorithms such as particle swarm optimisation (PSO) (Gopalakrishnan, 2009b; Öcal, 2014), differential evolution (DE) (Gopalakrishnan & Khaitan, 2010); shuffled complex evolution (SCE) (Gopalakrishnan, 2009b); and the Lévy ant colony optimisation (ACO_{RL}) (Scimemi et al., 2016) have been employed in back-analysis.

Each of the soft computing methods have their own advantages, based on their various natures. A combination of these methods may generate more robust back-analysis techniques. Some studies have proposed a combined back-analysis technique based on integrating an ANN and a metaheuristic optimisation method to back-analyse moduli and the thickness of pavement layers. Among these metaheuristic optimisation techniques, the GA has become a widely used method due to its robustness in global searches, which allows it to overcome the local minima problem. Combining the application of a GA and an ANN, Rakesh et al. (2006) have developed the ANN–BACKGA back-analysis technique for layer modulus predictions. In addition, a program named the Neuro-Genetic Optimisation Toolbox was developed to back-analyse nonlinear pavement layer moduli (Gopalakrishnan, 2009a). In these hybrid back-analysis techniques, the ANN acts as a surrogate forward model, with the GA as an optimisation algorithm, to find the optimum input value for the ANN (Gopalakrishnan, 2009a; Rakesh et al., 2006; Wang et al., 2019). In another study by Ghorbani et al. (2020), a GA is incorporated to optimise the internal parameters (e.g.,, weights and biases) of an ANN, rather than input the ANN's values. In a study conducted by Nazzal and Tatari (2013), the ANN and the genetic algorithm were used to estimate subgrade resilient moduli (M_R). The study's results showed that the ANN–GA models produce more accurate results than ANN-based models. In addition, a hybrid back-analysis technique was developed by Li and Wang (2019) that could predict pavement layer moduli, and the hybrid ANN–GA results were validated against experimental data from the Long-Term Pavement Performance (LTPP) database. This validation showed that the estimations of the layer moduli by the hybrid ANN–GA were highly accurate. The high reliability of this hybrid soft computing technique can be attributed to its independence from the seed modulus values that are required for complex material characteristics in classic back-analysis methods. The results of these studies indicate that using a combined technique can achieve the most accurate results within an efficient computation time.

Only a limited number of studies have been conducted into the application of back-analysis techniques to railway track systems using FWD test data. Burrow et al. (2007) employed FWD test data to back-analyse the moduli of a railway track's substructural layers. In their study, in order to identify the track substructures' layer moduli, a manual trial-and-error process was performed through a parametric study of the layer moduli. Although Burrow et al. (2007) have reported promising outcomes, due to the nature of their trial-and-error approach their study cannot be extended to other railway subsurface scenarios. Additionally, their proposed approach can be computationally demanding, particularly if the problem involves complex geometries and boundary conditions. Furthermore, their method is highly dependent on the user's experience to define seed modulus values. Recently, Haji Abdulrazagh et al. (2019) developed a back-analysis technique based on the rail falling weight test (RFWT) and ground falling weight test (GFWT). They used the multi-layered elastic theory as the forward model for a limited number of track substructure layers (up to three layers). The inversion part of their technique was based on an iterative method, in which seed moduli for each layer need to be assumed per each iteration; this, consequently, affects the accuracy of the results. In addition, their back-analysis technique's computation time for a three-layer substructure was reported to be around 900 seconds (s). This technique suffers from computational inefficiency due to the multi-running of forward simulations during the optimisation process, and its application is limited to three substructure layers. Considering the limited number of studies conducted on railway applications and their limitations, this thesis identifies the absence of an accurate and time-efficient back-analysis technique for use in railway track substructure condition assessment as a significant area in the field that requires improvement.

2.7 The need for further research

In this review of the literature, it is demonstrated that quantifying each substructure's layer moduli is a reliable railway track substructure condition assessment method, offering a way to detect local voids and structural weakness zones around a buried drainage pipe in the railway track substructure. It is also established that, although there are various physical and geomechanical properties (such as electric resistivity and elastic moduli) that have been used in railway track substructure condition assessment and void detection (such as in GPR), less attention has been paid to layer moduli for local condition assessment purposes.

Over the years, many research studies have considered the effect of railway track moduli on a track's performance and the various methods that can be used to measure this. However, the understanding of and knowledge about these parameters, their application to railway track substructure condition assessment and the methods by which they can be quantified have not as yet been sufficiently addressed. In addition, by reviewing various track modulus measurement methods and subsurface exploration techniques, it has been determined that continuous stiffness measurement equipment is strictly limited to only a few railway-sector companies, due to the high cost of these tools. Currently, the FWD test is regularly utilised in the UK railway industry; this method is very able to measure the moduli of different layers of track substructure, with a good repeatability, and has a practical application through the measurement of track surface deflection at various locations along the track structure.

Although there have been various studies that have considered the application of FWD test data to pavement condition assessment via back-analysis techniques, few have directly focused on their application to railways. As such, further studies are necessary to develop a systematic framework that can estimate railway track substructures' layer moduli for the purpose of accurate railway substructure condition assessment and effective maintenance action planning. Combining experimental test results, especially deflection-based methods such as FWD, with numerical modelling (such as FE) can contribute to gaining a more in-depth knowledge of the railway track substructure and its components; this, in turn, can be used in condition assessment and the detection of local anomalies (Boler et al., 2018).

Additionally, it should be noted that although various studies have been conducted that assess the condition of both railway and pavement substructures, most of these studies have considered idealised railway and pavement substructure layers, with no consideration of any buried anomalies (i.e., healthy condition). Furthermore, none of these studies address the application of back-analysed substructures' layer moduli (based on FWD testing data) to detect any local structurally weakened zones. Thus, the current research addresses this gap by developing a systematic back-analysis technique that can interpret FWD test data for railway track sections. This back-analysis technique can potentially offer great advantages in the shape of frequent, time- and cost-effective, reliable and robust condition assessment of railway track substructures.

Chapter 3

Development of an FE forward model for a railway track substructure under FWD testing

3.1 Introduction

This chapter presents the development of the FE forward model. This model simulates the mechanical behaviour of a railway track substructure under the FWD test. The FE forward model is developed based on a dataset from a railway track section near Leominster station in Herefordshire, UK (Figure 3.1). The FWD and CPT data from the test site near Leominster station were used to develop a 3D FE model of the railway track section using COMSOL Multiphysics software. The CPT data from the test site was used to define the substructure layers' geometrical configuration and offer the first estimation of the layer moduli in the FE simulation. The FWD test results reported from the Leominster station test site were then used to validate the developed FE forward model.

Figure 3.1: Leominster station site, Herefordshire, UK (Wikipedia, 14 March 2015.)

Details of the simulation (including model assumptions, model geometry and boundary and loading conditions) and the material properties of the model are explained in Sections 3.2 to 3.6, respectively. In Section 3.7, the FE forward model developed in this study is validated against a set of FWD test data from the literature to check the accuracy and reliability of the model. Section 3.8 presents a parametric analysis that uses the FE forward model to investigate the effect of each substructure's layer moduli on the surface deflection. Finally, Section 3.9 outlines the procedure through which the FE forward model can address the thesis objectives (i.e., developing an inversion framework and performing the trial tests).

3.2 Model assumptions

FE modelling requires sufficient detail and accuracy to simulate a realistic case. The level of detail should be optimised to maintain the required accuracy and avoid unnecessary computational time and energy (Potts et al., 2001). It is worth noting that the FE forward model here is used in the back-analysis framework, wherein the basin deflection database is generated to train the ANN surrogate forward model. Thus, from a practical point of view, the model's computation time becomes a significant matter. To this effect, the following simplifying assumptions have been made when developing the primary FE forward model:

1. All the materials in the simulation are assumed to be linear elastic, homogeneous and isotropic.
2. All the substructure layers, including the sleeper and ballast layers, are assumed to have fully bonded contacts (i.e., the model is continuous).
3. All substructure layers are assumed to be in healthy condition, with no buried drainage pipe, no soil weakness and no anomalies in the layers.

3.3 Model geometry

An FE model was used to simulate the 3D geometry of the test site's ballasted substructure under the FWD testing condition. Only a quarter of the system (including the geometry and loading conditions) was modelled, taking advantage of the symmetrical nature within the problem to reduce the computation time. Figure 3.2 shows a schematic configuration of the railway track substructure layers in the FE model. The modelled railway substructure consists of a loaded sleeper, two ballast layers, two clay layers (subgrades 1 and 2) and a sand-and-gravel layer (subgrade 3), shown in Figure 3.2. Moreover, in this simulation a half of the sleeper width which is 1.21 m modelled (see Figure 3.2).

In a vertical direction, the thickness and the material type (i.e., clay or sand) of each substructure layers layer was determined using the data from eight CPT results reported by Brough et al. (2006). The CPT plot reported by Brough et al. (2006) indicates that the ballast layer depth along the test site section varies between 0.9 and 1.3 m. In addition, the presence of a clay layer exactly beneath the ballast layer and up to the maximum depth of 3.8 m from the surface is shown in the CPT results. This clay layer was comprised of firm clay that becomes soft by depth; this is plotted in the CPT results. The stratigraphy of the test site shows that the clay layer is underlain by a continuous sand-and-gravel layer. For simulation purposes, the thickness of the railway track substructure layers is idealised as 0.9 m of ballast, 2.8 m of clay and 6.1 m of sand-and-gravel layer, as shown in Figure 3.2. It is worth noting that further experimental test results, as reported by Brough et al. (2006), have shown the ballast layer to be contaminated with the soft clay from the layer below. Based on these results, the first 0.3 m of the ballast layer (named ballast 1) was assumed to be a clean ballast layer, while the 0.3 to 0.9 m beneath the clean ballast layer is considered to be a contaminated ballast layer (named ballast 2), see Figure 3.2.

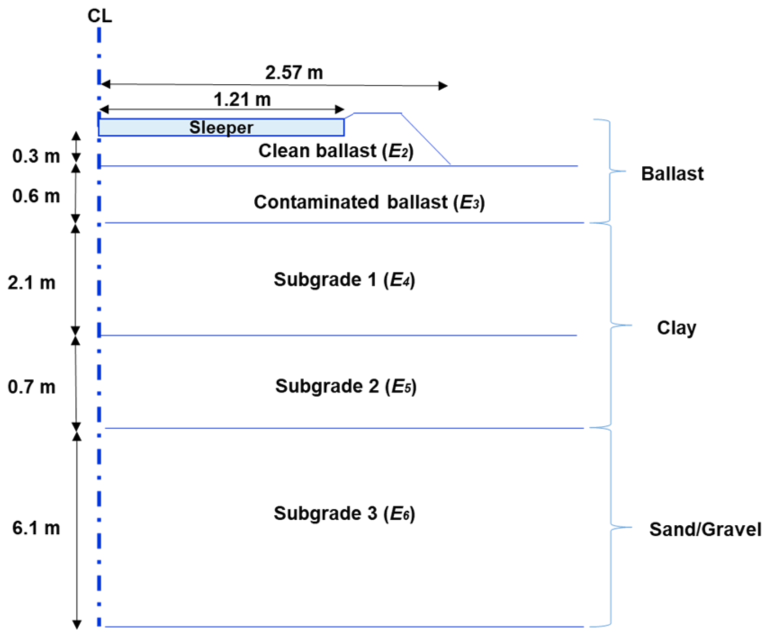
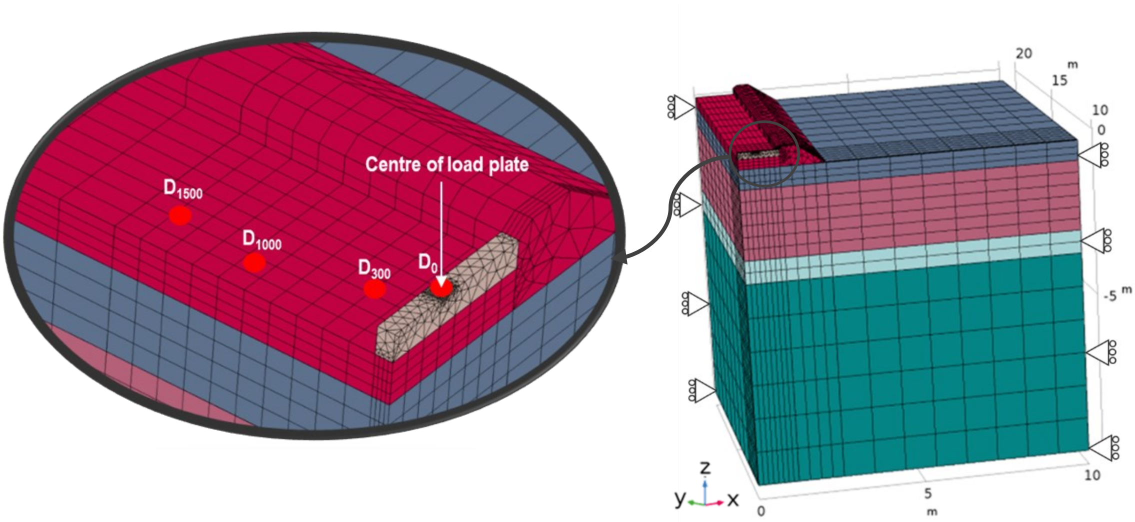


Figure 3.2: A cross-section of the railway track section near Leominster station, UK

The above details were implemented in an FE model of the railway track. The geometry of the track substructure and the FE mesh employed to model the system are shown in Figure 3.3. For the meshing of the FE model, quadratic brick elements were used to represent the ballast, subballast and subgrade layers. The slope side of the ballast layer is meshed with tetrahedral elements to create a more precise representation of its geometry.



