Rolling Weight Deflectometer for Stiffer Pavements: Combining Machine Learning and Field Data

MSc Thesis

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Performance of the Rolling Weight Deflectometer for Stiffer Pavements: Combining Machine Learning and Field Data

Thesis

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by

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Abstract

Pavement structures are assessed based on its functional and structural capacity in order to evaluate the safety of its use. Structural pavement evaluation is often carried out by road authorities or consulting companies that use non-destructive testing (NDT) methods to assess the remaining life and structural capacity of a road structure at project or network level. In Western Europe and in most parts of the world, the most common equipment used as part of the NDT method is the use of the Falling Weight Deflectometer (FWD). The FWD is able to capture deflection values that can be used for the backcalculation of moduli and to determine remaining life of a structure by mechanistic-empirical equations.

In the Netherlands, like in many other countries, motorways have an increased number traffic flow based on high population densities accumulating in major cities. Due to this, pavement evaluation with stationary equipment such as the FWD can become relatively expensive due to the disruption of traffic. To solve this problem, research institutions and consulting companies have developed different versions of continuous evaluation equipment that are able to perform the structural analysis in a similar way to the FWD. In 2018, Dynatest® launched the Rapid Pavement Tester (RPT or RAPTOR) which aims to perform functional and structural evaluation of road networks at traffic speed.

Continuous evaluation devices such as the RAPTOR are in constant development in order to achieve the quality and guaranty of use that equipment such as the FWD have in the pavement engineering industry. Currently this type of device uses technology that is less accurate than the sensors (Geophones) used in FWD equipment. This becomes a significant impediment in the evaluation of high stiffness pavement structures as the calculated deflections are in the lower end of the spectrum. This research aims to find a methodology that can be used in order to find limitation stiffness parameter values for which it is viable to use continuous evaluation equipment.

Additionally, this research aims to find a method that can be used in the pavement engineering industry and research that is able to aid the data collection process of pavement layer information by means of machine learning tools. This was a problem faced during the elaboration of this research as the data collected to perform the analysis was incomplete in terms of layer thicknesses information. This process is carried by means of an artificial neural network (ANN) that is able to predict layer thicknesses and moduli based on deflection values and deflection parameters that obtained with the FWD.

The analysis of this research is carried by comparing deflection values in different road networks collected with the FWD and the RAPTOR under similar weather conditions, where the predicted layer information is used to assess the cut-off values and limitations that the current version of the RAPTOR has when compared to the FWD.

From the presented results it was found that the asphalt layer modulus showed the highest correlation to the limitation values where the RAPTOR is able to present reliable results when compared to the FWD. Additionally, promising results were found in the use of ANN method to predict missing layer information which are assumed to improve with a specific build in the ANN architecture.

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1 Introduction

The first chapter of this thesis serves as an introduction that gives structure to the rest of the document. This chapter displays the motivation, aim and scope for the presented research and will conclude with the research questions and methodology towards the completion of the research.

1.1 Motivation

The conditions of a pavement structure are evaluated both by its surface layer quality, which guarantees commodity and security for the user, and structural quality, which corresponds to the structure's ability to withstand the design axle loads (Solanki, Gundalia, & Barasara, 2014). Structural condition evaluation is determined by the composition of the structure, specifically by determining the layer thicknesses and the layer moduli. This information is key to determine the remaining life of a pavement structure, leading to preventive maintenance (Goel & Das, 2008).

Destructive and non-destructive testing (NDT) are the methods used to evaluate the structural conditions of a road network (Goel & Das, 2008). Although more information can be obtained with destructive testing methods, it is significantly higher in cost and time when compared to in-situ NDT methods (Lytton). One of the most common NDT methods used by road authorities for structural pavement evaluation is the Falling Weight Deflectometer (FWD) in combination with the Ground Penetrating Radar (GPR). This method is able to give the information to determine structural capacity based on layer properties and layer thicknesses by backcalculation methods (Noureldin, 2003).

Layer thicknesses are key information towards the backcalculation analysis of pavement structures (Li et al., 2011). Nevertheless, for different reasons it may occur that this information is not recorded. Generally in these cases, the engineer who has the task of performing the backcalculation procedure uses their engineering criteria, taking into account the region where the testing occurred, how old is the structure, and if there are any studies in the area close by that might be representative (Terzi et al., 2013). By taking these criteria into account, an iterative process with predictive layer thicknesses is performed and the corresponding moduli are obtained. Good results might return from this process, but it is highly dependent on the skills and knowledge of the engineer at task.

In recent years equipment that performs non-destructive pavement evaluation at traffic speed has been developed by different companies (Flintsch GW, 2012). In 2018 Dynatest® developed their first version of a continuous evaluation device, the Rapid Pavement Tester or RAPTOR (Gokhale, 2016). This equipment was designed to perform both structural and functional analysis of road networks at traffic speed.

In the Netherlands the traffic intensities are very high and therefore disruption to traffic has to be avoided (EAPA, 2007). Because of this, the country has opted for a long life and maintenance strategy, in which the main highways of the country are composed by thick structures designed by empirical-mechanistic methods proposed as long-life pavements (EAPA, 2007).

The use of continuous pavement evaluation equipment could be beneficial for high density population countries such as the Netherlands (van Beinum & Wegman, 2019) as this type of equipment is able to assess pavement structures at traffic speed, reducing costs and time when compared to conventional methods (Levenberg et al., 2018). Nevertheless, recent versions of continuous evaluation equipment have failed to deliver data with the accuracy of the commonly used FWD. This is a particular problem for stiff pavement structures as deflections are commonly very low (Mehta & Roque, 2003). This might be the reason for national authorities of countries such as the Netherlands to be reluctant to the implementation of continuous evaluation devices for their structural pavement analysis.

1.2 Aim of the Research

In the past, different versions of continuous evaluation equipment have been introduced to the market for engineering application and research purposes. Lacking the accuracy of the well-known FWD, the continuous evaluation equipment under performs for different types of pavement structures (Briggs et al., 2000). At a current state, continuous evaluation devices have equipment that in theory is able to capture deflections with a 25 micrometers accuracy (Gokhale, 2016), in comparison to the 1 micrometer accuracy documented from traditional FWD. The accuracy of such equipment may occur in a significant impact for perpetual pavement structures present in many countries such as the Netherlands, where the three layer structure is composed of thick or high stiffness pavements, as these kind of pavement structures return low deflection values based on standard FWD set up.

Based on the presented problem, the aim of this research is to find the limits based on stiffness parameter values for which the RAPTOR is able to have high correlations when compared to the conventional FWD. Levenberg et al., 2018, has shown a methodology that can be used for the comparison of continuous pavement evaluation equipment and the commonly used FWD.

In NDT methods, FWD deflections are coupled with layer thicknesses in order to obtain the different layer moduli used to assess the structural capacity of pavement structures. As mentioned before, it may occur that the layer thicknesses are not collected during the on site evaluation of motorways. In such cases, experienced engineers are able to predict layer information based on the behaviour of the calculated deflection basins and known information from surrounding areas where the pavement is studied. This may lead to erroneous assessment and wrong predictions towards the evaluation of the pavement structures, because of this, studies such as Saltan et al., 2002, came to the conclusion that using an ANN approach with a well-equipped database could potentially lead to results that can be comparable to traditional means of backcalculation process with known layer thicknesses with an error margin of 10-15%.

The information obtained for the elaboration of this thesis lacks the layer thicknesses for most part of the test sections, therefore a machine learning approach is proposed as the solution for this problem. As it is presented in Section 3.2 of this document, the machine learning approach will consists of an ANN model that is able to predict the different layer thicknesses and moduli based on the available FWD deflections.

From the obtained results, an investigation is carried to find if the FWD should be compensated based on the RAPTOR layout in which the different wheels could have an impact in the generation of deflection bowls, where in return the correlation of both equipment at deflection level might be able to improve.

1.3 Research Questions

Based on the problems established in the aim of the research, the following questions have been elaborated in order to present innovative solutions that can be used in the field of pavement engineering, both for industry and research purposes.

The aim of this research will be tackled and assessed based on the following questions:

1.3.1 Is it possible to obtain reliable predicted structural layer parameters using a machine learning approach?

1.3.2 Is the effect of the wheel load close to the load cell in the RAPTOR taken into account in the deflection model?

1.3.3 Is it possible to set a range of validity from the layer structural characteristics by comparing the deflection results of the RAPTOR and the FWD at similar testing conditions?

1.4 Research Scope

In order to answer the presented research questions, Dynatest® contributed with deflection results from the RAPTOR and the FWD for 8 different road networks collected around Europe between 2018 and 2019 as shown in Table 1. In the presented test sections only two of them were presented with layer thickness information. As mentioned in section 1.2, the prediction of the remaining test sections will be performed by a machine learning approach.

Table 1 Collected Data

Test Section	RAPTOR		FWD		layer thicknesses
	meters covered	number of repetitions	meters covered	number of stations	
Firenze	15980	1	12430	139	GPR
Bologna	15940	1	11770	140	GPR
ANAS	13920	3	1583	121	N/A
DRD	10180	4	10000	295	N/A
DTU	207	3	155	51	N/A
Furesoe	1547	1	1538	57	N/A
Palunka	3040	4	3000	107	N/A
Vejlandsalle	680	3	662	30	N/A

From the presented dataset and the predicted stiffness parameters, the study was conducted to find the limitations of the RAPTOR. Initially, the idea of this research was to collect data in motorways in the Netherlands, and have a direct assessment based on these values. Unfortunately, it was not possible to obtain field collected data in the Netherlands. Despite of this, a possible solution was assessed based on the stiffness parameters of the available dataset, in which section points that share structural layer parameters such as pavement structures in the Netherlands will be categorized as high stiffness pavements in order to validate the use of the RAPTOR. This categorization is based on the typical cross-section of asphalt pavement structures in the Netherlands that is composed of a 3 layer structure consisting of thick asphalt layers (around 350mm) with high elastic modulus in the range of 7,000 to 8,000 MPa as shown in Figure 1.

Based on the given dataset with known stiffness parameters, it was assessed that none of the section points shared the structural composition as the pavement structures in the Netherlands. A work around to this problem was achieved by using a forward calculation analysis, in which the standard FWD set up is modelled in order to obtain the deflection bowl that corresponds to the typical cross-section of Dutch asphalt pavements, in which the deflections under the load are found to be around 177 micrometers for a standard FWD set-up (50kN load in a 300mm diameter plate). This deflection value under the load will be crucial to assess the comparison of the RAPTOR against the FWD.

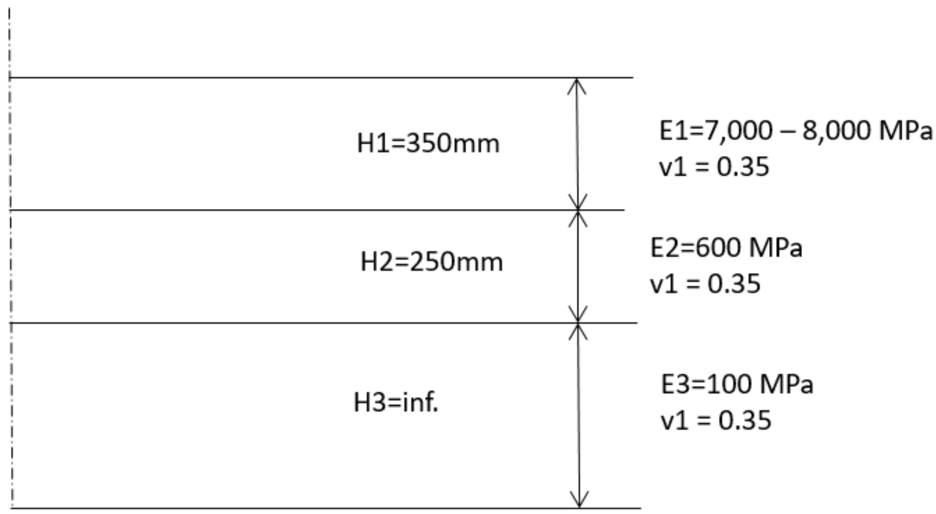

Figure 1 Typical cross-section example of Dutch asphalt pavement

1.5 Research Methodology

The aim of this research is to validate the use of the RAPTOR for high stiffness pavements. This will be determined by comparing RAPTOR deflections to FWD deflections, and classifying the data based on the different stiffness parameters. A hypothetical solution was developed to achieve an analytical procedure that can be followed to determine the validity of a continuous pavement evaluation equipment when compared to the traditional FWD. As stated earlier, the proposed data analysis is done based on the deflections resulting from both devices and their corresponding stiffness parameters, named as RAPTOR & FWD deflection database and Layer thicknesses and moduli database respectively. These databases are the product of a series of frameworks elaborated in this research based on the information and knowledge acquired from the literature study and discussions with engineers and researchers in pavement engineering. Figure 2 shows the different frameworks developed to acquire the information needed to perform the data analysis process.

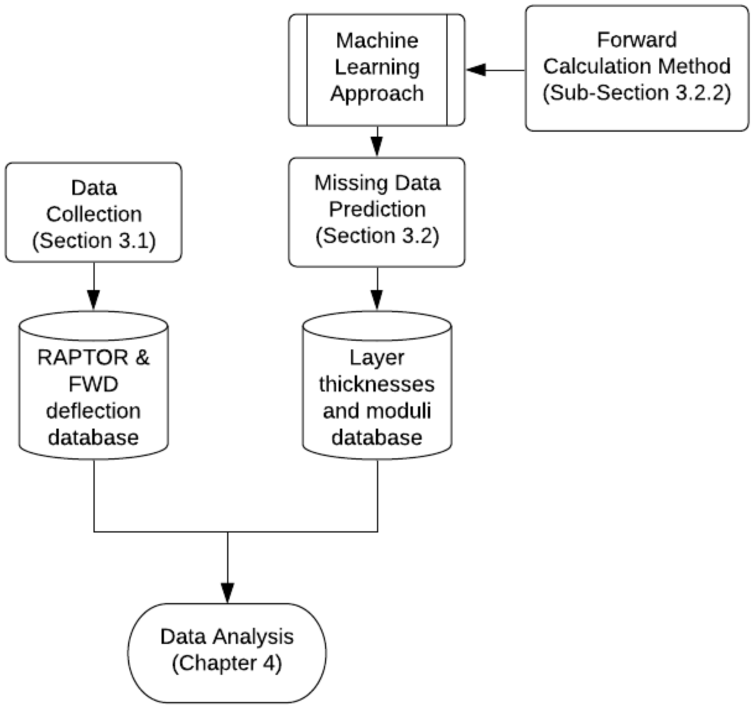

Figure 2 Research framework

The first database acquired in this research is the RAPTOR & FWD deflection database. This database is the result of the data collection process, were the aim of this process is to couple the deflections obtained with the FWD and the RAPTOR by transforming the RAPTOR deflections into FWD relatable data (Section 3.1.1).

The layer thicknesses were not part of the data collection process for most of the test sections, therefore the determination of the layer thicknesses and moduli database does not comply with a direct approach as the deflection database. Instead, a machine learning approach has been proposed as the missing data prediction procedure. The proposed machine learning approach is based on a model created with a software database developed with forward analysis programs. The different frameworks as shown in figure 2 are thoroughly explained in Section 3.2 of this research and will finalize with the determination of the layer thicknesses and moduli database.

With the databases resulting from chapter 3, the data analysis will continue in chapter 4. Chapter 4 consists of the different methods of analysis used towards the evaluation of the RAPTOR against the FWD. As a first approach, the impact of the second wheel axle of the RAPTOR will be studied in order to assess if the FWD should be compensated with this load in order to have a better correlation between the devices. Based on this results, a full data analysis will be performed in order to find which stiffness parameters can be used as classifiers for the RAPTOR viability when compared to the FWD and which are the limits based on the different stiffness parameters. Finally the low deflection section points will be used to evaluate the reliability of the RAPTOR in high stiffness pavements.

Finally, in chapter 5 the different frameworks established in chapters 3 and 4 will be used to create a practical application tool. This tool is presented as a semi-automated application that can be used for different pavement evaluation equipment comparisons with an example based on simulated data.

2 Literature Review

This chapter is the collected information to have the initial background towards the completion of this research. This chapter is divided in 6 sections divided as the following: Structural pavement evaluation, non-destructive testing equipment, analytical methods towards pavement engineering, comparison of discrete and continuous structural evaluation, problems and practical difficulties with current analysis approaches and finally a brief description of artificial neural networks use in pavement engineering.

2.1 Pavement Evaluation

Pavement evaluation is used to determine the current state of a pavement structure, assessing the structural and functional characteristics of a pavement structure. Functional performance evaluates the safety and commodity for the user, therefore, it is assessed through the pavement surface condition based on visual distress, surface friction, rutting and roughness. On the other hand, structural evaluation focuses on the structural characteristics such as layer thicknesses and moduli, along the design load history in order to determine if maintenance, overlay or rehabilitation must be performed in segments of the road network to achieve the designed remaining life (Solanki, Gundalia, & Barasara, 2014).

This process is performed by destructive and/or non-destructive testing. In the destructive (DT) methods, in situ pavement sections are drilled to extract cores in order to assess the pavement properties through laboratory testing (Domitrović & Rukavina, 2013). This method is very expensive and time consuming, although it is frequently used for research purposes as more information can be acquired. Since this method is expensive and time consuming, a more practical approach is performed by industry and research using non-destructive (NDT) methods. The NDT methods use a combination of deflection induced measurement systems that can be discrete or continuous. The most common practice among the NDT structural pavement evaluation is the use of equipment such as the Falling Weight Deflectometer (FWD) and the Ground Penetrating Radar (GPR) (Solanki, Gundalia, & Barasara, 2014).

The structural response of pavement structures can be determined by different measurements such as stress, strains, and deflections. Stresses and strains can be obtained through laboratory experiments based on the coring of the pavement structures. Therefore in the NDT evaluation methods deflections are calculated from equipment such as the FWD. Based on deflections and mechanistic pavement models, stresses and strains can be calculated in order to determine the remaining life of the structures (Hamim et al., 2018).

NDT methods can be separated into different ways to carry out the structural evaluation of pavement structures depending on the equipment at use. Different methods such as *Structural evaluation by static loading* and *Structural evaluation by dynamic loading* are often used for NDT evaluation. Structural pavement evaluation can also be classified by the deflection measuring system. Another ramification for the classification of equipment is obtained by *Discrete evaluation* and *Continuous evaluation* (Solanki, Gundalia, & Barasara, 2014).

2.2 NDT equipment

This section focuses in the equipment used with NDT methods. As mentioned in the previous section, the most common equipment for NDT methods consists in the combination of the FWD and the GPR. Besides of the FWD and GPR devices, a continuous measuring device will also be explored.

2.2.1 Ground Penetrating Radar

The ground penetrating radar (GPR) is an electromagnetic tool used to evaluation the depth and to investigate the presence and continuity of natural subsurfaces without drilling or digging that is able to estimate pavement layer thicknesses and subsurface defects (Baili et al., 2009). This type of device performs an intrusive analysis in the structure without any major damages or discontinuities in the test field. The concept of the GPR relies on radio waves that are transmitted from a point towards a receiver in an adjacent point that is able to capture the reflected waves. The reflections take place whenever there is a change in material properties. It analyses the elapsed time of the wave, and by this means is able to measure the distance where the discontinuities occur (Thom, 2014).

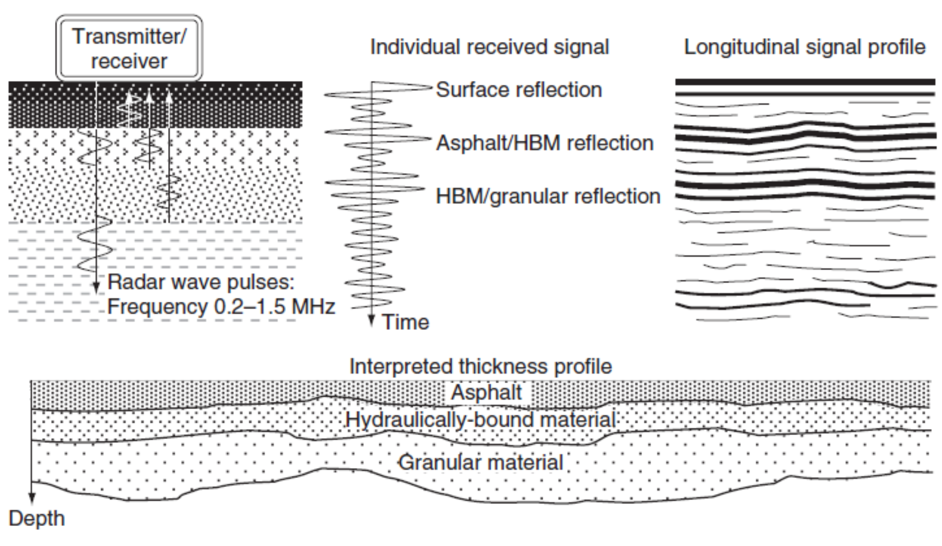

Figure 3 Ground-Penetrating Radar (Thom, 2014)

2.2.2 Falling Weight Deflectometer

The Falling Weight Deflectometer (FWD) is a non-destructive structural testing device that uses an impulsive transient load application that generates deflection response at a series of radial points (D4694-96, 2003). The method of transient load application has resulted in different set ups depending on loading plate size, load applied and number of applications (ASTM D4694, 2003). The FWD tries to simulate a rolling wheel when the application method consists of a 300mm diameter plate loaded between 4kN and up to 120kN impacting on the surface of the pavement structure as a dynamic impact load with loading times between 0.025 and 0.3 seconds (ASTM D4694, 2003). The setup also includes a number of velocity transducers called Geophones placed at a radial distance from the loading cell that record the deflection at different points away from the load (ASTM D4694, 2003).

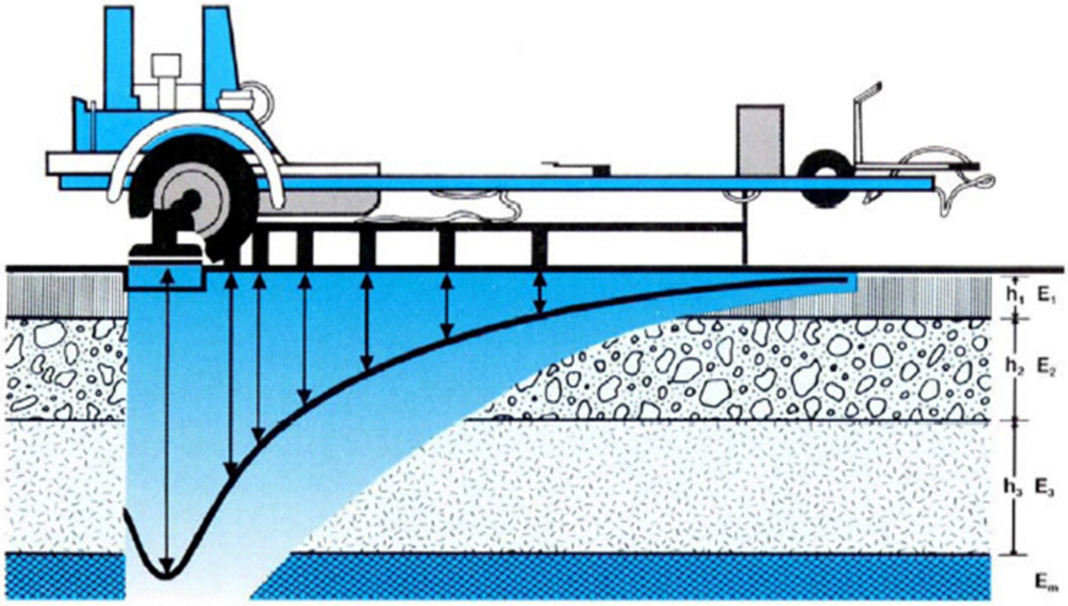

Figure 4 FWD deflection basin (Dynatest®)

2.2.3 Rapid Pavement Tester (RAPTOR)

With the use of 12 line laser profilers (Gocators), the RAPTOR is able to measure distance differences of the pavement structure. These Gocators are mounted on a stiff 5.1m long beam, mounted 1.5m away from the loaded wheel.

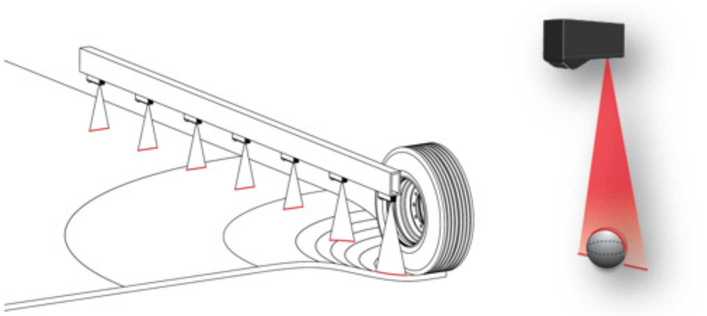

Figure 5 Measurement setup on the RAPTOR and the line laser profilers (Gocators)

Each Gocator is able to reproduce 1280 measurements per sample (1m, 2m, 5m, etc.). This measurements are correlated among different sensors and wheel encoders. This data is passed through an image recognition software as the first filtering process.

The filtered measurements are correlated among sets of three different lasers equidistant to each other. This values is calculated as “curvature” or RDI (RAPTOR Deflection Indices). The process to calculate the RDIs is the following, Using geometrical values from the height of the beam over the pavement *(h),* the angle of the beam *(b)*, the deflection *(d_0, d_1, and d_2)* under each Gocator (z_0, z_1, *and* z_2) and its corresponding texture (r_0, r_1, *and* r_2).

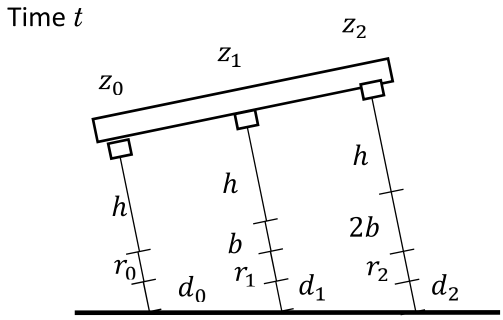

Figure 6 Beam measurement at time t

Once the truck has displaced to a distance equal to the difference between the Gocators, the measurement is taken to be at time *t'* as shown in Figure 7.

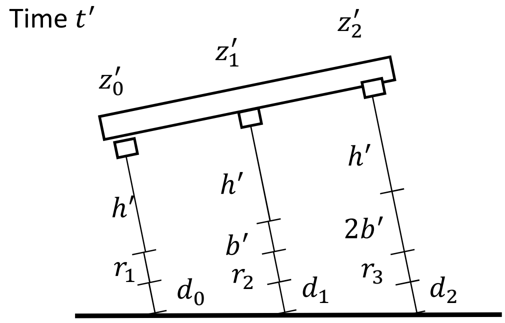

Figure 7 Beam measurement at time t'

Following the parameters from instances *t* and *t',* a set of coupled linear equations can be defined as presented in Figure 8.

$$z_0 = h + d_0 + r_0 \qquad z'_0 = h' + d_0 + r_1$$
$$z_1 = h + b + d_1 + r_1 \qquad z'_1 = h' + b' + d_1 + r_2$$
$$z_2 = h + 2b + d_2 + r_2 \qquad z'_2 = h' + 2b' + d_2 + r_3$$

Figure 8 Linear equation system from distance measurements

$$s = z_1 - z_2 = -b + d_1 - d_2 + r_1 - r_2$$
$$s' = z'_0 - z'_1 = -b' + d_0 - d_1 - r_1 - r_2$$
$$s' - s = b - b' + d_0 - 2d_1 + d_2$$
$$RDI = s' - s + b' - b = d_0 - 2d_1 + d_2$$

Figure 9 RDI equations

The current version of the RAPTOR includes 12 different Gocators that are placed on the carbon beam. With these Gocators, 22 different sets of RDI are generated as the original output from the RAPTOR.

