Bachelor Thesis

Do we build what we design?

Using data-driven approaches to couple the construction process into air void ratio regression

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Abstract

A high percentage of the roads are paved with asphalt in the Netherlands. The construction process of asphalt pavement has many activities, such as paving, compaction, marking and striping, etc., but the most important process is the compaction because it can affect the asphalt quality. In the conventional quality control scheme in road construction industry, to evaluate if the compaction process is effective, the verification of various pavement mechanical properties will be conducted, focusing on factors such as density, air void ratio, permeability, stiffness, etc. Among these mechanical properties, the air void ratio plays an important role in providing the required structural durability, particularly for the porous asphalt, which is currently the primarily utilized material for the surface layer of the Dutch highway network. More specifically, if the achieved air void ratio is really low or really high compared to the target values in the design phase, the quality of the asphalt pavement will be affected significantly and more prone to grow structural failures, such as crackings, ravelings, etc., in the operation phase.

During the design phase of the road construction project, the target value of the air void ratio will also be determined as the functional requirement to verify whether or not the construction process implemented can result in ideal quality. However, nowadays, there is no effective and efficient measuring methods that can accurately measure the asphalt air void ratio covering the entire pavement without destroying the pavement. Thereby this research project aims to develop an empirical model that can provide an accurate prediction of pavement air void ratio based on construction characteristics.

To develop such a predictive model for the air void ratio, a data-driven approach was proposed. Firstly, a literature study was performed to explore which factors will affect the air void ratio of pavement. Subsequently, existing asphalt air void ratio predictive models from previous studies have been investigated regarding the performance, considered input parameters, and regression methods. One model was selected as the baseline model for the follow-up research, given its adequate performance. Because this model did not sufficiently include the two most relevant parameters, namely the deviation of roller passes to the target passes and the percentage of roller passes within the temperature window, which can comprehensively represent the significance of the construction process quality, an improvement was made by integrating these two input parameters into the original input-output structure used by the baseline model. In addition, to address the nature of the system's complexity and non-linearity, another improvement has been made regarding the utilized regression method. Thus, two improved models were built considering with the updated input-output structure,

using linear regression (as utilized by the baseline model) and Random Forest (RF), respectively.

To validate the models, a case study was performed, which provided construction and verification result data from a highway construction project on A50 in the Netherlands. Subsequently, the predictive performances of the two models were compared based on R-squares. The comparison shows the empirical model using linear regression failed to provide desirable results, with R^2 of 0.0076, while the obtained RF model achieved a satisfying predictive r-squared of 0.84.

This has shown that the RF model can predict reliable air void percentages and help to have a better overview of how the air void ratio on the road will look when it is being paved. Lastly, the air void ratio predictions and other information will be visualized in GIS as the extension to the construction process quality assessment scheme of ASPARi.

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1 Introduction

The following thesis aims to investigate how variability in compaction parameters, such as the total number of roller passes and the number of roller passes within the compaction window, can affect the air void ratio of porous asphalt. The introduction has 4 different sections, the problem context (section 1.1), defining the problem statement (section 1.2), the research objectives and questions (section 1.3), and the outline of this thesis report (section 1.4).

1.1 Problem context

Roads undertake the function of connecting places and people, which is essential for the development and growth of the country (Mead, 2021). Most of these roads are paved with asphalt, providing good load transmission to the sub-base and underlying soil (TNO, n.d.). To ensure the pavement has sufficient quality to resist rapid performance degradation and thus stay in appropriate condition, it would require the asphalt mixture to be designed properly based on the weather conditions and the intended use, well-controlled construction process, as well as periodic inspections and maintenance (Button et al., 2007).

Many factors alter the pavement quality, meaning if they undergo drastic inconsistency in the construction process, the result is different than planned when the pavement was designed; these inconsistencies could arise in the asphalt production, transportation, or asphalt construction process operations, such as compaction process (Micaelo et al., 2019). In this last activity, inadequate compaction is more likely to have an unfavourable effect on the quality of the asphalt pavement, because low compaction effectiveness would result in either over- or under-compacted pavement, thus leading to excessively low or high air void ratio respectively (Dubois et al., 2010). Air voids provide space for the asphalt mixture to deform under traffic loads, which reduces the stress transferred to the underlying layers of the pavement. The air void ratio also affects the permeability of the pavement, which is important for drainage and water infiltration (Meerkerk et al., 2006). Therefore, from a long run, undesirable quality in the achieved air void ratio will eventually lead to structural failures such as crackings, ravelling, etc.

1.2 Problem statement

The encountered problem is to define if during the construction phase of the asphalt pavement, the ineffective compaction reduces the quality of the pavement since, according to Yoder and Witczak (2008), the pavement should keep its efficiency high or over the standard line, which is achieved by the periodic maintenance. An effective compaction process ensures that the internal factors measures, such as the air void ratio in an appropriate-end threshold value results (Tran et al., 2016).

If the air void ratio is above or below the threshold result, the asphalt pavement's quality will be influenced negatively; thereby, the compaction has to be as effective as possible so the durability of the asphalt will be more extended. Most of the time, the air void ratio values cannot be estimated since the conventional measuring methods only measure the air void ratio of small areas or do not provide accurate values; this makes contractors assume that the obtained values from the small sections are the same of the whole section and with this, they cannot ensure the best quality of the asphalt or just do not control the air void control and assume that the other process steps such as the compaction are being done in the right manner, therefore the air void ratio percentage is the expected (Inoue and Penuelas, 2001). Because of this, an air void ratio prediction model will be developed to ensure the quality of the asphalt, allowing the contractors to monitor and control the quality of the asphalt pavement more effectively. By accurately predicting the air void ratios, contractors can make necessary adjustments in real time, ensuring that the pavement meets the desired specifications.

To assess the effectiveness of the compaction process, it will be necessary to collect and analyse the data through parameters related to the compaction, such as the number of roller passes, asphalt temperature, and mix design characteristics which are essential in determining the air void ratio.

In addition, it will provide information that will help to map out the air void ratio in the software GIS which will be georeferenced and will intuitively show, based on a colour scale, whether the compaction is effective or not, which will mean the road will have good or poor air void ratio (Russo et al., 2018).

1.3 Research objectives and questions

The research objective of this thesis is to develop an accurate air void ratio prediction model in asphalt pavements during the compaction process, with a focus on improving quality control practices. The air void ratio is a pavement's internal factor that significantly affects the quality of the asphalt pavement.

The model developed in this research will be directly linked to the construction process quality. It will enable contractors to assess and predict the air void ratios during the compaction process, allowing them to monitor and control the quality of the asphalt pavement more effectively since the existing methods are not reliable enough. Furthermore, the integration of the research results into a geographic information system (GIS) software will enhance the prediction and management of the air void ratio.

To achieve these objectives, the following research questions will be addressed:

- **How to develop a pavement air void ratio predictive model by identifying and incorporating relevant parameters in the compacting process?**

  The answers to the following sub-questions will support the above research question:

  - What is the widely applied pavement air void ratio predictive model? And what are the parameters considered in the model?
  - Which parameters may be helpful to increase the accuracy in the predicted air void ratio?
  - If the parameters helped to increase the accuracy, can these parameters be included in the air void ratio prediction model, and why?
  - What is the way to reflect the difference in air void ratio on the road?

1.4 Thesis outline

The outline of this thesis report starts with the theoretical background related to the relation between the compaction within the compaction window and the air void ratio, the data obtained from the Process Quality improvement (PQi), the model that will be used and improved and the application either of the linear regression or the random forest regression algorithm to improve the chosen model in section 2; then, the methodology used to answer the research questions are explained in section 3, which explains how the chosen model is used to calculate the air void ratio from a paved road where the data used for the PQi method is used as inputs for the model and how the application of an interpolation method improves the model.

Further, a case study is presented where the new model is used to get the air void ratio of an asphalt pavement project; the results can be interpreted by the percentages of air void ratio or the number of roller passes and by the reading of diagrams in section 4. It is followed in section 5 by a discussion about the results obtained, and section 6 presents the conclusion reached from this research. Finally, in section 7, a set of recommendations about the project are given, followed by the list of references in Section 8 and appendices in Section 9, which support the main text of the thesis.