(a) A close view of the loading point and four geophone locations

(b) Geometry and meshing

Figure 3.3 (a-b): (a) A close view of the loading point and four geophone locations; (b) Geometry and meshing of the 3D FE forward model of a quarter of the railway track section near Leominster station test site, UK

3.4 Boundary conditions

Assigning appropriate boundary conditions to the physics of the railway track substructure is necessary to solve the FE model (Rabbi & Mishra, 2021). For this reason, in this analysis the size of the model is considered sufficiently large as to nullify the effect of shear wave reflection from the outer boundaries that occurs due to the dynamic loading conditions (Burrow et al., 2007). The size of the model is calculated based on the subgrade shear wave velocity, estimated using Equation 3.1, and on the analysis of the distance travelled by the subgrade shear wave during the test (Davis & Selvadurai, 2005). In Equation 3.1, *E* is the layer modulus, *v* is Poisson's ratio, and *ρ* is the material density.

$$V_s = \sqrt{\frac{E}{2(1+\nu)\rho}} \qquad \text{Equation 3.1}$$

Taking into account the fact that the FWD load is applied at 0.55 m from the sleeper centre (point D_0 in Figure 3.3), the wave travel distance analysis shows that the horizontal dimension of the model that is perpendicular to the track (in *x* direction in Figure 3.3b) should be at least 9.25 m, while the model dimensions in *y* and *z* directions should be at least 8.7 m. For this reason, a geometry of 10 m x 10 m x 10 m is modelled to prevent the wave from being reflected by the outer boundaries and to avoid any boundary effects on the surface deflection calculations in the FWD test. In addition, deflections in all three directions (*x*, *y* and z) are fixed at the bottom of the model, and a symmetry boundary condition is applied to both the near-end perpendicular and left-sided planes parallel to the track direction (see Figure 3.3b). Furthermore, because the model is symmetrical in two *x* and *y* directions, to reduce the computational cost the roller boundary condition is assigned to both the right side and the far end of the model boundaries.

3.5 Loading conditions

Based on the FWD loading data reported at the test site near Leominster station (Brough et al., 2006), the dynamic FWD pulse load in the FE model is defined by an idealised haversine function with a duration of 40 milliseconds. This load is assumed to be applied at the same location as the geophone 1 that is located on the sleeper (see Figure 2.3). The magnitude of the load is considered to be 31.25 kN, which is a quarter of the FWD load magnitude defined in the UK standard (i.e., $\frac{1}{4} \times 125\ kN$), because the symmetry boundary conditions in the model are used twice. The load is applied to the sleeper through a load plate, and the centre of the plate is modelled at 0.55 m from the centre of the sleeper (see Figure 2.3).

3.6 Material properties

As mentioned in the model assumptions section (Section 3.2.1) a linear elastic material model is employed to describe the soil layers. The linear behaviour of the substructure soil layers is reasonable due to the small deflection values under the FWD test, wherein the material behaviour remains in the elastic zone (Sadrossadat et al., 2020). However, a non-linear material model was considered for both clean and contaminated layers to investigate the effect of this assumption on the errors. Although, the result of this simulation shows that the considering non-linear material model cause 1.32% decreasing of the average error compared the linear model, its' simulation time increased by 2 times (around 20 minutes). So, employing the linear elastic material model reduces the computational cost of the FE solution. The elastic modulus is the dominant parameter used to define a linear elastic material.

The CPT data reported by Brough et al. (2006) is used in this study to define the track substructures' layer moduli as inputs for the FE model. The cone resistance (q_c) and sleeve friction (f_s) profiles that are presented as the CPT results are digitised, following which their corresponding values are substituted in Equation 3.2 to calculate the elastic modulus for each substructure layer.

$$E = 0.047 \times \left[1 - \left({}^{q}/_{q_{ult}}\right)^{0.3}\right] \times \left[10^{0.55 I_c + 1.68}\right] \times (q_t - \sigma_{v0}) \qquad \text{Equation 3.2}$$

Where,

${}^{q}/_{q_{ult}}$ is assumed to be 0.5 (Hertzberg et al., 2020)

$I_c = [(3.47 - logQ_{tl})^2 + (logF_r + 1.22)^2]^{0.5}$

Where,

q: Applied stress

q_{ult}: Ultimate tensile strength$F_r = \left[{}^{f_s}/_{(q_t - \sigma_{v0})}\right] \times 100\%$

$Q_{tl} = {}^{(q_t - \sigma_{v0})}/_{\sigma'_{v0}}$

q_t= cone tip resistance

f_s= cone sleeve resistance

σ_{v0}= total overburden stress

σ'_{v0}= effective overburden stress

It is worth noting that, since the analysis period is short, it is presumed that the contaminated ballast layer and subgrade layers have undrained behaviour. Therefore, a Poisson's ratio of 0.49 is assigned to these layers (Burrow et al., 2007).

Table 3.1 presents the mechanical properties of the substructure layers' material employed in the FE forward model.

Table 3.1: Mechanical properties of the track and soil used to model the railway section near Leominster station, UK

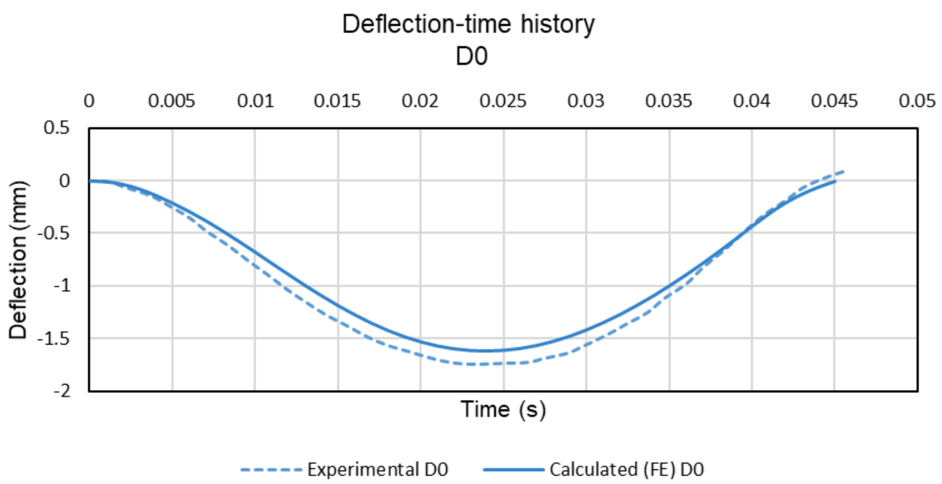
Layer	Property	Value	Reference
Sleeper	Layer modulus, *E* (GPa)	20.7	Brough et al. (2006)
	Poisson's ratio, v	0.15	Burrow et al. (2007)
	Density, ρ (kg/m^3)	2,500	Burrow et al. (2007)
	Damping ratio	0.05	
Clean ballast (ballast 1)	Layer modulus, *E* (MPa)	110	Brough et al. (2006)
	Poisson's ratio, v	0.2	Burrow et al. (2007)
	Density, ρ (kg/m^3)	1,700	Burrow et al. (2007)
	Damping ratio	0.05	
Contaminated ballast (ballast 2)	Layer modulus, *E* (MPa)	32.5	Brough et al. (2006)
	Poisson's ratio, v	0.49	Burrow et al. (2007)
	Density, ρ (kg/m^3)	1,800	Burrow et al. (2007)
	Damping ratio	0.05	
Subgrade 1	Layer modulus, *E* (MPa)	71.83	Brough et al. (2006)
	Poisson's ratio, v	0.49	Burrow et al. (2007)
	Density, ρ (kg/m^3)	1,900	Burrow et al. (2007)
	Damping ratio	0.03	
Subgrade 2	Layer modulus, *E* (MPa)	33.96	Brough et al. (2006)
	Poisson's ratio, v	0.49	Burrow et al. (2007)
	Density, ρ (kg/m^3)	1,900	Burrow et al. (2007)
	Damping ratio	0.03	
Subgrade 3	Layer modulus, E (MPa)	362.1	Brough et al. (2006)
	Poisson's ratio, v	0.49	Burrow et al. (2007)
	Density, ρ (kg/m^3)	1,800	Burrow et al. (2007)
	Damping ratio	0.025	

3.7 FE model results and validation study

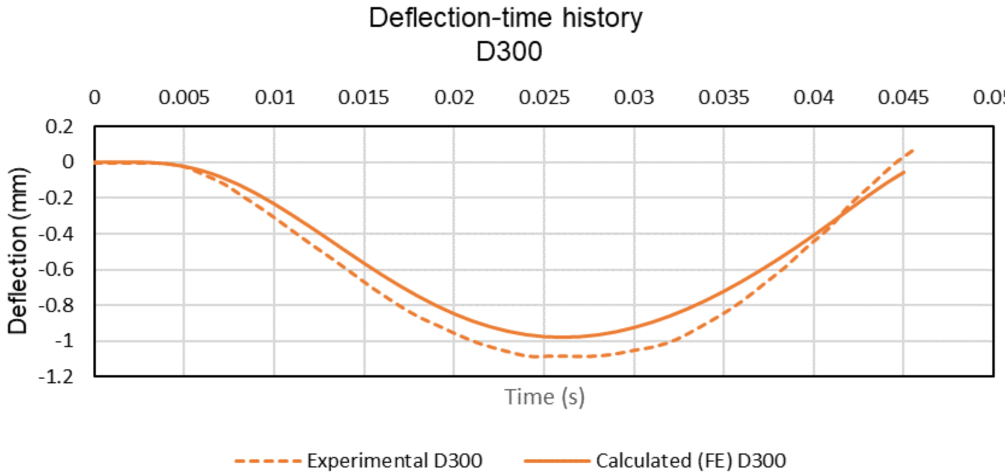
In this section, the results of the FE model of the railway track substructure developed under the FWD testing were analysed and compared against a set of FWD trials from the literature. This validation study was carried out to investigate the reliability and accuracy of the FE model developed in this study, as well as its ability to capture the track substructure behaviour under FWD loading test conditions. This step needs to be undertaken before employing the FE forward model in further analysis and before developing a back-analysis technique for railway track substructure condition assessment. In addition, the validated model is used to analyse the performance of a commercial back-analysis software product namely, BAKFFA, for railway track application:

To validate the FE forward model developed in this study, the deflection values calculated by the FE model were compared to the FWD field trial data acquired at the test site near Leominster station, Herefordshire, UK reported by Burrow et al. (2007). The deflection-time history calculated by the FE model and the corresponding experimental FWD deflection-time history, obtained for four geophones at different offsets from the FWD loading point, are illustrated in Figure 3.4a–d. The four geophones that were used in the comparison of the FE results and the experimental data are located 0, 300, 1000 and 1500 mm from the loading point. Accordingly, the deflections at these geophones are named D_0, D_{300}, D_{1000} and D_{1500}.

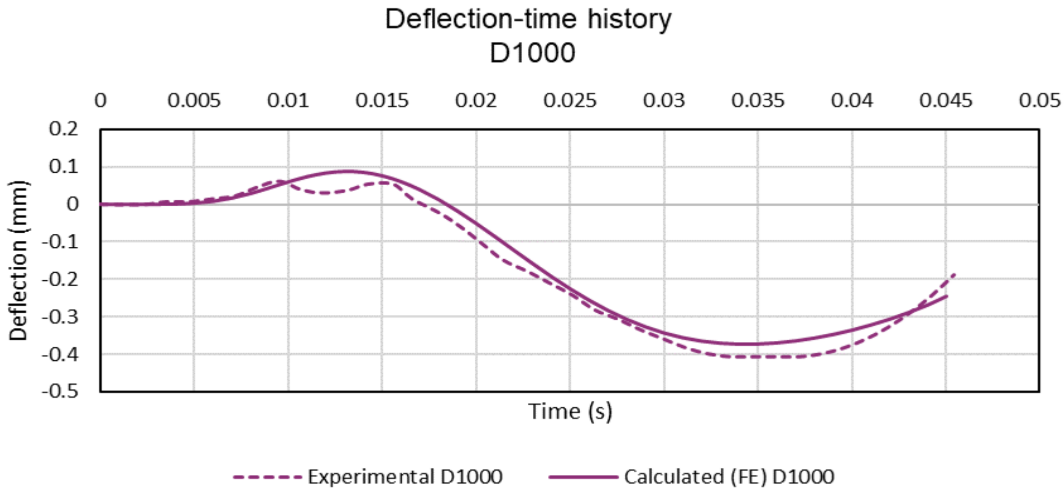
The FWD load applied to the sleeper generates a deflection-time history, shown at Figure 3.4a–d, where the deflections decrease the further from the loading plate. It can be observed that the calculated (FE model) deflection-time history follows a similar trend to that of the experimental data, and the FE model developed in this study shows a close agreement with the experimental deflections for all four geophones (D_0, D_{300}, D_{1000} and D_{1500}).