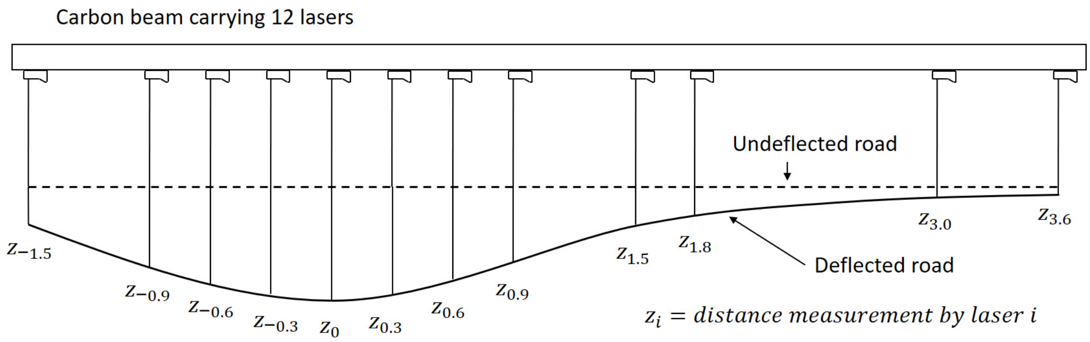

Figure 10 Laser configuration RAPTOR measurement beam

The output of the RAPTOR is measured in deflection differences, therefore the data is processed through a pavement model in order to generate deflections. This pavement model parts from assumed structural characteristics in order to output deflections that can be compared to the FWD. The following flowchart is a representation of the complete process of the RAPTOR:

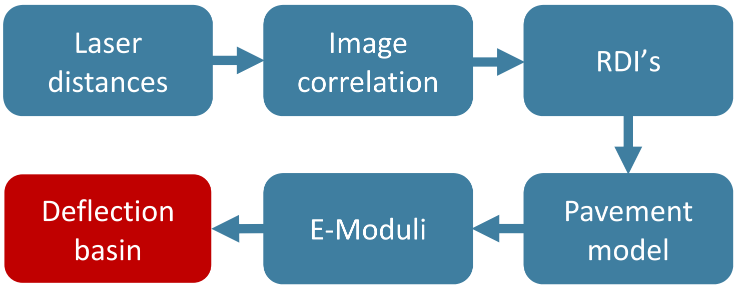

Figure 11 Laser distances to deflection basin methodology

2.3 Analysis and Methods for Pavement Structures

The use of the FWD for pavement evaluation had a drastic increase in the 1980's, which lead to the introduction of analytical methods into the pavement engineering practice (Goktepe et al., 2006). Since then, the use of the FWD can be considered essential for structural pavement evaluation in order to optimise pavement rehabilitation. From the deflections measured with the FWD device, a backcalculation process is used to obtain the effective stiffness moduli for the principal layers of the structure (Mehta & Roque, 2003). From the backcalculated layer moduli, pavement engineers are able to determine stresses and strains at critical locations under the replicated axle load. Later on these values can be related to the maximum number of equivalent standard axle loads (ESAL) in order to determine the remaining pavement life of the layered structure. The data as backcalculated from the FWD calculated deflections can also be aided with laboratory tests to support the information acquired from the NDT procedure. Finally the pavement life is compared to the predicted future traffic flow in order to determine which strengthening design of the layered structure is needed to achieve the expected lifetime (Hakim & Brown, 2006).

Structural evaluation based on pavement deflection response using NDT methods has been continuously increasing over the years as the methods continued to improve in measure capabilities and developments from analytical techniques. This has resulted in the use of backcalculation techniques alongside empirical-mechanistic procedures in order to do proper maintenance, rehabilitation or reconstruction of the pavement structure (Ullidtz & Coetzee, 1995).

2.3.1 Pavement Models

Different mathematical models have been developed to describe pavement response based on ideal scenarios trying to simulate real life pavement materials and structures. In order to validate the use of these models, the analytical results are compared to real life measurements in pavement structures. It was shown in the research presented by Ullidtz et al., 1994, that one of the best representations of a pavement model when compared to real life pavement structures occurs when the analysis is performed with the Finite Element Method (FEM). Since the implementation of FEM analysis incurs in higher cost due to computational power and process speed, it was also determined in the presented research that traditional Boussinesq-Odemark transformations can be used in case the non-linearity of the subgrade modulus is taken into account.

This research relies heavily in the analytical response of pavement structures due to induced loads to acquire deflections. In order to achieve the goal of this thesis, the description of the methods that are used for backcalculation are displayed.

Backcalculation is presented as the analytical technique used to determine equivalent elastic moduli of pavement layers based on deflection basins yielding from a loading method. (*Standard Guide for Calculating In Situ Equivalent Elastic Moduli of Pavement Materials Using Layered Elastic Theory*, 2008). For the calculation of layer moduli as conducted in pavement engineering, the process is commonly done by an iterative procedure in which deflections are calculated using different set of moduli trying to achieve similar deflection basins as the ones given as the original data. Although this procedure is widely used in the industry, it is known that the deflection basins are not unique solutions as explored in section 2.5 of this document.

2.3.1.1 ELMOD6

ELMOD6, developed by Dynatest® is the backcalculation software used alongside the FWD for pavement structural evaluation. This software uses traditional Boussinesq-Odemark method based on the assumption of equivalent thickness with the supposition that the strains within layers depend only on stiffness. Presented in the research (Ullidtz et al., 1994) it was demonstrated that the method yields acceptable results if implemented correctly. The first criteria states that the moduli of layer n is higher than that presented in layer n-1. The other implementation made by ELMOD is the implementation of a non-linear layer in the subgrade modulus. The inputs required for the moduli calculation in this software is the deflection basin or deflection at various geophone positions, load cell parameters (loading weight and area) and layer thicknesses based on GPR information or engineering criteria estimations (Picoux et al., 2009).

2.4 Comparison of Discrete and Continuous Structural Evaluation

With the introduction of state of the art continuous evaluation equipment, the field has investigated their reliability by comparing it to traditional equipment such as the FWD. These late studies have been carried by comparing equipment such as the TSD, and RWD as these equipment have been trying to enter the market of research and consultancy for pavement evaluation at network level.

Earlier studies presented that the implementation of continuous deflection equipment such as RWD and TSD were not reliable to perform pavement evaluation at network level (Diefenderfer et al., 2010 and Briggs et al., 2000). It was concluded by Briggs et al., 2000, that with technological improvements the continuous evaluation of pavement response could be used as a screening device if the measurement device has an accuracy in the order of 25 micro meters as recently achieved by Dynatest's Raptor.

To this day the comparison of continuous pavement evaluation equipment is under study. Levenberg et al., 2018, has shown a methodology for the comparison of this type of equipment and the commonly used FWD. This methodology has been used to support the methodology implemented in this research.

In order to compare the TSD and the FWD Levenberg et al., 2018, implemented a methodology in which both equipment are tested for the same road stretches in similar environmental conditions. As presented in the introduction to the RAPTOR, the output for continuous evaluation equipment is constructed based on the measurements at different locations along the beam. The same concept is applied in the TSD results where the output is presented in TSD indices. Since the output of the TSD is not given in deflections at geophone positions as yielded from the FWD, the deflections from the FWD were transformed to represent the same indices as presented in the TSD. To perform this transformation, a second FWD loading plate is placed on the position of the second wheel of the rear axle to represent the behaviour of the TSD. With this setup a linear interpolation is done to determine the indices from the TSD. Finally the comparison is performed based on the deflection basin peak values for the TSD composed of TSD_{300} index and the transformed FWD deflections (u_z) to the same index.

$$TSD_{300} = u_z(x = 0) - u_z(x = 300mm)$$

Equation 1 TSD_{300}

2.5 Problems and Practical Difficulties With Current Analysis Approaches

Nondestructive pavement analysis has encountered several problems when it comes to the use of FWD measured deflections for the backcalculation procedure of stiffness moduli. This problems rely on the assumption of linear elastic analysis, which is the most common mechanistic-empirical procedure to assess pavement structures. One of the main problems encountered in the backcalculation techniques is the non-unique solution from a single deflection bowl. (Hakim & Brown, 2006). These problems have been reported in literature and will be explained in this section in order to have a clear view of the different problems faced while doing pavement evaluation as shown in (Uzan, Lytton, & and Germann, 1989) (May & Von Quintus, 1994) (Ullidtz & Coetzee, 1995).

2.5.1 Discontinuities, cracks and distresses

Pavement analysis takes into account that the layers above the subgrade are finite in depth but infinite in horizontal direction, this assumption becomes invalid if cracks or different types of distresses are present at different sections of the layered structure. As a consequence, backcalculated layer moduli are taken as effective values that are a representation of the layered structure condition with the corresponding pavement defects.

This problem can be aided by additional surveys such as analysing visually the state of the layered structure, coring and laboratory test of the cored samples.

2.5.2 Edge effect

One of the assumptions of multi-layered linear elastic analysis is that the horizontal plane is infinite. This is not true as the horizontal plane is determined by the width of the road. In order to have a better kind of analysis when performing deflection calculation with equipment such as the FWD is to carry the corresponding tests at least 1 meter away from the edge. This can sometimes be a problem in narrow road sections since the testing should be carried where the wheel load line. Because of this problem a careful interpretation of results has to be performed to minimize the errors in the analysis.

2.5.3 Layer de-bonding

In multi-layered linear elastic analysis it is assumed that the layers have a homogeneous bond between each other. Sometimes this is not the case as it is possible that the layers are not properly bonded to each other, leading to poor results of the lower layers stiffness moduli reflecting poor material condition.

2.5.4 Layer thickness variation

Layer thicknesses are needed in order to perform backcalculation analysis as traditional software is able to predict layer moduli when deflection bowls and layer thicknesses are known. The layer thicknesses are commonly obtained with the use of the GPR or by coring if possible. Nevertheless this procedure is performed on a discrete manner and average thickness is traditionally used in order to perform the backcalculation analysis. Nevertheless, this assumption can lead to different predicted layer moduli to the one present in the structure, as it is common to have different thicknesses along the same layer.It is possible to obtain detailed measurements of the various thickness values but is often not feasible from a practical point of view.

Another problem that may occur is the lack of data from the layer thicknesses, which is tackled in practice by experienced engineers taking into account information of the surrounding areas to predict different sets of layer thickness values and have a proper interpretation to which values can lead to almost valid results. This is also validated due to the fact that if different layer thicknesses are used to those presented in-situ, the backcalculation analysis compensates with higher or lower moduli which lead to similar residual life.

2.5.5 Temperature correction factors

The asphalt layer is heavily influenced by the temperature at which the road is tested. Since this influence has a high effect on the backcalculated asphalt modulus, the FWD measured deflections should be corrected to a common design temperature. This correction factor is dependent of material type and condition, where higher factors are used with undisturbed pavement structures in comparison to cracked, or old pavement structures where the asphalt material has lost its viscoelastic properties, having less effect over the backcalculated moduli.

3 Methods and Tools

As presented in the methodology section of chapter 1, the methods and tools chapter will explore the different processes needed to obtain the information needed to answer the presented research questions. The information corresponds to the coupled database of the deflections obtained with the FWD and the RAPTOR with stiffness parameters based on the FWD deflections. In the first section of this chapter, the process of data collection will be shown and explained, leading to the framework used to obtain the relevant information for this research. The second entry in this chapter will be used to explore the missing data prediction procedure by means of machine learning tools.

3.1 Data Collection Process

Before the continuation of this research, it is imperative to take into account that due to lack of data and information in the elaboration of this document, several assumptions had to take place. These assumptions correspond to the problems and practical difficulties as shown in section 2.5 of this research. These assumptions take place particularly in the temperature correction factors and the layer thicknesses variation.

Since no temperature information was available during the elaboration of this research, it is assumed that the presented data consists of normalized deflection values for both equipment. Although the temperature takes a major role in the backcalulated layer moduli, the framework of this research consists in the procedure to make a proper comparison at deflection level of the FWD and RAPTOR.

The presented document relies heavily in the prediction of layer thicknesses and moduli since GPR information was not available for all the test sections. Therefore it is assumed that the layer thicknesses prediction are compensated in the backcalculation procedure with their corresponding layer modulus.

In section 1.5 the framework designed to answer the research questions was presented as the thesis framework (figure 2). The first step of this framework corresponds to the data that is used to carry out the analysis. This data is described as two main databases that correspond to the RAPTOR & FWD deflections and the layer thicknesses and moduli from FWD data. In order to define these databases, a data collection framework was elaborated as presented in Figure 12, described in the sub-sections 3.1.1 and 3.2.2.

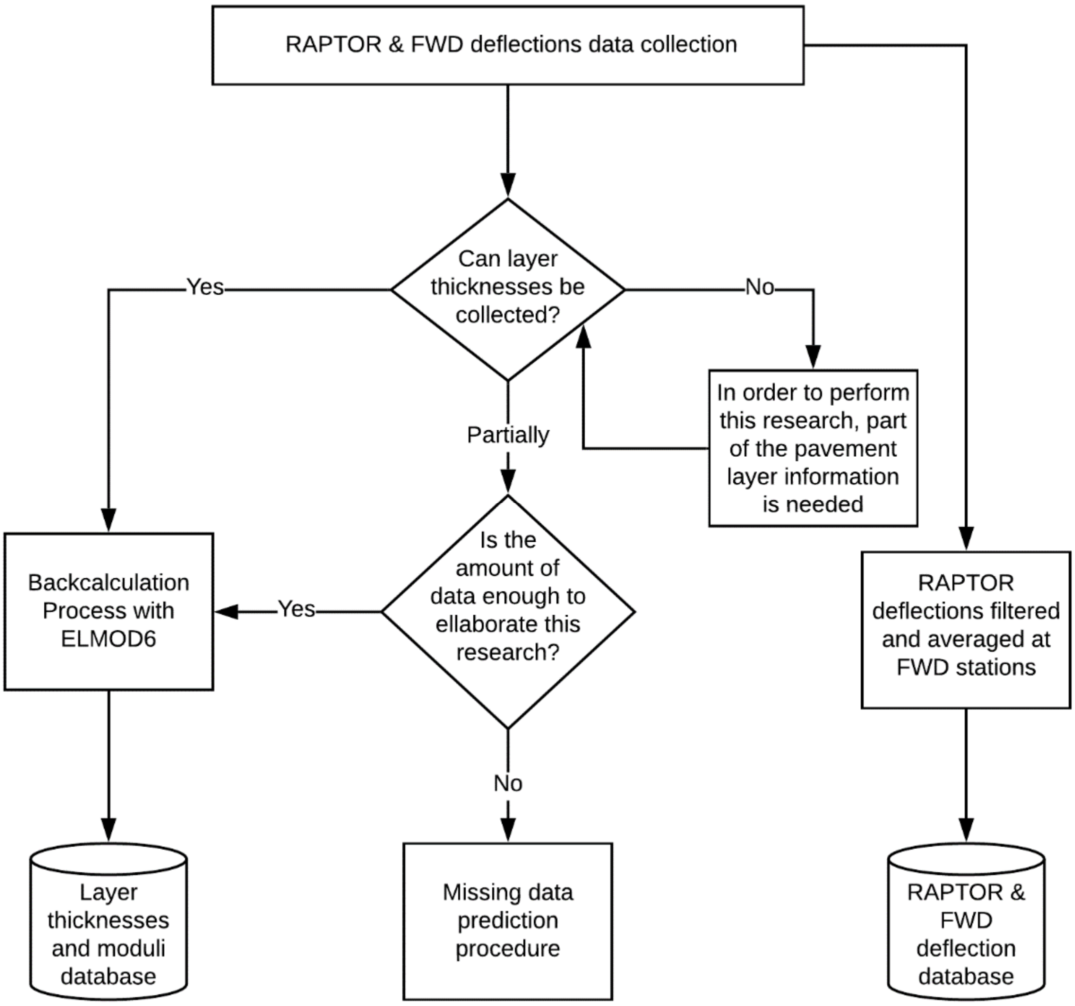

Figure 12 Data collection flowchart

3.1.1 RAPTOR & FWD Deflection Database

As shown in figure 12, a direct approach is implemented to find the RAPTOR & FWD deflection database. The aim in this process is to couple the deflections obtained with the FWD and the RAPTOR by transforming the RAPTOR deflections into FWD relatable data.

In Section 2.2 the RAPTOR is described as an equipment that is able to measure distance differences with the use of 12 line laser profiles or Gocators. Based on the laser distances an image correlation algorithm is applied and the distances differences are converted into RDI's. These RDI's correspond to the deflection differences among 3 sets of Gocators, and the different RDI's are used in a pavement model that transforms them into conventional deflection basins. As the equipment is continuously analysing the pavement structure, the deflection basins generated from the model can be generated every 1, 5 or 10 meters.

In the data set presented in Section 1.4, for the different pavement sections the RAPTOR deflection basins correspond to measurements taken at every meter. On the other hand, the deflection as measured with the FWD correspond to discrete measurements varying in distance between 15 and 100 meters.

In order to have comparable measurements between these devices, the data collected from the RAPTOR is averaged to the closest FWD station within a 30m range. The raw data and the filtered data is shown in figures 13 and 14 respectively (road network: Bologna, deflection under the load). Each figure is divided in two parts to show the deflection at every recorded station (top, x axis correspond to the station point in km and the y axis corresponds to deflections in micrometers) and the combined correlation of these deflections based on the FWD station points (bottom, x and y axis correspond to deflection points in micrometers).

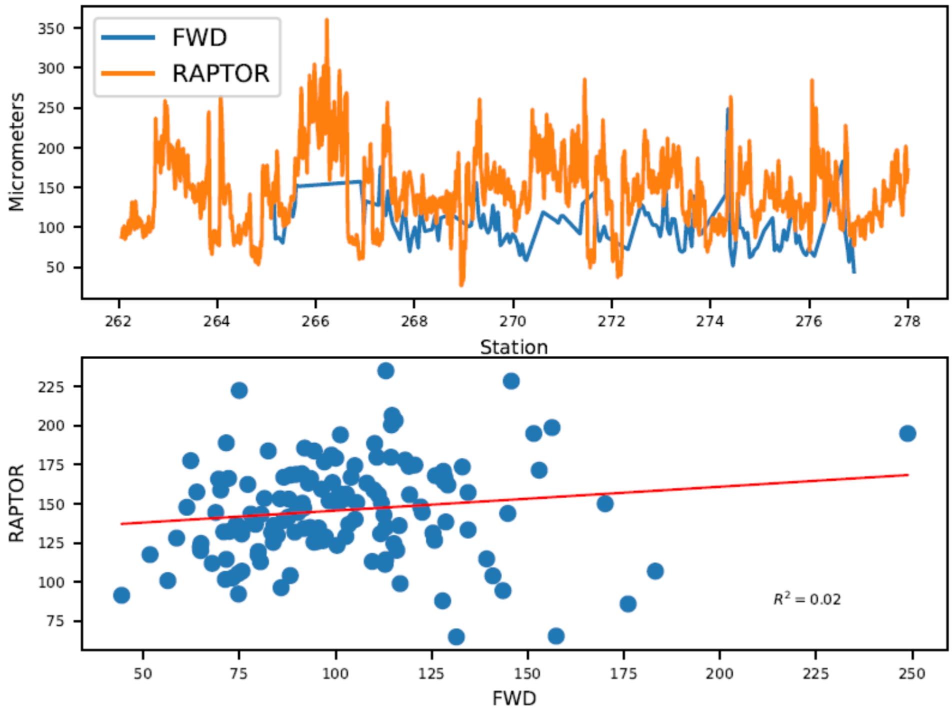

Figure 13 Raw RAPTOR deflections vs. FWD

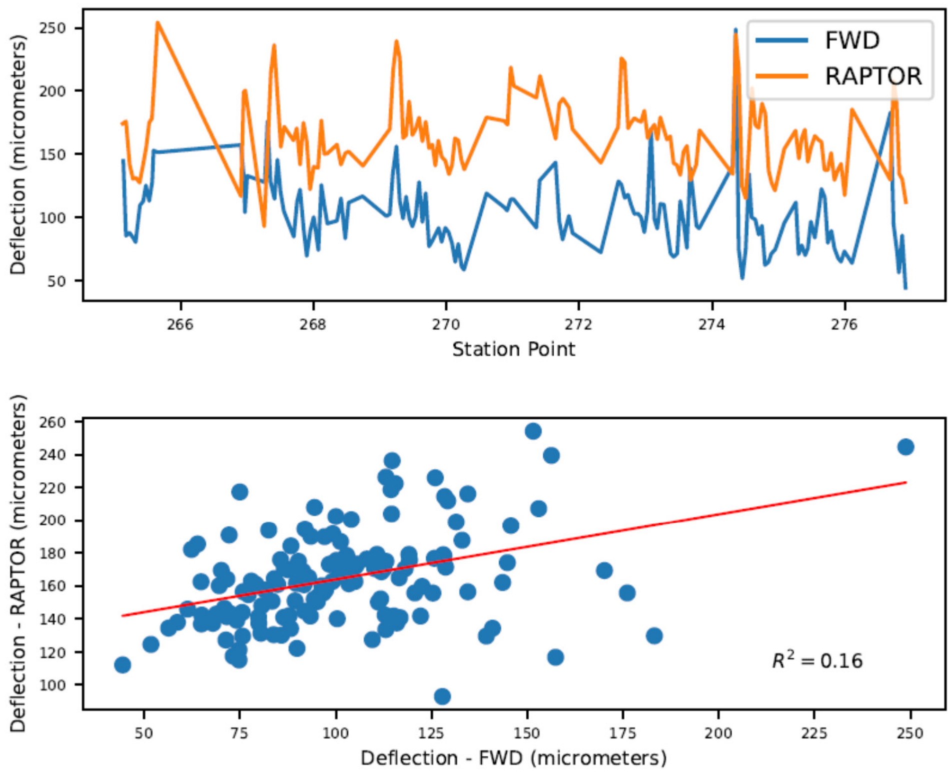

Figure 14 Averaged RAPTOR deflections under the load

In figure 13, the raw data of the RAPTOR is directly compared with the deflections measured at every FWD station, and their correlation is almost null as a 0.02 R^2 value was calculated. With the filtering process, the correlation value increased to a 0.16 R^2 as shown in Figure 14. Although the correlation value is still very low, similar trends were generated for both devices. The finding of similar trends was the only validation criteria used for this method of filtering, this conclusion is also based on the assumption that the GPS coordinates are properly calibrated. With this conclusion, the rest of the test sections were processed in a similar way to obtain the RAPTOR & FWD deflection database.

3.1.2 Layer Thicknesses and Moduli Database

Following the thesis framework flowchart presented in Figure 2, two databases are needed in order to answer the research questions through a data analysis procedure. It was described in the data collection flowchart presented in figure 12 that the layer thicknesses and moduli database is the result of a series of conditional statements.

In order to obtain the layer thicknesses and moduli database at least partial recollection of the layer thicknesses data must be performed. In this research the layer thicknesses were obtained for 2 out of the 8 test sections. As the recollection of data is partially true, the framework is divided in two directions.

The first direction taken in this process is the acceptance that the test sections where layer thicknesses are available is enough to carry the data analysis process as presented in figure 2. As the amount of data is taken as enough to perform the data analysis, the second step is to perform a backcalculation process for the test sections where the layer thicknesses are known in order to obtain their corresponding layer moduli.

3.1.2.1 Backcalculation of Layer Moduli

As shown in Table 1, two out of the eight road networks were provided with layer thickness information from the GPR. With the collected layer thicknesses and deflection bowls, the corresponding layer moduli were backcalculated using the software ELMOD 6.

This backcalculation procedure was performed by means of Method of Equivalent Thicknesses (MET). This method uses the traditional Odemark transformations (Ullidtz, 1998) for the top and middle layer, adjusting the thickness towards the subgrade modulus. Following this procedure, the corresponding layer moduli were obtained.

Again, with the FWD deflection measurements in combination with the GPR provided data, the backcalculation of layer moduli was performed with the use of ELMOD 6. The mentioned analysis converged in different layer moduli for the three-layer structure system for the test sections of Bologna and Firenze. The different layer moduli and layer thicknesses were plotted into histograms (figures 15 – 18) to determine if the test sections have enough data that is relatable to the high stiffness pavement structures from the Netherlands (Section 1.4).