2 Theoretical background

2.1 Relation between compaction within the compaction window and air void ratio

Compaction is a critical step in the construction phase of asphalt pavements (Wang et al., 2012). Also, it is essential to achieve the appropriate air void ratio for the quality of the pavement. The air void ratio refers to the volume percentage in the asphalt mixture occupied by air voids or empty spaces between the aggregate particles (Sun, 2016). The air void ratio is an important parameter that provokes structural failures affecting the pavement quality (Tedla et al., 2023).

Compaction of asphalt mixtures is typically carried out using heavy vibratory rollers that apply pressure to the mix, causing it to increase density and reduce the air void ratio (Flores et al., 2021). According to Poeran and Slue (2016), the temperature of the mix during compaction is a critical factor that affects its workability, viscosity, and compaction characteristics. That is why the compaction is typically performed within a specific temperature range known as the compaction window (CW) to achieve the desired air void ratio (Vasenev et al., 2012).

When compaction is carried out within the compaction window, several factors come into play to improve the air void ratio:

- **Mix design considerations:** Asphalt mixtures are designed based on specific mix design parameters, such as the aggregate gradation, asphalt binder content, and type of binder. The compaction window is selected to ensure that the mix achieves the desired air void ratio as specified in the design. It is important to stick to the specified compaction temperature range as deviating from it may result in changes to the air void ratio which could affect pavement quality (Bijleveld et al., 2012).

- **Optimal viscosity:** The viscosity of the asphalt binder changes with temperature, as hotter temperatures lead to lower consistency. When compacting the asphalt, the optimal consistency allows it to stick to the aggregate particles, leading to better compaction. This results in fewer air voids and stronger aggregate interlace, which leads to a more stable, long-lasting pavement that resists moisture damage (Zhang et al., 2015).

- **Workability of mix:** To achieve proper compaction of asphalt mix is important to use the correct compaction window. If the mix is too cold, it becomes stiff and challenging to compact which leads to get insufficient compaction and air voids. On the other hand, if the mix is too hot, it becomes too fluid and prone to segregation, which results in uneven compaction and reduced air voids. Compacting the mix within the appropriate compaction window ensures that the mix is optimal for effective compaction, resulting in a lower air void ratio (Vasenev et al., 2012).

- **Compaction efficiency:** When the compaction is done within the compaction window, it increases the efficiency of the process. This is because the mix becomes more manageable, making it easier to compact with fewer roller passes or lower compaction efforts. As a result, it becomes easier to achieve the desired air void ratio, which leads to a higher quality pavement (Makarov et al., 2021).

A clear example can be seen in figure 1, where the air void ratio is too low, the asphalt may not allow a proper drain, leading to possible problems such as standing water, cracking, and other forms of damage. On the other hand, if the air void ratio in asphalt is too high, it can allow water to penetrate more easily, leading to a series of problems that can reduce the quality and safety of the pavement significantly (Ahmad et al., 2020).

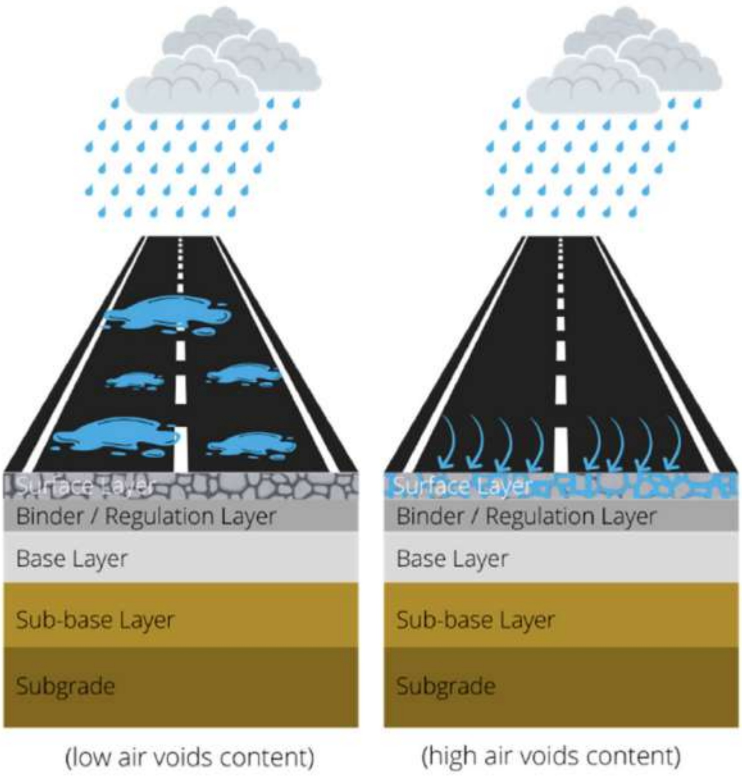

Figure 1: Low air voids content vs High air voids content (Koneru et al., 2008)

2.2 Process Quality improvement

Process Quality improvement (PQi) is a methodology used to closely monitor and assess the quality of the asphalt construction process. This framework makes use of the Internet of Things (IoT) concept to collect data from different nodes involved in the compaction process, namely Asphalt, Paver, Roller, and Processing nodes. These nodes are equipped with sensors and data transmission hardware to collect and transmit data to the Processing node.

The data collection and transmission process follow a centralized architecture, where all the data are collected and processed in a central Processing node. This architecture is chosen to reduce communication load, eliminate redundant computation, and maintain a global database for post-processing. The data collection involves various sensors and devices, such as thermocouples in the Asphalt node to measure core temperature, an infrared camera in the Paver node to capture surface temperature, and GPS rovers in the Roller nodes for tracking roller activities.

Once the data is transmitted to the Processing node, the data analysis phase begins. The collected data is structured into a relational database, which includes design data, sensory data, and analytic data. Design data includes information about the project, weather conditions, client, and contractor. Sensory data comprises the raw data collected from different nodes, such as temperature measurements and equipment location. Analytic data is generated by processing and integrating sensory and design data.

The Processing node performs various analyses, including generating a cooling curve for the newly laid asphalt, temperature contour plots, and compaction contour plots. The cooling curve provides information on the asphalt's thermal behavior and helps determine the optimal timing for compaction. The temperature and compaction data are integrated to determine the compaction priority of different parts of the asphalt mat. The generated guidance, in the form of a priority map, is then transmitted back to the Roller nodes for visualization and operator guidance.

The framework utilizes a cell-based grid structure to organize and analyze the data. Each cell in the grid contains analytic data such as temperature, compaction passes, time left for compaction, and compaction priority. The size of the cells is determined based on factors like the resolution of the infrared camera, processing power, roller size, and GPS accuracy.

In order to be able to measure the quality of the compaction process, according to Makarov (2021), an index should represent the quality of the procedure. This index is the Effective Compaction

Rate (ECR), which indicates the quality of the compaction process by measuring the number of cells that have been compacted exactly for the target compaction passes, and at least a percentage of those passes were within the appropriate temperature window.

The ECR is defined as:

$$ECR_{p,k} = \frac{n_{p,k}}{N}$$

Where:

- $n_{p,k}$= the number of cells that have been compacted exactly for target compaction passes ± k, and at least p% of the compaction passes were within the compaction window
- N= the total number of cells

In conclusion, the PQi enables real-time data collection, analysis, and guidance for the compaction process of asphalt pavement. It takes advantage of IoT concepts and centralized architecture to efficiently collect and process data from multiple nodes, ultimately improving the quality and efficiency of the compaction process.

2.3 Air void ratio prediction model

In the field of asphalt construction, the development of accurate models for predicting air void ratio are limited. Existing models either demonstrate low accuracy or incorporate factors that lack a direct relationship with the air void ratio. Two notable models were found in two different articles. The first model proposed is, in principle not a pure method to measure air void ratio but more a method to describe the plastic deformation of hot mix asphalt; therefore, when the variable of the number of roller passes is too high the shear stress levels also increase because when granular materials shear, they expand, become less compacted with high air void ratio percentages and structural failures can develop (Huerne, 2004). The second model presents a low accuracy for modelling the air void ratio and as stated by its author, only a few data points were considered for developing the model, and therefore that could be the cause of its low performance (Meerkerk et al., 2006).