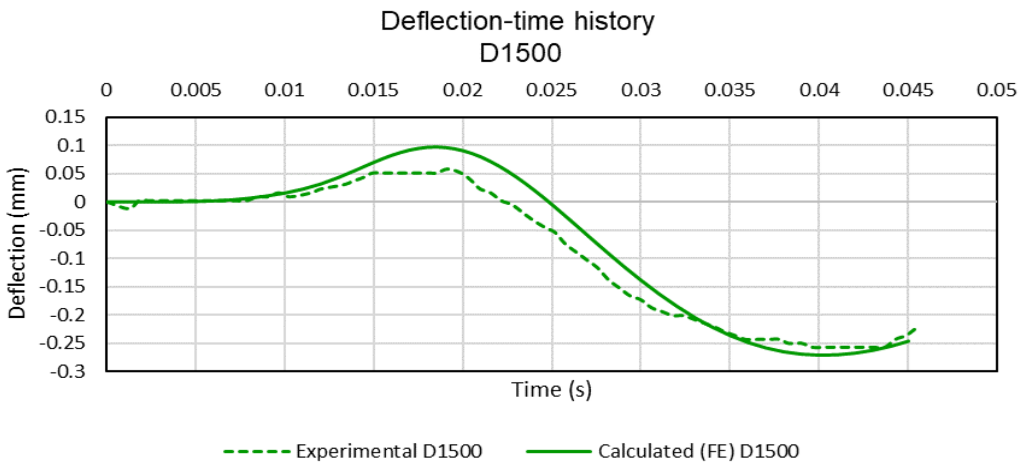
(a) D_0 (Geophone 1)



(b) D_{300} (Geophone 2)



(c) D_{1000} (Geophone 3)



(d) D_{1500} (Geophone 4)

Figure 3.4: Experimental FWD deflection-time histories versus calculated deflection-time histories at (a) D_0, (b) D_{300}, (c) D_{1000} and (d) D_{1500}

In addition, the peak deflections calculated by the FE model were compared to the measured peak deflection in the FWD experiment; Table 3.2 presents the percentage error for the peak deflections seen in the field data, comparing them to the FE model's results. The percentage error values of the calculated and measured peak deflections, i.e., D_0, D_{300}, D_{1000} and D_{1500}, were 6.961%, 9.473%, 7.821% and 5.378%, respectively. According to the scale used in this study, these percentage error values (which are consistently less than 10% and have an average of 7.4%) confirm the accuracy of and significant agreement seen in the FE model's predictions when compared to the experimental data.

Table 3.2: Comparisons of the FWD measured and FE model's calculated deflections for the railway section near Leominster station, UK.

Data point	Maximum surface deflection (mm)		Percentage error
	Measured (experiment)	Calculated (FE model)	
D_0	−1.73658	−1.616	6.961
D_{300}	−1.08288	−0.980	9.473
D_{1000}	−0.40584	−0.374	7.821
D_{1500}	−0.2566	−0.270	5.378

3.8 Parametric analysis

This section offers a parametric analysis of the FE forward model developed in this study, the purpose of which is to study the effect of layer moduli on the deflections of a railway track and to quantify the relative effect of each layer on the deflections. The layer moduli is the most significant parameter on railway track deflections under loading (Kouroussis et al., 2013). Thus, understanding the extent to which layer modulus affects surface deflections is crucial to the development of a deflection-based condition assessment back-analysis technique.

In this regard, a uniformly distributed non-random range of values for each of the five substructure layer moduli (i.e., E_2, E_3, E_4, E_5 and E_6) was introduced to the FE model developed in this study. The modulus of each layer and the range of values assigned for the purpose of parametric analysis are presented in Table 3.3. The actual layer moduli values were estimated based on the CPT results reported at the Leominster station test site. The ranges presented in Table 3.3 contain modulus values that show a 2 to 8% difference (increment of 2%) compared to the actual layer modulus values.

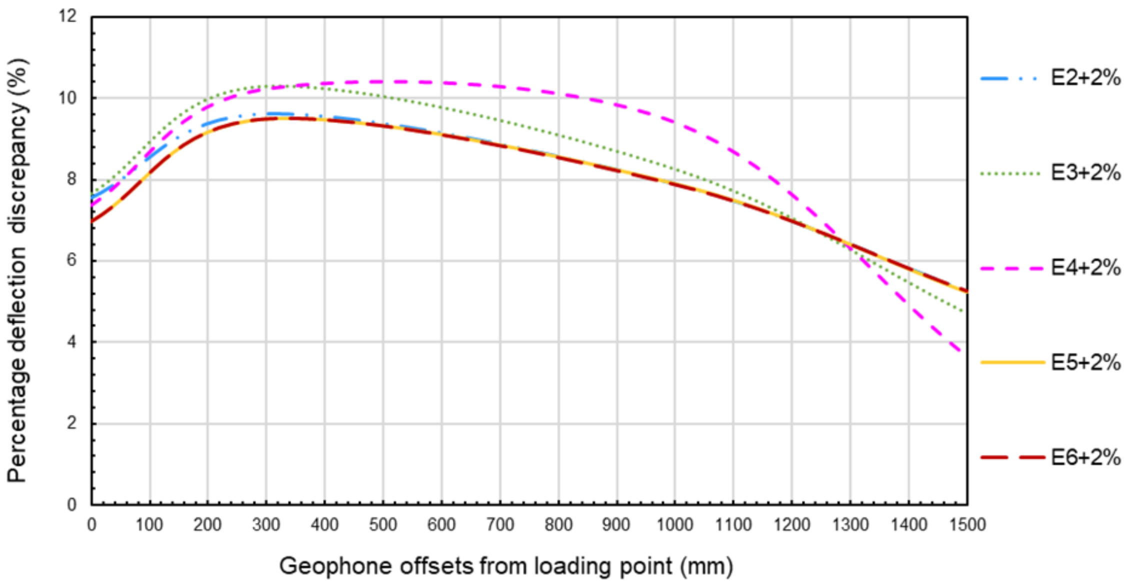
The railway track deflections at the four offsets from the FWD loading point (i.e., D_0, D_{300}, D_{1000} and D_{1500}) for each set of the layer modulus values were calculated using the FE model developed in this study.

Table 3.3: Layer moduli of the railway substructure tested in a parametric analysis

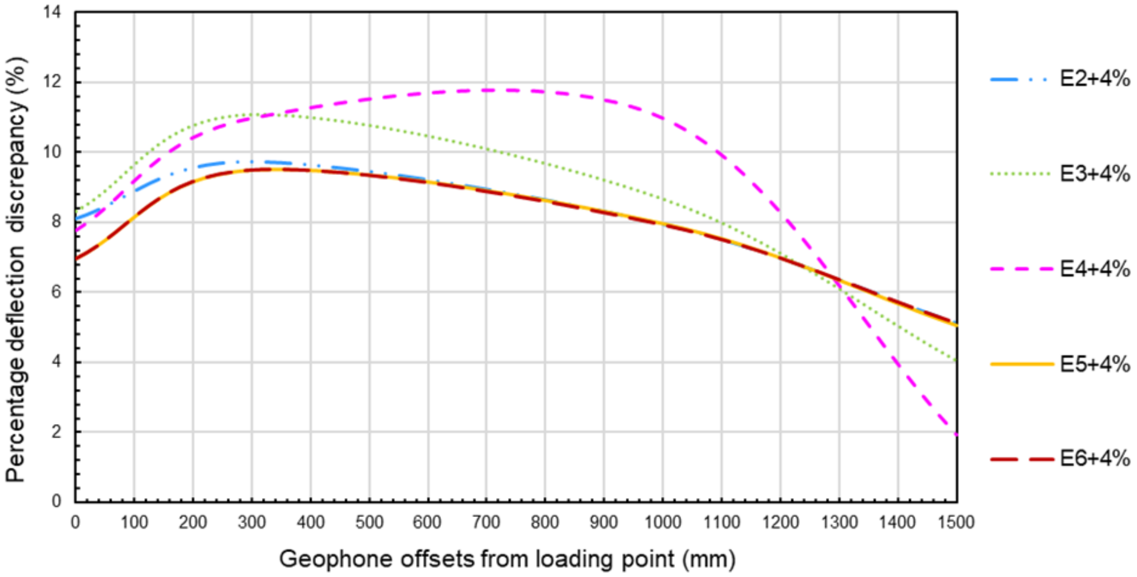
Layer	Layer moduli	Initial layer moduli	Layer moduli values tested
Clean ballast (ballast 1)	E_2	*110*	112.2, 114.4, 116.6, 118.8
Contaminated ballast (ballast 2)	E_3	*32.5*	33.15, 33.8, 34.45, 35.1
Subgrade 1	E_4	*71.83*	73.265, 74.7024, 76.138, 77.575
Subgrade 2	E_5	*33.96*	34.635, 35.314, 35.993, 36.673
Subgrade 3	E_6	*362.1*	369.342, 376.584, 383.826, 391.068

Figure 3.5a–d presents the percentage discrepancy in the surface deflections caused by substructure layer moduli variations at 2%, 4%, 6% and 8%, and initial layer moduli values, versus the geophone offsets from the loading point, which serve as the deflection recording points.

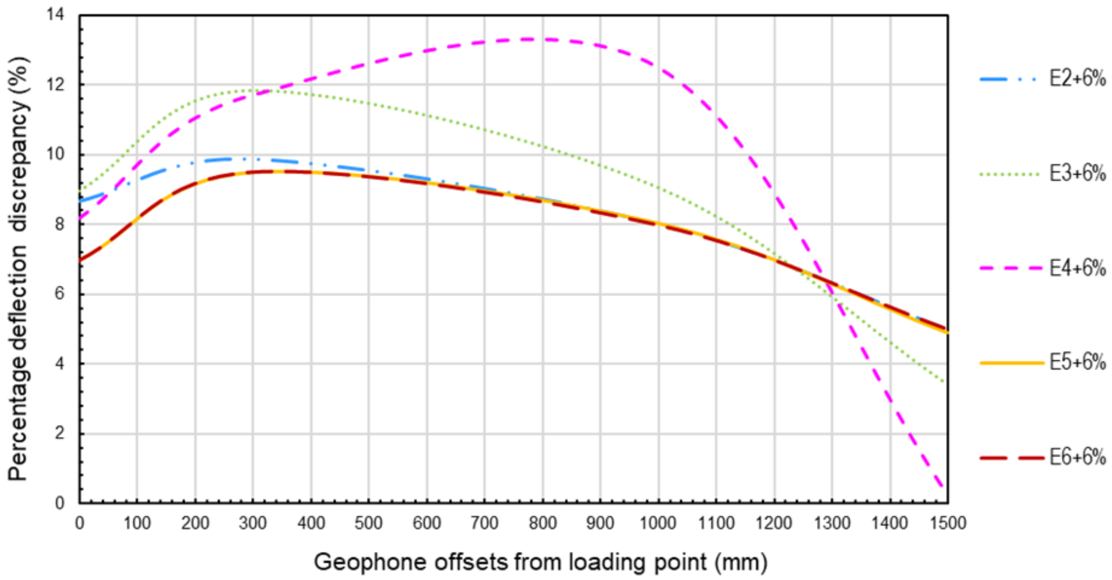
It can clearly be observed, by comparing the results shown in Figure 3.5a–d, that the variation in the subgrade 1 layer modulus (E_4) had the highest impact on the track surface deflections recorded by the geophones up to 1300 mm from the loading point. The same variations in E_5 and E_6 had the least effect on the percentage of the deflection discrepancy at the geophones located 0, 300 and 1000 mm from the loading point. The E_4 variation causes the lowest percentage discrepancy for the last geophone, located 1500 mm from the FWD loading point, and variations in both E_5 and E_6 produced the highest percentage deflection discrepancy. In conclusion, this parametric study shows that the basin deflections for the nearest geophones to the loading point are more affected by the moduli of the layers nearest to the surface.



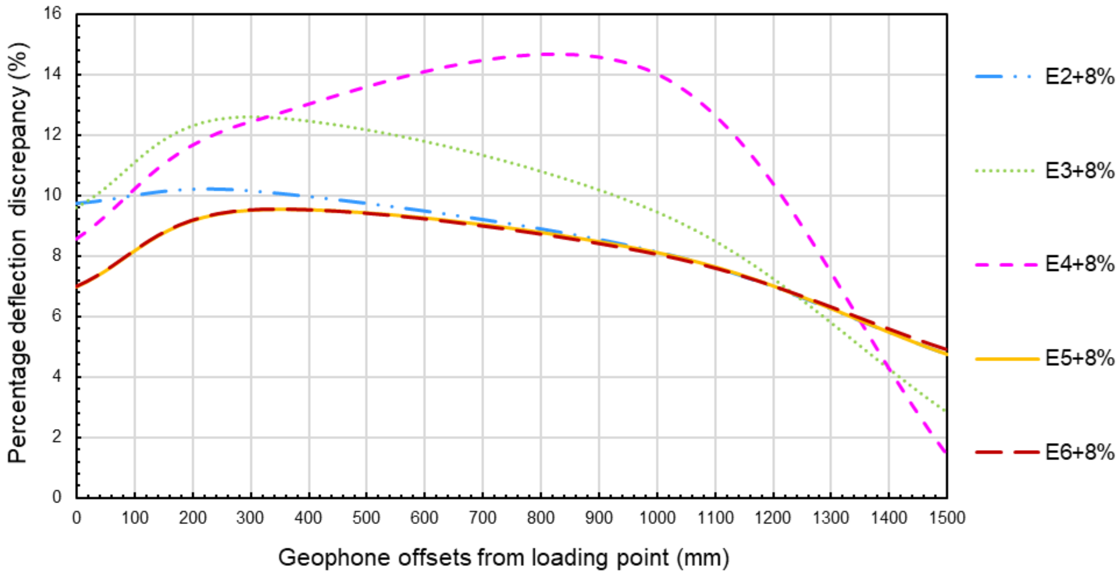
(a) Percentage deflection discrepancy for various geophone offsets, with a 2% variation in E_2 to E_6



(b) Percentage deflection discrepancy for various geophone offsets, with a 4% variation in E_2 to E_6



(c) Percentage deflection discrepancy for various geophone offsets, with a 6% variation in E_2 to E_6



(d) Percentage deflection discrepancy for various geophone offsets, with an 8% variation in E_2 to E_6

Figure 3.5: Parametric study of the FE model of the railway track section near Leominster station test site, UK over the substructure's layer moduli: (a) a 2% variation in E_2 to E_6; (b) a 4% variation in E_2 to E_6; (c) a 6% variation in E_2 to E_6; and (d) an 8% variation in E_2 to E_6

3.9 Summary

In this chapter, details of a primary FE forward model of a railway track substructure under the FWD testing condition were explained. A 3D geometry of a five-layer railway track substructure was built in the COMSOL Multiphysics software, and a time-dependent simulation of FWD loading on the railway track section near Leominster station, UK was developed. Details of the railway track section geometry and substructure layers' thickness and layer moduli were obtained from CPT results reported in an experimental study in the literature (Brough et al., 2006). The FE forward model developed in this study was validated against a set of experimental FWD test data from Burrow et al. (2007).