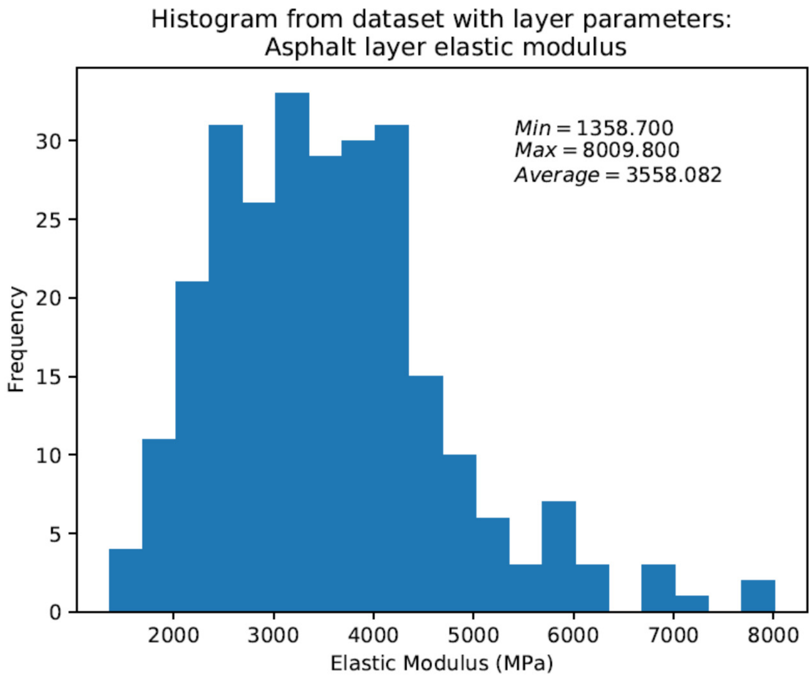

Figure 15 Asphalt layer elastic modulus distribution

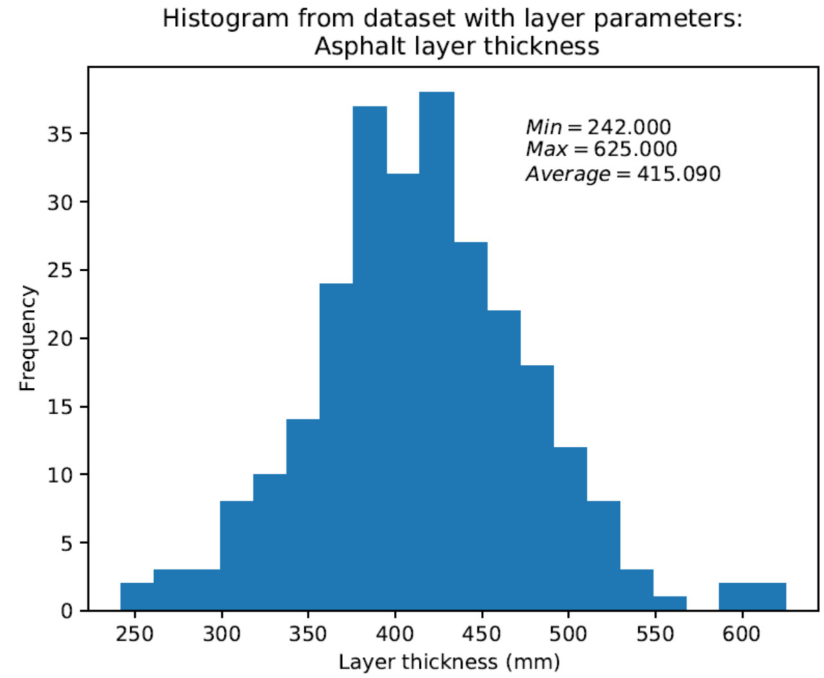

Figure 16 Asphalt layer thickness distribution

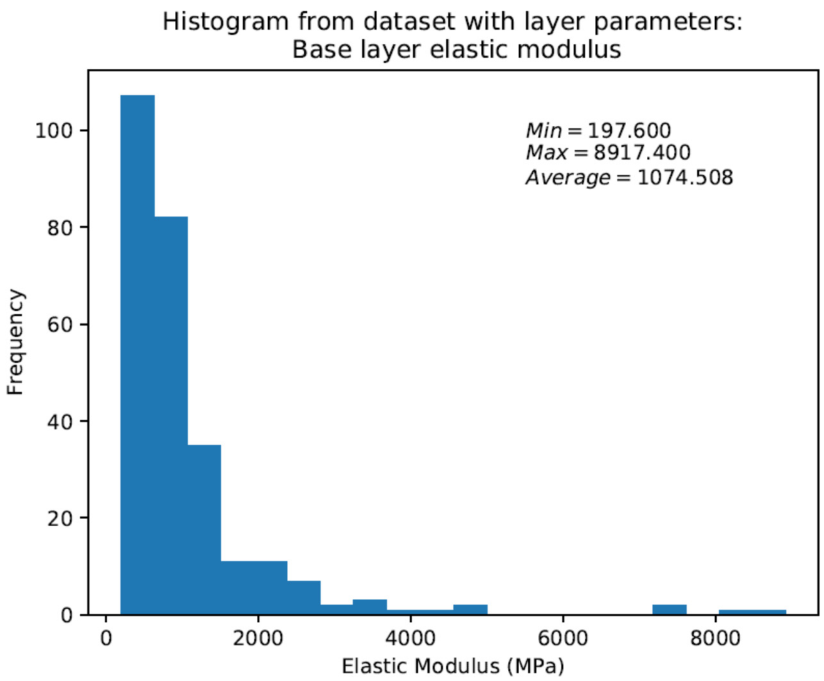

Figure 17 Base layer elastic modulus distribution

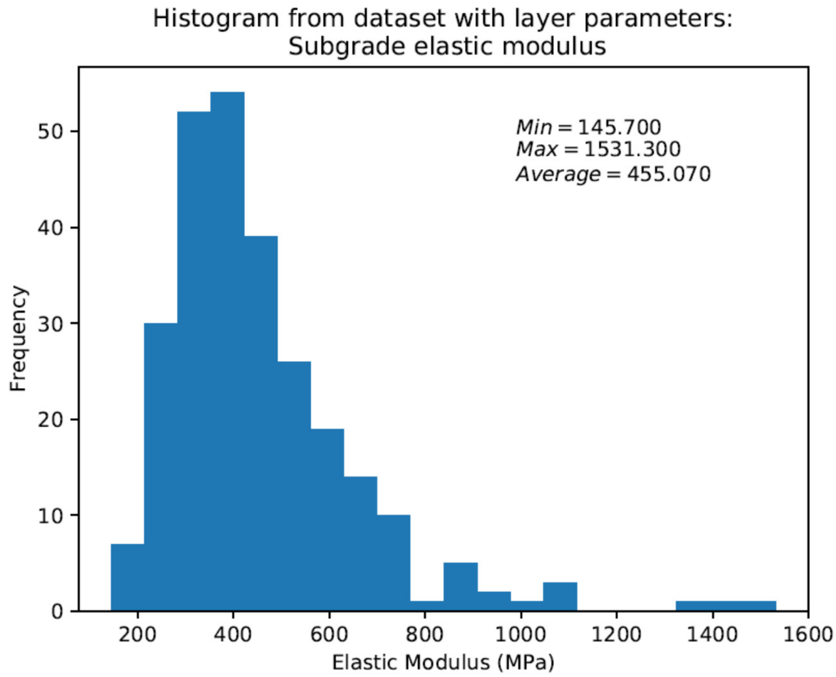

Figure 18 Subgrade elastic modulus distribution

Based on the results displayed in figures 15 – 18 it is determined that the stiffness parameters presented in the given test sections do not follow the same regulations as the typical pavement structures in the Netherlands. The highest difference applies to the asphalt layer elastic modulus as shown in figure 15 that has an average stiffness of 3,552 MPa, a stiffness significantly lower than the average 7,000 – 8,500 MPa presented in the Netherlands. Nevertheless, this parameter is compensated by thicker asphalt layer thickness (figure 16), with an average value of 415mm. But most of the difference in these road networks is that the subgrade (figure 18) has higher stiffness values, with an average of 455MPa displaying a significant difference with pavement structures in the Netherlands that can achieve subgrade modulus lower than 100MPa.

3.1.2.2 Data Validation

In order to validate the process in which the test sections with known layer thicknesses is enough to carry out the data analysis, the test sections are verified to have enough representative data of high stiffness pavement structures. As shown in the results from section 3.1.2.1, it was found that the test sections do not have a relatable composition as the pavement structures in the Netherlands. Because of this, the analysis was performed based on the deflection under the load based on the characteristics of the pavement in the Netherlands. This procedure is done with 3D-Move Analysis software (section 3.4), where the standard FWD equipment results in a deflection under the load “D_0” equal to 177 micro meters.

In order to assess if the test sections with known layer stiffness are enough to perform the data analysis procedure (figure 2), a histogram of the datasets where full layer thicknesses and moduli are known was plotted inside the complete dataset deflection histogram (figure 19).

As shown in figure 19, the dataset with known layer thicknesses consists of 266 data points, or 25.6% of the total dataset. Within this dataset, it was found that 129 data points followed the criteria where the deflection under the load is less than 177 micro meters. Combining all the test sections, 525 points were found to have deflections under the load with less than 177 micro meters, showing that the test sections with known layer thicknesses only represent 34% of the total amount of data that is presented as valid in this research.

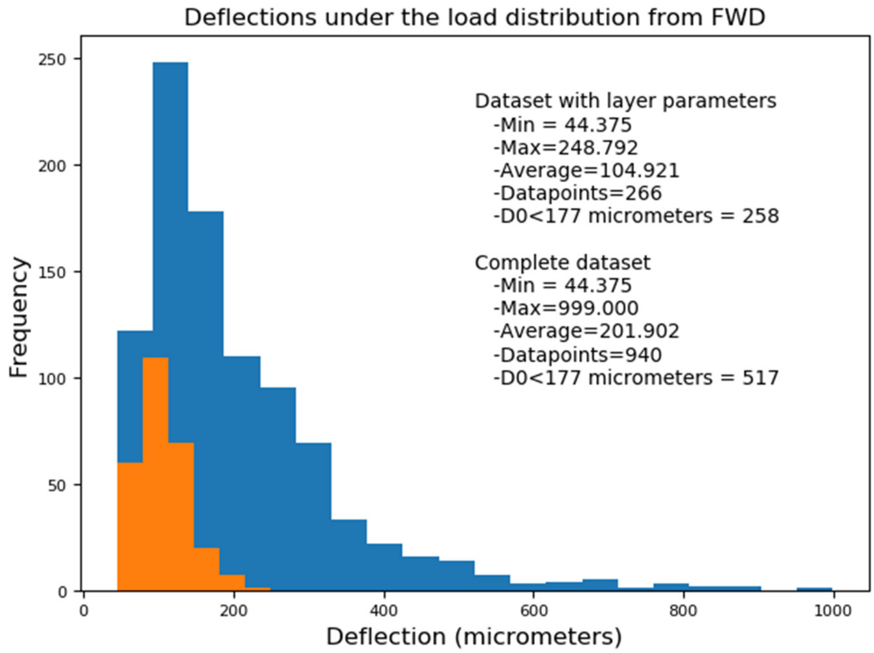

Figure 19 FWD deflection distribution from the 2 sets under the full distribution

It was found that the data with known layer thicknesses only corresponds to 34% of the total amount of data that could be relevant to answer the research questions. Because of this, it was decided to not only take into account the test sections with known layer thickness but all the test sections. In order to include all the test sections to the data analysis, a missing data prediction procedure must be performed to have relevant pavement information that is able to help answer the presented research questions as shown in the conditional statement from figure 12.

3.2 Missing Data Prediction Procedure

As described in the data collection flowchart, a missing data prediction procedure is implemented in case the dataset with known stiffness parameters is not enough to perform the proposed data analysis. Where the missing data is taken to be the unknown layer thicknesses and moduli for the remaining 6 test sections. In this research, missing data prediction consists of the implementation of a machine learning procedure, specifically an Artificial Neural Network (ANN) to predict layer thicknesses and moduli for the remaining test sections. Studies such as Saltan et al., 2002, came to the conclusion that using an ANN approach with a well-equipped database could potentially led to results that can be comparable to traditional means of backcalculation process with known layer thicknesses with an error margin of 10-15%.

The missing data prediction procedure is validated based on research question 1.3.1, and will be validated by comparing the deflections generated with a forward calculation analysis of the predicted layer thicknesses and moduli with the original deflections fed in the model. As shown in figure 20, the unknown layer thicknesses and moduli are the result of a machine learning regression analysis that uses a database built with analytical data procedures.

The following subsections will present the machine learning approach and structure, the database elaboration, and the machine learning analysis results.

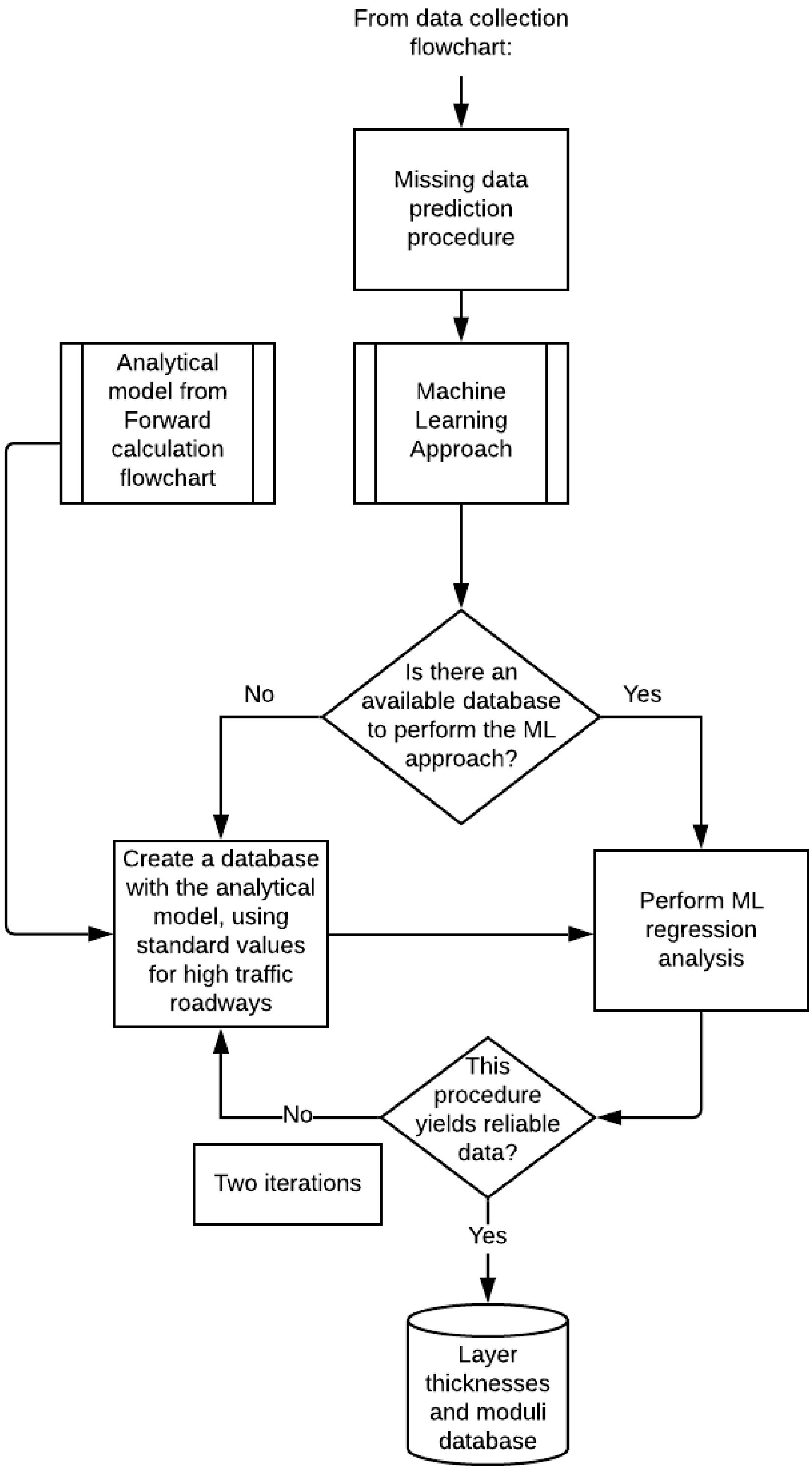

Figure 20 Missing data prediction flowchart

3.2.1 Machine Learning Approach and Structure

In recent years the use of Machine Learning (ML) tools towards engineering and research have become more popular, as computational power is increasing at the level where with a conventional computer you are able to perform complex mathematical problems in a fraction of the time it was possible before (Whitehall & Lu, 1991). Current machine learning tools are used to increase the productivity of systems and processes based on past information. This type of machine learning procedure is commonly called supervised learning, as it is able to make classification or regression analysis based on recollected information in the form of a database (Wang et al., 2018).

In this research, a supervised machine learning approach was proposed to predict missing information such as layer thicknesses and layer moduli. This process is based on the studies presented by Saltan et al., 2002, Sharma & Das, 2008 and Terzi et al., 2013 where data mining and ANN were studied as backcalculation tools for FWD data measurements. In order to obtain the desired results from the machine learning approach, first the different elements that will be taken into account must be defined.

This machine learning process will be performed with an ANN model, specifically a Multi-Layer Perceptron (MLP) regression analysis that is composed by a layer of inputs, a layer of outputs and the hidden layers in between that connect and will predict the outputs based on the defined inputs as shown in figure 21.

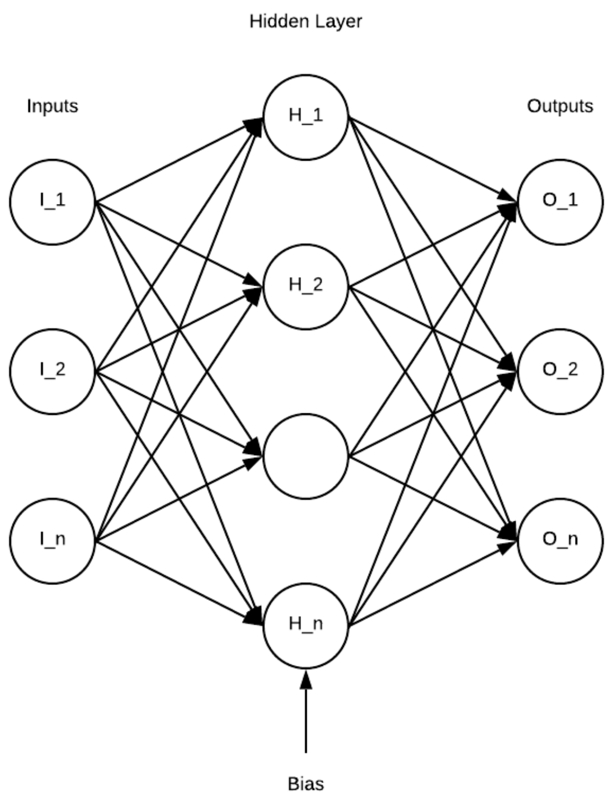

Figure 21 MLP regression structure

Following the MLP regression structure, it is necessary to prescribe the inputs and outputs of the model. As defined earlier, the aim of the machine learning approach is to make an educated prediction for the layer parameters in the test sections where the layer thicknesses are unknown. These layer parameters (layer thicknesses and moduli) are defined as the desired output of the process. With the defined outputs, it is imperative to identify which inputs could potentially yield the best results. As a first approach the deflection bowl values are set as the input parameters of the ANN structure. In order to assess the correlation between the inputs and outputs, a heat map plot has been drawn as a screening method.

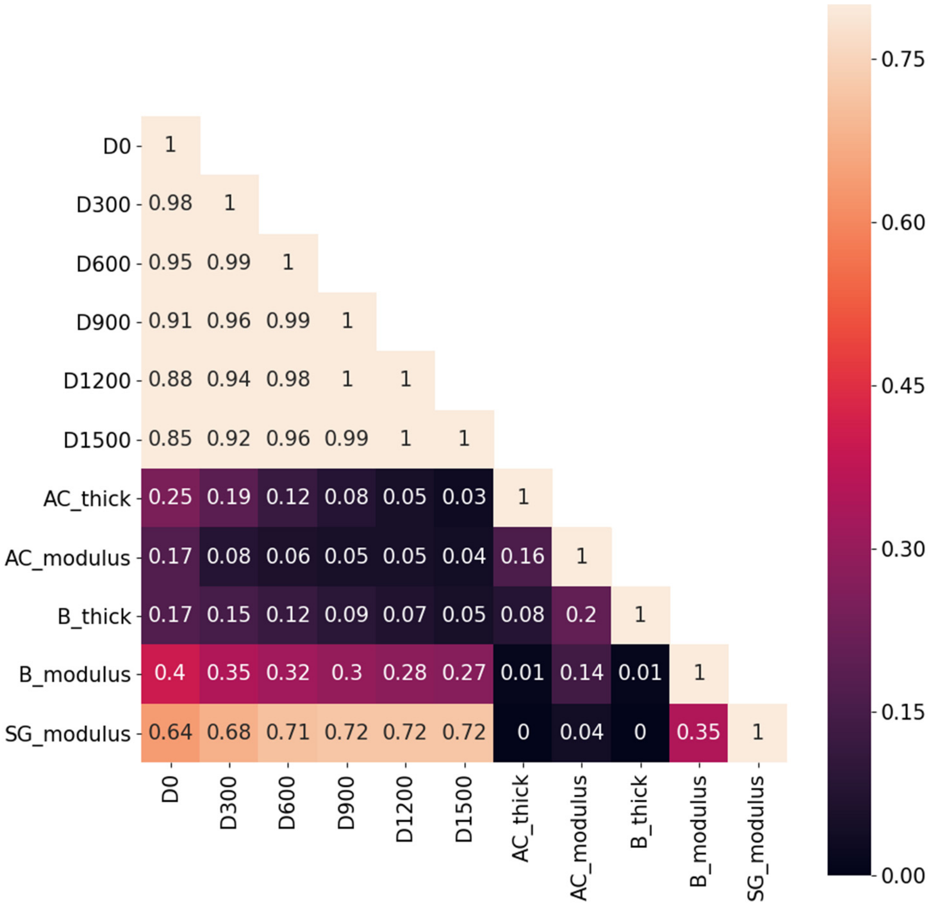

Figure 22 Heatmap plot deflection bowl vs. layer parameters

As shown in figure 22, very low correlation values were found for the deflections at geophone positions and the different layer thicknesses and moduli. The exception of this occurs for the subgrade modulus that is able to display high correlation values with the last 4 geophone deflections.

Due to the low correlation found between the deflection bowls and the different layer parameters, a different approach was considered in order to obtain better correlation with information that can be derived from the deflection bowls. Horak, E., Emery, S., and Maina, 2015 presented a research of the different benchmarking tools that can be derived from FWD generated deflection bowls described as deflection bowl parameters as shown in Table 2.

Table 2 Deflection bowl parameters

	Parameter	Formula	Structural indicator
1	Maximum deflection	D_0 as measured	Gives an indication of all structural layers with about 70% contribution by the subgrade
2	Radius of Curvature (RoC)	$RoC = \frac{L^2}{2D_0[(D_0/D_{200}) - 1]}$	Gives an indication of the structural condition of the surfacing and base condition
3	Base Layer Index (BLI_300)	$BLI\_300 = D_0 - D_{300}$	Gives an indication of primarily the base layer structural condition
4	Base Layer Index (BLI_600)	$MLI\_600 = D_0 - D_{600}$	Gives an indication of primarily the base layer structural condition for low deflection pavement structures
5	Middle Layer Index (MLI)	$MLI = D_{300} - D_{600}$	Gives an indication of the subbase and probably selected layer structural condition
6	Lower Layer Index (LLI)	$LLI = D_{600} - D_{900}$	Gives an indication of the lower structural layers like the selected and the subgrade layers
7	Spreadability, S	$S = \frac{\{[(D_0 + D_{300} + D_{600} + D_{900})/5]100\}}{D_0}$	Supposed to reflect the structural response of the whole pavement structure, but with weak correlations
8	Area, A	$A = \frac{6[D_0 + 2D_{300} + 2D_{600} + D_{900}]}{D_0}$	The same as above
9	Shape factors	$F_1 = (D_0 - D_{600})/D_{300}$ $F_2 = (D_{300} - D_{900})/D_{600}$	The F_2 shape factor seemed to give better correlations with subgrade moduli while F_1 gave weak correlations
10	Slope of Deflection	$SD = tan^{-1}(D_0 - D_{600})/600$	Weak correlations observed

11	Additional shape factor	$F_3 = (D_{600} - D_{1200})/D_{900}$	Lower layer condition or depth to a stiff layer
12	Area under pavement profile	$A_{UPP} = \frac{(5D_0 - 2D_{300} - 2D_{600} - D_{900})}{2}$	Characterizing condition of the pavement upper layers
13	Additional areas	$A_2 = \frac{6\,[D_{300} + 2D_{450} + D_{600}]}{D_0}$ $A_3 = \frac{6\,[D_{600} + 2D_{900} + D_{1200}]}{D_0}$	A_2, Condition of middle layer A_3, Condition of lower layers
14	Area indices	$AI_1 = \frac{D_0 + D_{300}}{2D_0}$ $AI_2 = \frac{D_{300} + D_{600}}{2D_0}$ $AI_3 = \frac{D_{600} + D_{900}}{2D_0}$ $AI_4 = \frac{D_{900} + D_{1200}}{2D_0}$	AI_1, Condition of upper layer AI_2, Condition of middle layer AI_3, Condition of middle layer AI_4, Condition of lower layer

Besides the deflection bowl parameters presented in Table 2, another parameter commonly taken into account when performing the structural evaluation of a pavement structure is the Surface Modulus. This modulus is a method of quantification of the compressed material in the deflection bowl zone below the depth from the deflection that is calculated. In other words it is a rough estimation of the subgrade modulus when calculating the formula for the deflection at D_{900}-D_{1500} This modulus can be calculated at any point of the deflection bowl different from the point under the load, using Boussinesq's equation (Ullidtz, Modelling flexible pavement response and performance, 1998) as follows.

Equation 2 Surface Modulus

$$SM_{(r)} = \sigma \cdot (1-\mu^2) \cdot (\frac{a^2}{r \times d_{(r)}})$$

Where:

$SM_{(r)}$ = Surface modulus at distance r from the center of the loading plate (MPa)

σ = Loading stress of the plate, 710 MPa

μ = Poisson's ratio, 0.35

a = Radius of the loading plate

$d_{(r)}$ = Deflection at a distance r

r = Radial distance from the centre of the loading plate

The different deflection parameters were constructed based on the presented formulas in Table 2. In addition to these equations, the Surface Modulus was also calculated for the distance r=900mm and used as potential inputs for the ANN structure. With the calculated deflection parameters, a new heatmap plot was developed to check the correlation when compared to the layer thicknesses and moduli.

The best correlations using the heatmap plot were obtained using the following deflection parameters: (a) BLI_{300}, (b) BLI_{600}, (c) MLI, (d) LLI, (e) RoC, (f) S and (g) A. Parameters described in table 2.

The defined deflection parameters showed better correlation to the different layer thicknesses and moduli than simply using the deflection bowls. As shown in figure 23, the subgrade modulus is highly correlated with the deflection bowl parameters S and A that correlate the deflections at D_0, D_{200}, D_{600} and D_{900}. Besides these deflection parameters, the surface modulus calculated with the deflection at D_{900} showed a perfect correlation with the subgrade modulus. The rest of the layer thicknesses and moduli do not display good correlations as the ones presented for the subgrade modulus, but significantly increased when compared to only using the deflection bowls as the results presented based on figure 22. For example the asphalt layer modulus shows a correlation of 0.57 with the Radius of Curvature parameter which is significantly higher than the 0.17 correlation to the deflection D_0 as shown in figure 2.

As better correlations are achievable with the different deflection parameters than the deflection themselves, the deflection parameters are taken as the input criteria to use in the ANN structure.

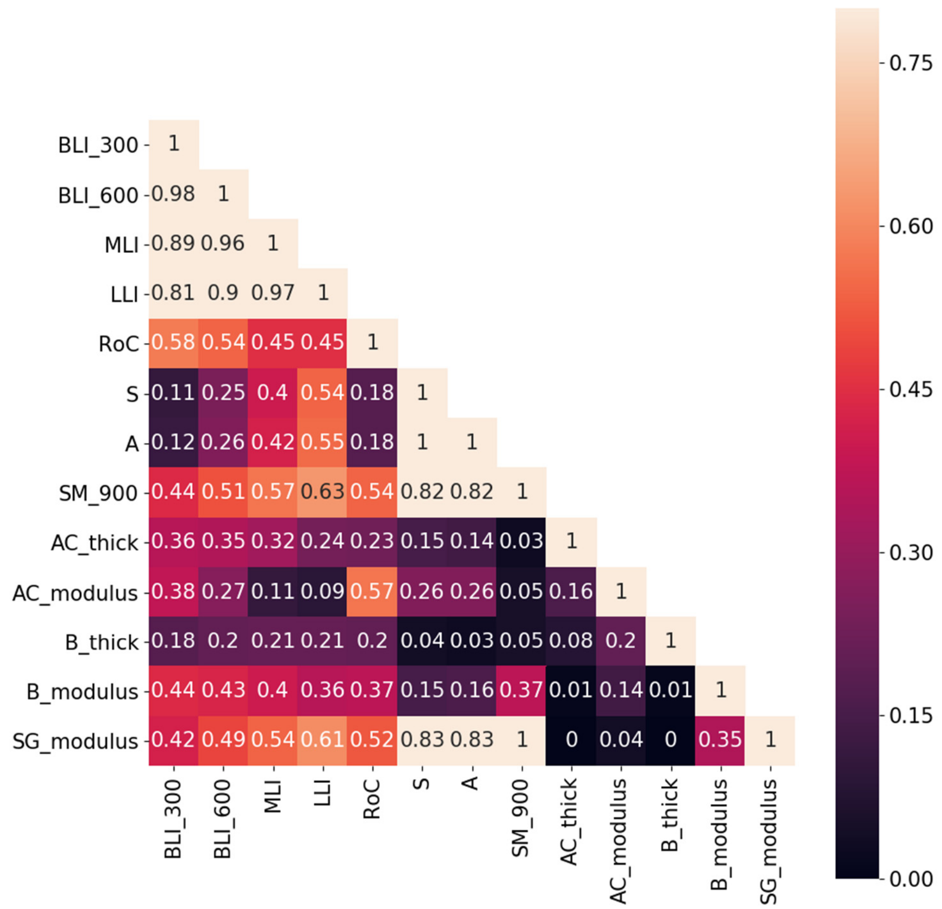

Figure 23 Heatmap plot pavement parameters vs. layer parameters

3.2.2 Database Elaboration

The next step in the missing data prediction procedure is to define a database that can be used with the ANN in order to obtain the layer thicknesses and moduli for the test section with unknown information. Described in chapter 4 of “Intelligent and Soft Computing in Infrastructure System” (Gopalakrishnan, K. Ceylan, 2009), the database used in the ANN model should be taken from actual field data and in case this is not possible, analytical software can be used to elaborate the database considering a wide range of pavement profiles to cover all possible conditions. To elaborate the database that will be used in this research a pool of typical layer thicknesses and moduli were proposed as inputs for the analytical model. It is estimated that the available test sections are within the range of values taken into account, these layer thicknesses and moduli are presented in Table 3. The presented values converge in 26,052 combinations of pavement structures.