Even though their authors specify that their models are not highly accurate, the second model will be described in more detail in this section since the considered variables have a direct relationship with the air void ratio. In addition, it will be possible to determine if the model's accuracy can be increased using more data as inputs during its testing phase and if not, adding variables that were not considered before are considered this time.

2.3.1 Air void ratio prediction model by Meerkerk

To be able to predict the air void ratio during asphalt construction, a model was developed in order to create a relationship based on the prevailing conditions such as temperature, compaction, etc. Linear regression techniques were used in the analysis to establish the relationship between the parameters before mentioned (Meerkerk et al., 2006).

The resulting generalized equation to predict the air void ratio is defined as follows:

$$VC = 39.51 - 0.09X_1 - 0.81X_2 + 0.05X_3 - 0.23X_4 - 0.01X_5$$

Where:

- VC = air void ratio [%]
- X_1 = $T_{asphalt}$ in hopper [$°C$]
- X_2 = bitumen percentage [%, m/m]
- X_3 = percentage aggregate on sieve C8 [%, m/m]
- X_4 = percentage filler [%, m/m]
- X_5 = roller characteristic = nP/LD^2
- n = number of roller passes
- P = load on drum [kN]
- L =length on drum [m]
- D = diameter on drum [m]

The equation was capable of predicting the air void ratio of 45 data points where 35 of the 45 data points, the predicted air void ratio was ±1% of the observed values and the remaining values (10) were within ±2% of the observed values (Meerkerk et al., 2006).

In addition, the air void ratio parameters had to fulfil some characteristics to be considered part of the model (Meerkerk et al., 2006); these values can be seen in the following table:

Table 1: Influence of individual parameters on the air void ratio (Meerkerk et al., 2006)

Parameter	**Unit**	**Min. value**	**Max. value**	**Influence on air void ratio [%]**
X_1= Temperature of mix at plant	$[°C]$	148	165	1.58
X_2= Bitumen	$[\%, m/m]$	3.8	4.4	0.49
X_3= Aggregate on sieve C8	$[\%, m/m]$	59	68	0.45
X_4= Filler	$[\%, m/m]$	3.8	6.6	0.64
X_5= Roller characteristic	$[kN/m^3]$	97	700	5.91

The equation described above shows an R-squared of 0.7, which indicates that the model is not highly accurate. For a model to be considered high-performing, its R-squared should mostly fall in the range from 0.8 to 1, where values closer to 1 have a strong correlation between model predictions and real-world observations. To enhance the accuracy of the model, it is essential to make use of various regression methods, starting with simpler ones until reaching the more complex techniques. This process aims to refine the air void prediction model's capabilities and improve its overall performance.

2.4 Regression methods

In this section, two commonly used regression techniques will be described, linear regression and random forest regression. Both methods are used to predict the value of a dependent variable based on one or more independent variables. According to Su et al. (2012), linear regression is a simple and interpretable method. In contrast, random forest regression is a more complex and powerful technique that can handle non-linear relationships and interactions between variables (Liu et al., 2012). Furthermore, this section will provide guidance on which technique may be more suitable for improving the air void ratio prediction model.

2.4.1 Lineal regression

Linear regression is a statistical technique that models the relationship between two variables by fitting a linear equation to observed data points. The goal of applying the linear regression technique is to find the best-fitting line that represents a trend or pattern in the data (Montgomery et al., 2021).

The basic concept of linear regression involves working with two variables: the dependent variable (Y) and the independent variable (X). The dependent variable is the variable that will be predicted or modelled, while the independent variable is the variable used to predict the variation in the dependent variable (Weisberg, 2005).

The linear equation is defined as:

$$Y = mX + b$$

Where:

- m= slope of the line
- b= y-intercept.

According to Weisberg (2005), the process of linear regression involves different steps. The first step is data collection, which consists of selecting data on the variables that will be studied, this data has to include the dependent and independent variables. The next step is data analysis, in this stage, the data is analyzed to identify any patterns or trends. A good way to visualize the relation between the variables is by plotting the data on a scatter plot.

Model fitting is the thirst step; it consists in determining the best-fitting line that represents the relationship between the variables. This can be done by finding the values of the slope and y-intercept; this means finding the sum of the squared differences between the observed and the predicted values from the linear equation. The next phase is the evaluation of the performance of the linear regression model by analyzing statistical measures such as R-squared, which indicates the proportion of the variance in the dependent variable that is explained by the independent variable (Rights and Sterba, 2018).

The last step starts when the linear regression model is fitted and evaluated since it can already be used to predict new data points. This is done by plugging in the values of the independent variable into the linear equation, so the model can predict the corresponding values of the dependent variable.

As can be seen in figure 2, there are two examples of linear regression applied to different data points. The left diagram shows that some of the data points are away from the line of best fit, which means that the r-squared will be low, in this case, 0.72, and the model that generated those data points is not highly accurate. On the other hand, the right diagram shows data points closer to the line of best fit, even though some of them follow the same path. Therefore the r^2 is higher, 0.86, compared to the left plot; this is because the model that estimated the data points has a lineal nature and, therefore, a high accuracy.

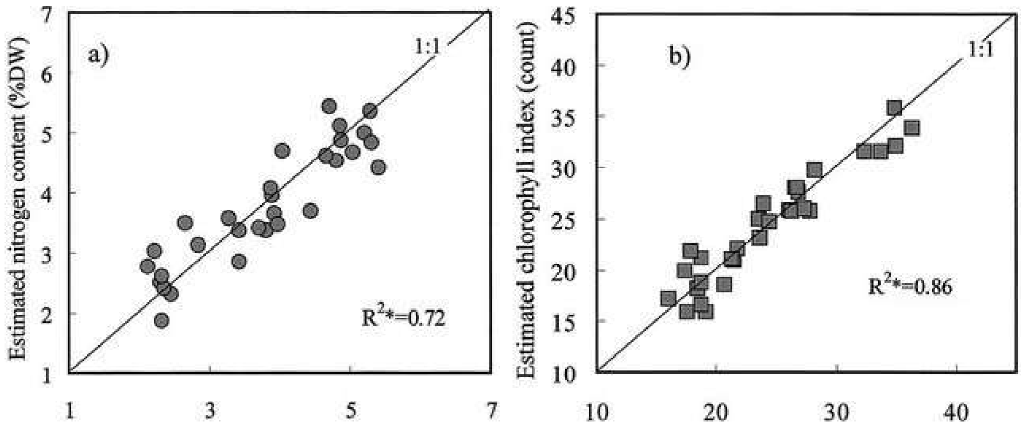

FIGURE 2: R-squared differences (Inoue and Penuelas, 2001)

2.4.2 Random Forest Regression

Random Forest Regression (RFR) is a machine-learning algorithm that creates multiple decision trees during training and calculates the average prediction of each tree. To create each tree, a subset of features and training data is randomly selected, and the data is divided into two smaller subsets based on the value of one feature.

As can be seen in figure 3, the decision trees are created by recursively dividing the data into smaller subsets according to the selected feature until it reaches a maximum depth or only one class is left in the subset (Breiman, 2001).