A parametric analysis was carried out with the aim of investigating the effect of each substructure's layer moduli on the surface deflection. In this investigation, uniformly distributed non-random values (a range covering up to an 8% variation from the actual layer moduli estimation that was based on the CPT data) were assigned to each substructure's layer moduli. The railway track surface deflections were then obtained and analysed at four different offsets from the FWD loading point.

The FE forward model presented in this chapter will be used in further investigations in the following chapters. In Chapter 4, due to the lack of experimental FWD test data for railways, the validated FE forward model is adapted to generate a virtual experimental database, with the aim of checking the BAKFAA software's performance in a railway track application. In Chapter 5, the FE forward model will be used to generate a database that will train an ANN surrogate forward model to develop a hybrid ANN–GA and ANN–ACO_R back-analysis technique. These methods are explained in the following pertinent chapters. This technique is designed to assess the condition of a railway track substructure in a healthy condition, without any local defects or soil weakness in the layers. Chapter 6 sees the final use of the validated FE model, wherein it is used to generate a new database for ANN training that considers a buried drainage pipe in the substructure layers and different types of weakness in the geometry and moduli of the surrounding soil. The goal of the following chapter is to extend the hybrid back-analysis technique developed in this study so that it can identify the presence of any soil weakness around a buried drainage pipe in an assumed five-layer railway track substructure.

Chapter 4

Evaluation of the use of BAKFAA software in railway track applications

[Pages 63 - 84 redacted for containing commercially or otherwise sensitive material]

Chapter 5

Development of FWD-based hybrid back-analysis techniques for railway track condition assessment

5.1 Introduction

In Chapter 2: Literature review, various limitations of the currently available back-analysis techniques for railway track condition assessment were comprehensively discussed. These limitations range from time inefficiencies and cost requirements to neglecting the dynamic nature of in-situ tests, such as the FWD. In addition, discounting the effect of the number of substructure layers and the dependency of back-analysis on the seed values are other limitations of the current techniques. In Chapter 4, the performance of BAAKFA, a widely used back-analysis software package, was evaluated. It was observed that using BAKFAA to estimate the elastic modulus of railway track substructure layers is unreliable for multi-layer substructures under dynamic loading tests. Therefore, this chapter is dedicated to developing a novel hybrid back-analysis technique that will address these limitations. The proposed back-analysis technique integrates two analyses: a forward model that uses a soft computation technique (i.e., an ANN) and a back-analysis technique that uses evolutionary optimisation algorithms (i.e., a GA and ACO_R).

As demonstrated in the literature review, ANNs have been widely implemented in the back-analysis context for the assessment of pavement structures. This is due to ANNs' robust function approximation ability in either forward modelling or inverse function approximation problems (Ceylan et al., 2005; Meier, 1995; Pekcan, 2011). In this study, the FE forward model developed in Chapter 3 was used to train and develop an ANN and then replace the FE forward model. Using an ANN instead of an FE model in forward modelling offers various advantages over the condition assessment applications that are discussed in this chapter. This ANN, which replaces the FE forward model, is referred to as the ANN surrogate forward model (Kargah-Ostadi & Stoffels, 2015). An FE-based forward model, despite being accurate at simulating the mechanical behaviour of railway track substructures, causes the iterative back-analysis process to be time consuming and computationally inefficient (Haji Abdulrazagh et al., 2019; Ling Ong et al., 1991; Loizos & Scarpas, 2005; Salour & Erlingsson, 2013). However, an ANN, as a robust and fast soft computation tool, offers considerable advantages for the back-analysis of railway track substructures. Thus, the purpose of this chapter is to develop a computationally time efficient back-analysis technique using ANN.

In the hybrid back-analysis technique proposed in this research, the ANN surrogate forward model operates as a function, with specific input and output information. The input information was the elastic modulus values of the layers of a railway track substructure, and the output information was the surface deflections of the railway track under FWD loading test at four offsets from the FWD loading point. From a technical point of view, the FE forward model and the trained ANN surrogate forward model carried out the same operations (i.e., calculating the surface defections of a railway track substructure under FWD testing).

In the back-analysis framework for railway track substructure condition assessment, the known outputs of the ANN surrogate forward model (i.e., surface deflections under FWD test) were known in real field experiments. The unknowns were the input information for the ANN; that is, the railway substructures' layer moduli. Estimating these unknown inputs for the ANN surrogate forward model was defined as the back analysis. To solve this estimation problem, (i.e., to run the back analysis) an optimisation method was incorporated into the ANN surrogate forward model to find the optimal input values for the model. The process of solving the optimisation problem is iterative, and a defined objective function calculates the improvement in the estimates at each iteration. In the current problem, the objective function was based on the deflections calculated at each iteration, comparing these with the target deflections. The objective function calculated the difference between the deflections calculated by the ANN surrogate forward model and the target deflections from the FWD test. The target deflections were also referred to as the actual, or measured, deflections. Starting from a random initial set of values for the substructures' layer moduli, referred to as seed values, the back analysis minimised the objective function by updating the layer moduli at each iteration. The result was a set of substructure layer modulus values that caused the same deflections under the FWD test; thus, they were an estimation of the actual substructures' layer moduli.

As discussed in Chapter 2, using a combination of heuristic algorithms and artificial intelligence methods leads to the improved robustness and reliability of the back-analysis techniques, with a lower computation time. However, there is no hybrid metaheuristic technique developed for the back analysis of the elastic modulus of a railway track substructure with up to five layers. Therefore, the technique developed in this chapter is the first attempt at a railway track system application.

In the following sections of this chapter, the steps required to develop the hybrid back-analysis techniques are explained in detail, as follows: (1) database generation for training the ANN surrogate forward model using the validated FE forward model of the railway substructure; (2) a definition of the proper ANN architecture for this problem; (3) execution of the ANN training process; and (4) hybridisation of the ANN with the GA and ACO_R to carry out the optimisation of the back-analysis technique.

Finally, a two-step validation study was performed to investigate the performance of the back-analysis technique. In the first step of the validation, a comparison study was conducted between the back-analysed layer modulus values from the hybrid back-analysis technique and the target layer moduli inferred from the CPT. In the second step of the validation, the layer moduli resulting from the back analysis were substituted into the validated FE forward model, following which the estimated track surface deflections were compared with the measured (experimental) deflections from the FWD test at four different offsets from the loading point.

5.2 Development of the ANN surrogate forward model

Using the developed FE forward model to calculate the surface deflections in the back-analysis procedure, which is an iterative procedure and requires multiple simulations, is computationally intensive. For this reason, to develop an effective back-analysis technique with no dependency on seed modulus values, an ANN model was developed to replace the FE forward model in the back-analysis technique. Using the ANN surrogate forward model improved the computation time for the track deflections when compared with the FE forward model.

In the following sections, the training process of the ANN, including database generation, database division, pre-processing and definition of the ANN architecture, is explained. In addition, the details of using the optimisation algorithms, including the GA and $ACO_{R,}$ as global search techniques and their hybridisation with the ANN surrogate forward model to construct a robust hybrid back-analysis technique for railway track substructure condition assessment, are presented. A description of the results and the validation study of the developed techniques concludes this chapter.

5.2.1 Synthetic database generation

To train an ANN surrogate forward model as a replacement for the FE forward model, a synthetic database, including specifically defined inputs and outputs, is required. A total of 536 sets of basin deflection data were generated by running various scenarios of railway track substructures in the validated FE model that was explained in Chapter 3. All these scenarios were simulated in the FE model in COMSOL Multiphysics, which was coupled to the developed MATLAB code via LiveLink™. LiveLink is a software tool provided by COMSOL to link MATLAB codes to FE models. To generate this database, the LiveLink COMSOL with MATLAB was used to achieve an efficient computation time for data generation. The layer moduli values used to generate the database consisted of 100 uniformly distributed random values over the defined range of layer moduli for each layer (including the maximum and minimum values). Table 5.1 presents the defined range of layer moduli, as well as giving the other characteristics of the layers. In addition, a set of uniformly distrusted non-random values of layer moduli obtained from the available CPT data were used in the database. Sampling the layer moduli from both of the above distributions, which were adopted to generate the synthetic database, made the scenarios more representative and inclusive of real-world conditions.

In this study, the elastic modulus of the railway track substructure was used to assess the condition of the track, because elastic modulus values are the dominant and most effective parameters relating to railway surface deflections. Furthermore, it has been recognised in the literature as an important factor in railway track substructure condition assessment (Kouroussis et al., 2013). Studies on pavement analysis in the literature have reported that Poisson's ratio has a negligible effect on the pavement system's response (Huang, 2004). On this basis, in this study fixed Poisson's ratio values, presented in Table 5.1, were used throughout the analysis. Moreover, all layers' thicknesses were considered constant in order to focus on the elastic modulus values of the layers.

The layers' configurations and thicknesses were defined based on the CPT results from the test site, which were used for the validation of the forward model, as discussed in Chapter 3. This assumption decreased the complexity imposed on the back-analysis problem and ensured that the focus remained on the elastic modulus values and their effect on surface deflections. The details of each layer of the five-layer railway substructure, including thickness, Poisson's ratio and the range of layer moduli used to generate the database, are presented in Table 5.1. The database generated here includes the elastic modulus of the substructure layers, layer thicknesses and Poisson's ratio (i.e., the inputs for the ANN), and their relevant surface deflections under the FWD test (i.e., the outputs of the ANN).

Table 5.1: The input values and range (used to generate the ANN training database based on the railway section near Leominster station, UK)

Railway track system	Layers	Thickness (mm)	Poisson's ratio	Range of layer moduli (MPa)
Five-layer system	Clean ballast (E_2)	300	0.2	70–170
	Contaminated ballast (E_3)	600	0.49	20–50
	Subgrade 1 (E_4)	2,100	0.49	50–100
	Subgrade 2 (E_5)	700	0.49	15–50
	Subgrade 3 (E_6)	6,100	0.49	100–400

5.2.2 Data division and pre-processing

The key application of ANNs is to generalise the correlation between two sets of data (e.g., the input and output of a function) using a limited database. Using a limited, scattered database, an ANN can learn the correlation between datasets. The trained ANN can then be used to generalise the correlation to data outside the initial database; for example, estimating the output of a function for an input that does not exist in the training database.

If a mathematical or numerical function is available, an ANN can be trained based on a limited number of input and output datasets for the function. The trained ANN can then replace the original mathematical or numerical equation. For example, in the current study the FE forward model, developed as a numerical model (i.e., a function) was used to produce a dataset of inputs and outputs to train an ANN. The FE forward model was then replaced with the trained ANN (i.e., the surrogate ANN forward model) which improved the calculation efficiency of the model while maintaining its accuracy.

However, the application of ANNs requires diligence to avoid the overfitting phenomenon. Overfitting occurs when ANNs are overtrained and, as a result, capture the noise in the data as actual data. Consequently, an overtrained ANN generalises the noise into its estimates, which can cause significant errors in its estimates. To avoid overfitting and improve the generalisability of the ANN, in this research a cross-validation method was employed that used the generated database. In this regard, the database was divided into three subsets: training data; testing data; and validation data (Maier & Dandy, 2000; Stone, 1974). Accordingly, 80%, 10% and 10% of the 536 synthetic data points were used for training, validation and testing, respectively (Baldo et al., 2019; Sebaaly et al., 2018). The training dataset was used to train the ANN on the correlation between the input and output data. The validation data were used during the training process to validate the training and avoid overfitting. The testing data were withheld from the ANN until after the training process and were then used to assess the performance and accuracy of the trained ANN model. Once the training was complete, the performance of the trained ANN was quantified by inputting the test dataset into the trained ANN and comparing its estimates with the actual values. It is worth noting that all the input–output values were normalised into the range [−1,1] before training the ANN, using mapminmax built-in function of MATLAB. This normalisation is useful as it maintains the effect of all the parameters consistently throughout the training process and increases the efficiency of the training process (Baldo et al., 2021; Johnson, 2010).

5.2.3 ANN architecture

An ANN is composed of a collection of basic processing units called artificial neurons (or neurons). These units are interconnected in a specific configuration to transfer information. These connections are called synapses, and the configuration of the neural connections is referred to as the architecture of the ANN. Each synapse, i.e., neural connection, has a specific synaptic weight that controls the data transfer between the two neurons.

The ANN architecture must be defined before the ANN training process. Of the ANN architectures available, the multilayer perceptron (MLP) feed-forward neural network was employed in this research (Leondes, 2018). This type of ANN is the most common type used in civil engineering applications, specifically owing to its ability to analyse pavement structures, and has been shown to be effective in various engineering problems (Adeli, 2001; Ghanizadeh et al., 2020; Gopalakrishnan et al., 2006).