Table 3 Layer thicknesses and moduli for database elaboration

Asphalt Layer Thickness (mm)	100	200	300	400	500	
Asphalt Layer Modulus (Mpa)	1500	1900	2300	2700	3100	
	3500	3900	4300	4700	5100	
	6000	8000	10000	12000		
Base Layer Thickness (mm)	100	200	300	400	500	600
Base Layer Modulus (Mpa)	200	450	700	950	1200	
	1450	1700	1950	2500	3000	
Subgrade Modulus (Mpa)	50	100	250	400	550	700
	850	1000	1150	1300	1450	

In order to create the database, the 26,052 combinations of pavement structures will be used in a forward calculation analysis to build the database. A framework was established to assess which forward calculation method yields the best data when compared to the original deflections presented in the test sections with known layer thicknesses and moduli. In this framework the software 3D-Move Analysis and a SEM-based model developed at TU Delft will be used. Finally the forward analysis method that is able to give the best results when compared to the original data will be chosen to create the database. In case none of the available forward analysis tools are able to give good correlation to the field calculations from the used test sections, a FEM software will be used to create the database. A visual representation of the described framework is shown as figure 24.

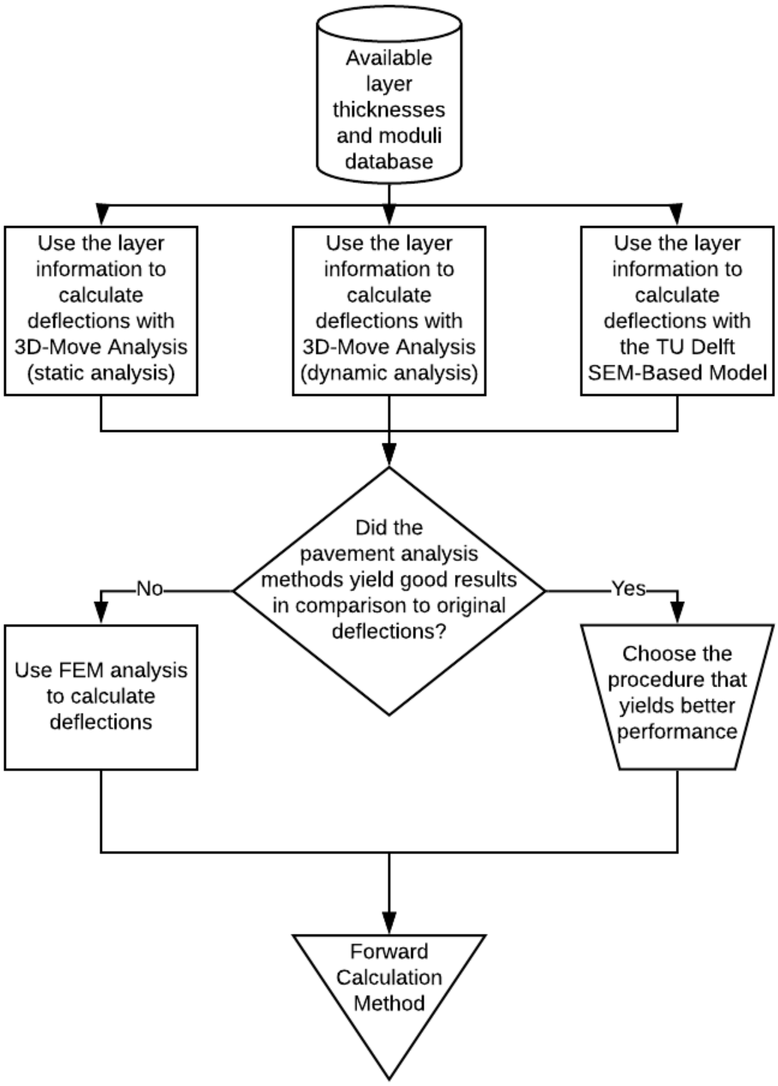

Figure 24 Forward calculation method

3.2.2.1 3D-Move Analysis

3D-Move Analysis Software is an open source software developed at University of Nevada, Reno that utilizes a continuum-based finite-layer method to determine the structural response of a pavement structure under different loading and set up conditions. This program has the ability to calculate displacements, stresses and strains in all directions and at any position of the pavement structure (Elseifi & Ph, 2012). This program is able to perform the analysis on the basis of a moving load (dynamic analysis) and a static load (static analysis). In this research, the analysis was performed with both methods to assess which of these simulated more accurately the behaviour of the FWD device.

In order to simulate the FWD device, the circular loaded area was taken into account with the same dimensions as that of the loading plate of the FWD. As well as the same loading and contact pressure as measured by the FWD. The first approach was to simulate both the static and dynamic analysis to check if there are any major differences when calculating the deflections. It is predicted that both analysis yield similar results taking into account that the analysis is carried over an elastic response since the data available only shows elastic moduli.

This analysis was performed at three different velocities, 40km/h, 60km/h and 80km/h and compared to the static analysis.

The analysis is based on an elastic response from the setup presented in figure 25, and as predicted, there is no difference among the deflection calculations based on the speed of the dynamic analysis. Nevertheless, when the static analysis is compared to the dynamic analysis, the dynamic analysis yields a deflection value of 0 micrometers convergence quicker than that of the static analysis as shown in figure 26. In order to assess if the static analysis converges to zero, an extended analysis was performed with the static analysis.

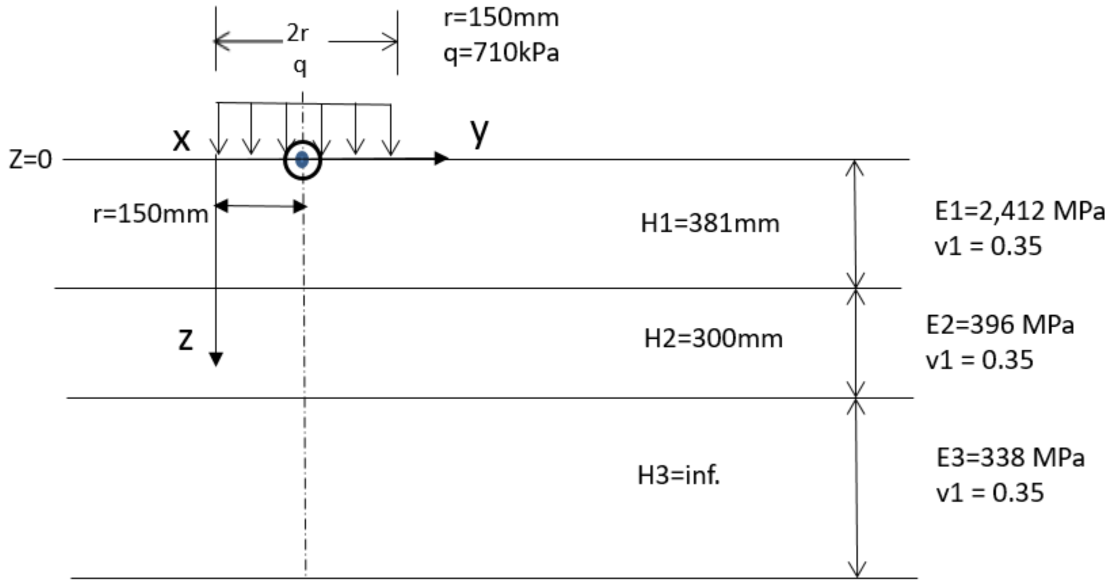

Figure 25 Layer configuration

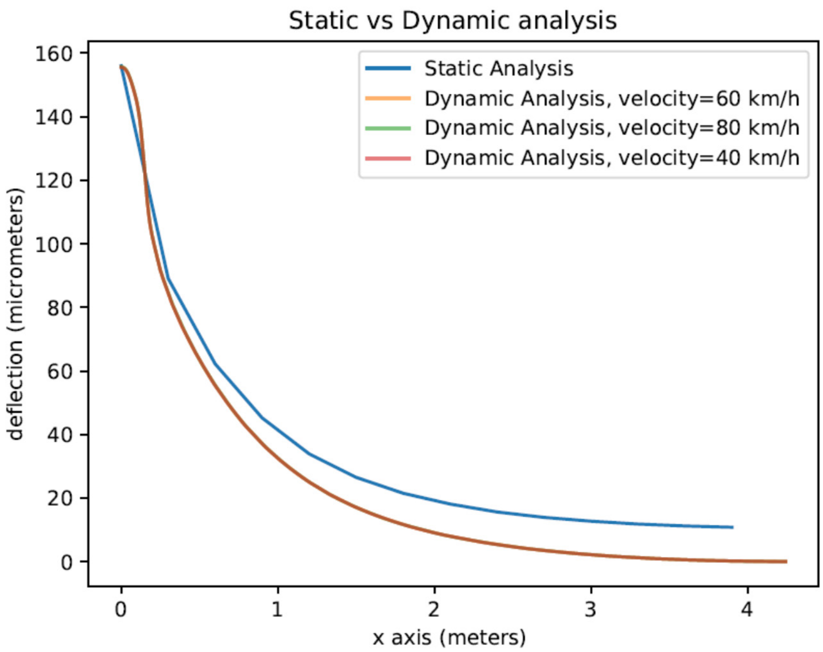

Figure 26 Static vs. dynamic analysis

As shown in figure 27, it was found that the static analysis of 3D-Move never converges to a deflection value of 0 micro meters. The lowest deflection yields at the position were the dynamic analysis deflection bowl converges to 0, and after that position, the deflection bowl is repeated. This shows a flaw in the way this program calculates the deflection bowl in a static analysis. Due to this, it was taken into account that the dynamic analysis is the type of analysis that can yield reliable results if compared to that of the FWD.

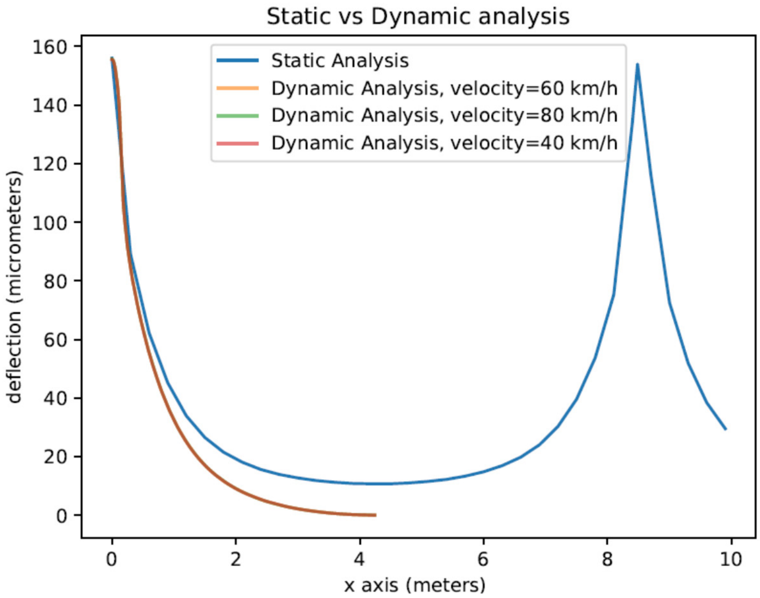

Figure 27 Convergence of static analysis

Following the framework presented in figure 24, the next step is to validate the use of 3D-Move Analysis software by comparing the calculated deflections with the FWD deflection values as obtained from the test section of Bologna. This assessment is performed by correlating the field collected deflections with the deflections generated by the forward analysis tool based on the stiffness parameters available (test sections Bologna and Firenze). As shown in figure 28, the results from 3D-Move displayed high correlation in the Bologna test section for the forward analysis deflection results are compared in a one to one relation with the field collected deflections, presenting an R^2 value of 0.73.

3.2.2.2 SEM Based Model

The next forward analysis tool available in this research is a SEM-Based forward calculation model developed at TU Delft (Sun et al., 2019). This model is able to predict the 3D dynamic response of elastic layered system subject to a rectangular surface load by means of a spectral element method (SEM) base model.

Following the framework presented in figure 24, the next step is to validate the SEM-Based model by comparing the calculated deflections with the FWD deflection values as obtained from the test section of Bologna. As shown in figure 29, the results from the SEM-Based model displayed high correlation in the Bologna test section as a R^2 value of 0.86 was found when compared in a one to one relation with the field collected data for the deflection under the load (D_0).

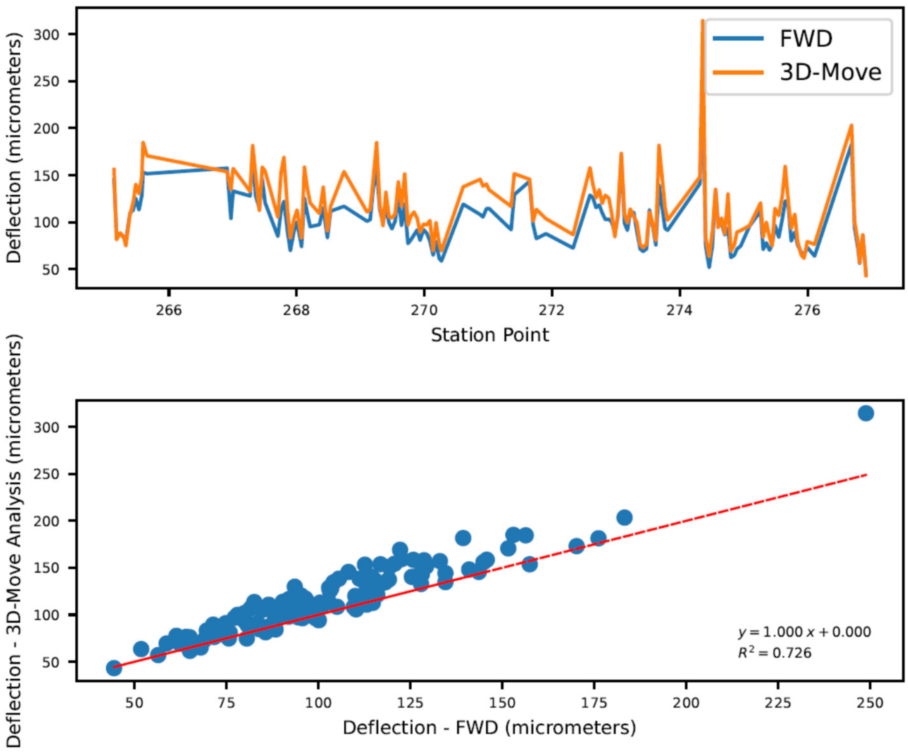

Figure 28 Calculated deflection under the load (micrometers): 3D-Move vs. original

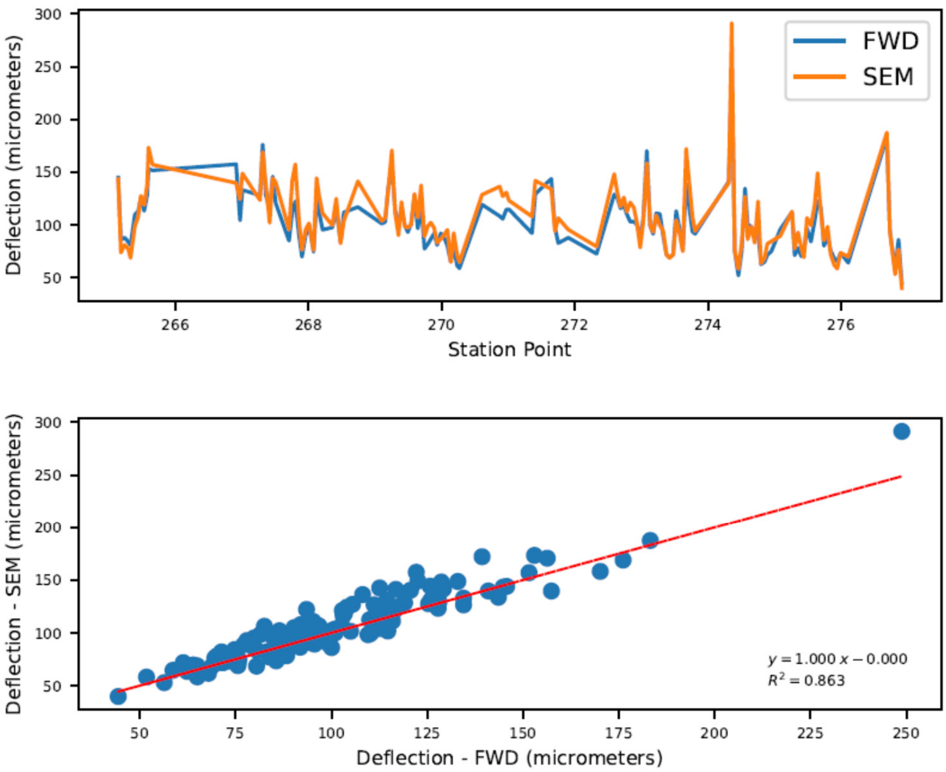

Figure 29 Calculated deflection under the load (micrometers): SEM-Based model vs. original

Based on the results presented in figure 28 and 29, both analysis tools were able to give a good correlation when compared to the original deflections provided with better results coming from the SEM based model. Therefore the SEM-Based model was decided to be used as the forward calculation analysis tool for the development of the database based on the 26,052 combinations based on the layer parameters shown in Table 3.

3.2.3 Building the ANN model

Scikit-learn was the module of choice to perform the proposed ANN model. Within this module, the MLP regression was chosen as this ANN is able to make a regression analysis for several outputs. Following the iterative process of this approach, different parameters were used to obtain the best fit of the model. A loop process was performed taking into consideration different combinations of the parameters where the best results from the iterative process were obtained by using the following combination on parameters.

Hidden layer size = 8192

Activation formula = tanh

Solver = adam

Maximum iteration = 10,000

Learning rate = adaptive

3.2.4 MLP Regression Analysis Results

In the previous subsections corresponding to Section 3.2, the different elements needed to process the data with the machine learning approach have been identified and will be used in this subsection to obtain the final results of the missing data prediction procedure. In order to obtain the missing layer thicknesses and moduli, a framework that follows an iterative approach was created for this research. A step by step guide will be shown to describe how the process was performed, also shown in figure 30.

1. The 26,052 different combinations of pavement structures (Table 3) were analysed with the SEM-based model developed at TU Delft to create the initial database to train the MLP regression model.
2. The set of original deflections were transformed to the layer parameters as described in Section 3.2.1 and these parameters are fed as inputs to the model.
3. The MLP regression analysis returns the predicted layer thicknesses and moduli as outputs for the corresponding layer parameters as fed in step 2.
4. The predicted layer parameters are used as input in the SEM-Based model to return their corresponding deflection bowls.
5. The resulting deflection bowls from step 4 are compared to the original deflection bowls used to construct the deflection parameters from step 2. Based on this comparison it is assessed if the predicted layer thicknesses and moduli are taken as valid.
6. In case the results do not display a good correlation at deflection level, the predicted layer information is used to feed the database and retrain the model, repeating the process from step 1.

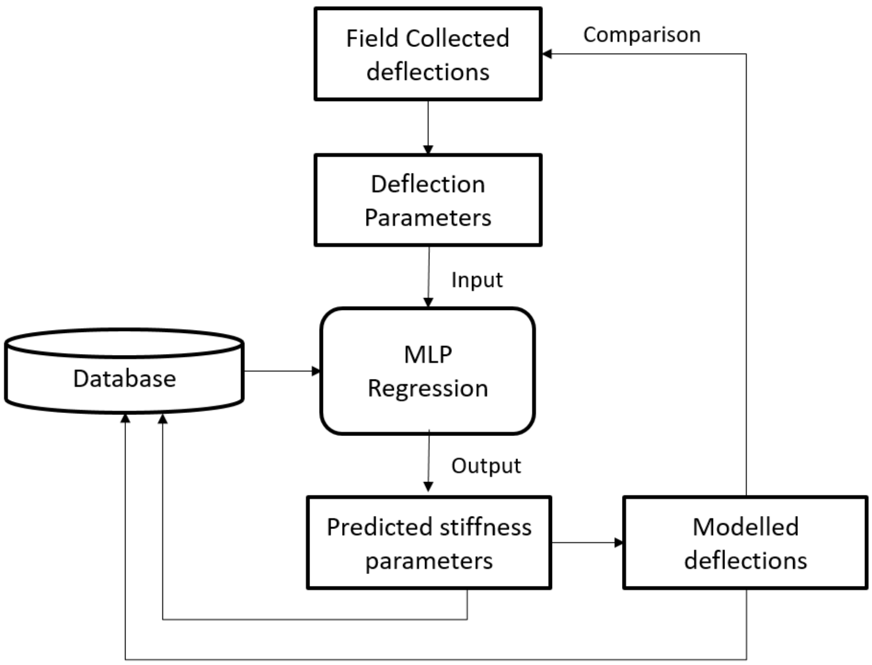

Figure 30 Machine learning process

The subquestions of Research question 1.3.1 were designed as the acceptance criteria for the machine learning approach to predict the missing data information. The questions are presented as follows:

1. Are the predicted layer parameters reliable?
    - No negative values are predicted.
    - Higher stiffness modulus are shown for stiffer layers?
        i. Asphalt layer > Base Layer > Subgrade
2. Do the deflection bowls generated by the analytical model display a high correlation with the original deflections?

The machine learning process was performed in all the test sections, where no negative values were predicted and where the stiffness parameters showed higher moduli for the stiffer layers as required from the questions above. At a later stage the different moduli were used in the forward analysis in order to obtain their corresponding deflections. These deflections followed the same trends as the original deflection values as shown in figure 31 and 32. As the process followed an iterative approach as indicated earlier, the predicted stiffness parameters and their deflection bowls were fed into the existing database and the process was performed again. From the second iteration of the machine learning process, the stiffness parameters resulted in deflection bowls that were closer to the field collected deflections as presented in figures 31 and 32.

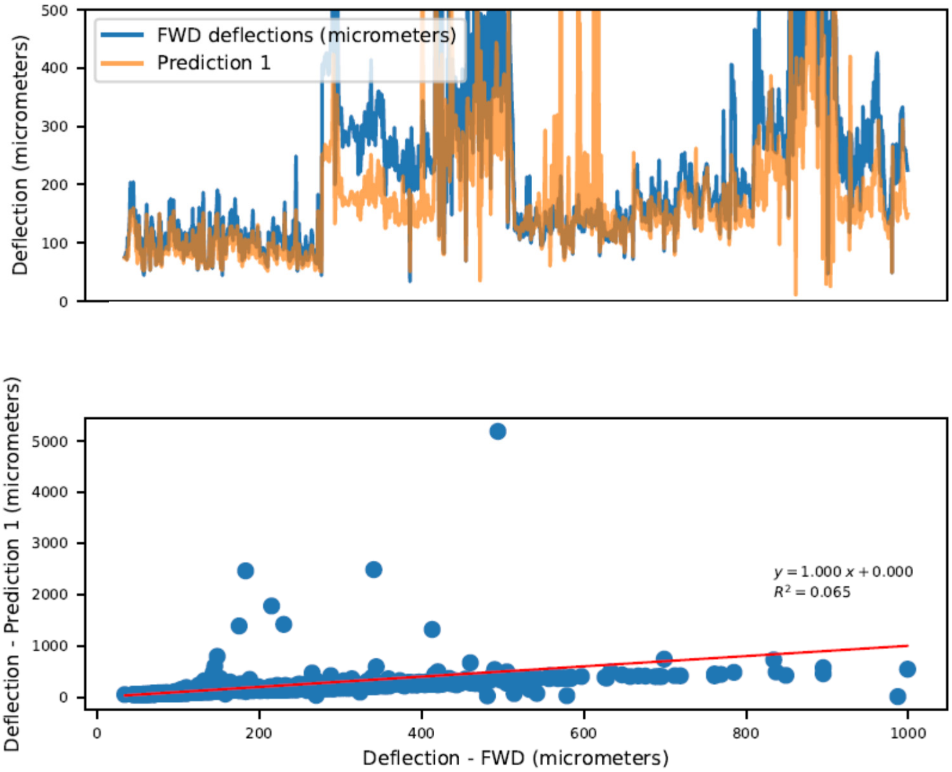

Figure 31 D_0 comparison between field collected data and forward analysis of first round of stiffness parameter prediction. Trend (top), correlation based on 1 to 1 relation (bottom)

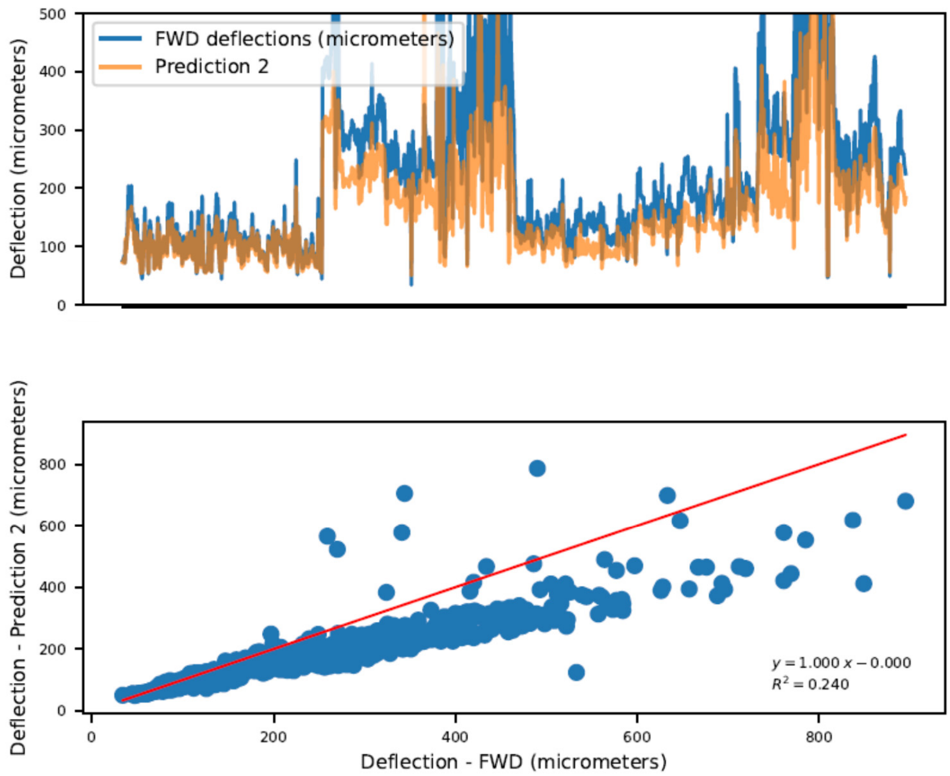

Figure 32 D_0 comparison between field collected data and forward analysis of second round of stiffness parameter prediction. Trend (top), correlation based on 1 to 1 relation (bottom)

Although the criteria to validate the result were met, the stiffness parameters did not show very good correlations when compared to the available stiffness parameters from the test sections in Bologna and Firenze. Another problem that was found is that the machine learning prediction resulted in stiffer deflection bowls as can be seen in figures 31 and 32 where the predicted deflections are below the field collected deflections. Comparing the deflection results from the predicted data in a one to one relation with the field collected deflections indicated that their correlation is in a low end with a calculated R^2 of 0.24 from the second prediction parameters.

As shown in figure 32, the trend of the calculated deflections based on prediction 2, the deflections due follow a similar trend than the original deflections, suggesting that the low correlation occurs due to the comparison at a 45° angle based on the field calculated deflections. Therefore a simple regression line comparison was used to find the correlation between these deflections as high correlations could be obtained based on the trending line.

As shown in figure 33, the correlation based on a simple regression line was found to be an R^2 value equal to 0.84, indicating a much higher correlation than the comparison at a 45° angle. Although a simple regression line is not an indicative that the results are reliable, based on the questions established as criteria for the validation of the process and for research purposes the predicted stiffness parameters will be used as valid in order to formulate the methodology of this research. This will be presented in the conclusions chapter, where an expanded analysis will be stated alongside the recommendations that could lead to better results.