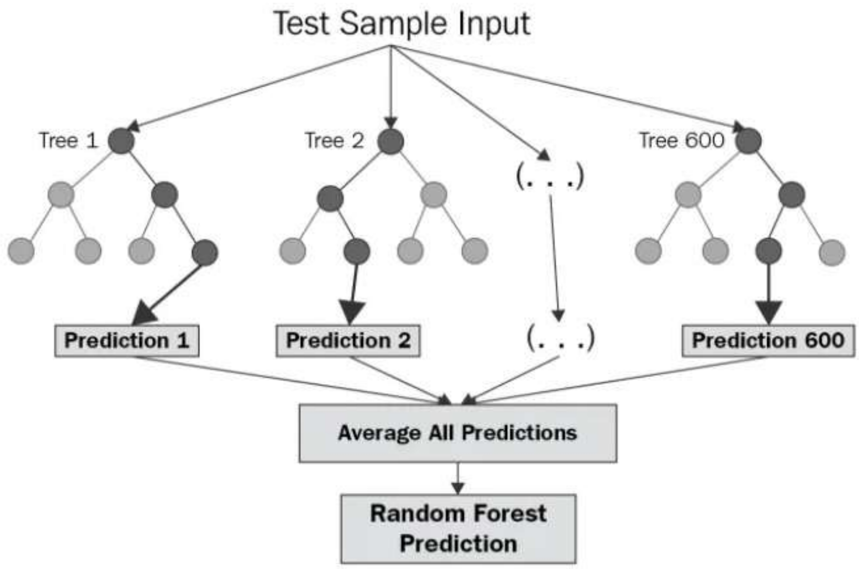

FIGURE 3: Decision trees sample (Gitconnected, 2022)

The RFR algorithm predicts new inputs by passing them through each decision tree and averaging the predicted values. This helps prevent overfitting, which is a common phenomenon that has to be reviewed every time a machine-learning model is being trained. Overfitting occurs when a model focuses excessively on the precise details of the dataset it was trained on. This means the model identifies patterns that only apply to the data it was trained on and cannot be applied to other data. The model performs well in predicting data it was trained on but struggles to make accurate predictions on new data it has not experienced during training. A clear example of overfitting can be seen in figure 4, where at the moment of testing the model found a different path since the new data is totally different to the one used during the training phase (Schonlau and Zou, 2020).

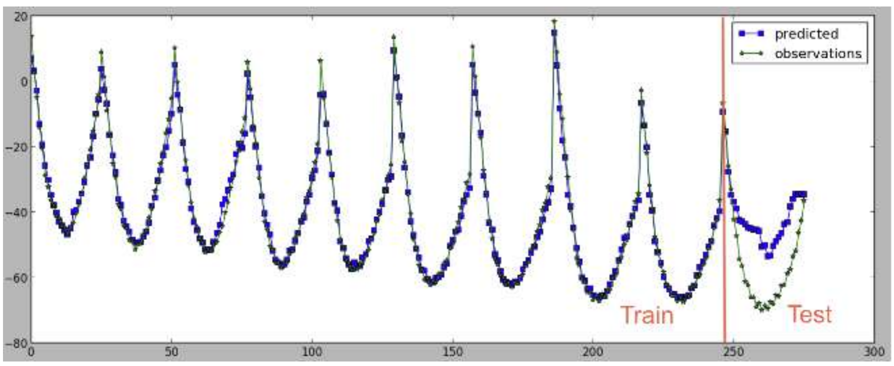

FIGURE 4: Overfitting example (Gitconnected, 2022)

The RFR algorithm is a highly capable and adaptable algorithm that can be used for different regression tasks. It can manage categorical and continuous input features and detect non-linear relationships between the features and the output (Auret and Aldrich, 2012).

3 Methodology

The goal of this chapter is to provide a detailed description of the procedures and methods used in order to answer the research questions of this study. The beginning of this chapter refers to the section 1.3, where the overview of the research questions can be found.

Based on the division of sections, the workflow with the methods used for each section to answer the research questions is shown in figure 5. This workflow presents an overview of the steps followed in order to obtain the research objective of this research project.

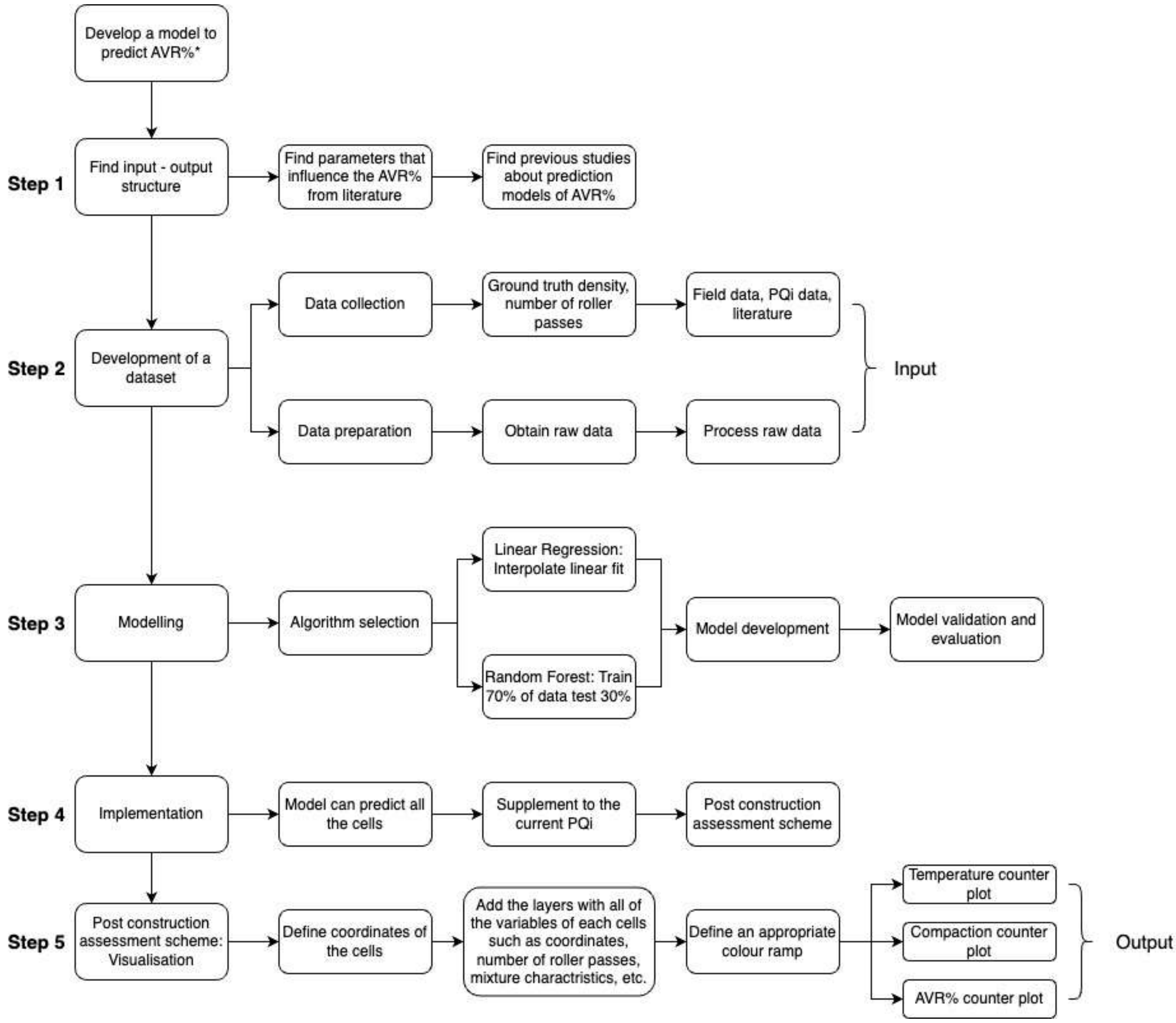

Figure 5: Workflow

AVR%*= Air void ratio percentage

3.1 Compaction window

To determine the compaction window in this research project, it was necessary to use the information from the PQi report from ASPARi. In this report can be found a diagram that shows the density and cooling progress of the asphalt at the hectometer 196.9; this diagram can be found in Appendix A, section 7.1. This diagram has to be read from right to left since it contains three different types of data: the density of the asphalt, the time at which the measure was taken, and the temperature at which the asphalt was at the moment of been applied. Therefore, only the first and last density measures will be taken as a reference to determine the temperature at which these measurements were taken since this would mean that the compaction started when the first density measure was taken and ended at the moment of the last density measurement.

3.2 Data parameters

To address the research questions, the initial stage involved an analysis of the type of data collected by the PQi. It was necessary to determine whether all the variables from the PQi would be utilized as input in the compaction model or not. The variables include:

- **Cell ID:** This variable refers to the total number of cells along the road.
- **Local time:** This variable refers to the time ($h : min : s$) when the roller compacted over a cell.
- **Latitude:** This variable refers to the coordinate that specifies the north–south position of a cell on the surface of the Earth.
- **Longitude:** This variable refers to the coordinate that specifies the east-west position of a cell on the surface of the Earth.
- **Temperature:** This variable refers to the temperature ($°C$) of the mix at the moment of its appliance on the road.
- **Section:** This variable refers to the distance (100 m) that there is between one hectometer to another; these signals are located on the right side of the road. The hectometers are road signs that are located every 100 m on the side of each road in the Netherlands; these indicate the location of the sign in the road, so in case of an accident, the emergency services can easily find it due to this unique sign.
- **Number of roller passes from n number of rollers:** This variable refers to the number of roller passes made by each roller.