The number of neurons in the input layer corresponds with the number of inputs in the problem. In the current study, the 19 inputs to the ANN were the mechanical properties of the railway track substructure: namely, the elastic modulus (E_1-E_6), Poisson's ratio (υ_1-υ_6), and the thickness of the layers (t_1-t_6) and the FWD loading magnitude. The outputs of the ANN were the surface deflections corresponding to the number of predefined geophones at different offsets from the FWD loading point (4 geophones- see Figure 2.3). Based on the number of inputs and outputs, the number of neurons in the input and output layer of the ANN were decided.

Aside from the number of neurons in the input and output layers, defining the architecture of an ANN is a problem-dependent exercise that depends on multiple factors, including the number of hidden layers and the number of neurons in each hidden layer, and there is no systematic procedure for defining an ANN architecture. In this research, the network architecture was chosen based on a trial-and-error study that was considered various ANN architectures to find the optimal network architecture. In each trial, the constructed ANN, with its specific architecture, was trained and tested with an identical subset of the generated database. It was then tested to calculate the RMSE of the ANN's estimation at each datapoint (D_i) with the target values. The RMSE values corresponding to D_0, D_{300}, D_{1000} and D_{1500} for some of the trials are presented in Table 5.2.

Table 5.2: Trial-and-error process for ANN architecture definition

Architecture of the hidden layers	RMSE D_0	RMSE D_{300}	RMSE D_{1000}	RMSE D_{1500}
3-2	0.0034110	0.0106670	0.0099440	0.0058707
4-2	0.0033565	0.0106340	0.0100270	0.0059303
5-2	0.0034463	0.0105700	0.0099161	0.0058598
6-2	0.0031782	0.0104710	0.0100900	0.0059636
7-2	0.0039363	0.0106710	0.0097974	0.0057853
5-6-5	0.0006358	0.0004020	0.0003163	0.0002815
5-6-6	0.0007631	0.0005183	0.0013865	0.0021501
5-4-4	0.0004733	0.0004858	0.0002821	0.0002905
6-5-4	0.0003503	0.0004199	0.0002493	0.0002512
6-6-5	0.0006885	0.0003969	0.0003369	0.0002327
7-6-6	0.0008208	0.0004491	0.0003731	0.0003680
8-8-7	0.0014908	0.0005822	0.0006585	0.0003932

As these results show, the ANN with three hidden layers with 6, 5 and 4 neurons, respectively (i.e., the highlighted row in Table 5.2) produced the lowest RMSE values. Therefore, the optimal network architecture of 19–6–5–4–4 (number of neurons in the input layer, hidden layer 1, hidden layer 2, hidden layer 3 and output layer, respectively) was used to analyse the railway track with five substructural layers. It is worth mentioning that the minimum number of neurons in the hidden layers improves the performance of the ANN surrogate forward model by decreasing the computation time and the probability of overfitting (Shahin et al., 2008). However, the current trial-and-error analysis showed that the 19–6–5–4–4ANN architecture was the least populated architecture for the current problem that could provide an accurate modelling of the railway substructure.

The next step is the determination of the transfer function in the ANN surrogate forward model (i.e., the synapses). In this study, the tan-sigmoid transfer function was issued between the hidden layers, and the linear function was used to transfer data to the output layer. These two types of transfer functions are typical functions that have been highly recommended and widely employed in training ANN networks (Johnson, 2010; Li & Wang, 2019; Rakesh et al., 2006; Wang et al., 2021).

5.2.4 ANN training

After the optimal ANN architecture was defined, as detailed in the previous section, the training process was carried out. A subset of the database, including input and output values, was fed into the ANN repeatedly until the relationship between the inputs and outputs (i.e., the pattern or function correlating the input and output values) was learned by the ANN. This type of training is known as supervised training, in which the ANN parameters are updated by a training algorithm at each iteration (Rahimi Nahoujy, 2020).The parameters of the ANN include synaptic weights and biases. The synaptic weight is a coefficient between two neurons that scales the information transferred between them. The bias is a threshold function that controls data transfer out of a neuron.

The training algorithm that was used to train the proposed network in this study was the Levenberg–Marquardt backpropagation algorithm (Beale et al., 2010). This training algorithm is one of the popular search methods for training ANNs owing to its speed, stable convergence and efficient implementation in the MATLAB software (Beale et al., 2010; Das & Basudhar, 2006; Ullah et al., 2021). The initial synaptic weights and biases for ANN training were chosen randomly in the Levenberg–Marquardt backpropagation algorithm. In this process, the ANN was trained to predict the FWD deflections for a set of railway track substructure properties by adjusting weights and biases in the network. During the ANN training, the mean squared error (MSE) was checked to assess the predictive performance of the network. In the current case, an MSE of 1.034e−7 was achieved at epoch 600 of the training as the best validation performance. Once the training process was complete, the model's performance for each output was checked using the RMSE, MSE and coefficient of correlation (R) criteria. Figures 5.1 to 5.4 show the predicted deflection results of the ANN surrogate forward model at four different offsets from the FWD loading for the test dataset. In Figures 5.1b–5.4b, R represents the correlation between the predicted deflections (ANN outputs) and measured FWD deflections, which was approximately equal to 1 for the cases in the testing dataset in this study. Figures 5.1c–5.4c show that MSE values of 1.2271e−07, 1.7628e-07, 6.2147e−08 and 6.3088e−08 and RMSE values of 3.503e−04, 4.1986e−04, 2.4929e−04 and 2.5117e−04 were achieved for the D_0, D_{300}, D_{1000} and D_{1500} datapoints, respectively. The high value of R and the low values of MSE and RMSE in the figures confirm the high accuracy and excellent performance of the 19–6–5–4–4ANN model configuration for the prediction of peak deflections recorded by the geophones D_0, D_{300}, D_{1000} and D_{1500}.

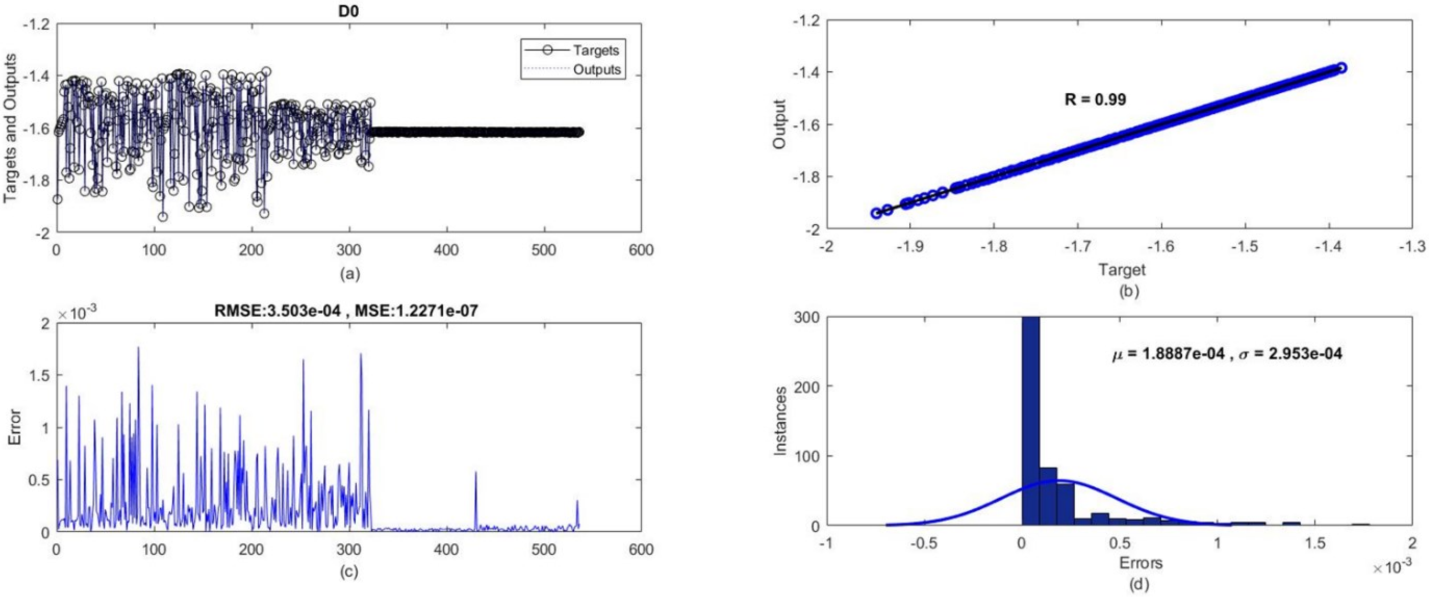


Figure 5.1: ANN predictive accuracy for track surface deflection at datapoint D_0

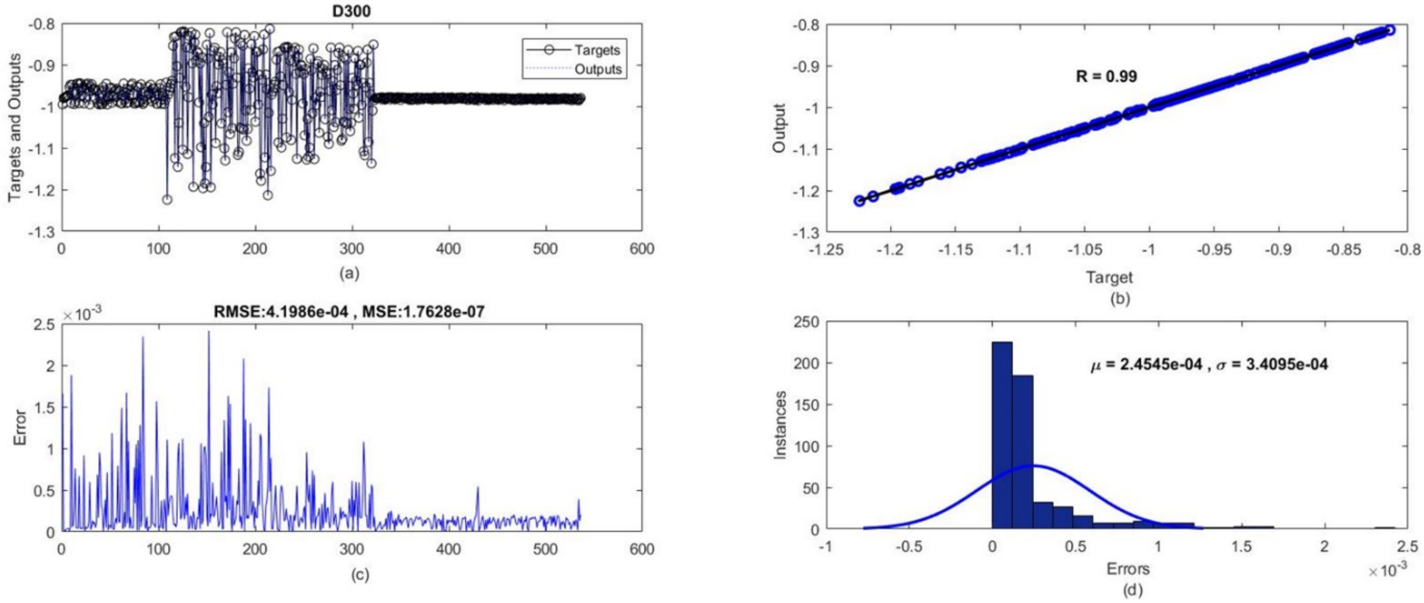


Figure 5.2: ANN predictive accuracy for track surface deflection at datapoint D_{300}

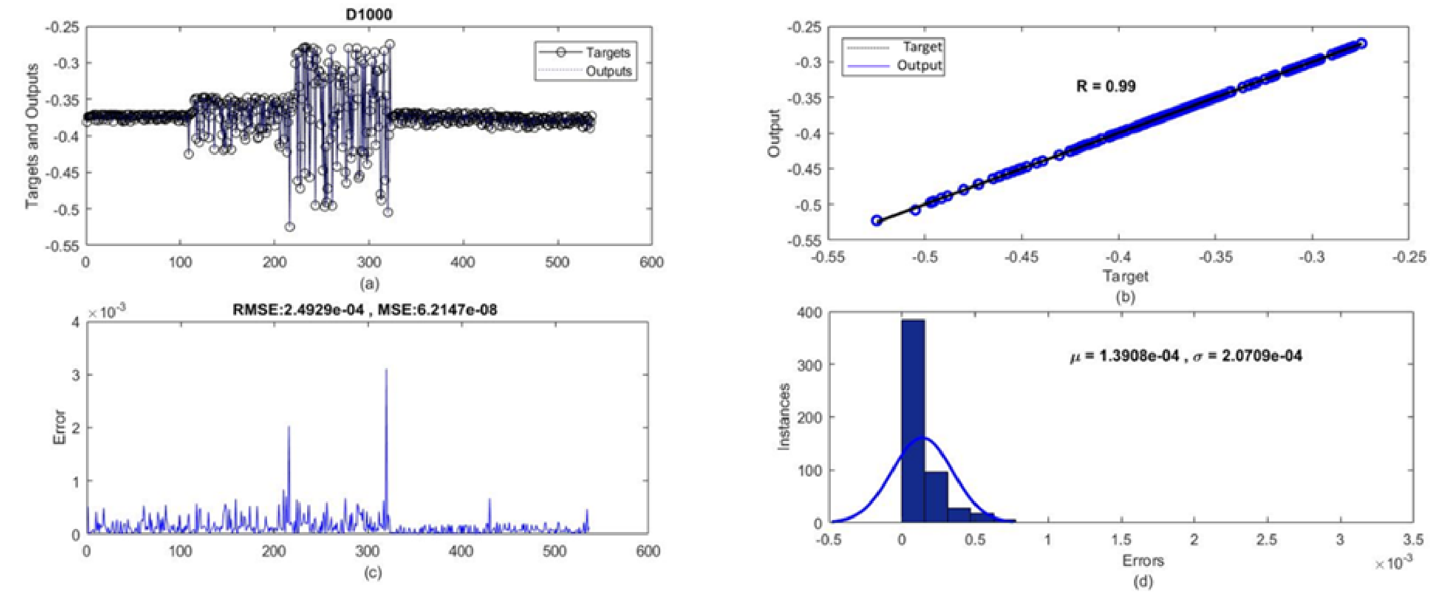


Figure 5.3: ANN predictive accuracy for track surface deflection at datapoint D_{1000}