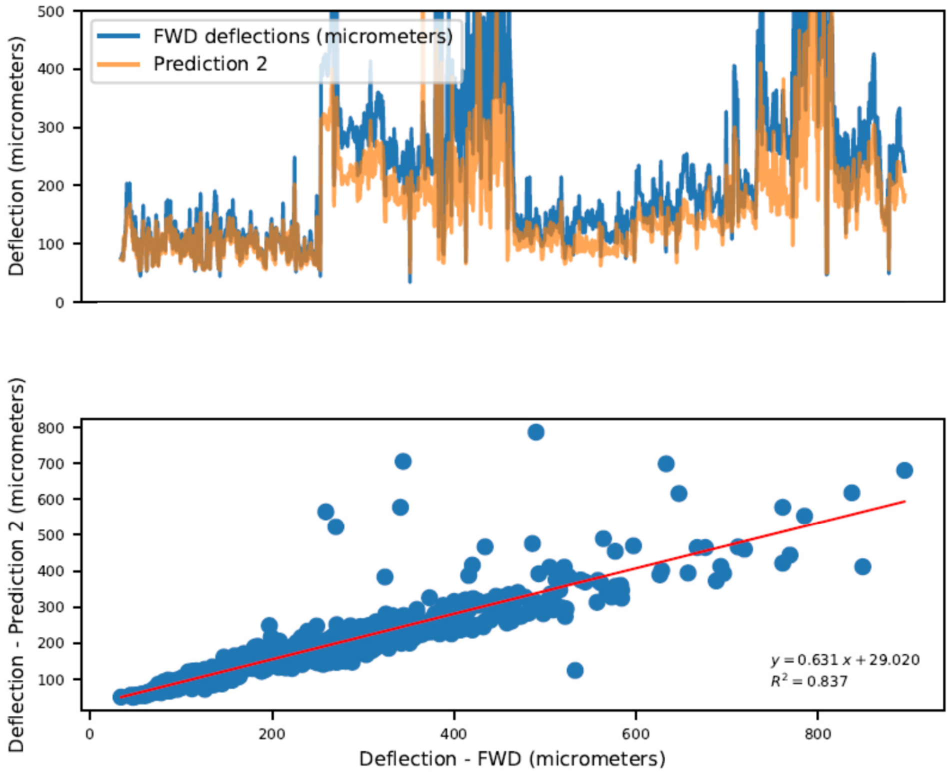

Figure 33 D_0 comparison between field collected data and forward analysis of second round of stiffness parameter prediction. Trend (top), correlation based on linear regression (bottom)

As mentioned earlier, with the predicted stiffness parameters, similar trends and very good correlations based on simple regression lines can be obtained from the machine learning process, especially with a second iteration of the process. Figures 34 and 35 are an example of the impact that feeding the database with the first prediction can lead to better results, where the calculated deflections significantly improved from the first prediction.

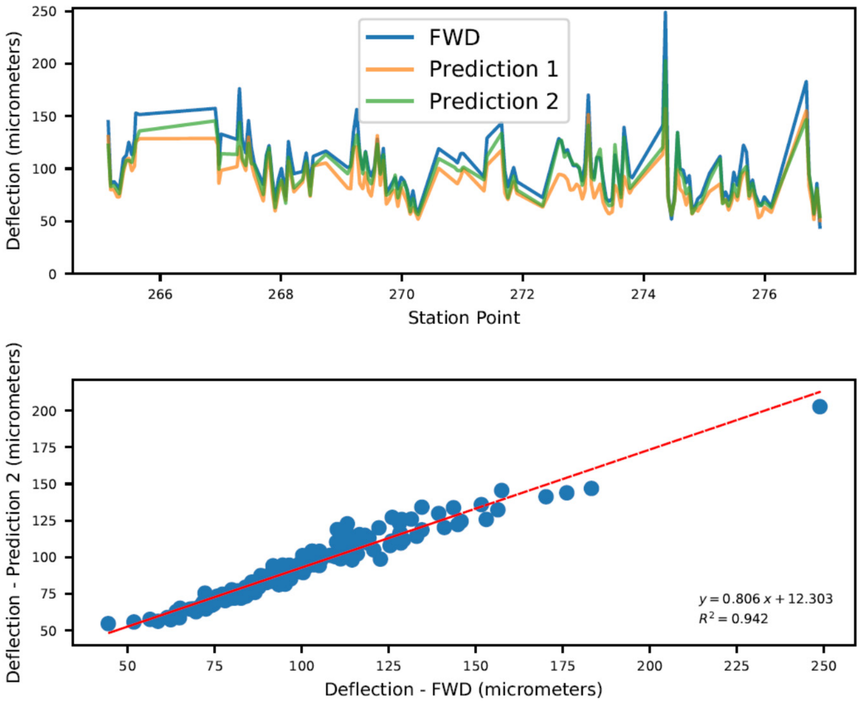

Figure 34 SEM-Based model calculated deflection D_0 from predicted data vs. original deflections

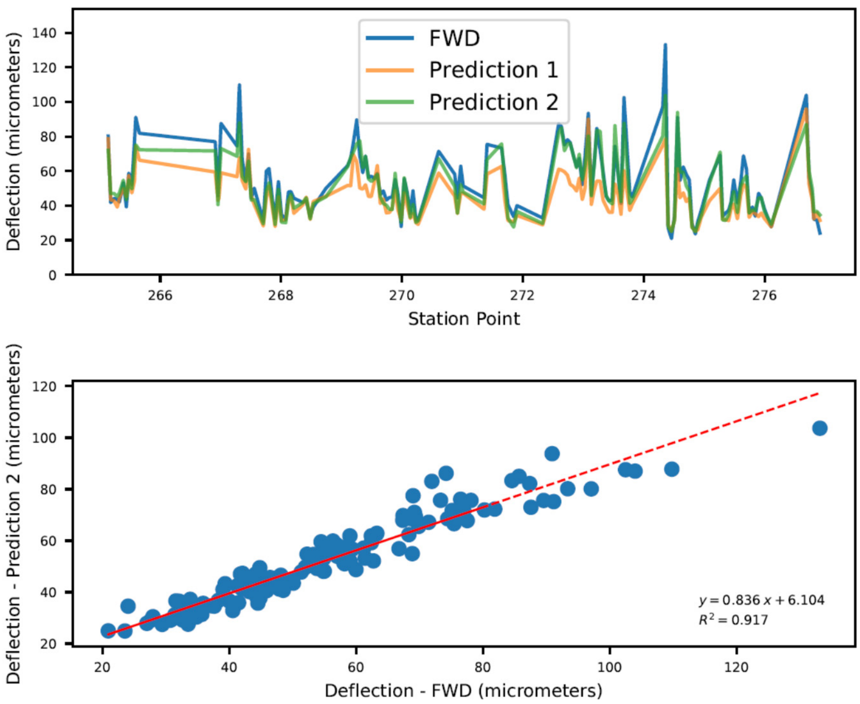

Figure 35 SEM-Based model calculated deflection D_{300} from predicted data vs. original deflections

The improvement of the data based on a second prediction occurred for all the test sections, to demonstrate this, tables 4 and 5 show the calculated R^2 value based on the different geophone positions of all the test sections from the first and second prediction respectively. Test sections such as Tuborgvej, DRD and Furesoe had major improvements from this process, as shown in table 4 the initial prediction resulted in correlations of R^2 values lower than 0.05 and increased to correlation values of 0.52, 0.80 and 0.69 respectively. These improvements are also visible in test sections where the first prediction already resulted in high correlations such as DTU, Firenze and Bologna where the correlation values from the second prediction resulted in R^2 higher than 0.94.

Table 4 R^2 values from the first iteration of the model

Section	D_0	D_{200}	D_{300}	D_{450}	D_{600}	D_{900}
DTU	0.907839	0.841513	0.815166	0.826994	0.86187	0.812997
ANAS_2	0.570368	0.45794	0.450074	0.498407	0.54687	0.583437
ANAS_1	0.839595	0.858486	0.788049	0.701602	0.604079	0.483476
Palunka	0.350697	0.700978	0.635291	0.497161	0.384292	0.304742
Bologna	0.887511	0.863897	0.825731	0.810415	0.830538	0.855745
Firenze	0.911	0.902446	0.886015	0.880012	0.885137	0.876892
Tuborgvej	0.036864	0.017738	0.023976	0.042803	0.066849	0.104444
DRD	0.044042	0.081478	0.126437	0.166119	0.182186	0.177517
Vejlandsalle	0.197518	0.201528	0.15401	0.113399	0.105453	0.041211
Furesoe	0.012601	0.0125	0.012518	0.015995	0.017264	0.01789

Table 5 R^2 values from the second iteration of the model

Section	D_0	D_{200}	D_{300}	D_{450}	D_{600}	D_{900}
DTU	0.935046	0.873067	0.794797	0.758472	0.764868	0.70075
ANAS_2	0.878066	0.760747	0.650711	0.575006	0.542279	0.523472
ANAS_1	0.924118	0.890393	0.755837	0.609067	0.466368	0.224507
Palunka	0.517158	0.751546	0.659002	0.537725	0.466724	0.424447
Bologna	0.942285	0.896028	0.917067	0.917086	0.931753	0.956123
Firenze	0.963015	0.922623	0.919593	0.922191	0.927965	0.942334
Tuborgvej	0.519184	0.399575	0.391044	0.416239	0.441043	0.431409
DRD	0.797141	0.664686	0.608567	0.640399	0.702657	0.778684
Vejlandsalle	0.386852	0.421261	0.439654	0.425678	0.37149	0.354365
Furesoe	0.687861	0.622322	0.603952	0.584822	0.562163	0.497616

4 Analysis and Results

This chapter will explore the methodology that was used to compare the field collected data from the FWD and RAPTOR. Following the methodology and results displayed in chapter 3, the RAPTOR deflections will be compared to FWD deflections. The data from both equipment will be grouped by the different pavement layer information obtained from the missing data prediction procedure results as presented in Section 3.2.3. A methodology that aims to give results to answer research questions 1.3.2 and 1.3.3 will be displayed and shown as a framework that was built based on the different frameworks presented in chapter 3.

The analysis will be performed in three parts and will be explored in the presented sections of this chapter. The first assessment in this section aims to detect if there is a positive effect on the impact of the wheel opposite to the loading wheel from the RAPTOR. If a better correlation is acquired by the compensation of the second wheel on the FWD deflections, the compensated deflections will be taken to perform the correlation analysis. Based on the results presented by the compensation of the load for the FWD deflections, the data will be grouped based on the stiffness parameters, and the filtering of the data will be displayed based on the different stiffness parameters ranges in order to obtain the limitations of the RAPTOR. At a final stage, the analysis will be performed for the section points defined as high stiffness (D_0 <177 micrometers) as described in Section 1.2 in order to assess the validity of the RAPTOR for high stiffness pavement structures.

4.1 Load Compensation on FWD Deflections

In order to determine if the impact of the second wheel should be taken into account in the FWD deflections, a correlation analysis is implemented based on a 45° angle line from the FWD deflections. As a first approach, the original deflections from the RAPTOR and FWD were plotted against each other in order to determine the R^2 value at the different geophone positions. Using the field collected data a R^2 equal to .64 was calculated for the deflection under the load (D_0), and a R^2 equal to 0.57 for the deflection 300mm (D_{300}) away from the load as shown in figures 36 and 37.

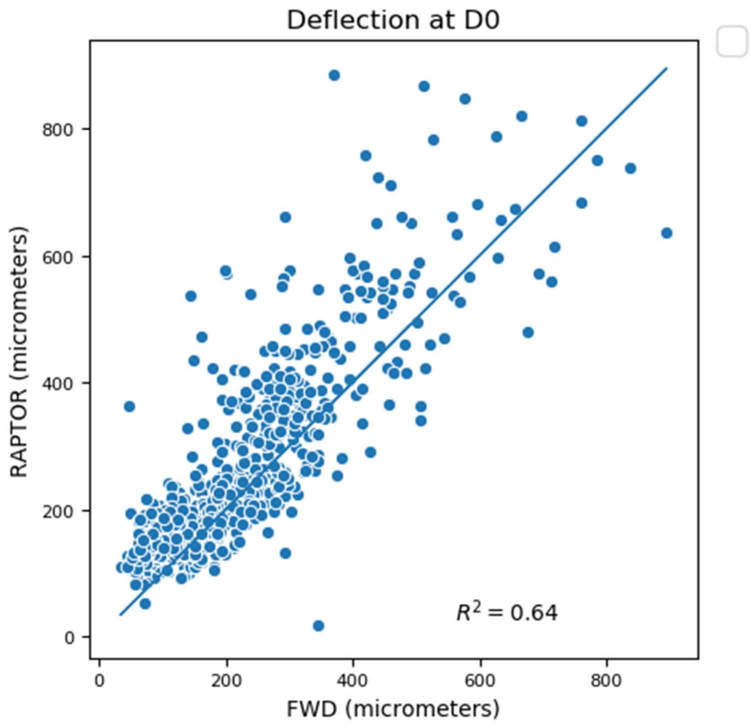

Figure 36 FWD vs. RAPTOR at D_0

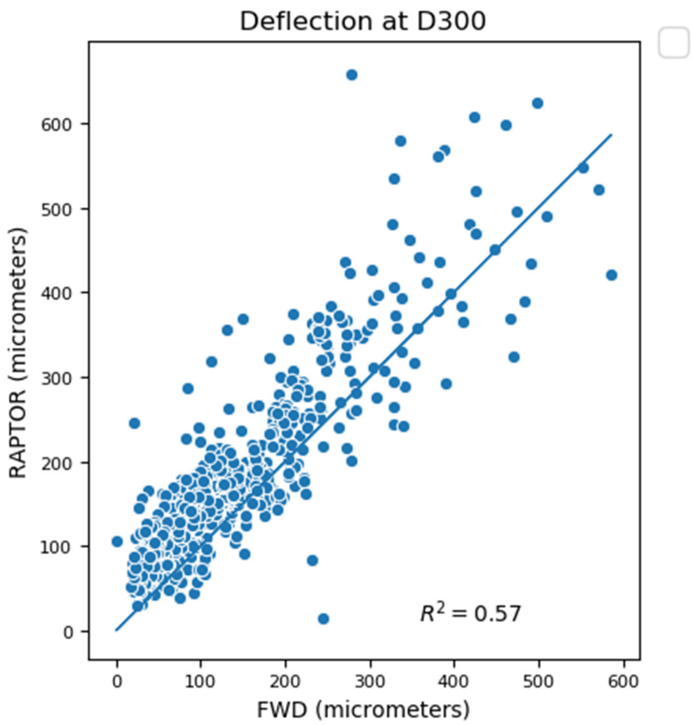

Figure 37 FWD vs. RAPTOR at D_{300}

Prior results were obtained by directly comparing the deflections as measured from the FWD and the RAPTOR, for which the RAPTOR was yielding higher deflection values than its homologue the FWD. This raised concerns, as the FWD is a pulse load and it should measure higher deflection results than those from the RAPTOR.

A possible explanation for this behaviour is that the RAPTOR has a second load of 50kN 2.16m away from the wheel where the laser measurement is performed. By taking into account this load for the FWD, higher correlation deflections are expected. If this statement is proven right, the analysis at deflection level will take place taking into account the second wheel load.

Since the analysis is based on a linear elastic behaviour of the pavement structure, the second wheel load compensation is done by extrapolating the deflection bowl from the FWD, and adding the value of the deflection point at 2.16m away to the deflection under the load. Following this, a new correlation value between the RAPTOR and the compensated FWD was found to be a R^2 equal to 0.70, improving the correlation among the devices as shown in figure 38. This improvement to the R^2 is a direct indicator that the pavement model used for the RAPTOR to calculate the deflections at geophone positions, does not take the second wheel load into account.

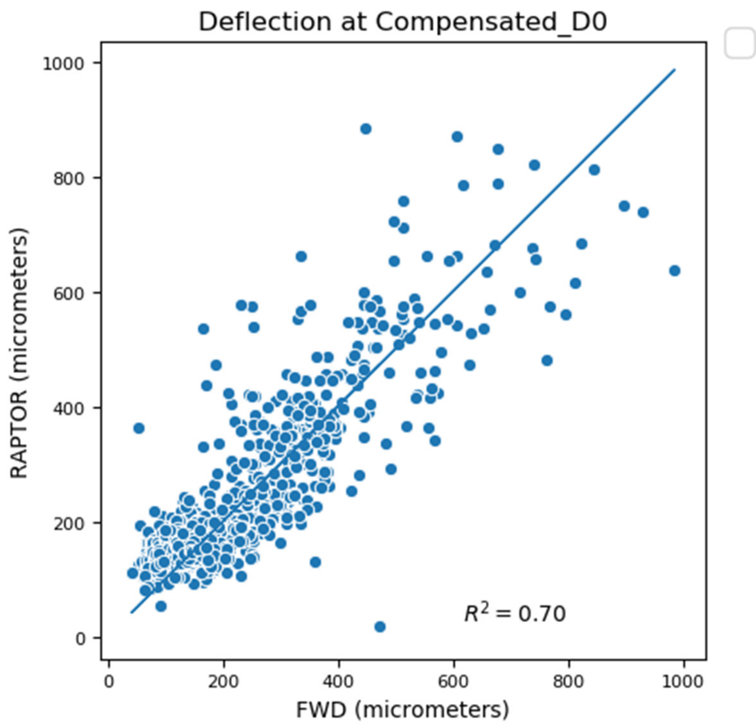

Figure 38 RAPTOR vs. compensated FWD deflections

It was found that the correlation at deflection level was satisfactory for the deflection directly under the load, but for the geophones further away this correlation becomes lower. Due to this, the focus will remain to take into account only the behaviour under the load and make a proper correlation of the stiffness parameters based on this deflection parameter.

4.2 RAPTOR vs. Compensated FWD

In order to assess the validity of the RAPTOR in high stiffness pavements a data analysis framework has been developed as described in Section 1.5. This data analysis procedure is divided in 3 parts as shown in figures 39 and 40.

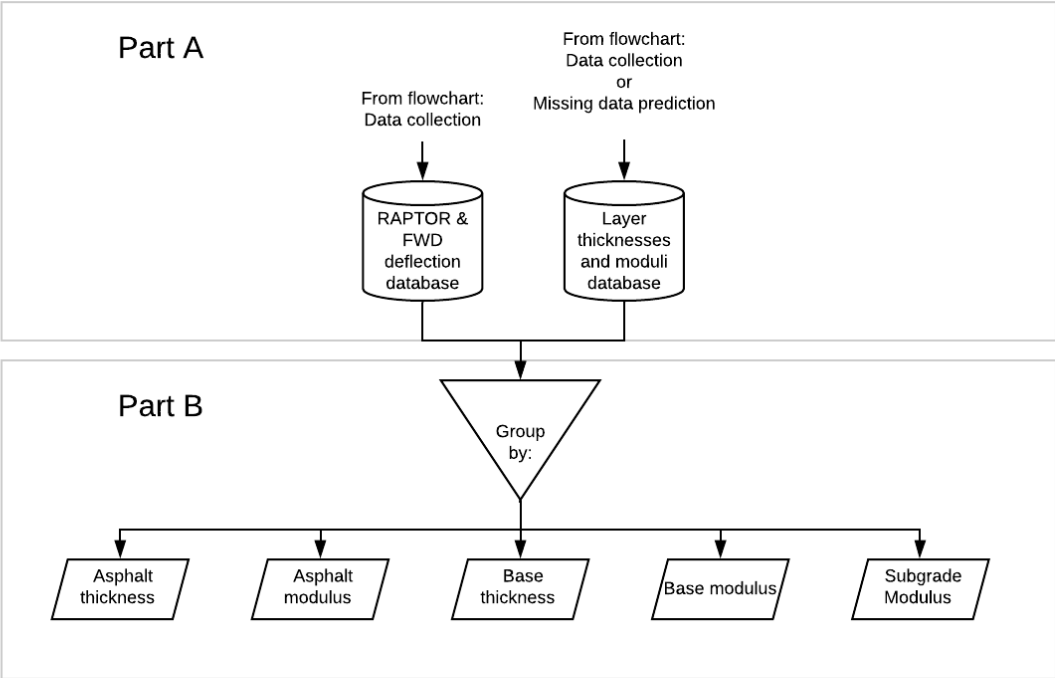

Figure 39 Data analysis flowchart (Part A and B)

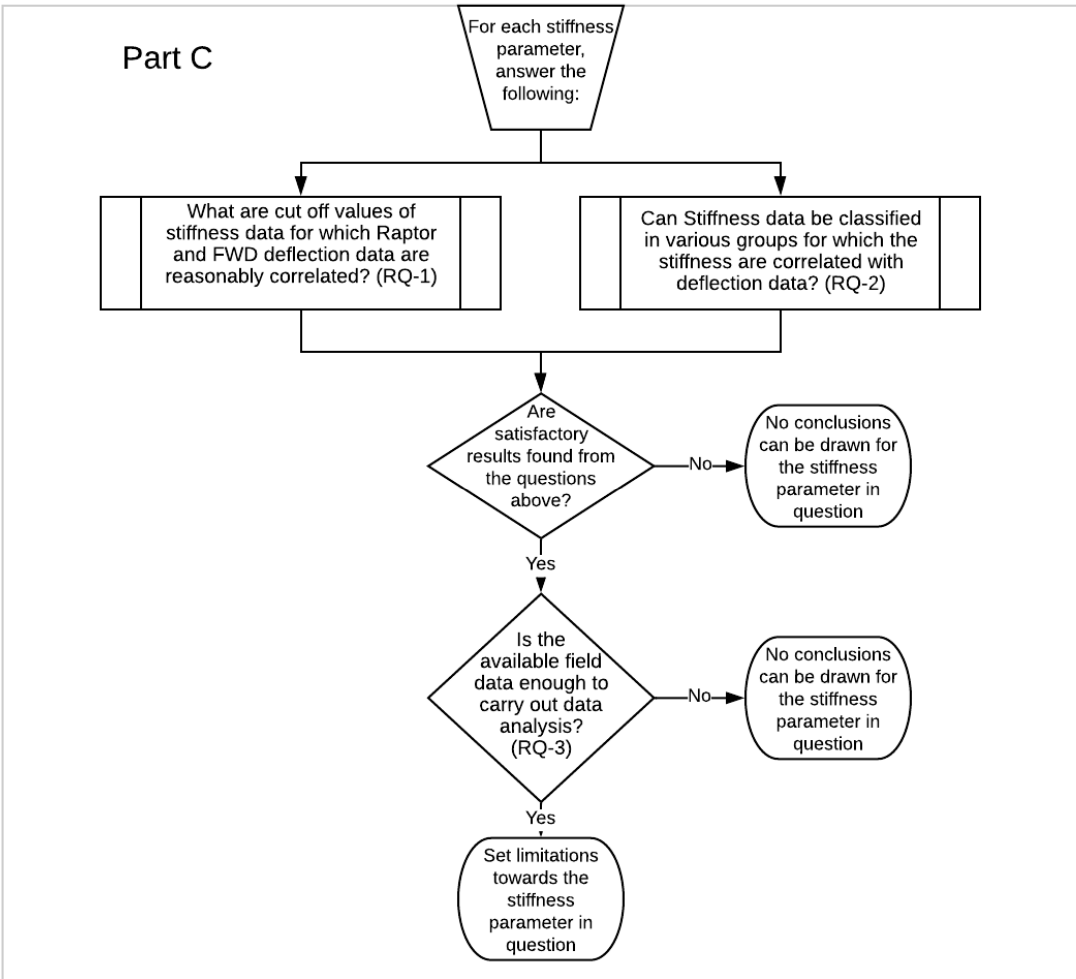

Figure 40 Data analysis flowchart (Part C)

The first part of the data analysis framework (Part A) consists in the identification of the databases corresponding to the deflections of both equipment and their corresponding stiffness parameters. These databases are the result of the different frameworks implemented in chapter 3, where the deflection database has been obtained from the averaging and filtering of RAPTOR deflections to simulate the position of the FWD deflections, and where the layer stiffness parameters have been obtained by a machine learning approach used as a missing data prediction procedure. From this point it is taken as an assumption that the databases built upon the results of chapter 3 are valid, as in this section the framework to compare and validate the RAPTOR will be shown.

The second part of the data analysis framework (Part B) consists in coupling both databases and grouping the information based on the different stiffness parameters (layer moduli and thicknesses). With the data grouped on the different stiffness parameters, the datapoints are classified in 10 different groups based on the stiffness parameters values found within the database. Finally the dataset is plotted based on their RAPTOR and FWD deflection values and the correlation value between the general data set and the different ranges of stiffness parameters are identified.

Finally, the last part of the data analysis framework (Part C) consists in the analysis of the identified data. In this part of the process, the plotted information will be used to determine the limitations of the RAPTOR based on the different stiffness parameters. In order to perform the presented framework, the process will be taken based on the compensated FWD deflections as it was shown in Section 4.1 where the RAPTOR displays a higher correlation when compared to the compensated FWD deflections. With this change in the FWD deflection database, the subquestions from research question 1.3.3 will be used as criteria for the analysis.

1. For stiffer pavement structures, what are cut off values of stiffness data for which Raptor and FWD deflection data are reasonably correlated?
2. Can Stiffness data be classified in various groups for which the stiffness are correlated with deflection data?
3. Is the available field data enough to carry out data analysis?

The first analysis was carried out by grouping the dataset by their corresponding asphalt layer modulus. From the backcalaculated data it was found that the asphalt layer elastic modulus for the dataset is set within a range of 0 MPa to 12,000 MPa. The range of moduli was grouped in fractions of 1,500 MPa in order to have a better data classification procedure, and to be able to answer question 2 from the established criteria. In the correlation analysis based on asphalt layer moduli, high R^2 values ranging between 0.68 and 0.74 were found for the different groups in the ranges between 3,000 and 7,500 MPa, representing 742 section points out of the total 940 (79%) as shown in figure 41.

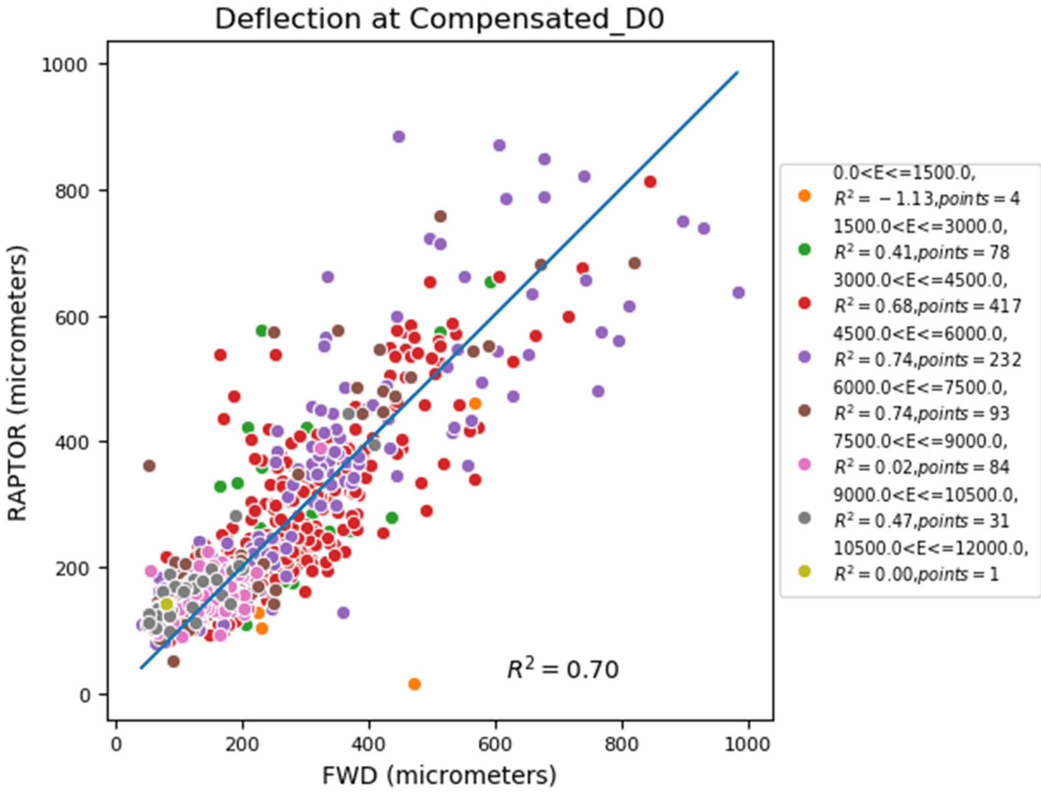

Figure 41 RAPTOR vs. FWD deflections under the load, grouped by the elastic modulus of the asphalt layer

The same data classification process shown for the asphalt layer modulus was conducted for the remaining layer moduli and the layer thicknesses shown in figures 42 to 45. From the analysis conducted in the remaining stiffness parameters it was found that only the base layer thickness could not achieve correlations as high as the 0.70 calculated from the general dataset as presented in figure 44. The results in the remaining moduli and in the asphalt layer thickness did show correlations close to or as high as the 0.70 calculated from the general dataset as shown in figures 42, 43 and 44. Although high correlation values were calculated for the remaining stiffness parameters, none of them have enough representation of highly correlated data as it was the case for the asphalt layer modulus.