- **Total number of roller passes:** This variable refers to the total number of roller passes made by all of the rollers over each cell.
- **Total number of roller passes above the compaction window (CW):** This variable refers to the total number of roller passes above (out) the CW.
- **Number of roller passes below the CW:** This variable refers to the total number of roller passes below (out) the CW.
- **Number of roller passes in the CW:** This variable refers to the total number of roller passes that are in the CW.
- **ID:** This variable refers to the number that occupies each cell in the whole data file.

The variables that will be used as input in the model are the temperature, the number of roller passes from n number of rollers, the total number of roller passes, and the number of roller passes in the CW. The other variables will be used in later phases of this research project.

3.3 Data analysis

After analyzing the variables obtained from PQi, the next step is to test the air void ratio prediction model with the inputs and determine its accuracy in predicting air void ratio. To achieve this, the model will predict the air void ratio and the results will be compared with existing field data. However, due to logistical issues, access to the field data was not possible, so available data was used instead. Among the accessible data were the bulk specific gravity (G_{mb}) and the theoretical maximum specific gravity (G_{mm}). With the help of these two densities, it is possible to calculate the air void ratio at a specific point. In this case, a thermocouple stand was placed 30 cm from the border of the road to measure the density after a certain period of time. The equation used to determine the ground truth air void ratio is defined as:

$$Air\ \ void\ \ (percent) = (\frac{G_{mm} - G_{mb}}{G_{mm}})\ \ x\ \ 100$$

Where:

- G_{mm}= Density of the mix with air
- G_{mb}= Density of the mix without air

For the calculation, the theoretical maximum specific gravity is 2507 $\frac{Kg}{m^3}$, and the bulk specific gravity varies from 1680 to 1880 $\frac{Kg}{m^3}$.

To identify all the cells within the radius of the thermocouple stand (30 cm) that have the same density measurement, the corresponding cells must be located. This requires the use of a Matlab code that calculates the distance between the thermocouple stand and the cell's coordinates surrounding the density sensor. This will be explained in more detail in the chapter 4: Case study.

The output of the code is a file containing data such as the temperature, roller pass count, total number of roller passes, clockwise roller pass count, and ID, which is unique to each cell.

3.4 Air void ratio prediction model

Once the ground truth air void ratio is determined, an air void ratio prediction model is created using Matlab to estimate the air void ratio of cells within the radius of the thermocouple stand. The predicted results are then compared to the ground truth values and plotted on a graph. By analyzing this graph, Matlab generates the r-squared value of the model. However, the obtained r-squared value falls below the acceptable range of 0.8 to 1.

To enhance the accuracy of the model, two additional parameters have been included that were previously overlooked. This will result in an increase in the r-squared value. The parameters in question are as follows:

$$ToPass - TaPass \quad \& \quad \frac{InPass}{ToPass}$$

Where:

- $ToPass$= Total number of roller passes
- $TaPass$= Target number of roller passes
- $InPass$= Total number of roller passes within the compaction window

It is important to consider certain parameters when evaluating the model. The author's focus was only on the total number of roller passes required to achieve the target air void ratio, but there is no clarification on whether it falls within or outside the compaction window. Therefore, the addition of the first parameter is necessary to determine the correlation between the factors that comprise this parameter. A small deviation would indicate a positive correlation, whereas a large deviation would suggest the opposite.

The second parameter indicates the ratio of roller passes within the CW compared to the total number of roller passes. This ratio determines the relationship between the numerator and denominator. If both factors are equal, it means that all roller passes were done within the CW and none outside, meaning that there was an effective compaction. These parameters hold significant relevance in the coming model's analysis.

The new air void ratio prediction model is as follows:

$$VC = 39.51 - 0.09X_1 - 0.81X_2 + 0.05X_3 - 0.23X_4 - 0.01X_5 + (ToPass - TaPass) + \frac{InPass}{ToPass}$$

3.5 Regression methods

The new air void ratio prediction model experienced initial testing with linear regression, but there was no improvement in its performance due to the model's non-linear nature. It was observed that there is no direct linear relationship between the input variables and the output variable. Essentially, a change in one input variable does not have a proportional effect on the output variable and is independent of the other input variables. Consequently, another regression method was chosen for the model.

The chosen regression method is the random forest regression which, as a machine learning algorithm, trains 70% of the data and tests the remaining 30% of the data. With its application, the model shows that its r-squared value is greater than 0.8, meaning that its accuracy has improved and is now capable of predicting the air void ratio of a road that will be paved.

4 Case study

In this chapter, the results of this research project will be explained in detail. For this case study, the PQi data was taken from a specific section of road located between the cities of Beekbergen and Loenen, in the southern part of Apeldoorn. The road section in question is part of the A50 and it is comprised by the hectometers 197.3 and 194.85. The compaction window in this project goes from $40°C$ to $150°C$.

4.1 Calculation of spherical distances between two cells and conversion from degrees to meters

The first stage of this research is to determine the distances of the coordinates which are within the radius ($30cm$) of the thermocouple stand and the sensor coordinates. For these calculations, Matlab software is used. The coordinates' sensors and their location in the sections are the following:

Table 2: Thermocouple stand' cooordinates

Section	Hectometer	Latitude	Longitude
4-5	196.9	52.135405	5.981001
6-7	196.7	52.13427	5.978715
8-9	196.5	52.133149	5.97643
10-11	196.3	52.132037	5.974135
12-13	196.1	52.130939	5.971822
14-15	195.9	52.129852	5.969497
16-17	195.7	52.12877	5.967152
18-19	195.5	52.127672	5.964724

In the code, the latitude and longitude of the sensor are taken as the first variable of the estimation; the second variable is taken from the PQi data. The result of the calculation is in degrees; therefore, the next step is to transform it from degrees to meters, and as result, only the cells that are within the radius will be saved in a new file.

There are 60 cells in total that are within the radius of the sensor; these data points will be used as input of the air void ratio prediction model and can be found in Appendix B section 7.2.

4.2 Ground truth air void ratio calculation

To be able to calculate the ground truth air void ratio is necessary to use the equation from section 3.3. The G_{mm} and G_{mb} are defined in the table below by Shen and Miller (2022) in the ASPARi PQi report and are delimited as $\frac{Kg}{m^3}$. The G_{mb} was taken from the density diagrams provided in the report mentioned. An example of the diagram that belongs to the G_{mb} in the hectometer 196.9 can be found in the Appendix C section 7.3 where the G_{mb} is the last measured density which is the one when after an n number of roller passes the density is in balance.

TABLE 3: Theoretical maximum specific gravity (G_{mm}) and bulk specific gravity (G_{mb})

Hectometer	G_{mm}	G_{mb}	Air void (percent)
196.9	2507	1800	28.20
196.7	2507	1650	34.18
196.5	2507	1825	27.20
196.3	2507	1680	32.99
196.1	2507	1880	25.01
195.9	2507	1720	31.39
195.7	2507	1830	27.00
195.5	2507	1700	32.19

4.3 Application of regression methods

4.3.1 Application of linear regression to the basic air void ratio prediction model

In this phase, the air void ratio prediction model is modelled and has as inputs the data points obtained in the last step. As can be seen in figure 6, the r-squared ($4.687x10^{-}5$) is really low and does not fall within the range of 0.8 and 1, which means that the model is not accurate enough to be used in any situation for predicting the air void ratio.