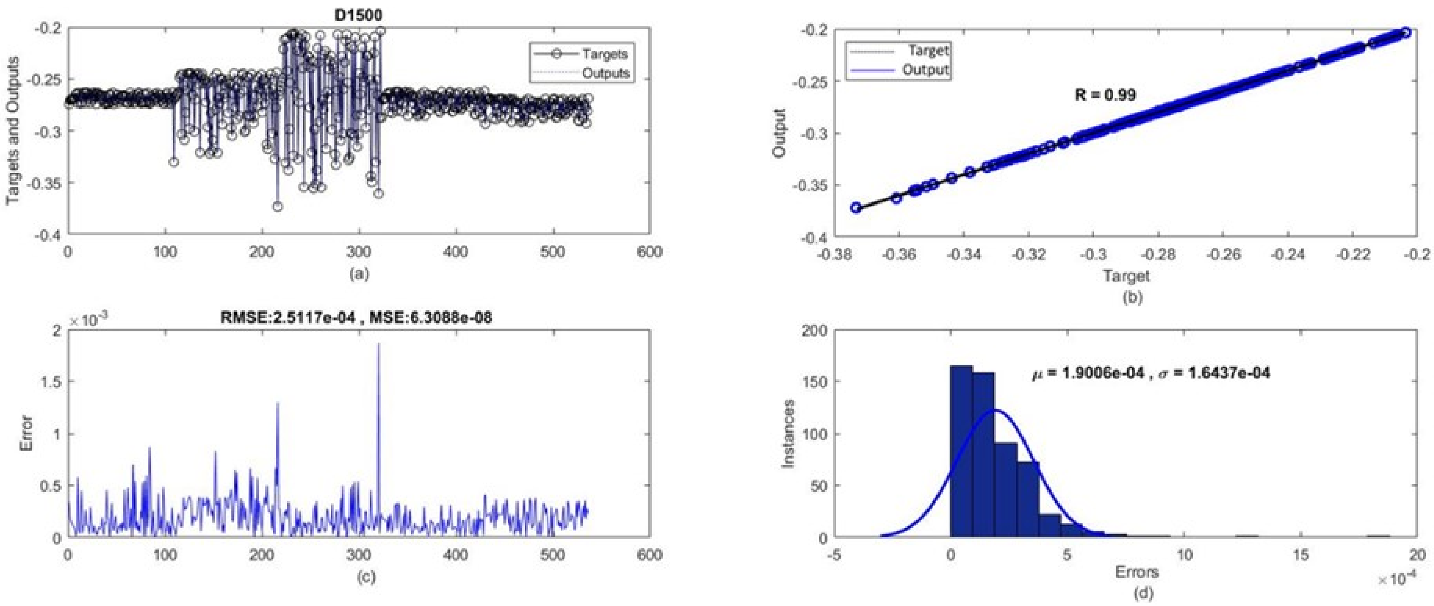


Figure 5.4: ANN predictive accuracy for track surface deflection at datapoint D_{1500}

The low values of MSE and RMSE indicate the high accuracy of the ANN. Thus, the ANN model can be confidently employed as a surrogate forward model for the prediction (i.e., estimation) of railway track surface deflections under the FWD test for various track substructure configurations and properties.

5.3 Optimisation technique

The ANN surrogate forward model, which was explained in the previous section, can predict the surface deflections of a five-layer railway substructure at four different offsets from the loading point, based on the various given geomechanical properties of each layer (including the layer moduli). In the current study the four surface deflections (D_0, D_{300}, D_{1000} and D_{1500})

were the known variables of the problem, i.e., the FWD test results, and the modulus values of the substructure layers were the unknown variables. In order to estimate the substructures' layer moduli and thus perform the condition assessment of the substructure based on the FWD deflection results, an optimisation process was utilised. This process optimised the substructures' layer moduli (i.e., the inputs to the ANN) to match the forward model deflections, (i.e., the outputs of the ANN) with the actual deflections. In other words, the optimisation process estimates the substructures' layer modulus values by minimising the percentage error between the predicted and measured (experimental) deflections through the use of an optimisation algorithm. As outlined in the literature, classic optimisation techniques, such as gradient methods and interpolation methods, the quality of the results depends on the initial estimates. Moreover, general speaking, these methods converge to the local minima unless the initial estimates selected are close enough to the global minima, which makes the process dependent on the user's experience.

The GA and ACO_R are two metaheuristic optimisation techniques that can address the shortcomings of classic optimisation algorithms by converging to a global, as opposed to a local, solution. Based on the research objectives, this section details both the optimisation algorithms and their coding in MATLAB, which are hybridised with the ANN surrogate forward model to construct the proposed hybrid back-analysis techniques.

5.3.1 Genetic algorithm optimisation

The GA is an evolutionary search and optimisation technique inspired by natural selection (Kumar et al., 2007). It was first proposed by John Holland in 1992 as a means of solving nonlinear optimisation problems that could not be solved using classic gradient-based optimisation techniques (Engelbrecht, 2007). This algorithm is based on Charles Darwin's idea of survival of the fittest, in which a population of solutions to the optimisation problem evolve through an iterative process to achieve a globally optimal solution (Man et al., 1996). Figure 5.5 shows a flowchart of the GA process. As shown in the flowchart, the GA optimisation process starts by generating an initial set of random estimates for the variables of the problem, (i.e., the parent generation). Then, the GA uses the trained ANN to determine the surface deflection for each set of potential solutions (i.e., estimated variables). The GA selection, mutation and crossover are the main GA operators that use the parent generation to produce the next generation (i.e., mating) in order to maintain the best estimation in each iteration. The mutation function introduces random variations in the estimations to promote a wider solution's search space and prevent the algorithm from converging too quickly on a local optimum.

Crossover function operates over the variable estimations by merging them in a way that gives the better estimations to be preserved and increasing the likelihood that they will be incorporated into the new solutions. The fitness function is another operator of the GA that determines the fitness, and consequently survival, of each set of estimates. This process continues until a global optimal estimate is achieved that satisfies the accuracy required to address the problem.

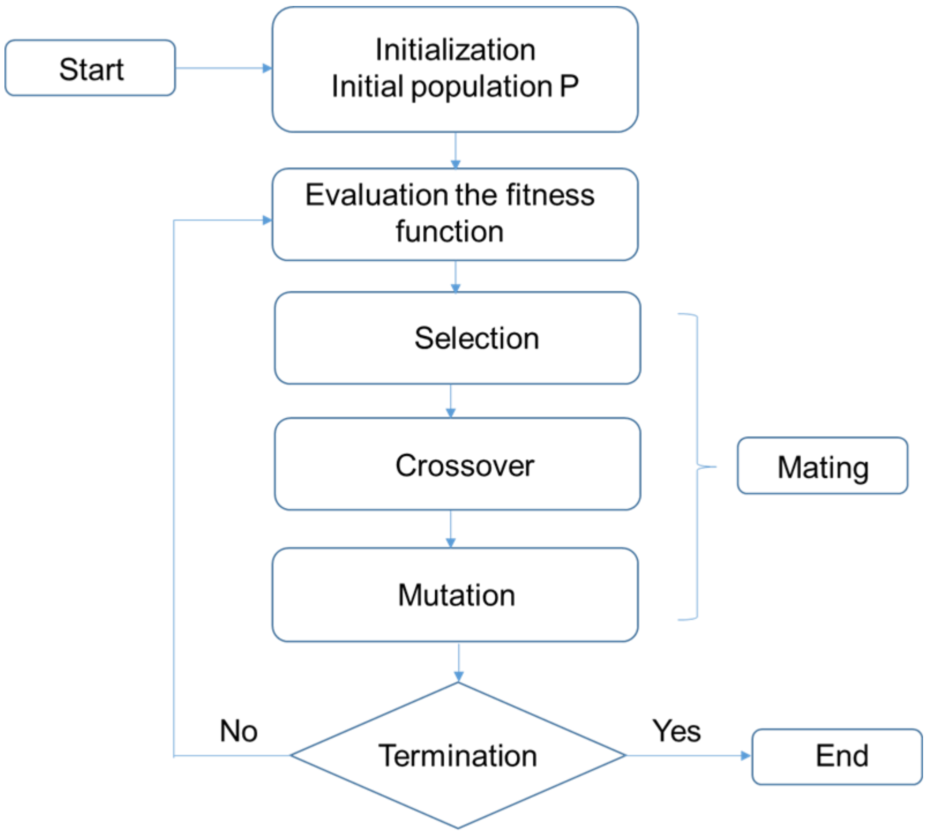


Figure 5.5: The GA process flowchart

Defining the fitness function is a crucial part of solving an optimisation problem. The RMSE percentage (RMSE%), shown in Equation 5.1, was chosen as the deflection-based fitness function in the current optimisation problem (Ghorbani et al., 2020; Gopalakrishnan & Khaitan, 2010):

$$Fitness\ Function\ (RMSE\%) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}((D_i - d_i)/d_i)^2} \times 100 \qquad \text{Equation 5.1}$$

Where,

D_i is the calculated deflection at datapoint *i*

d_i is the measured experimental deflection at datapoint *i*

n is the number of datapoints, i.e., geophones

The GA uses a number of functions and criteria to perform the optimisation: namely, the selection function, crossover function, mutation function and the stop criteria. In this research, the most commonly used selection function in GA optimisation (i.e., the roulette wheel) was used, which selects a subset of the population based on their fitness for the mating and reproduction (the higher the fitness, the higher the chance of reproduction) to create a new generation (Terzi, 2005; Tutumluer et al., 2009). An arithmetical crossover function used to generate offspring was employed to introduce diversity into the GA optimisation (Gopalakrishnan, 2012).

The selection of the GA parameters (the pre-analysis phase) is an important step in this algorithm because the performance of the GA is highly dependent on these parameters (i.e., the population size and number of generations). Various values for the population size and number of generations were investigated to find the optimal values for these parameters in the current problem. The result of this analysis is presented in Figure 5.6. This figure shows that a population size of 350 and 200 generations were selected for the current problem.

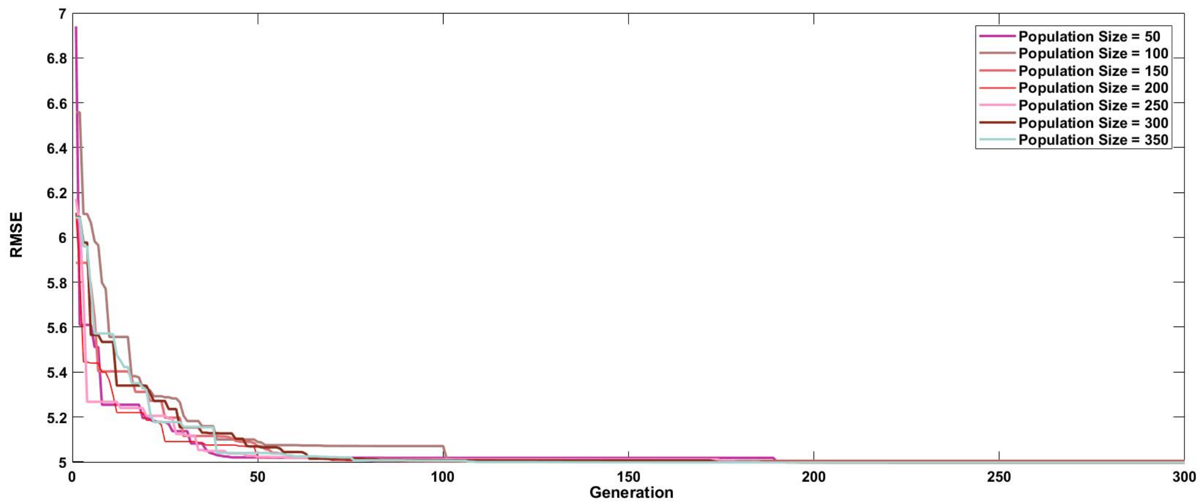


Figure 5.6: Pre-analysis of the population size parameter in the GA optimisation for the ANN–GA back-analysis technique

Mutation probability and crossover probability are two other parameters of GA optimisation that were defined based on the literature (Reddy et al., 2004). Table 5.3 summarises the GA parameter values used in this study.

Table 5.3: GA parameters

Parameter	Value
Population size	350
Generation size	200
Crossover probability	0.85
Mutation probability	0.01

5.3.2 ACO for continuous domain

ACO_R is inspired by the path that an ant takes to reach a food source. In an ACO_R problem, the food source is considered as the global minimum of the objective function, the neighbourhood is the search space for the algorithm and the ant's chosen path is the solution to the problem (Srivastava et al., 2014).

To solve a continuous optimisation problem, such as the one in this research, ACO_R was employed with no major amendments to the core structure of the algorithm. The key advantage of ACO_R over the classic ant colony optimisation (ACO) is the continuous probability density function, which replaces the discrete probability distribution in ACO (Dorigo et al., 2006; Liu et al., 2021). ACO_R algorithm includes the following three main functional components (Dorigo et al., 2006; Liu et al., 2021; Socha & Blum, 2007; Socha & Dorigo, 2008):

a) Initialisation
b) Probabilistic solution construction
c) Pheromone updating

The ACO_R algorithm was coded in the MATLAB software and run simultaneously with the ANN surrogate forward model. Figure 5.7 presents the steps in the ACO_R algorithm as a flowchart.