In the case of the asphalt layer thickness, shown in figure 42, valid correlations in the ranges of 0.61 to 0.66 were found for the data ranging in asphalt thickness between 100 and 250 mm. The amount of datapoints present in this range of values is equal to 386 out of the 940 total datapoints, nearly 50% less datapoints than the ones displayed in the asphalt layer modulus.

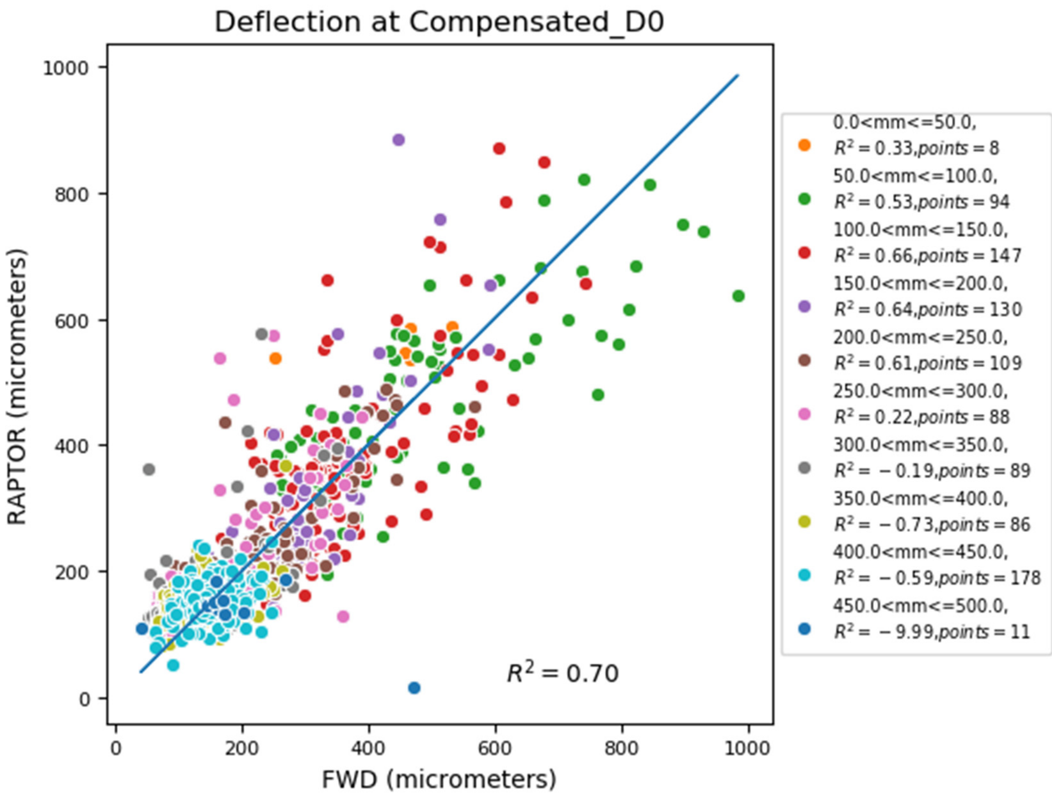

Figure 42 RAPTOR vs. FWD deflections under the load, grouped asphalt layer thickness

For the base layer modulus, Figure 43, good correlation results were found for the data with a modulus range between 1,000 and 1,250 MPa. Although a correlation of R^2 equal to 0.70 was found in this range of moduli, it was found that it is only valid for 194 section points out of the total 940, significantly lower than the datapoints with a valid correlation found in the asphalt layer modulus.

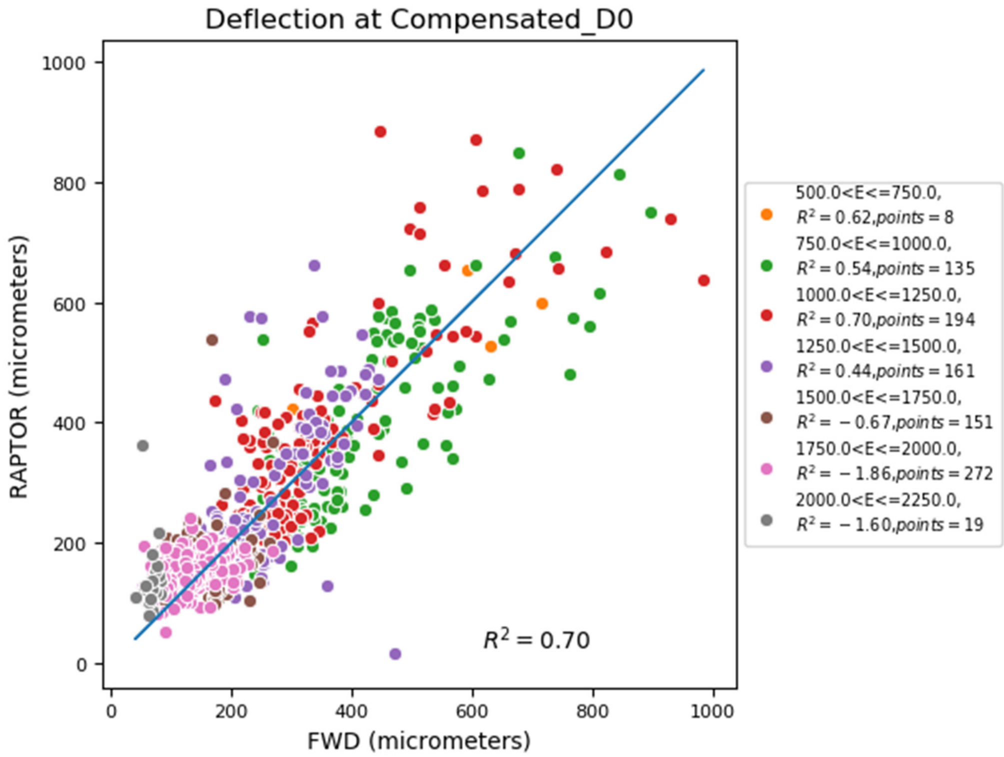

Figure 43 RAPTOR vs. FWD deflections under the load, grouped base layer modulus

As it was described earlier, in the analysis performed based on the base layer thickness, no ranges of values were found to have high correlation values, as the highest calculated R^2 was found to be 0.56 for the data with base layer thickness ranging between 275 and 330mm, valid for 179 data sections out of the total 940 as shown in figure 44.

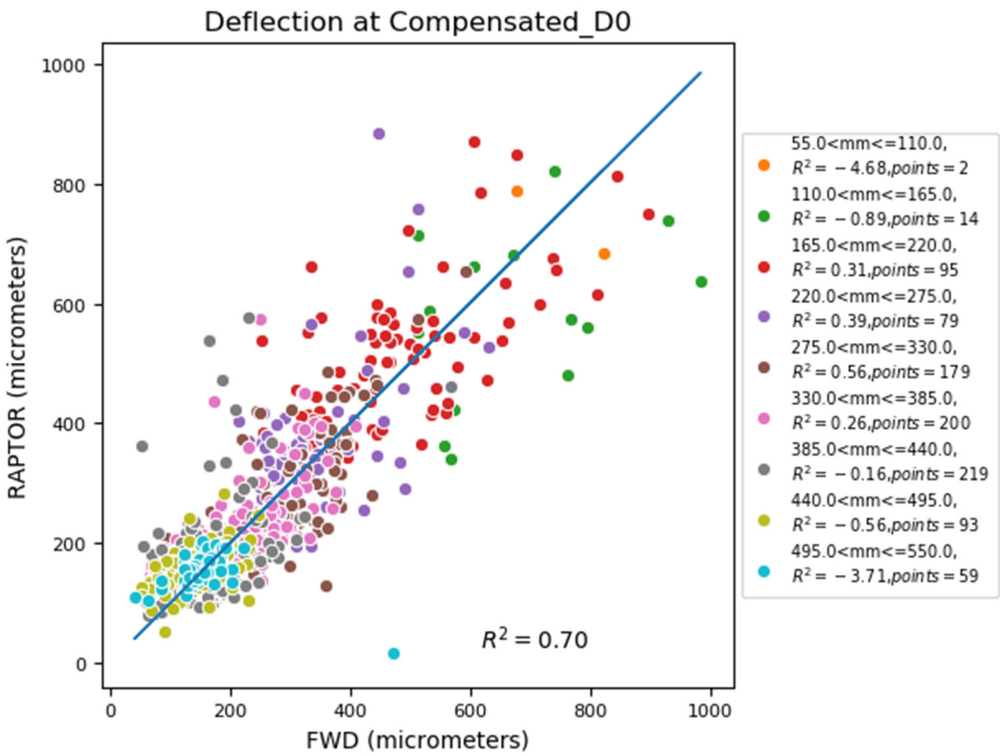

Figure 44 RAPTOR vs. FWD deflections under the load, grouped base layer thickness

Finally in the analysis performed based on the subgrade modulus, a correlation of 0.70 was found in the ranges between 0 and 300 MPa corresponding to 589 datapoints out of the 940 as shown in figure 45.

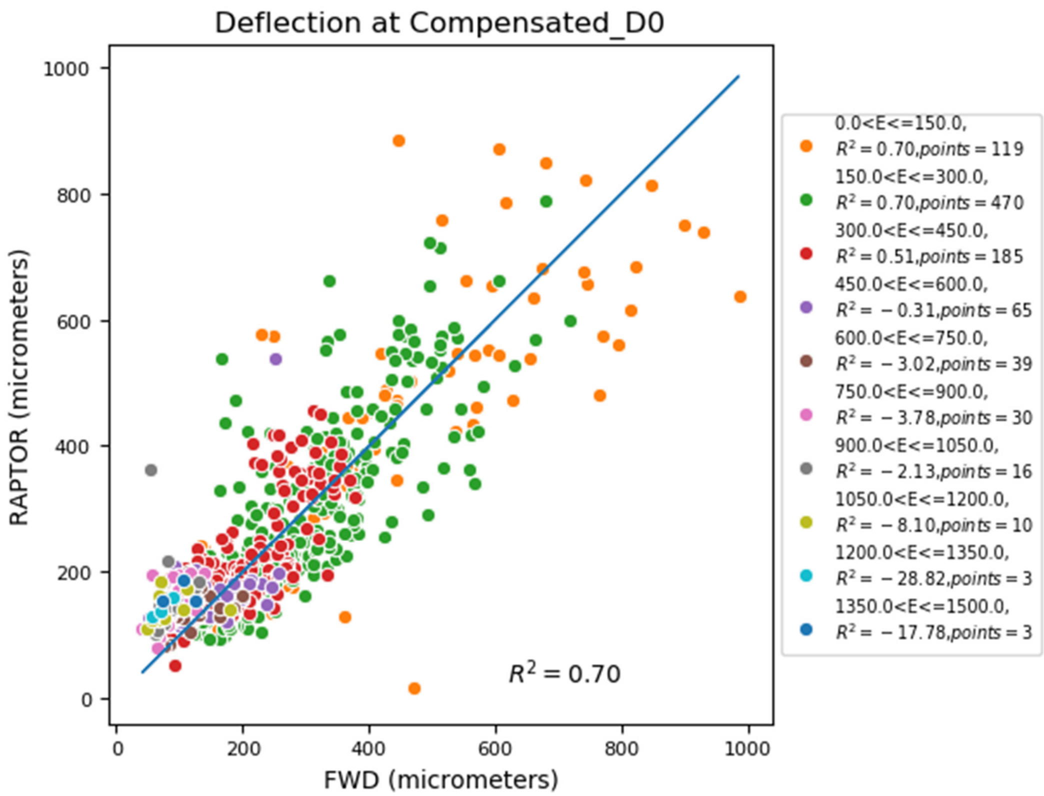

Figure 45 RAPTOR vs. FWD deflections under the load, grouped subgrade modulus

From the presented results, it can be concluded that the asphalt layer modulus is the stiffness parameter that leads to a better classification of data, as for this parameter high correlation results were found for the most amount of data points. Subsequently it was found that the classification based on subgrade modulus can return good correlations for a significant amount of data. Finally it can be stated that the base layer has the least impact when trying to perform the classification of the data as good correlation results were found for a fraction of the total amount of data points. Based on this conclusion, the analysis will be recreated for the datapoints where the asphalt layer modulus is in the ranges of 3,000 to 7,500 MPa in order to check if more details can be acquired to make a proper classification and find the best stiffness parameter ranges where the RAPTOR is highly correlated to the FWD.

4.2.1 Data Filtering

In order to investigate further the limitation of the RAPTOR in relation to the FWD at deflection level due to different pavement stiffness parameters, the data was filtered down based on the results from the asphalt layer modulus, to find the correlations where the data correlation showed reliable information. This is done in order to check if the global correlation of the deflections under the load as evaluated from both equipment give better correlation values. If this approach is successful, a proper classification for the limitation of the RAPTOR will be established.

The first filtering parameter is the asphalt layer modulus. The data has been filtered down to the points where the asphalt layer modulus is between 3,000 and 7,500 MPa. Narrowing down the data to the points in this range concludes with 742 data points out of the 940 in total, representing 79% of the total amount of data.

Based on this filtering it was found that the new general correlation between the RAPTOR and the FWD was a R^2 value equal to 0.72 as shown in figure 46. Although the R^2 was increased by filtering down the data, it only improved by 0.02 based on the original data set. To investigate further, the same analysis criteria was performed with the filtered data in order to assess if a better classification of data could be derived from the results.

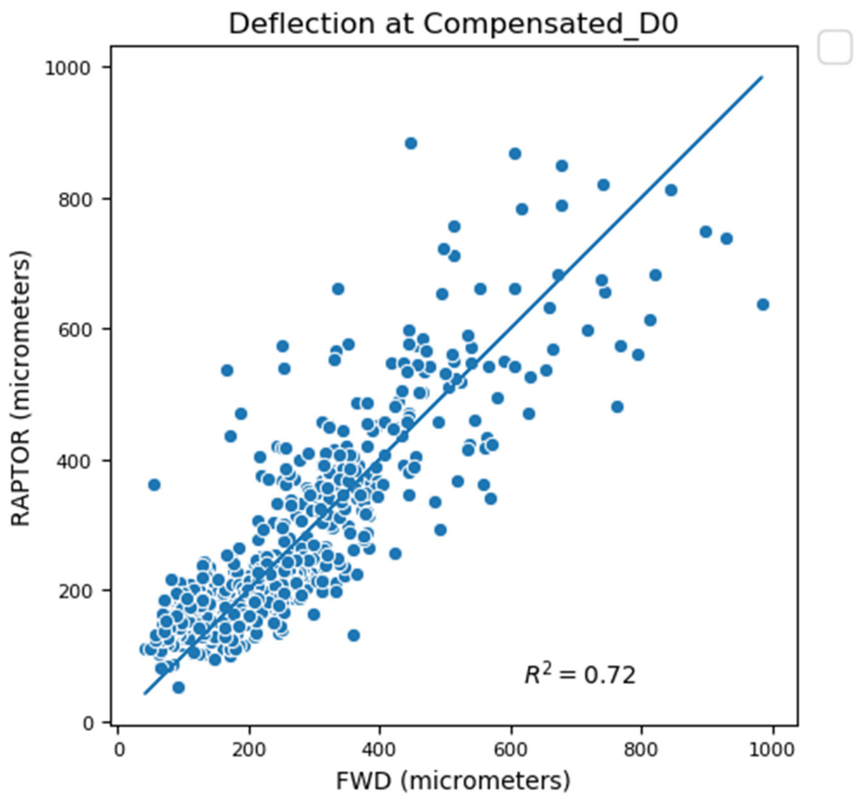

Figure 46 RAPTOR vs. compensated FWD deflections, data points with asphalt layer modulus 3,000 to 7,500 MPa

Performing the analysis based on the filtered data set, it was found that for the data points linked to an asphalt layer modulus between 3,750 and 6,750 MPa a very high correlation between the RAPTOR and the compensated FWD could be achieved with calculated R^2 values ranging between 0.71 and 0.78 as shown in figure 47. Based on the results it was found that the datapoints linked to an asphalt layer modulus ranging between 5,250 and 6,750 MPa a correlation value of 0.78 was achievable between the deflections of the RAPTOR and the compensated FWD for 137 datapoints of the total data set, representing 14.5% of the field collected data, displaying the highest correlation points between the devices.

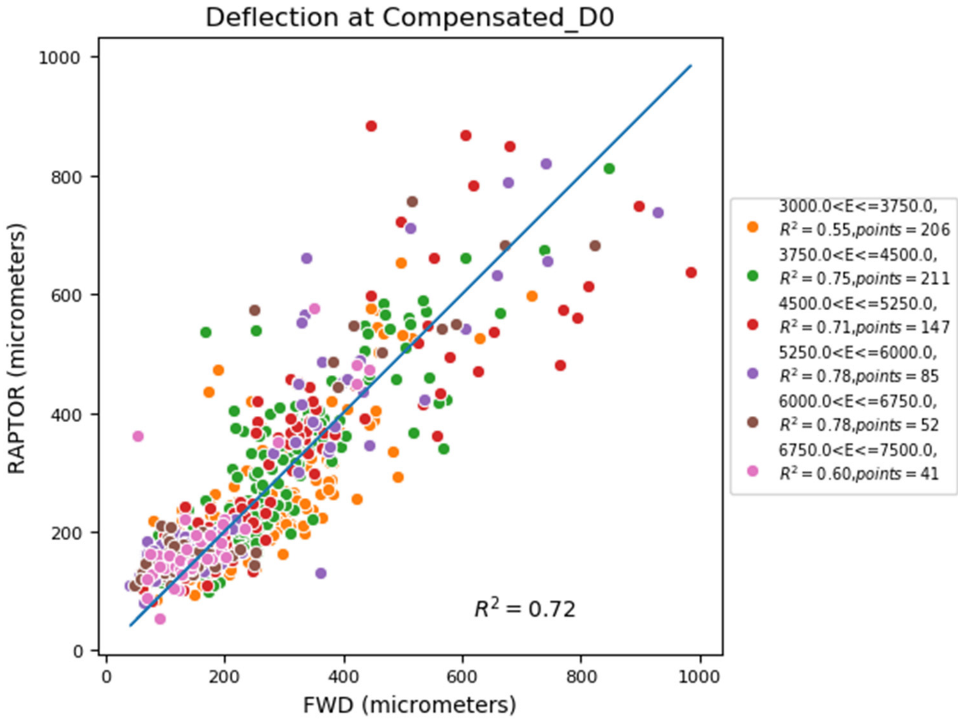

Figure 47 RAPTOR vs. FWD deflections under the load, grouped by the elastic modulus of the asphalt layer

Although it was found that by filtering the data based on the asphalt layer modulus improved the correlation between the RAPTOR and the compensated FWD, as shown in figures 48 to 51 it was also found that there was no improvement in the data classification for the remaining stiffness parameters. This behaviour can be assessed from Tables 6 to 9 as it is shown that in most cases the correlation for the filtered data set was lower than on the original data set. One interesting conclusion based on the presented analysis was found in the base layer thickness, where initially it was thought that not much information could be interpreted from this stiffness parameter, as none of the range groups classified as good correlation results. Despite of this, it was found that the filtered data only had an effect for the layer thicknesses that are greater than 275mm as shown in table 8.

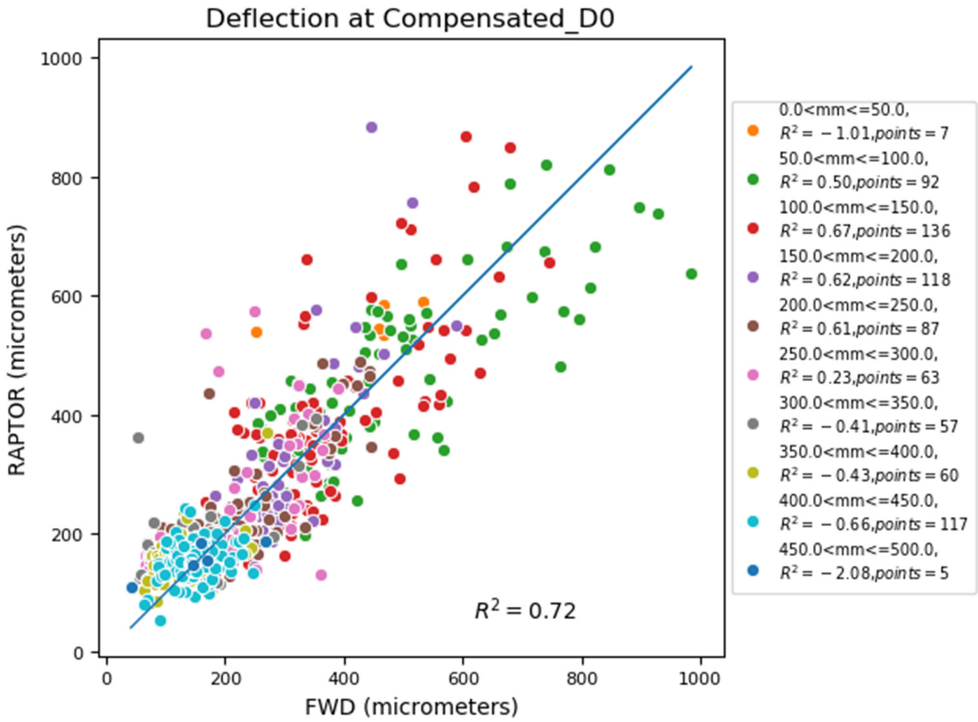

Figure 48 RAPTOR vs. FWD deflections under the load, grouped by the asphalt layer thickness

Table 6 Asphalt layer thickness correlation comparison between original dataset and filtered dataset

Thickness Range	Original Dataset		Filtered Data Set	
	R^2	# data points	R^2	# data points
0.0< t <=50.0	0.33	8	-1.01	7
50.0< t <=100.0	0.53	94	0.50	92
100.0< t <=150.0	0.66	147	0.67	136
150.0< t <=200.0	0.64	130	0.62	118
200.0< t <=250.0	0.61	109	0.61	87
250.0< t <=300.0	0.22	88	0.23	63
300.0< t <=350.0	-0.19	89	-0.41	57
350.0< t< =400.0	-0.73	86	-0.43	60
400.0< t <=450.0	-0.59	178	-0.66	117
450.0< t <=500.0	-9.99	11	-2.08	5

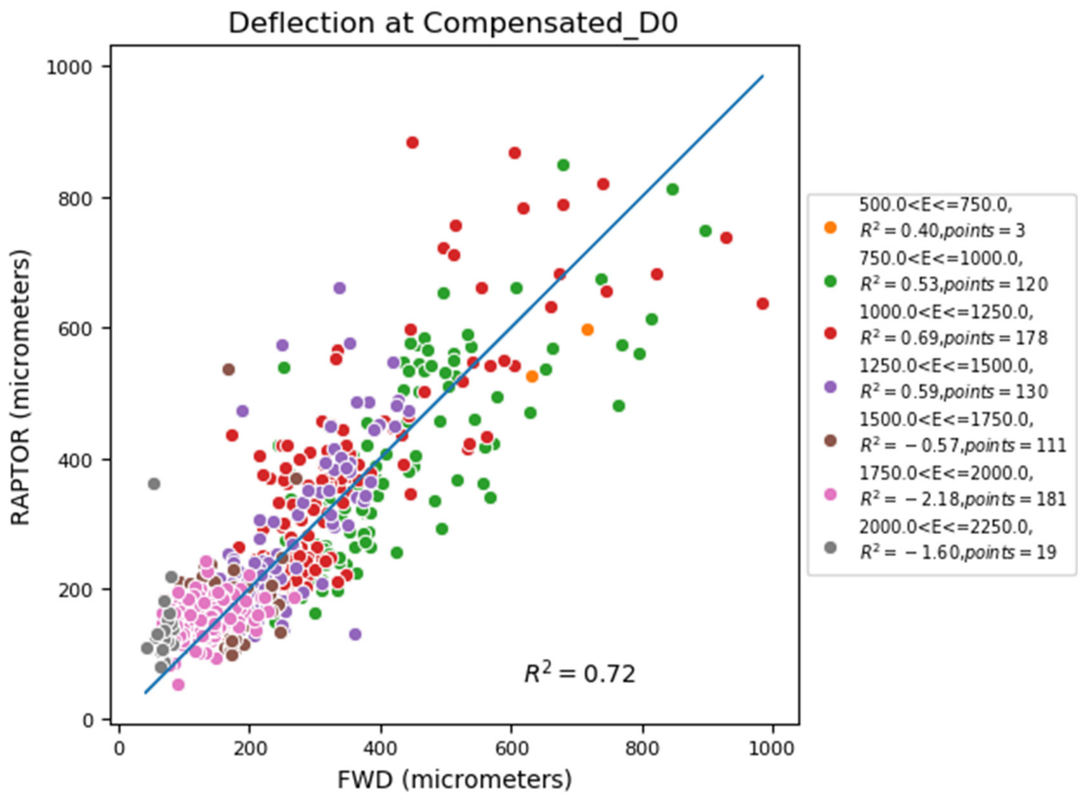

Figure 49 RAPTOR vs. FWD deflections under the load, grouped by the elastic modulus of the base layer

Table 7 Base layer modulus correlation comparison between original dataset and filtered dataset

Modulus Range	Original Dataset		Filtered Data Set	
	R^2	# data points	R^2	# data points
500.0< E <=750.0	0.62	8	0.40	3
750.0< E <=1000.0	0.54	135	0.53	120
1000.0< E <=1250.0	0.70	194	0.69	178
1250.0< E <=1500.0	0.44	161	0.59	130
1500.0< E <=1750.0	-0.67	151	-0.57	111
1750.0< E <=2000.0	-1.86	272	-2.18	181
2000.0< E <=2250.0	-1.60	19	-1.60	19