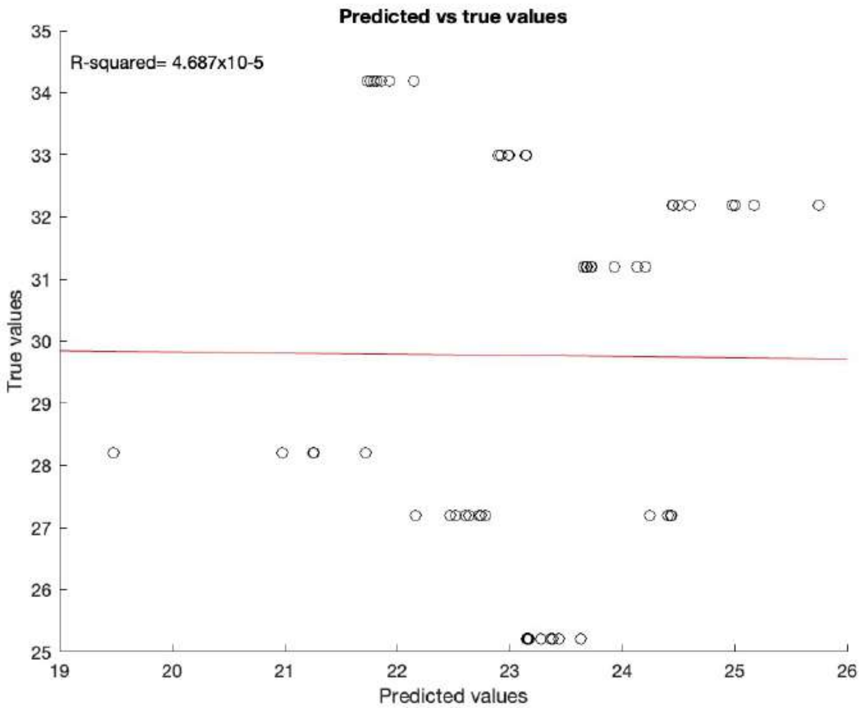

FIGURE 6: Air void ratio prediction model performance

4.3.2 Application of linear regression to the air void ratio prediction model with the 2 parameters

After being modelled the air void ratio prediction model and getting a low accuracy, the two new parameters are added to the model. The inputs were the same as on the first model try, but as can be seen in figure 7, the r-squared (0.0076) increased significantly compared to the first try, which means the added parameters help to improve the model's performance. Even though the r-squared increased does not mean the model has better performance because it is still under the range of an accurate model.

This occurs because the model has a non-linear nature. This can be seen in the figure 6 and the figure below, where the points are very apart from each other, and they are not surrounding the line as it supposed to do it; that is why a different regression method has to be applied to this model.

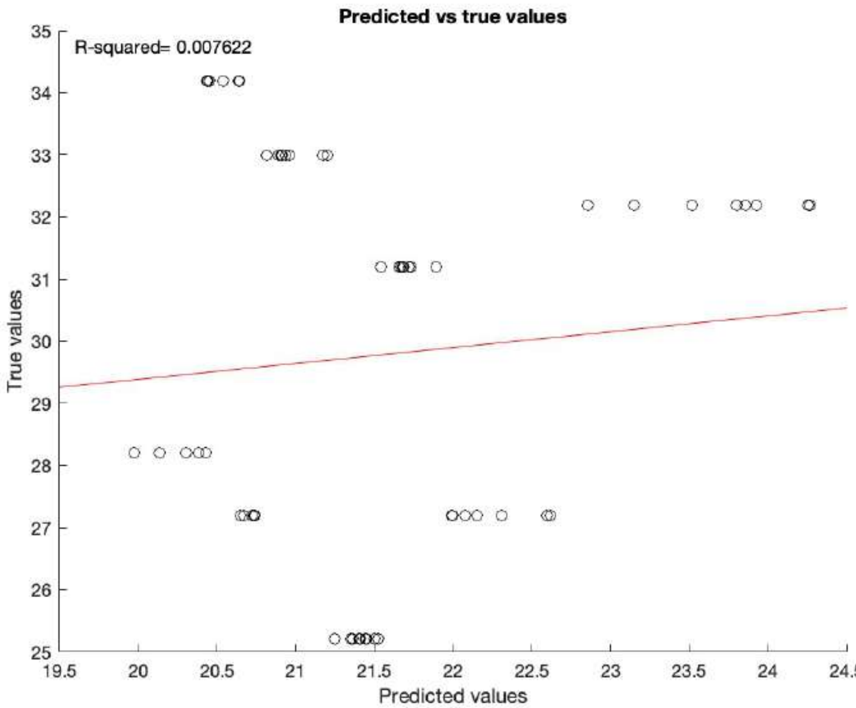

FIGURE 7: Air void ratio prediction model plus the 2 new parameters

4.3.3 Application of random forest regression

The regression method used to model the air void ratio prediction model is the random forest regression algorithm. As it is stated in the section 2.4.2, this method will split the data in 2, 70% will be used for training the data and 30% to test the model.

When the regression method was training the data for modelling, it obtained an r-squared of 0.8879, which means the model is accurate enough to predict the air void ratio; this can be seen in figure 8. After defining that the model has a great performance, the remaining data is used to model the air void ratio and reach an r-squared of 0.8429; this can be seen in figure 9. This value falls in the range of accuracy of a model and can be used to predict the air void ratio of a paved road.