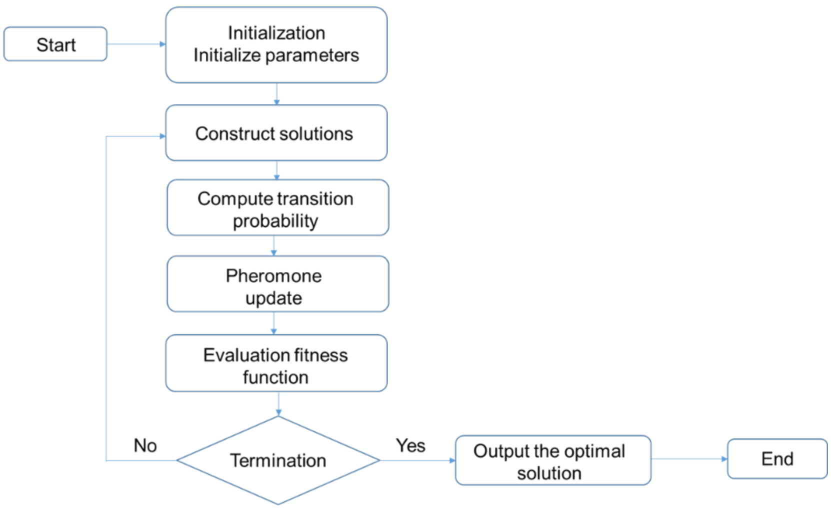


Figure 5.7: ACO_R process flowchart

ACO_R algorithm is simulation of the ant's behaviour searching for food and try to converge to the shortest path from their nest to the food source. The main behaviour of ants which enables them to find this shortest path is communicating using chemical pheromone trails.

ACO_R starts with setting up the problem parameters, generate initial population of ants randomly, and initialising the pheromone level on each component of the solution (i.e., estimated variables). The main phase of ACO_R is construction solutions, in which each ant construct a solution sampled from a probability density function (PDF) (Abdelbar & Salama, 2019). As ants start travelling through the search space including edges and nodes, and the movement is defined using the transition probability. The transition probability determines the likelihood of moving from current position to a new position (Zhao et al., 2017).

Once the construction solution completed, in the pheromone update phase, the new constructed solutions are added to the to the archive solutions. Then the new solution archive is sorted based on the solution quality (Zhao et al., 2021),

Similar to the GA, a deflection-based objective function, shown in Equation 5.1, was used for ACO_R. An important user-defined parameter, i.e., pheromone evaporation rate (ξ), is responsible for controlling the speed of convergence and balancing the exploitation and exploration. Increasing the value of ξ increases the rate at which the ant forgets the worse paths (i.e., the worst solutions) causing it to search a wider space, which decreases the convergence speed of the algorithm and vice versa (Scimemi et al., 2016). Moreover, the selection pressure (q) is an algorithmic parameter that affects the selection from the solutions archive. A small value of q produces a sorted set of solutions ranked from best to worst, which increases the probability of selecting a better solution, while a large value of q makes the probability more uniform (Omran & Al-Sharhan, 2019). As mentioned earlier, during the construction solution phase, the algorithm updates the archive with the best solutions. The archive size (k) is another factor in ACO_R, which determines the number of best solutions that are stored in the memory of the algorithm.. A parametric study was conducted to find the optimum value for k. Figure 5.8 shows the effect of various values for k on the RMSE. It can be observed that, for k = 200, the value of the RMSE is lowest in the algorithm for the current problem.

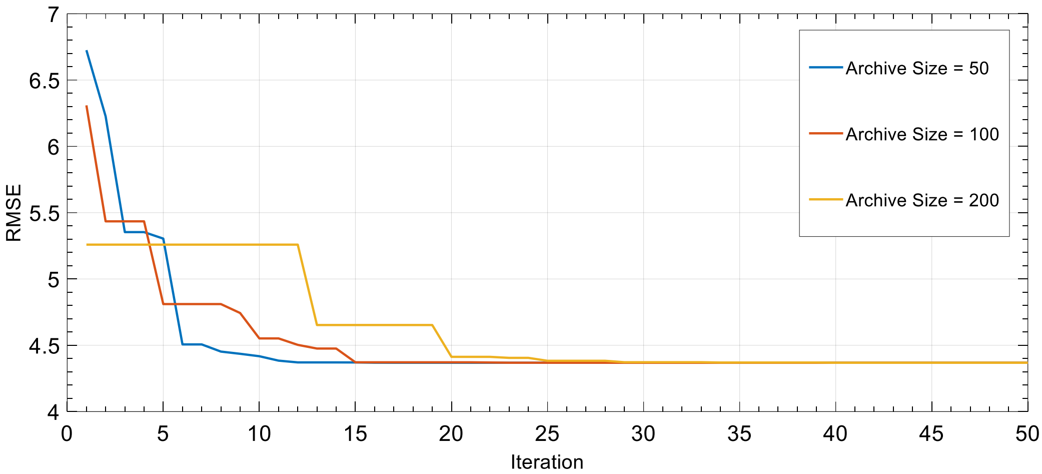


Figure 5.8: The effect of variations in the archive size on the ANN–ACO_R back-analysis technique

The ACO_R parameter values for the number of ants (m), q, ξ and iteration number were derived from the literature and set to 100, 0.1, 0.85 and 50, respectively (Cottone et al., 2010; Scimemi et al., 2016). Table 5.4 illustrates the ACO_R parameters used in this study.

Table 5.4: ACO_R parameters for this study

Parameter	Value
Number of ants	100
Solution archive size	200
Selection pressure	0.1
Pheromone evaporation rate	0.85
Iteration number	50

5.4 Hybrid ANN and GA back-analysis technique

The FE model, ANN surrogate forward model and two optimisation algorithms were the main components of the back-analysis technique developed in this study. For condition assessment purposes, this systematic and computationally efficient hybrid back-analysis technique was developed to estimate the railway substructures' layer moduli based on the FWD test results. The FE model developed in this study was employed to generate an inclusive database that covers the values representing the substructures' layer moduli. This database was used to develop and train the ANN surrogate forward model. In this research, the ANN surrogate forward model was replaced with a computationally expensive FE model to improve the computation time. The GA in the hybrid back-analysis technique generated a random initial set of layer moduli for the problem. The ANN surrogate forward model was then run with this set of initial values as its inputs (initial pool of parent solutions) to predict the surface deflections. In this stage, based on the difference between the predicted and measured surface deflections (i.e., evaluating the parent pool using the ANN network shown in Figure 5.8) the estimated values of the layer moduli were evaluated. The estimates (parent pool) were passed into the crossover and mutation functions to generate a new set of estimates for the layer moduli. This iterative process continues until the difference between the predicted and measured surface deflections was minimised and optimal values for the estimates are predicted. Figure 5.9 presents the flowchart of the proposed hybrid ANN–GA back-analysis technique used to assess the condition of a railway substructure.

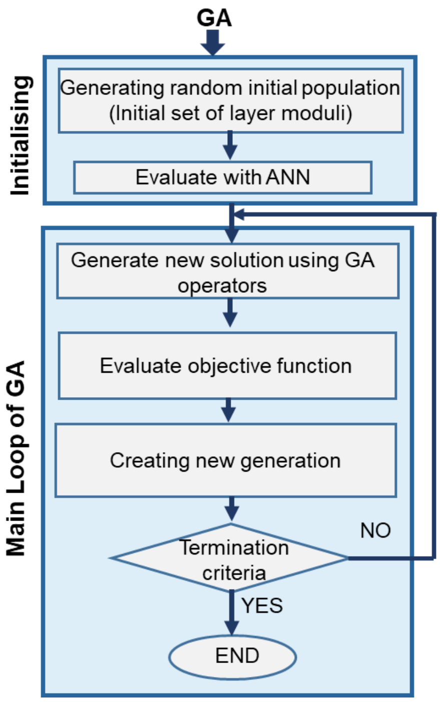


Figure 5.9: Flowchart of the hybrid ANN–GA back-analysis technique

5.5 Hybrid ANN and ACO_R back-analysis technique

In this research, in addition to the hybrid ANN–GA back-analysis technique, a secondary hybrid back-analysis technique using an ANN and ACO_R was investigated. An ACO_R algorithm was incorporated into the ANN surrogate forward model that replaced the FE model, to develop the ANN–ACO_R back-analysis technique for railway track systems. Figure 5.10 illustrates the steps taken to use the ACO_R algorithm to optimise the inputs of the trained ANN in the MATLAB software. The main steps toward developing the ANN–ACO_R back-analysis technique were as follows:

1. Developing a 3D FE model to simulate a five-layer track substructure under the FWD testing conditions and validating against the FWD trial field data.
2. Generating a database using the validated FE model, which covers the typical range of the different layer moduli of each substructure layer to represent real-world conditions.

3. Developing an ANN surrogate forward model to replace the FE model.
4. Defining the unknown variables of the problem, i.e., substructures' layer moduli (E_2, E_3, E_4, E_5 and E_6).
5. Developing an ACO_R algorithm that starts the optimisation process by generating a solution archive of size k with n decision variables (corresponding with the layer moduli).
6. Predicting surface deflections at four different offsets from the FWD loading point using the ANN surrogate forward model and sorting solutions in this step based on the calculated objective function (output of the ANN).
7. Evaluating the initial set of ACO_R estimates and calculating the RMSE of the predicted versus measured deflections.

In step 5, above, the estimated values at each iteration are updated using a Gaussian probabilistic distribution based on the current best solution. After generating a new set of solutions with a size of m at each iteration, the value of the pheromone parameter (ξ) is updated. The new set of solutions are then added to the solution archive, with a size of k (k + m). The new archive is sorted, and the worst m solutions are removed. In this way, the solution archive is updated, but it remains the same size.

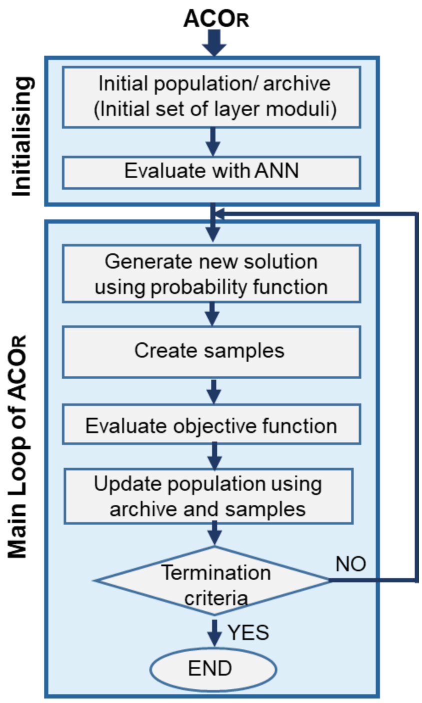


Figure 5.10: ANN–ACO_R back-analysis technique flowchart

5.6 Results and validation of the proposed hybrid back-analysis techniques

5.6.1 ANN–GA

Table 5.5 presents the results of the unknown layer moduli (back-analysed layer moduli) for a five-layer track substructure, and the target values calculated from the CPT data. The details of the percentage error in this table, which were employed to evaluate the ANN–GA technique, will be discussed later.

Table 5.5: ANN–GA back-analysed layer moduli for the railway section near Leominster station, UK

Layers	Back-analysed layer modulus (MPa)	Target layer modulus (MPa)	Percentage error
Clean ballast (E_2)	103.671	110.000	5.754
Contaminated ballast (E_3)	27.635	32.500	14.969
Subgrade 1 (E_4)	68.485	71.829	4.656
Subgrade 2 (E_5)	47.905	33.956	41.080
Subgrade 3 (E_6)	388.849	362.100	7.387
		Average percentage error	**14.769**

Table 5.5 includes the percentage error used to compare the back-analysed values of the unknown layer moduli against the target values based on the CPT data. The error values show that the back-analysis technique underestimated the elastic modulus of the clean ballast, contaminated ballast, and top subgrade layer (subgrade 1; see Figure 3.2) by 5.754%, 14.969% and 4.656%, respectively. In addition, the minimum error value obtained for the subgrade 1 layer (i.e., 4.656%) confirms the accuracy of the ANN–GA technique. This result supports the parametric study carried out in Section 3.4 of this thesis, in which the considerable sensitivity of the predicted surface deflections to variations in the top subgrade layer modulus compared to the sensitivity to other layers' moduli was illustrated. Moreover, the back-analysed modulus values of the subgrade 2 and subgrade 3 layers were overestimated by 41.080% and 7.387%, respectively. However, the high percentage error corresponding to the subgrade 2 layer modulus (E_5) could be due to the low sensitivity of the surface deflection to the subgrade 2 layer, based on the parametric analysis conducted in Chapter 3 (see Section 3.4).

In order to further investigate the performance and accuracy of the ANN–GA back-analysis technique developed in this study, a validation study was carried out. In this validation study, the back-analysed layer moduli from the ANN–GA technique (presented in Table 5.5) were implemented in the FE model of a railway track section near Leominster station (see Chapter

3) in order to calculate the exact deflections at different offsets from the loading point. Both the calculated deflections (FE model results) and measured deflections (FWD test data) are presented in Table 5.6.