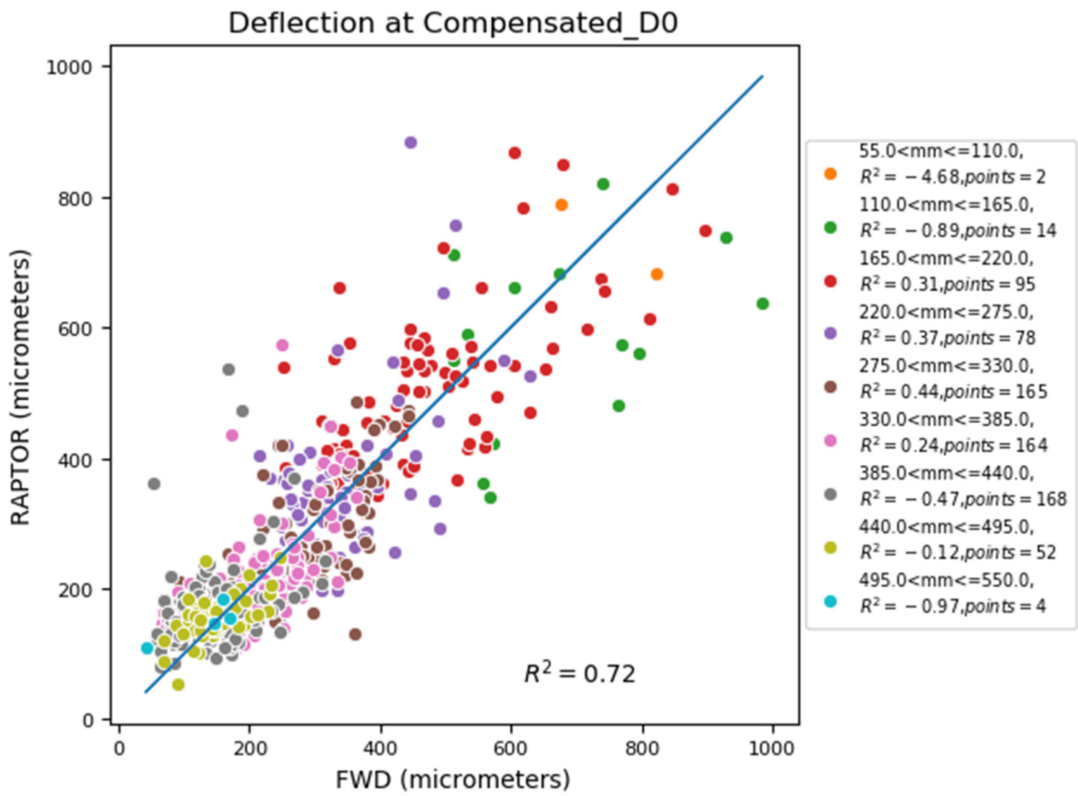

Figure 50 RAPTOR vs. FWD deflections under the load, grouped by the base layer thickness

Table 8 Base layer thickness correlation comparison between original dataset and filtered dataset

Thickness Range	Original Dataset		Filtered Data Set	
	R^2	# data points	R^2	# data points
55.0< t <=110.0	-4.68	2	-4.68	2
110.0< t <=165.0	-0.89	14	-0.89	14
165.0< t <=220.0	0.31	95	0.31	95
220.0< t <=275.0	0.39	79	0.37	78
275.0< t <=330.0	0.56	179	0.44	165
330.0< t <=385.0	0.26	200	0.24	164
385.0< t <=440.0	-0.16	219	-0.47	168
440.0< t <=495.0	-0.56	93	-0.12	52
495.0< t <=550.0	-3.71	59	-0.97	4

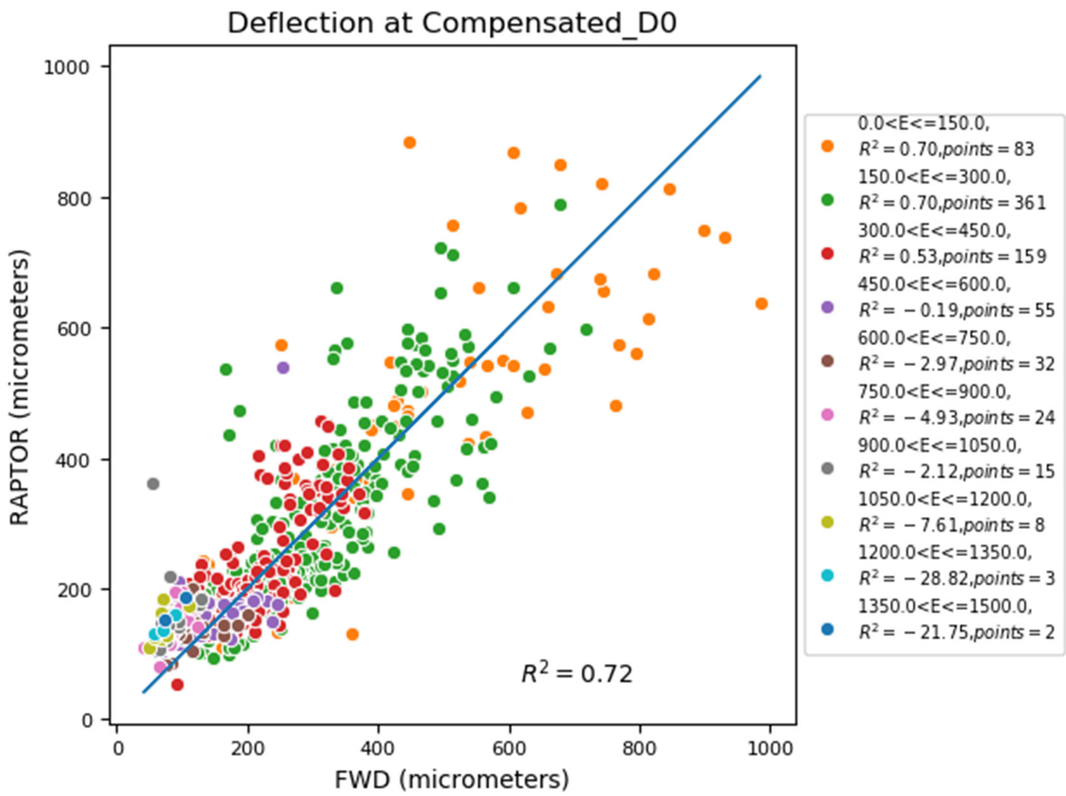

Figure 51 RAPTOR vs. FWD deflections under the load, grouped by the elastic modulus of the subgrade

Table 9 Subgrade modulus correlation comparison between original dataset and filtered dataset

Modulus Range	Original Dataset		Filtered Data Set	
	R^2	# data points	R^2	# data points
0.0< E <=150.0	0.70	119	0.70	83
150.0< E <=300.0	0.70	470	0.70	361
300.0< E <=450.0	0.51	185	0.53	159
450.0< E <=600.0	-0.31	65	-0.19	55
600.0< E <=750.0	-3.02	39	-2.97	32
750.0< E <=900.0	-3.78	30	-4.93	24
900.0< E <=1050.0	-2.13	16	-2.12	15
1050.0< E <=1200.0	-8.10	10	-7.61	8
1200.0< E <=1350.0	-28.82	3	-28.82	3
1350.0< E <=1500.0	-17.78	3	-21.75	2

The final results concluded that the inclusion of the second wheel for the load compensation demonstrated better results in the data analysis. It was also demonstrated that higher correlation resulted from filtering the data and using only the data points where the asphalt layer modulus was in the range between 3,000 and 7,500 MPa. Following the presented process, the general correlation between the FWD and RAPTOR increased from a R^2 value of 0.64 to 0.72 as shown in figures 38 and 46 respectively, displaying high correlation values of the RAPTOR when compared to the FWD.

4.3 RAPTOR vs. FWD

In section 1.2 it was stated that one of the aims of this research is to come up with parameters to identify the validity of the RAPTOR when compared to the FWD, specifically for high stiffness pavements as the structures in the Netherlands. It was also shown that the criteria to identify a high stiffness pavement could not be assessed based on the stiffness parameters as the field collected data corresponds to layered structures with a different composition. In order to classify the field collected data as high stiffness structure, the layered structure composition of pavements in the Netherlands was used as input in 3D-Move analysis to find which deflection values correspond to the referred high stiffness pavements. It was found that the standard pavement structure composition found in the Netherlands results in deflections under the load of 177 micrometers or less. This deflection will be used as a threshold in order to identify what is the correlation between the FWD and the RAPTOR based on high stiffness pavements. The same process applied in section 4.2 was performed for the data points considered as high stiffness pavement structures filtering the data points where the original FWD deflection under the load is less or equal than 177 micrometers, but the correlation is assessed based on the compensated FWD deflections.

This process concluded that the RAPTOR is not able to show good correlations against the classified high stiffness data points based on FWD deflections under the load lower than 177 micrometers. As it is shown in figure 52, the RAPTOR and the compensated FWD do not have a good correlation when compared at a 45° angle, as it is shown that the FWD deflections are dispersed in a range between 25 to 225 micrometers, and the RAPTOR deflections are in a range higher than 100 micrometers for almost all the data points. Due to this behaviour of the RAPTOR against the FWD deflections, a negative R^2 value was calculated in the presented data set, meaning that the correlation between the data has better representation with a horizontal line instead of the proposed 1 to 1 correlation.

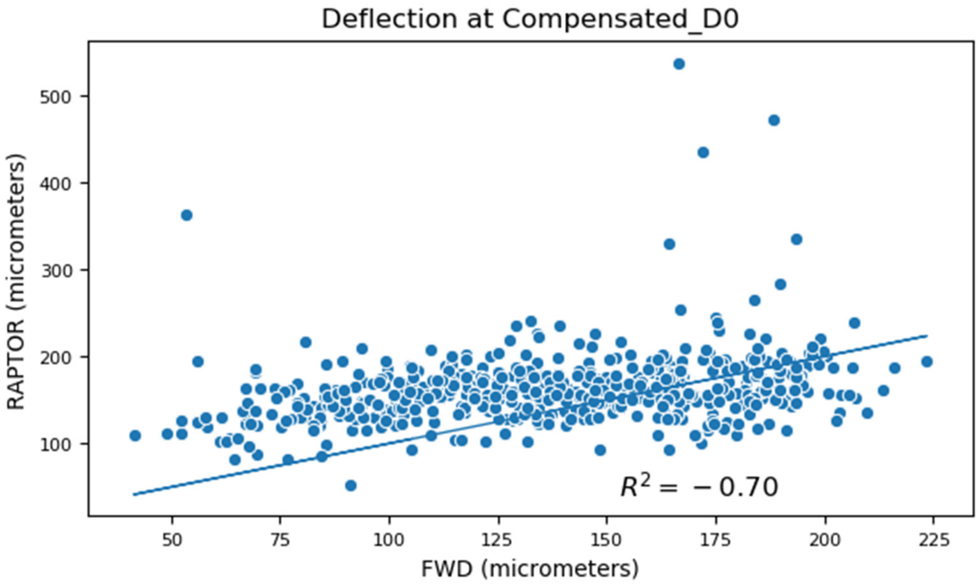

Figure 52 RAPTOR vs. compensated FWD deflections, data points with D_0 <= 177 micrometers

Based on the presented results it can be defined that the RAPTOR is not able to display accurate deflection values in the data points where the FWD results in deflections under the load of 177 micrometers or less. This means that at the current state, the RAPTOR is not able to give reliable results for high stiffness pavements.

5 Practical Application Procedure

Based on the presented research, a practical application procedure has been elaborated by combining the validation of continuous evaluation equipment methodology alongside the machine learning process as a backcalculation tool. It is foreseen that the combination of both can have a potential impact for research investigation and engineering use within the pavement engineering community. This chapter encloses the implementation of the procedure and its potential benefits based on a fictitious data set produced with 3D- Move Analysis.

This chapter contains the description of the process, with a semi-automated method that can be used in applications where layer information is unknown and to determine differences between deflection calculating devices. In this process, a machine learning algorithm is set to run with the previously elaborated database, and a publicly available forward calculation method such as 3D-move analysis.

5.1 Introduction

It is predicted that this framework is able to perform different tasks such as the comparison of a continuous evaluation equipment with the FWD, or to compare data that was taken in a different period of the year with the same equipment (temperature corrections). It is also possible to use it for data management of a road network, as one of the benefits of continuous evaluation devices is that there is no traffic disruption and the networks can be assessed on a yearly basis to have a better knowledge of the deterioration of the structure.

In this example a set of 50 different three layered structures were plugged in to 3D-Move Analysis in order to obtain their corresponding deflection bowls. With this information the aim is to backcalculate successfully the different layer thicknesses and moduli and make a forward analysis to compare them at deflection level. The comparison will also be performed at the different benchmarking tools such as the slopes, and finally a comparison at strain level with the calculation of number of load applications to fatigue cracking will be performed.

5.2 Application Procedure Tools

5.2.1 Database

Since the proposed procedure is based on a machine learning process, a database containing enough information is needed. As explained in chapter 3, for the elaboration of this thesis a database was developed with TU Delft SEM-Based model. The original database consisted of 26,052 types of three-layered pavement structures, from the combination of layer parameters as found in table 10.

This database was elaborated with the SEM-Based model, although it was found that the outcome of this tool was very similar to the outcome of 3D-move analysis. As explained in chapter 3, the database is open to increase in size, as long as more information is fed. Currently, the database presented for the application consists of 33,709 different types of pavement structures, as it includes all the information from the predicted data as performed in the previous chapters of this report.

This application procedure is performed with simulated data, and therefore is prone to change at the cost of a large database recollected from real information. At a final state, with a large enough field collected database, a research for the comparison can be performed to check if the use of simulated data can be taken as true from a field collected database.

Table 10 Layer thicknesses and moduli for database elaboration

Asphalt Layer Thickness (mm)	100	200	300	400	500	
Asphalt Layer Modulus (Mpa)	1500	1900	2300	2700	3100	
	3500	3900	4300	4700	5100	
	6000	8000	10000	12000		
Base Layer Thickness (mm)	100	200	300	400	500	600
Base Layer Modulus (Mpa)	200	450	700	950	1200	
	1450	1700	1950	2500	3000	
Subgrade Modulus (Mpa)	50	100	250	400	550	700
	850	1000	1150	1300	1450	

5.2.2 Measured deflections

The measured deflections can be transformed from FWD device or continuous evaluation equipment into FWD geophone positions. This data is needed in order to predict the different layer parameters for a fast paced screening. The measured deflections at use will depend on the needs of the user, in which studies such as: FWD screening backcalculation, continuous evaluation equipment screening backcalculation, comparison of both sets of equipment, and in theory, comparisons between the same equipment at different seasonal periods to assess the climate impact, or to compare equipment developed by different companies (e.g. Greenwood TSD vs. RAPTOR). These different comparisons can be performed to extend the research, and assess the certainty of the application. A guideline of these comparisons are given in the final section of this chapter.

5.2.3 Forward Calculation Analysis Tool

As shown in previous chapters, the forward analysis tool used was TU Delft SEM Based model, but it was also shown that the outcome of the SEM-Based model was almost identical to that of 3D-Move analysis. Taking into account that 3D-move analysis is a publicly available forward calculation tool, the application will be explained with this tool. In theory, any forward calculation model is able to work, but only the mentioned have been used in the elaboration of this research. FEM tools are encouraged to be used for further study to corroborate that the method can be expanded to different analysis tools. In case this is done, the software based database must be at least correlated to fit the different model in use. If this is done, the recommendation is to perform part of the database with the new tool, and find correction factors that can be used instead of elaborating a large database from scratch.

5.3 Procedure

Once all the needed software and information are at hand, the user can continue with the procedure. In this section a full description of the application procedure following an example will be shown, so the process can be used at different levels.

5.3.1 Part 1: Problem definition

As a first step the user must know what type of problem will be faced with the use of the application procedure. In this example, the data is set as fifty different pavement structures consisting in random values, within the ranges from the database. The different pavement sections are shown in figure 53. From this figure it can also be determined that the dataset does not correspond to network stretch as the layer moduli and thicknesses are highly dispersed from one point to the next. For visual representation, the subgrade has been set to a thickness of 200mm, but the layer is modelled with an infinite depth.

The deflection bowls are calculated with the use of 3D-move Analysis in order to obtain the "Original" information that will be processed for the backcalculation method using the machine learning model.

In order to process the deflection bowls using 3D-Move Analysis, the following criteria were taken into account:

- Static/Dynamic Analysis: A static analysis was performed as it was found that there is virtually no difference when the dynamic analysis was compared to that of the static analysis in a linear elastic model. Therefore, taking into account the advantage that the static analysis takes less computer power to process.
- Axle Configuration: The loading plate that simulates the FWD device was used with the standard pressure and loading. This configuration consists of a single circular load cell with a diameter of 300mm and a of 50kN load.
- Response Points: As previously established in this application, the processed data must consist on deflections at geophone positions. Therefore in the 3D-Move Analysis program, the response points consists of 8 geophone positions from the center of the load up to 1.5m of radial distance, all of them at the surface of the top layer. Another position was set at the bottom of the top layer (h1-1mm) at the center of the load. This last response point is to measure the horizontal strain at the bottom of the top layer, which will be later used as a correlation factor.

Once all the data is analysed, the relevant data is collected from the 3D-Move Analysis including the layer thicknesses and moduli, vertical displacement (deflections) at geophone positions, and the horizontal strains at the bottom of the asphalt layer.

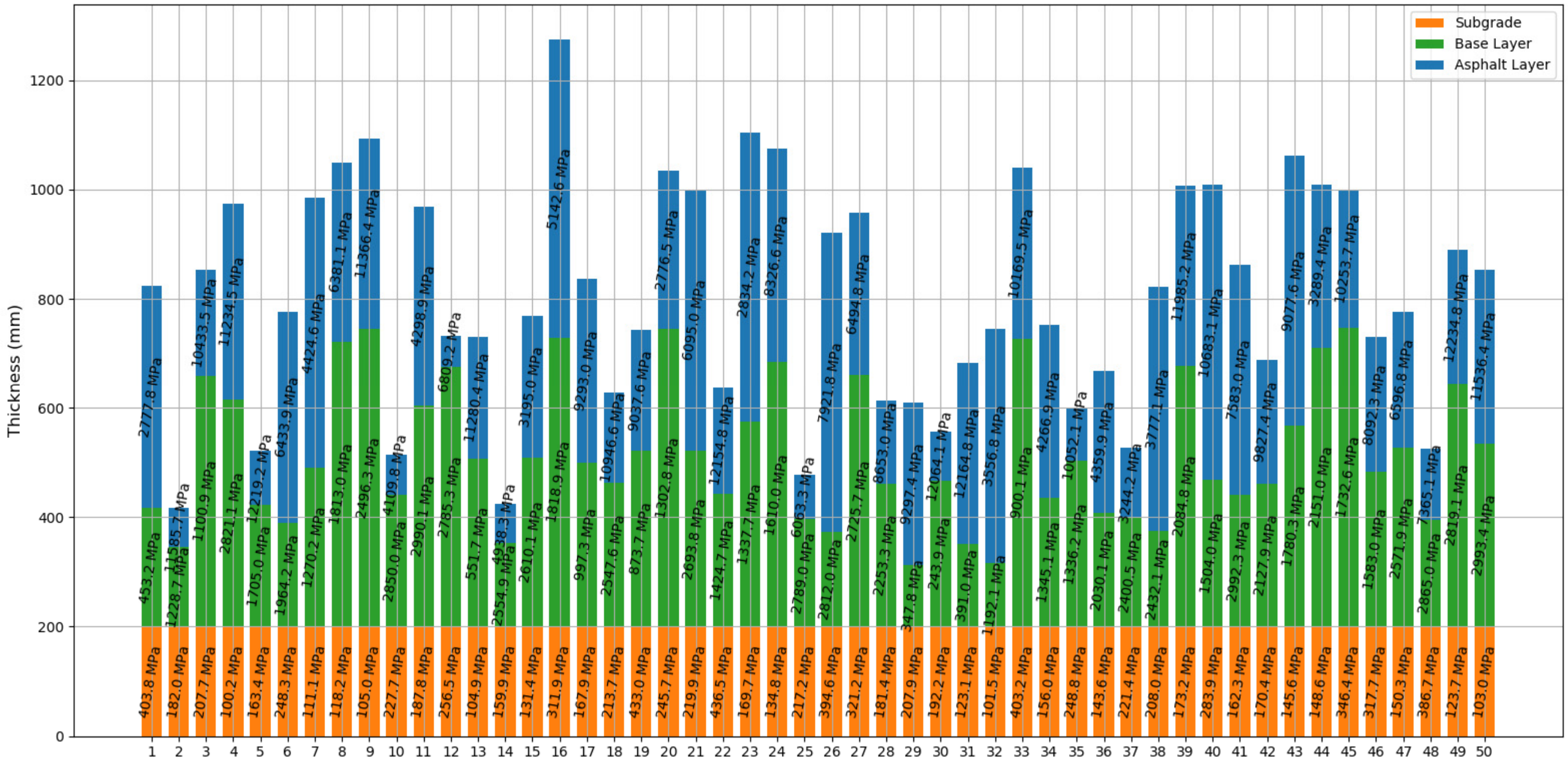

Figure 53 Example Test Sectio

5.3.2 Part 2: Machine learning process

Once all the information is acquired, the procedure towards the backcalculation analysis with the use of machine learning will be performed. At this level, the database and the new dataset must be at hand, with the relevant information to perform the backcalculation procedure. As shown in chapter 3, a heat map plot relation was performed to find correlation between the distinct layer parameters when compared to deflections from geophone positions and with the benchmarking tools. The benchmarking tools parameters are taken as the input data for the machine learning process, as these are able to result in a better correlation with the stiffness parameters.

In this example, the MLP regressor was used over the 50 deflection bowls as generated from 3D-Move Analysis. The procedure resulted in the corresponding predictions for each of the layer thicknesses and moduli. At this point a screening should be performed in order to check if the predicted values are congruent, and non-negative values are predicted. Following this screening, it was found that 4 of the deflection bowls resulted in predictions with a negative subgrade modulus for deflection bowls 13, 31, 32 and 50 as shown in tables 11 and 12.

Table 11 Original layer parameters

Station	AC_thick (mm)	AC_modulus (Mpa)	B_thick (mm)	B_modulus (Mpa)	SG_modulus (Mpa)
13	223.84	11280.41	306.68	551.72	104.93
31	332.88	12164.82	150.82	390.99	123.07
32	429.89	3556.82	115.51	1192.12	101.54
50	317.69	11536.39	334.92	2993.42	103.03

Table 12 Predicted layer parameters

Station	AC_thick (mm)	AC_modulus (Mpa)	B_thick (mm)	B_modulus (Mpa)	SG_modulus (Mpa)
13	468.48	8904.91	483.58	1823.99	-57.61
31	459.75	9898.51	487.60	1898.68	-3.61
32	498.00	4289.99	427.56	1821.62	-0.07
50	465.25	10546.59	501.74	1912.69	-5.42

As presented in tables 11 and 12, the machine learning tool was unable to predict acceptable values for all of the layer parameters. The negative subgrade modulus prediction corresponds to pavement structures that have a combination of high stiffness in the top layer and low stiffness at subgrade level. As a general problem of this approach is the fact that there is no unique solution when performing a backcalculation procedure for the pavement structural parameters. Errors such as this one may occur due to a bias in the database, in which not enough data close to the representation of high stiffness asphalt layer and a poor subgrade layer are found. In cases such as this one, it is suggested to feed the database with more information regarding these specific traits. As a general recommendation, it is suggested to segment the database with different types of structures, depending on the definition of the problem, in cases where insights are known about the structure.

Once that the screening is finalized, the rest of the predicted values are used as input for the calculation of the different deflection bowls. Again this process is performed with the use of the automated process for 3D-Move Analysis. The process is performed using the same criteria as before, following a static analysis, with the same load cell representation and the same response points at geophone position and the response point at the bottom of the top layer.

Once this process is done, the user is able to perform the corresponding data analysis, depending on the problem definition. In this example, it will be used to display which parameters can be correlated between the original values and the predicted information acquired.

5.3.3 Part 3: Data analysis

With the deflection bowls generated from the predicted data, the user is able to plot the different layer parameters that can be calculated from the response points at geophone positions, and the horizontal strain at the bottom of the top layer.

As a first analysis, the deflections are assessed in order to validate the certainty of the application procedure. If the deflection values calculated from the predicted values are not in accordance to those of the original deflections, the database should be fed with the acquired predicted information and the process as shown in section 5.2.2 must be repeated. This way the database keeps growing with information as acquired from predicted values, and therefore is able to make better approximations in the next round of the machine learning process.

In this example good correlation was found at deflection level between the original values and the predicted values where the deflections under the load and 300mm away from the load display R^2 values of 0.82 and 0.65 as shown in figures 54 and 55 respectively. In addition to this, the benchmarking parameters displayed outstanding correlations between the original and predicted data, where the parameters BLI_300, BLI_600 and MLI displayed R^2 values of 0.94, 0.96 and 0.96 respectively (figures 56-58). Demonstrating that the missing data prediction procedure is able to predict stiffness parameters that can result in data that has similar behaviour to the original information.