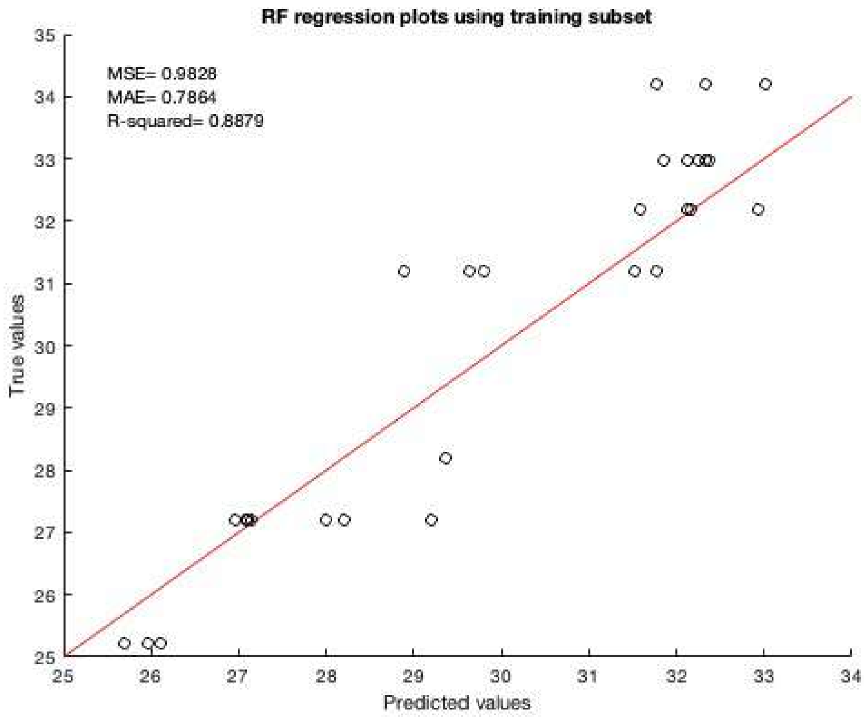

FIGURE 8: RFR plot using training subset

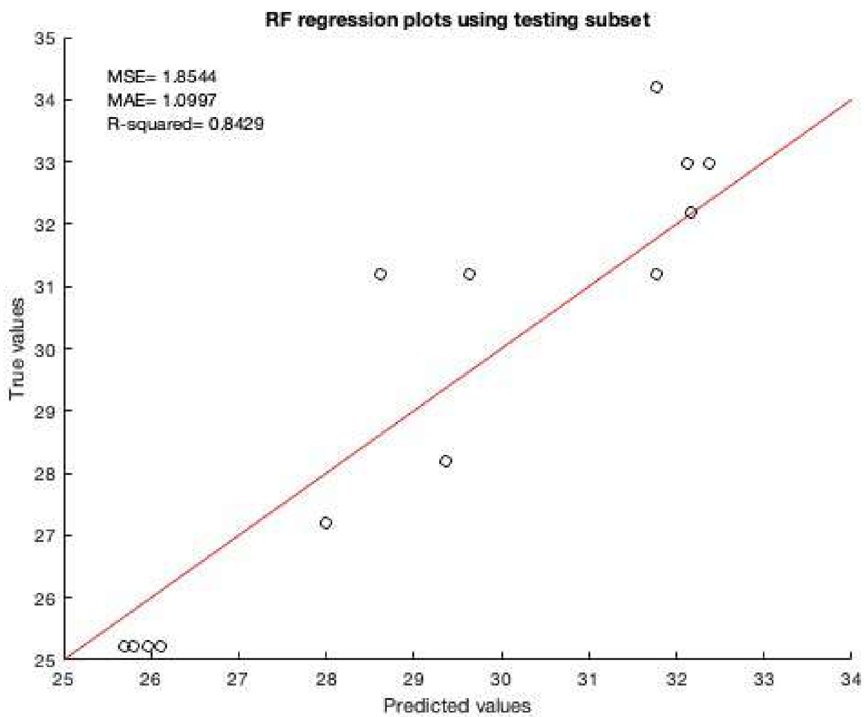

FIGURE 9: RFR plot using testing subset

4.4 Use of road maps to show the difference in air void ratio on different sections on the road

In order to test the model in a project, the data taken from a section of the A50 road will be used (Shen and Miller, 2022). The total data from this project is around half a million. Therefore, it is considered that the data will be shown in road maps. The following figure represents the air void ratio prediction along the paved section at the A50 road. On the right side of figure 10 can be seen a colour ramp where each colour represents the air void ratio in the road. Dark blue represents the lowest air void ratio prediction, and dark red shows the opposite of it. In this figure is not possible to distinguish each colour, that is why Appendix D section 7.4 can be found the road maps of every hectometer mentioned in the section 4.2 where the difference along the road can be seen in a proper way.

FIGURE 10: air void ratio prediction in the A50 road

For explanation purposes, one of the road maps that is located at the hectometer 196.1 can be seen below. On the southwest side of the road, the air void ratio varies from around 31% to 33.26%, while on the northeast side, the air void ratio is lower and varies from 28% to 30%, which means that in this area there was a better compaction.

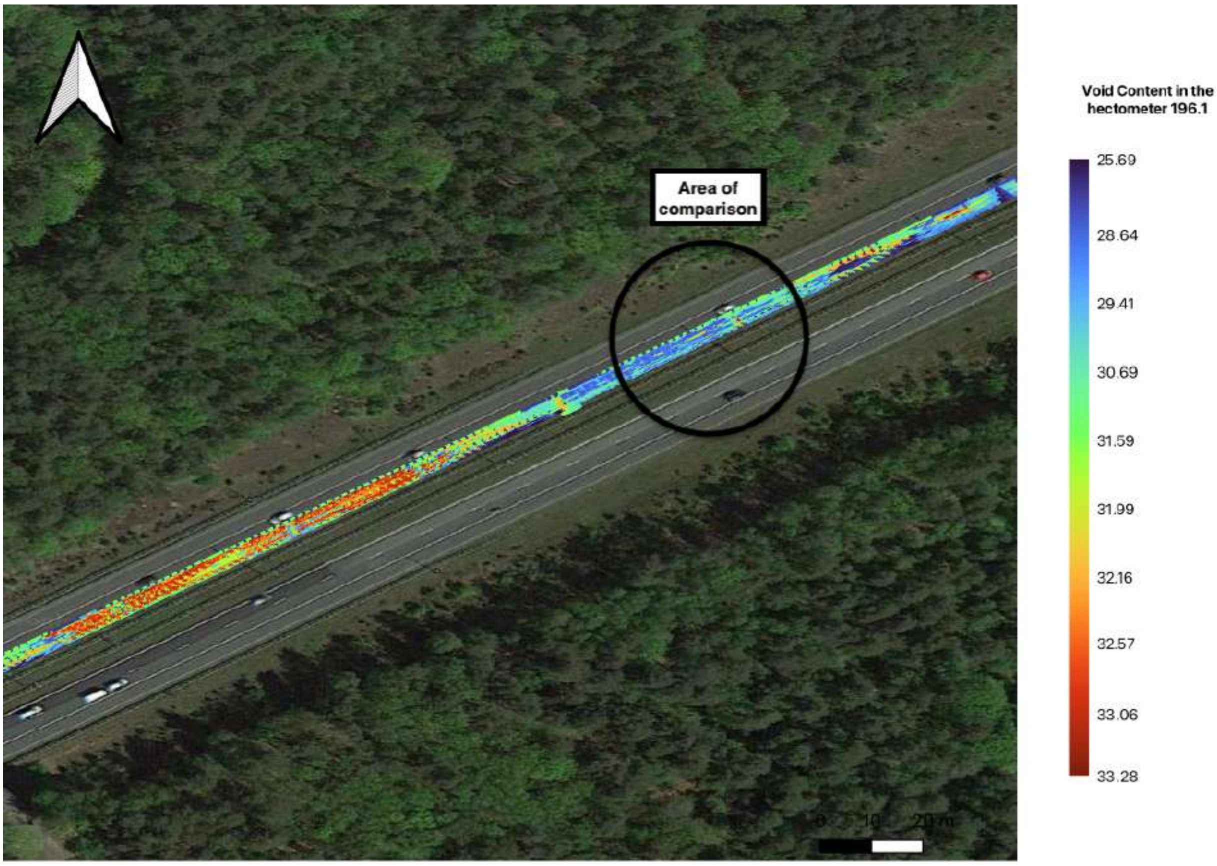

FIGURE 11: Air void ratio prediction in the hectometer 196.1

This model offers contractors a helpful tool to enhance the monitoring and control of asphalt pavement quality with more precision. By providing highly accurate predictions of the air void ratio, it enables contractors to make real-time adjustments, such as the number of roller passes which ensures that the quality of the pavement remains uncompromised. Furthermore, GIS facilitates the mapping of roller passes, allowing for the identification of cells that have reached the desired number of roller passes and those that still require attention. The two maps facilitate to the contractors the control of the air void ratio. The following figure shows how the deviation of the total and target number of roller passes is classified at the same location of figure 11.

As shown in figure 11, the air void ratio within the chosen comparison area ranges from 27% to 30%. The corresponding colour range, spanning from light blue to dark blue, with intermittent light green areas, represents the air void ratio variation and in the same area in figure 12, the colour gradient represents how the deviation of the total number of roller passes from the target number of roller passes affects reaching the desired air void ratio percentage in the pavement since if it is lower to 0 means the air void ratio percentage is high and vice versa. Considering the target number of roller passes to achieve the desired air void ratio is 7, a large proportion of the comparison area successfully achieved a good air void ratio.

Figure 12: Difference between total and target number of roller passes counter plot

5 Discussion

This research project aims to develop a tool that helps to estimate the air void ratio during asphalt construction. The existing tools have low reliability in predicting this factor due to some of them do not take into consideration all of the variables that have a relationship with the air void ratio. Among the two air void ratio prediction models evaluated, the chosen model has an initial R-squared value of 0.7. In order to refine the model performance, different regression techniques were applied. The first attempt using linear regression exposes that the model had a non-linear nature, resulting in low accuracy. Consequently, the random forest regression method was implemented, resulting in an improved R^2 value of 0.84, meaning the model is capable of estimating air void ratio percentages closer to the real world observations.

Despite the relatively limited dataset used for training and testing the model, which overcame the dataset size by the primary author, the model's performance was reached and can be attributed to the implementation of a more sophisticated regression technique, overcoming the linear approach employed previously. Furthermore, two additional variables were incorporated into the model, which were not considered by the main author. These variables are defined as follows:

- $ToPass - TaPass$
- $\frac{InPass}{ToPass}$

To facilitate a comprehensive analysis of the numerous air void ratio prediction values, the GIS software was implemented. This software enabled the geo-referential mapping of these values, allowing for intuitive interpretation through the use of colour ramps that differentiate a large amount of air void ratio percentages between them. This visualization approach greatly enhances the understanding of the distribution and patterns of air void ratio values. Moreover, the utilization of these maps helps the contractors to identify the specific areas and facilitates the determination of whether the desired air void ratio percentage has been achieved within those areas; therefore, the air void ratio is assessed and managed better during the asphalt construction process.