Table 5.6: FE model results verified by the prediction of the ANN–GA back-analysis technique for a railway section near Leominster station, UK

Data points	Measured deflection (mm)	FE deflection based on ANN–GA back-analysis output (mm)	Percentage error
D_0	−1.737	−1.763	1.543
D_{300}	−1.083	−1.073	0.954
D_{1000}	−0.406	−0.399	1.628
D_{1500}	−0.257	−0.288	12.075

The higher percentage error for D_{1500} (see Table 5.6) is consistent with the parametric analysis in Section 3.8, in which D_{1500} was the geophone least affected by the substructures' layer moduli (i.e., there was a weak correlation between them). In other words, the back-analysis is guided more by the dominant correlation between D_0, D_{300} and D_{1000} and the substructures' layer moduli than by the weaker correlation with D_{1500}. This could be owing to D_{1500} being further from the loading point than D_0, D_{300} and D_{1000}, which shows that more meaningful information is provided by the deflections closest to the loading point. The results show that the average percentage error between the predicted deflections using the back-analysed layer moduli and the measured deflections from the FWD test for all sensors was around 4%. Moreover, the RMSE was 6.1%. This error value is acceptable and comparable with the maximum variation criterion in pavement structures' back-analysis technique which is 10%, and shows a high accuracy for the proposed technique (Lee et al., 1988).

5.6.2 ANN–ACO_R

The values for the back-analysed layer moduli from the ANN–ACO_R back-analysis technique are given in Table 5.7. The results show that the ANN–ACO_R technique underestimated the first three layer moduli (similar to the ANN–GA technique).

The results from this technique show the same trend as the estimated values using ANN–GA, (i.e., clean ballast, contaminated ballast, and subgrade 1 layer moduli were underestimated. However, both subgrade 2 and subgrade 3 moduli were overestimated. In addition, the ANN–ACO_R technique did not estimate the subgrade 1 modulus as accurately as the ANN–GA did. The estimated subgrade 1 modulus (E_4), as the most effective layer modulus in regard to surface deflection (see Section 3.8), produced a 7.234% error by ANN-ACO_R compared to the target value. This error value has increased by 2.6%, compared to the error in the ANN–GA estimation.

Table 5.7: ANN–ACO$_R$ back-analysed layer moduli for a railway section near Leominster station, UK

Layers	Back-analysed layer moduli (MPa)	Target layer moduli (MPa)	Percentage error
Clean ballast (E_2)	107.376	110	2.385
Contaminated ballast (E_3)	27.500	32.5	15.385
Subgrade 1 (E_4)	66.633	71.829	7.234
Subgrade 2 (E_5)	50	33.956	47.249
Subgrade 3 (E_6)	400	362.1	10.467
		Average percentage error	**16.544**

Moreover, the performance of the ANN–ACO$_R$ back-analysis technique was further evaluated using the FE model developed for the five-layer track structure. Table 5.8 presents the details of the performance evaluation of the ANN–ACO$_R$ technique.

The percentage errors for the four geophones exhibited the same trend as in the ANN–GA back-analysis results. It can be observed that the predicted deflections based on the back-analysed layer moduli are closely correlated with the experimental FWD data.

Table 5.8: FE model results for the verification of the ANN–ACO$_R$ back-analysis technique for a railway section near Leominster station, UK

Data point	Measured deflection (mm)	FE deflection based on ANN–ACO$_R$ back-analysis output (mm)	Percentage error
D_0	−1.737	−1.758	1.209
D_{300}	−1.083	−1.085	0.185
D_{1000}	−0.406	−0.408	0.493
D_{1500}	−0.257	−0.293	14.010

Same as ANN-GA high percentage error for D_{1500}, high value of percentage error for this geophone observed in Table 5.8. This observation is consistent as well with the parametric analysis result presented in section 3.8. In other words, the last geophone has less effect on the back-analysis technique estimation due to the greater distance from the loading point.

The ANN–GA and ANN–ACO$_R$ estimates for the ballast and top subgrade layer moduli were smaller than the actual target values. This could be due to railway track tamping, which was reported by Burrow et al. (2007). As was discussed with regard to the D_{1500} percentage error value in Table 5.6, the higher error percentage for this geophone in Table 5.8 can be attributed to its weaker correlation with the substructures' layer moduli due to its distance from the loading point.

The estimated layer moduli values from the ANN–GA back-analysis had an average percentage error of 14.769%, in contrast to the 16.544% average percentage error in the ANN–ACO_R technique; therefore, the ANN–GA estimates were 1.8% more accurate than the ANN–ACO_R estimates.

5.7 Back-analysis computation times

In terms of the time efficiency of the methods, the ANN–ACO_R back-analysis required a considerably shorter computation time to obtain the best solution than the ANN–GA back-analysis technique. As mentioned before, time efficiency is one of the most crucial factors in a back-analysis technique, and this was significantly improved by the technique developed in this study. Table 5.9 presents the calculation time for each back-analysis technique.

Table 5.9: Comparison of calculation times for the ANN–GA and ANN–ACO_R back-analysis techniques

Technique	Calculation time (s)
ANN–ACO_R	104.8
ANN–GA	458.9

5.8 Summary

In this chapter, a systematic hybrid back-analysis technique to conduct an assessment of the mechanical properties and condition of railway track substructure layers was proposed, using the results from an FWD field test. The proposed back-analysis technique is composed of the following three components:

- An FE model to analyse the substructure layers of a railway track (idealised) under the FWD testing condition
- An ANN surrogate forward model to be trained via a generated FE-based database
- A hybrid back-analysis framework composed of the ANN surrogate forward model and an optimisation algorithm (i.e., GA or ACO_R).

After developing and validating the FE model, which simulates a five-layer substructure under the FWD test condition and calculates the surface deflections at four offsets from the FWD loading point, an inclusive database was generated, consisting of the FWD load value, thicknesses of the layers, Poisson's ratio, and layer moduli (i.e., input variables), as well as four predefined locations from the loading point representing FWD geophones (i.e., output variables). The ANN model was trained using this database and then replaced the FE model as the forward model in the back-analysis technique. In this problem, layer moduli were the unknown variables that needed to be estimated. To this effect, to solve the current problem the back-analysis was initiated by assigning a set of random values for the layer moduli that were produced by the GA or ACO_R, i.e., an initial set of estimates. These values were fed into the ANN surrogate forward model, which estimated the resultant surface deflections for each set of layer moduli. The differences between the estimated deflections and experimental target deflections were calculated using a deflection-based objective function (i.e., RMSE% of the calculated vs target deflections). The initial estimates were then evolved and updated by different operators in the GA and ACO_R algorithms to find optimal values for the layer moduli. At each iteration of this process, the estimates were updated, and their resultant deflections were calculated. This iterative process continued until the output of the objective function was minimised to less than RMSE%=10% or the gradient of the convergence became zero. Then, the corresponding layer moduli were reported as the final estimates of the unknown layer moduli (i.e., the solution to the problem).

The accuracy of the hybrid back-analysis techniques (i.e., ANN–GA and ANN–ACO_R) were investigated through a two-step validation study. Although the ANN–ACO_R analysis time was shorter than the ANN–GA, the average percentage error in the estimated layer moduli using the ANN–GA model was lower than in the ANN–ACO_R model (i.e., 1.8% less than in the ANN–ACO_R model).

In the next chapter, to further investigate the applicability of the back-analysis technique to detect the presence of soil weakness zone in the railway substructure, the proposed ANN–GA back-analysis technique is extended to a railway substructure condition assessment that includes a buried drainage pipe and its surrounding soil weakness.

Chapter 6

Application of the hybrid ANN-GA back-analysis technique for defect detection

[Pages 108 - 135 redacted for containing commercially or otherwise sensitive material]

Chapter 7

Conclusions

7.1 Introduction

This research was motivated by the considerable demand for maintance and renewal in the railway industry in the UK and worldwide, which requires effcient and reliable condition assessment techniques. Improvements in this field can result in significant financial returns due to the widespread usage of aged railway tracks. In addition, the reliability and cost efficiency of the current condition assessment techniques, as well as their operation time, require significant improvement.

On this basis, the current study aimed to develop a robust, reliable and computationally time and cost efficient technique for railway track condition assessment and their substructures. The proposed condition assessment technique in this reseach utilised the FWD test, ANNs, FE models and metaheuristic optimisation algorithms to estimate the elastic modulus of railway track substructure layers and identify weak zones around drainage pipes buried in the substructure.

In this chapter, the main findings of the research are summarised and suggestions for future research are presented.

7.2 Remarkable findings

In the first part of this study and as the basis for this research, a railway track substructure was simulated under the FWD trial test using a 3D FE model in COMSOL Multiphysics (see

Chapter 3). This FE model was validated against a set of experimental FWD test data, in which the deflections were measured at railway standard FWD offsets from the loading point. The validation results showed that the FE model could calculate surface deflections with less than 10% error when compared with the actual measured values in the test.

Next, the performance of a commonly used and commercially available back-analysis program for pavement structures, named BAKFAA, was investigated for railway track applications (see Chapter 4). This program was selected based on its compatibility with railway track structures (confirmed by its developer via email communications) and its widespread use in industry. BAKFAA uses FWD basin deflection data to estimate substructures' layer moduli. Thus, a virtual experimental FWD database was generated using the FE model to assess the performance of BAKFAA for the condition assessment of various railway track conditions. This database was generated using the FE model because of the limited available experimental FWD data for railway tracks. It was observed that the BAKFAA results were strongly dependent on the initial guess for each layer modulus value (i.e., seed modulus). Therefore, the accuracy of the estimated layer moduli by BAKFAA was highly dependent on the user's experience. The performance of the back-analysis algorithm in BAKFAA was investigated for both low and high error tolerance values. In both cases, the substructures' layer moduli were consistently overestimated by 1.6 to 5.3 times; maximum 5.3 times overestimation for the clean ballast layer with the error tolerance of 0.0001 and minimum 1.6 times overestimation for the subgrade 3 layer with the error tolerance of 0.01.

To overcome the limitations of the current techniques, including BAKFAA, a novel hybrid back-analysis technique for the railway track substructure condition assessment using FWD testing was introduced (see Chapter 5). The proposed technique offers time efficient back-analysis without dependence on seed values and user-defined information. The back-analysis framework in the proposed technique included ANN and metaheuristic optimisation algorithms for efficient interpretation of the FWD data. The ANN in the proposed back-analysis technique was a surrogate forward model, which replaced the computationally expensive FE forward model to improve the computational efficiency of the technique. Two metaheuristic optimisation algorithms, i.e., the GA and the ACO_R, were then employed and hybridised with the ANN surrogate forward model. Thus, the hybrid ANN–GA and ANN–ACO_R back-analysis techniques were developed. Although the ANN–ACO_R model was shown to be computationally more efficient than the ANN–GA model, the ANN–GA back-analysis technique was proposed as the main back-analysis technique due to its higher accuracy in estimating substructures' layer moduli.

In addition, the application of the developed hybrid ANN–GA back-analysis technique was further extended to not only assess the condition of the substructure layers, but also to detect any buried local anomalies in the substructure layers around a subsurface drainage pipe (see Chapter 6). The numerical example for a weak zone within 1 m of the loading point and a series of parametric analyses demonstrated that the proposed ANN–GA technique successfully estimated the substructures' layer moduli and identified the void adjacent to a drainage pipe with acceptable accuracy, i.e., less than 1% error.

A series of parametric studies showed that a void positioned at the crown of the drainage pipe had the highest detectability by the proposed ANN–GA technique. Additionally, it was shown that there is a direct correlation between void size and detectability of the void by the back-analysis technique. It was demonstrated that smaller voids and voids positioned near the pipe invert had lower detectability and a higher probability of remaining hidden than larger voids and those in other positions. Another series of parametric analyses were carried out using the defined values of void geometric parameters. It was observed that increasing V_w and V_L improved the performance of the proposed technique in identifying the void, while increasing the distance from the loading point decreased the accuracy of the model in detecting the void and estimating its parameters.

To summarise, the results presented in this study established the potential usefulness of the proposed FWD-based hybrid ANN–GA back-analysis technique for the railway track substructure condition assessment, where no similar technique exist. Moreover, the presented examples showed that it is a capable model to detect a weakness zone in the railway substructure caused by drainage system malfunction.

7.3 Recommendations for future research

- To carry out FWD tests and generate an experimental database for ANN training based on real-world data. As the current research was limited to the virtual experimental data generated by the FE models, this further step is necessary to improve the performance of the back-analysis technique by considering actual field conditions and to make it useable for practical applications.
- To obtain validation data from real experimental test case, either field measurements or laboratory experiments to check the performance of the developed ANN-GA back-analysis technique to detect weakness zone.
- To investigate the application of the ANN–ACO_R technique for anomaly detection and compare it with the ANN–GA technique, as the calculation time using the ANN– ACO_R technique is expected to be shorter than the ANN–GA technique.

- To develop a back-analysis package with a user-friendly interface for railway track condition assessment that can be used on-site by operators on a variety of platforms for the widespread application of the proposed back-analysis technique.
- To employ the proposed back-analysis technique for locating buried drainage pipes in railway substructures.

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Zhuang, Y., Wang, K.-Y., & Li, H.-X. (2020). Shakedown solutions for ballasted track structure under multiple uniform loads. *Transportation Geotechnics*, *22*, 100298.

Appendix

List of Publication

The following publications were accomplished during the Author's PhD study in the Aston University.

Journals

- Fathi, S., Mehravar, M., & Rahman, M. (2023). Development of FWD based hybrid back-analysis technique for railway track condition assessment. *Transportation Geotechnics*, *38*, 100894.

Conferences

- Fathi, S., & Mehravar, M. (2022). A Back-Analysis Technique for Condition Assessment of Ballasted Railway Tracks. In *Advances in Transportation Geotechnics IV* (pp. 931-941). Springer, Cham.
- Fathi, S., Mehravar, M., & Rahman, M. (2022). Impact of drainage defect on the railway track surface deflections; a numerical investigation.