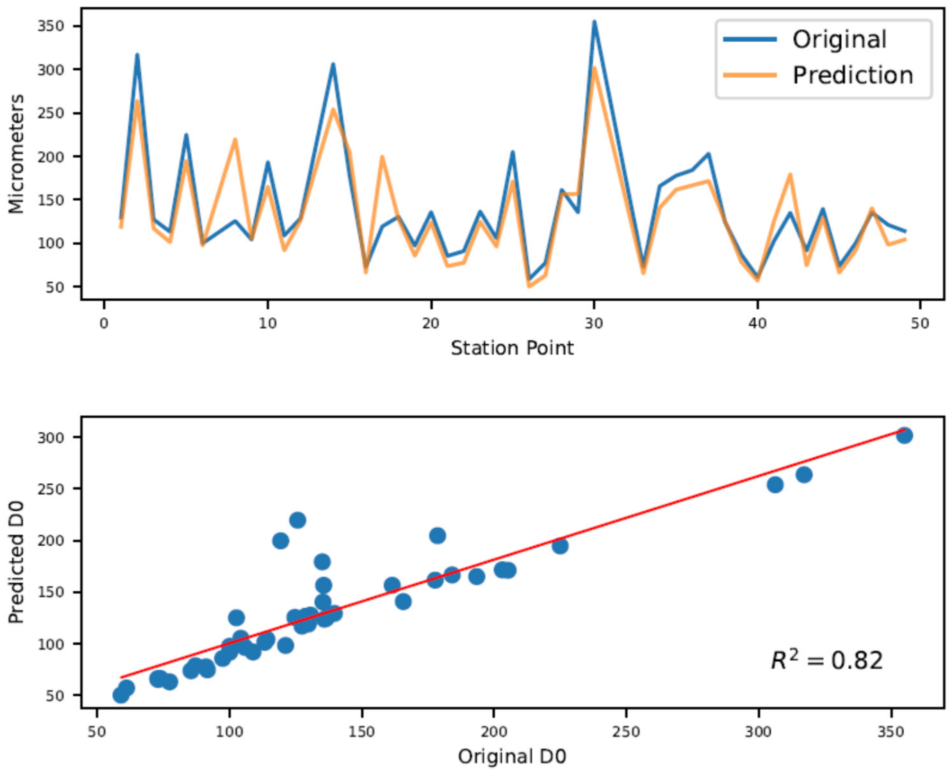

Figure 54 Correlation of calculated deflections at the center of the load from original data and predicted data

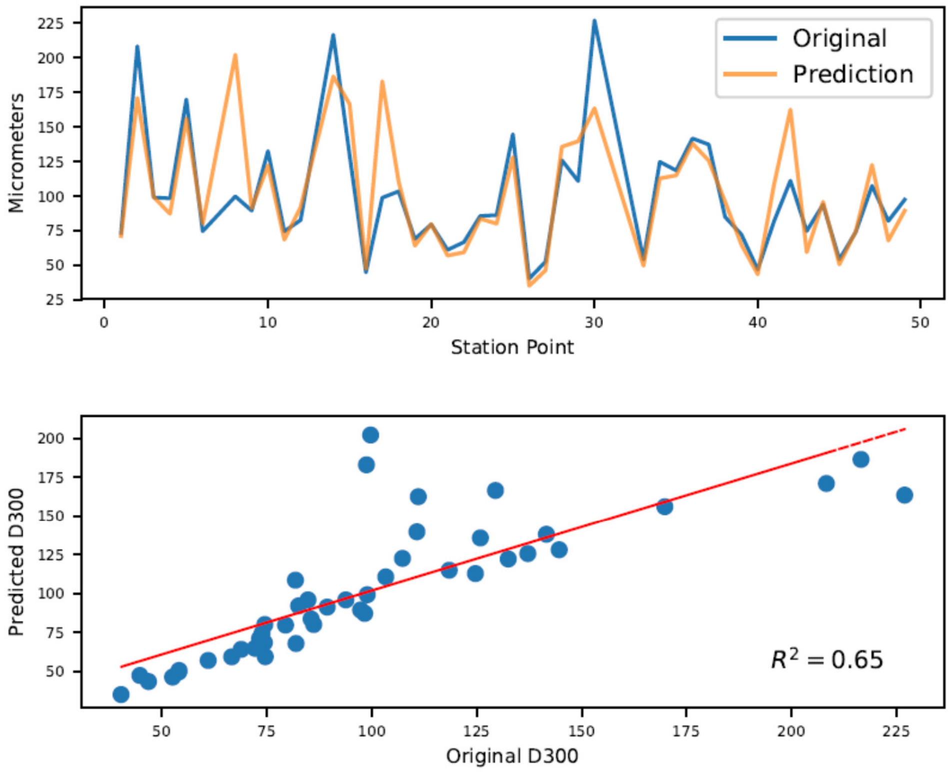

Figure 55 Correlation of calculated deflections at 300mm away from the load from original data and predicted data

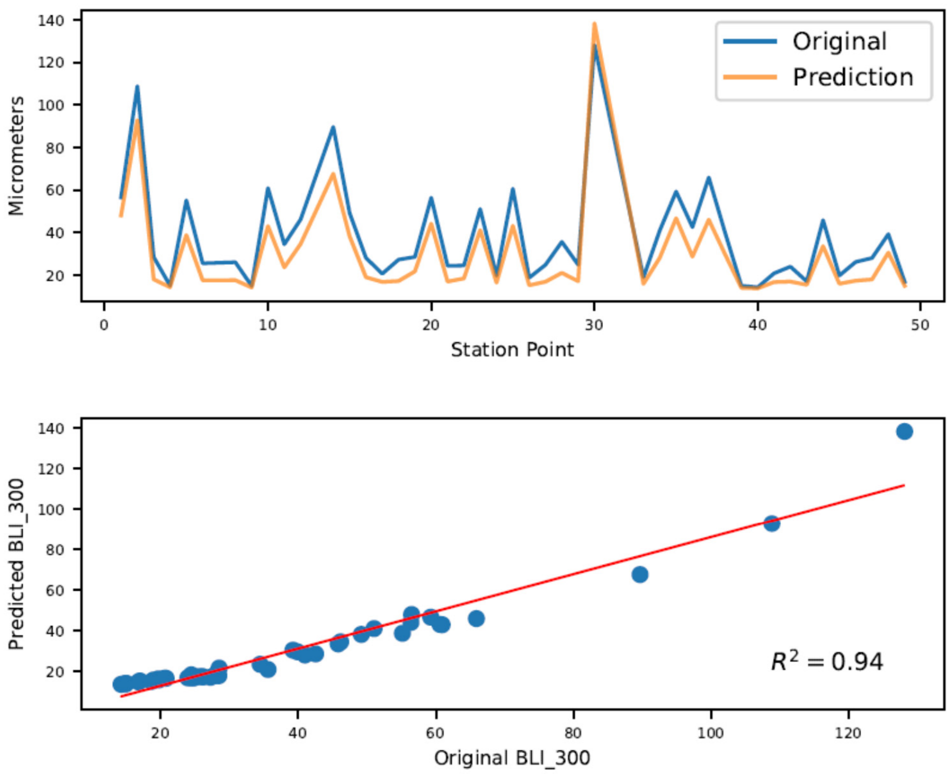

Figure 56 Correlation of calculated: base layer index (D_0-D_{300}) original data and predicted data

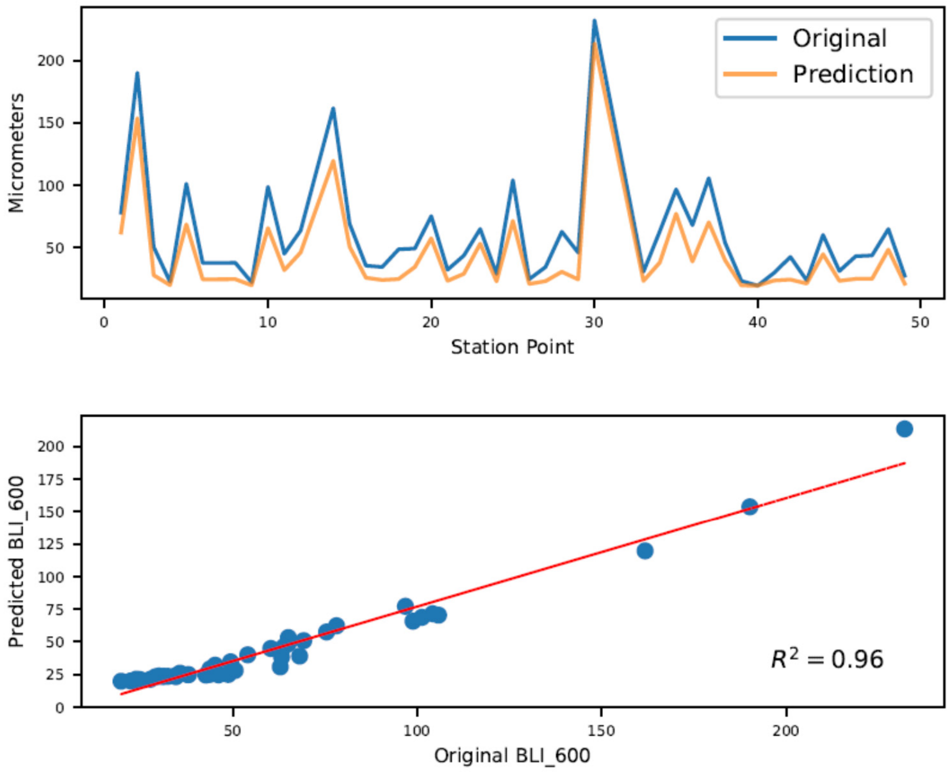

Figure 57 Correlation of calculated: base layer index (D_0- D_{600}) original data and predicted data

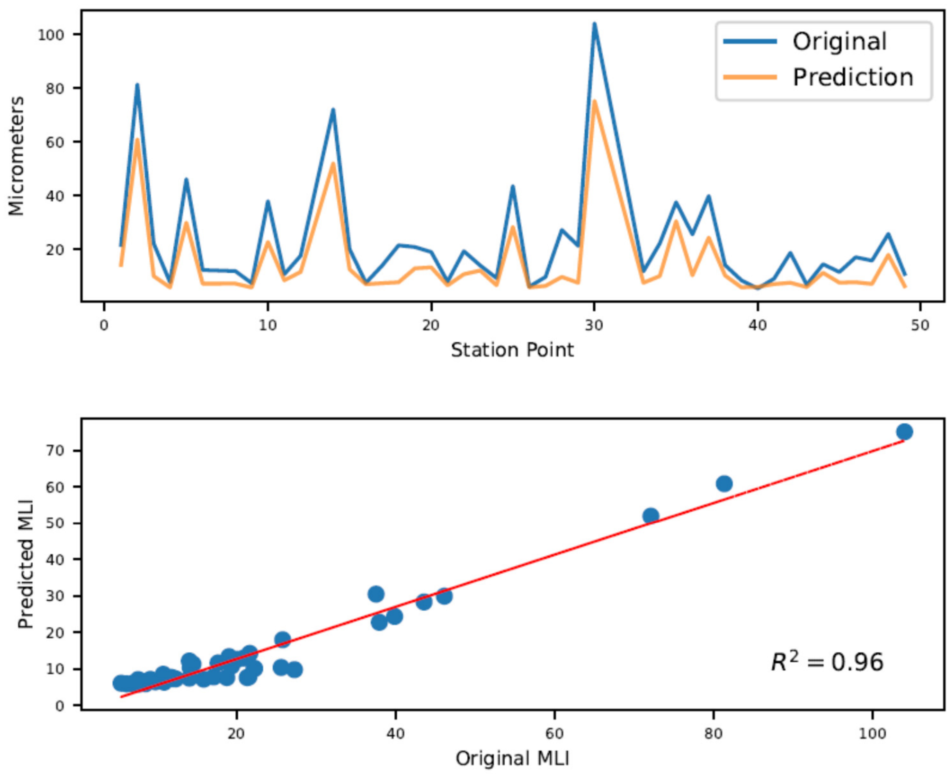

Figure 58 Correlation of calculated: middle layer index (D_{300}-D_{600}) original data and predicted data

Similar to the results presented in chapter 3, the asphalt layer modulus did not display a good correlation result as the deflection and benchmarking parameters, as for this parameter a correlation value of R^2 equal to 0.47 was found. This is an expected behaviour as the deflection bowl does not have a unique solution of stiffness parameters.

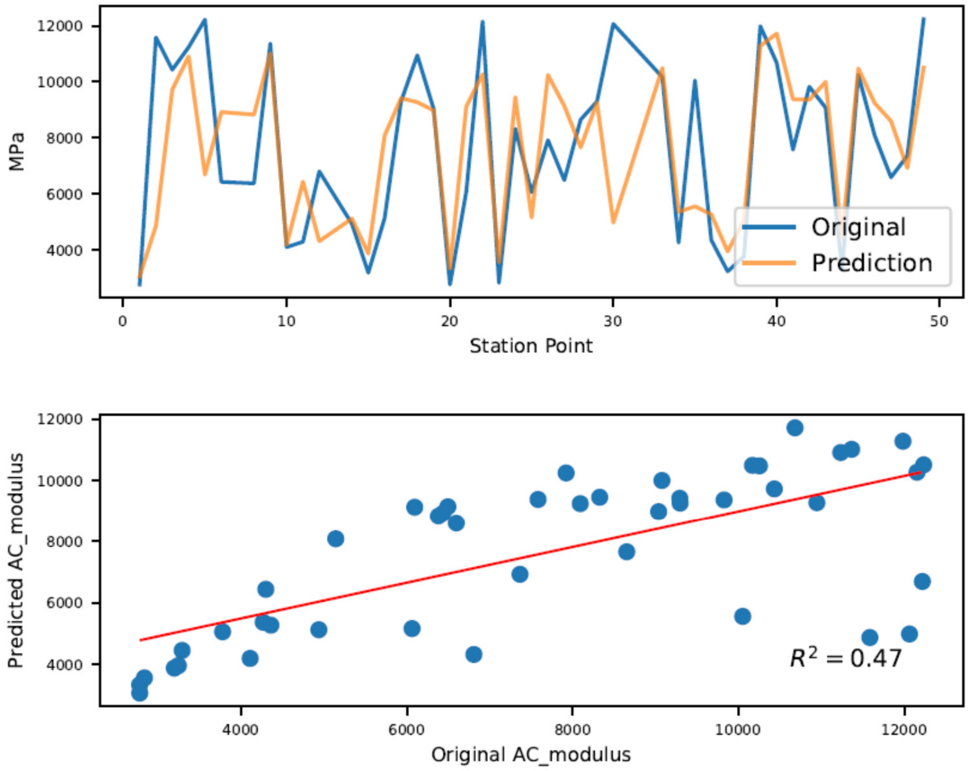

Figure 59 Correlation of asphalt layer modulus from original data and predicted data

The determination of stiffness parameters, especially the asphalt layer modulus is used alongside the deflection bowl information to determine the remaining life of a pavement structure by using mechanistic models that combine stress and strain. Since it has been shown that at the current state, the determination of stiffness parameters do not comply with the standard of acceptable correlation, it was proposed to find a different parameter that can potentially be used to calculate the remaining life of a pavement structure. This parameter was determined to be the horizontal strain at the bottom of the top layer (ε_{yy}). This horizontal strain can be combined with the asphalt layer modulus (E1) in order to calculate the number of load applications (Nf) to fatigue cracking over 10% of the wheel path area (Maaty, 2012) as shown in equation 3.

Equation 3

$$Log(Nf) = 16.664 - 3.291 \cdot \log(\varepsilon_{yy} \cdot 10^6) - 0.854 \cdot \log(E1)$$

Doing the analysis over the horizontal strain at the bottom of the top layer and the number of applications to failure (Nf), correlations 0.76 and 0.74 respectively were calculated as shown in figures 60 and 61. Based on this results, it is determined that the predicted asphalt modulus can be used in real life application procedures despite having a low correlation result when compared to the original modulus. As parameters such as Nf are used in the determination of remaining life of pavement structures.

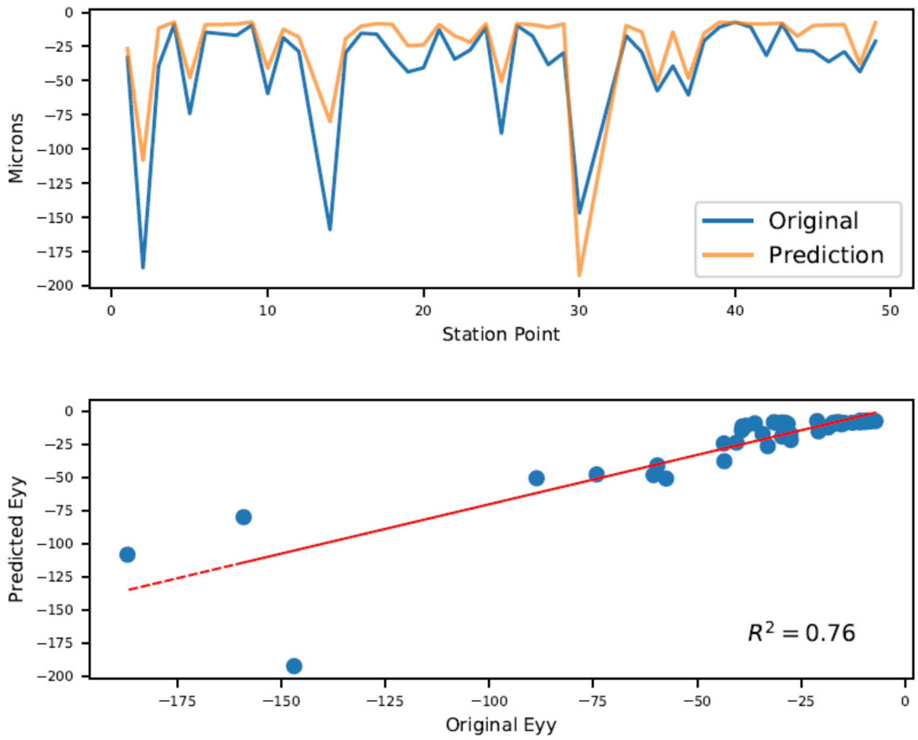

Figure 60 Correlation of calculated tensile strain at the bottom of the top layer from original data and predicted data

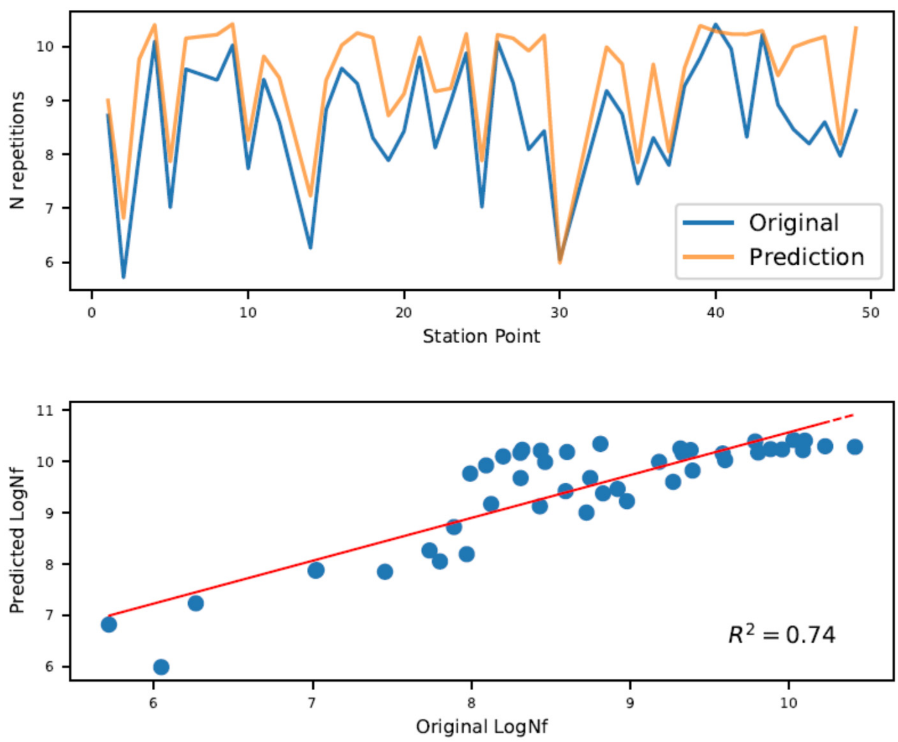

Figure 61 Correlation of calculated number of loading repetitions from original data and predicted data

In conclusion to this chapter, based on the presented results of the practical application procedure, it has been demonstrated that the machine learning process developed in this research can potentially be used in real life applications. It was demonstrated that this application procedure is able to predict stiffness parameters that result in highly correlated deflections and benchmarking parameters. Besides these, it was also found that the strain at the bottom of the top layer can be predicted with a satisfactory correlation, and this one can be used alongside the asphalt layer modulus to determine a parameter such as Nf which can be used to determine the remaining life of a pavement structure.

6 Conclusions & Recommendations

This chapter will present the final conclusions of the elaborated research. It is focused to answer the proposed research questions and give proper recommendations for the continuation of this work.

This conclusion chapter is divided in general conclusions that were obtained based on the complete scope of the thesis, the conclusions based on the answers to the proposed research questions, and the general recommendations for the improvement and continuation of this research.

6.1 General Conclusions

As presented in the introduction chapter, this research is presented to investigate the limitations of the RAPTOR against the FWD at deflection level for high stiffness pavements. In addition to this, a machine learning approach has been proposed as a missing data prediction procedure based on the lack of layer information problem faced during this research. These main points have been investigated and addressed with a series of frameworks that have been presented in chapter 3 and 4 of this research, based on the presented results the following can be concluded.

6.1.1 Conclusion: Machine Learning Approach

The implemented machine learning approach was a consequence of the lack of pavement layer information occurring at most of the test sections available. As presented in section 3.2, this was implemented by means of an ANN, specifically an MLP, as this type of ANN was the most convenient as it can perform a regression analysis with a given set of inputs (deflections) in order to identify the required outputs (stiffness parameters).

Based on the results presented in section 3.2 and subsequently in the analysis of chapter 4, the machine learning approach served its purpose as the outputs generated deflection values that reflected high correlation when compared to the original deflections used as inputs in the model. Therefore resulting in stiffness parameters that can simulate to an extent the real life conditions of the presented test sections.

6.1.2 Conclusion: RAPTOR and FWD Comparison

One of the motivations of this research is to determine the validity of continuous pavement evaluation devices use in countries where the main motorways are composed of high stiffness pavements. As this type of equipment can reduce the analysis time as it has the ability of analysis at traffic speed. This ability is gained at the cost of accuracy loss, where it is known that most of the current continuous pavement evaluation devices have an accuracy of plus/minus 25 micrometers, a number significantly higher to the well-established FWD with an accuracy of 1 micrometer.

In this research a framework that can be used to predetermine the validity of the continuous pavement evaluation devices has been elaborated based on a comparison at deflection level with the FWD. In this framework the deflection of both devices are coupled and grouped by the different stiffness parameters in order to determine cut-off values were the validity of continuous pavement evaluation device can be determined. Based on the performed research two major conclusions were derived.

The first conclusion is to take into account the physical set-up of the continuous pavement evaluation device. In the presented case it was found that the load acting on the second wheel of the same loading axle of the RAPTOR has a significant impact on the determination of deflection values, as a higher correlation result was found when the FWD deflection was compensated with a second loading plate at the same distance of the second wheel of the RAPTOR.

The second conclusion derived from this research is that it is possible to determine the validity of continuous pavement evaluation devices based on stiffness parameters. Particularly based on asphalt layer modulus and subgrade modulus. In this research it was found that these moduli related most of the deflection points from both devices, and higher correlation results could be found for the ranges of values where these two stiffness parameters had higher correlations. In a similar way it was found that the base thickness is the stiffness parameter that has little to no use in determining the validity of a continuous pavement evaluation device. For the asphalt layer thickness and the base layer modulus no conclusions could be derived, as part of the data could be related from the deflection correlation, but not for enough data points. It is predicted that this could be a flaw of the missing data prediction procedure.

6.2 Research Question Answers.

6.2.1 Conclusion: Research Question 1

The first research question presented in this thesis as shown in section 1.3.1 corresponds to the following: Is it possible to obtain reliable predicted structural layer parameters using a machine learning approach?

This research question was supported by three different sub-questions reading as follows:

1. Are the predicted layer parameters reliable?
    - No negative values are predicted.
    - Higher stiffness modulus are shown for stiffer layers?
        i. Asphalt layer > Base Layer > Subgrade
2. The deflection bowls generated by the analytical model show a high correlation with the original deflections?

The answer to this question is obtained from the results of Section 3.2. In this section it was found that the ANN applied as the missing data prediction procedure gave partially satisfactory results based on the presented sub-questions. As the predicted stiffness parameters were taken as reliable since no negative values were predicted, and that the predicted stiffness values of the asphalt were higher than the base, which were higher than the subgrade. Nevertheless, based on sub-question 2, the deflection bowls generated from the predicted stiffness parameters did not show a high correlation in a 1 to 1 comparison based on the original deflections, resulting in an R^2 value of 0.24.

Despite of the low correlation in a 1 to 1 comparison with the original deflections, it was found that based on a linear regression function that the predicted stiffness parameters were able to result in deflection bowls with a high correlation to the original deflections with an R^2 of 0.84. Although this was not the expected result, for research purposes this prediction is taken as true since sub-question 1 was answered properly, and the trends generated were very similar to the original deflection.

6.2.2 Conclusion: Research Question 2

The second research question presented in this thesis as shown in section 1.3.2 corresponds to the following: Is the effect of the wheel load close to the load cell in the RAPTOR taken into account in the deflection model?

The answer of this question is based on the results shown in section 4.1, where it was found that by compensating the FWD deflections with the second wheel of the rear axle of the RAPTOR leads to better correlation results at deflection level. Most notably at the deflection under the load, where the general correlation between the devices increased from an R^2 of 0.64 to 0.70.

This conclusion can be used for the different continuous pavement evaluation devices, as the load in the second wheel of the same axle has an equivalent load to the loading wheel. Including this behaviour improves the correlation between the device and the FWD at deflection level.

6.2.3 Conclusion: Research Question 3

The third and last research question presented in this thesis as shown in section 1.3.3 corresponds to the following: *Is it possible to set a range of validity from the layer structural characteristics by comparing the deflection results of the RAPTOR and the FWD at similar testing conditions?*

This research question was supported by three different sub-questions reading as follows:

1. For a stiffer pavement structures, what are cut off values of stiffness data for which Raptor and FWD deflection data are reasonably correlated?
2. Can Stiffness data be classified in various group for which the stiffness are correlated with deflection data?
3. Is the available field data enough to carry out data analysis?

This question is directly linked to the answers of research question 1 and 2. From research question 1, the stiffness parameters predicted in section 3.2 were coupled to the deflections of the FWD and the RAPTOR. Based on the results from research question 2, the FWD deflections were compensated with the second wheel of the rear axle of the RAPTOR, equivalent to a loading plate of 50kN 2.16m away from the loading cell.

Sub-question 1 is answered based on the results of section 4.2 and 4.3. In section 4.2 the whole dataset was used to perform the data analysis and in section 4.3 the dataset was shortened based on the section points considered as high stiffness points. Based on the results presented in section 4.2, subquestion 1 will be modified as "*what are cut off values of stiffness data for which Raptor and FWD deflection data are reasonably correlated?".*

6.2.3.1 Answer Based on the Complete Dataset

Modifying subquestion 1 as presented earlier, research question 3 is answered based on the results of section 4.2. In this section it was found that based on all the test sections, the RAPTOR displayed an acceptable correlation value of R^2 equal to 0.70 when compared to the compensated FWD deflections. The different data sections were classified based on the different stiffness parameters concluding that the only stiffness parameter that was able to answer porperly sub-questions 1, 2 and 3 was the asphalt layer modulus. For this stiffness parameter it was found that based on all the test sections, a higher correlation could be obtained from filtering the complete dataset to the data points where the asphalt layer modulus was in a range of 3,000 to 7,500 MPa. This range of values represent 79% of the complete dataset, and the R^2 increased from 0.70 to 0.72.

The rest of the stiffness parameters where able to display correlations close to the R^2 of 0.70 found from the general comparison of the RAPTOR and compensated FWD, but the "acceptable" correlation only corresponded for half the data points or less depending on the stiffness parameters. Therefore failing to answer sub-question 2 and 3 for the rest of the stiffness parameters.

6.2.3.2 Answer Based on Stiffer Pavement Sections

In the scope of this research (Section 1.4) it was presented that based on the acquired information a classification of high stiffness pavements taking the pavement structures of the Netherlands as a standard was not possible to achieve based on stiffness parameters. Instead, with the using of forward analysis tools, the typical cross-section of pavement structures in the Netherlands was used to find a threshold value based on the deflection under the load from a standard FWD.

As presented in Section 1.4 this threshold is a deflection under the load less or equal than 177 micrometers. This deflection number was used in the analysis as presented in Section 4.3. Performing the comparison of the RAPTOR and compensated FWD deflections where the original deflections are less or equal than 177 micrometers it was found that the RAPTOR was not able to give reliable information. It was presented in the results that a negative R^2 was calculated, meaning that the correlation between the data has better representation with a horizontal line instead of the proposed 1 to 1 correlation. Finally concluding that at a current state the RAPTOR is not able to perform with the same reliability that the FWD has, particularly in low deflection pavement sections.

6.3 Reccomendations and Future Work

As presented in the conclusions, not all the research questions were answered with the expected results. Because of this, a set of recommendations are presented that could lead to better results for future work.

This research had many limitations which were mitigated on different assumptions that could have influenced the presented results. The first recommendation is to reduce these limitations in order to validate the presented work, or improve it in further investigations. The following are taken as the limitations that could have a major impact in the results of this research.

6.3.1 Data Collection

The collected data encloses several limitations that were present during the elaboration of this research.

- First of all it is recommended that the collected data from the FWD and the continuous pavement evaluation device should have matching temperature measurements, as the asphalt layer is highly susceptible to temperature differences and will cause major differences in the deflection results.
- For further investigation it is recommended that the layer thicknesses should be acquired for at least a portion of the test section to be investigated. In the presented research the layer thicknesses were not available for most of the

6.3.2 Machine Learning Process

The machine learning process used the missing data prediction procedure displayed favourable results at deflection level for the comparison made based on simple linear regression. Nevertheless, it is expected that this results could potentially improve for the 1 to 1 relation if the following recommendations are followed.

- Improvement of the ANN black box. In this research, the ANN was performed based on the iteration of parameters in order to obtain the most favourable results using an existing python module. It is expected that the results could drastically improve if a customized black box is implemented as the ANN, for which the different deflection parameters used as inputs could have specific bias to the output they relate the most. As an example, the SM900 can have a predetermined bias of 1 to the subgrade modulus as it was shown in section 3.2 that these two parameters have a 1 to 1 relation based on the heat map plot results.
- Use of different databases. Based on the current structure of the machine learning approach, the database kept growing as it was fed with the information of the station points that were backcalculated. Because of this, it can happen that the database has more information for a group of pavement sections that share similar traits.

6.3.3 Data Analysis Process

As it was described in the conclusions of this research, cut-off values can potentially be determined following the developed data analysis framework of this research. This can be validated by the use of similar data at deflection level, coupled with verified stiffness parameters (layer thicknesses for all the test sections obtained from coring or GPR device). In addition to this, it is recommended to perform a similar data collection process for high stiffness pavements of countries such as the Netherlands in order to determine the validity of the RAPTOR or any other continuous pavement evaluation device for high stiffness pavement structures.

The last conclusion derived from this research is that at a current state continuous pavement evaluation devices such as the RAPTOR should be used alongside the FWD. The combination of both equipment can be used to have a fast paced structural evaluation (from the RAPTOR) and an accurate implementation of the results (from the FWD). As the RAPTOR can be used as a screening device, and the FWD should be used at critical points in order to validate and improve the information of the RAPTOR.

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