The reason for seeking alternative methods is due to the limitations of the existing methods, such as the nuclear density gauge test, which can damage the paved road and create voids. Contractors often rely on assumptions that the compaction process has been effective and that each section of the road achieved the desired air void ratio percentage. However, this approach presents a low precision and may lead to inconsistencies and compromised pavement quality. Hence, it is important to explore alternative techniques that do not destroy the asphalt that can provide accurate predictions of air void ratio, enabling contractors to ensure optimal air void ratios.

6 Conclusion

This research project was carried out to define if the air void ratio prediction model is sufficiently accurate to predict the air void ratio that there is in the asphalt after its compaction. The model by itself was not able to do it; therefore, two extra parameters were added in order to improve the performance of the model. These parameters were chosen because the author of the basic model did not consider the target of the number of roller passes and the number of roller passes within the compaction window; the only parameter related to the compaction or roller passes was the roller characteristics which was composed of the diameter, width and weight of the roller's drum, and the total number of roller passes.

The air void ratio prediction model plus the two parameters made a new model; this last did not show a great change in its accuracy since the r-squared still fell under the range of accuracy. Therefore, a machine learning regression method was applied to the new model, which after having applied a different regression method, the model's performance increased significantly and can be used to predict the air void ratio of paved roads by asphalt.

Due to the limited data at the beginning of the project, the methodology of this research had to change, but this did not alter its goal, which consisted of demonstrating if the air void ratio prediction model was accurate and, if not, how the model could increase its accuracy after having predicted the air void ratio percentage from an asphalt construction project, the best way to represent how varies the air void ratio along a road a software was used to symbolize the variation of the air void ratio in the asphalt.

In conclusion, using the random forest method to improve the prediction of air void ratio percentage could lead to better estimation at the moment of predicting the air void ratio before or even during its construction.

7 Recommendations

The results presented in this research report, the discussion, and the conclusion have led to propose a few recommendations for further studies and projects.

The first recommendation is about the importance of increasing the available dataset for training and testing the model. Although the model achieved satisfactory results with 70% of the available data points, it is important to consider that 60 data points are not a large amount of data points. By expanding the dataset the model has the potential to achieve even better accuracy and performance than what has been currently observed.

The second recommendation is to test the proposed model more extensively on various asphalt pavement projects to assess its applicability in different cases or conditions. This comprehensive testing process will provide valuable insights into the model's performance and its ability to offer a better estimation of the air void ratio throughout the entire asphalt construction process. Such testing will enable the identification of any limitations or areas for improvement.

The third recommendation is for the contractor and suggests the collection of more precise and reliable results; if the data collection is done by better techniques, contractors can enhance the accuracy and fidelity of the gathered data; therefore, the collected data can be used in research studies such as this research project, leading to having better findings and insights in the field of study.

Lastly, it is recommended to explore a more precise methodology for obtaining the ground truth air void ratio. This involves investigating alternative techniques or technologies that can help to obtain a higher level of accuracy in determining the air void ratio of the asphalt pavement; therefore, it will be possible to have better inputs for training models.

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Appendix

7.1 Appendix A: Compaction window

The following diagram shows how the compaction window was determined from the PQi ASPARi report.

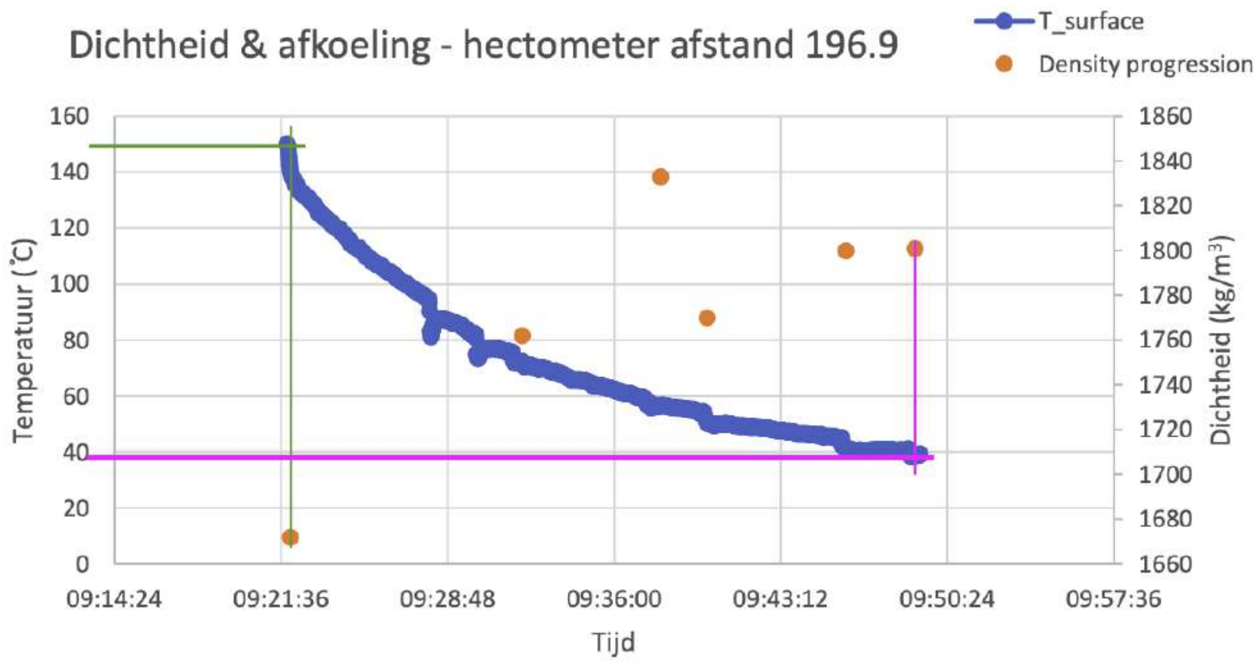

Figure 13: Density and cooling progress at hectometer 196.9 (Shen and Miller, 2022)

7.2 Appendix B: Ground truth cells within 30 cm of measurement device

The following tables show the cells that are within the radius of the thermocouple stand and also show the format of how the PQi data is obtained.

Table 4: Radius 30 cm data

Hectometer	SensorLatitude	SensorLongitude	paverIndex	LocalTime	Latitude	Longitude	cellID	Temperature
196.9	52.135405	5.981001	3626	09:22:34	52.1354071	5.98100519	5	133.74
196.9	52.135405	5.981001	3627	09:22:35	52.1354059	5.98100316	5	133.89
196.9	52.135405	5.981001	3628	09:22:36	52.1354047	5.98100071	5	133.93
196.9	52.135405	5.981001	3629	09:22:37	52.1354043	5.98099994	5	133.88
196.9	52.135405	5.981001	3630	09:22:38	52.1354039	5.9809991	5	133.98
196.7	52.13427	5.978715	5298	09:50:28	52.1342688	5.97871896	6	134.7
196.7	52.13427	5.978715	5299	09:50:29	52.1342681	5.97871757	6	134.48
196.7	52.13427	5.978715	5296	09:50:26	52.1342725	5.97871899	7	133.2
196.7	52.13427	5.978715	5297	09:50:27	52.1342718	5.97871763	7	133.25
196.7	52.13427	5.978715	5298	09:50:28	52.134271	5.97871608	7	133.31
196.7	52.13427	5.978715	5299	09:50:29	52.1342703	5.9787147	7	133.25
196.7	52.13427	5.978715	5300	09:50:30	52.1342697	5.97871337	7	133.28
196.5	52.133149	5.97643	6925	10:17:36	52.1331508	5.97643547	7	107.54
196.5	52.133149	5.97643	6926	10:17:37	52.1331499	5.97643377	7	109.18
196.5	52.133149	5.97643	6927	10:17:38	52.1331493	5.97643251	7	111
196.5	52.133149	5.97643	6928	10:17:39	52.1331488	5.97643133	7	112.36
196.5	52.133149	5.97643	6929	10:17:40	52.1331481	5.97643011	7	113.77
196.5	52.133149	5.97643	6926	10:17:37	52.1331522	5.97643095	8	108.23
196.5	52.133149	5.97643	6927	10:17:38	52.1331515	5.97642964	8	110.04
196.5	52.133149	5.97643	6928	10:17:39	52.1331509	5.9764284	8	111.49
196.3	52.132037	5.974135	8553	10:44:46	52.1320378	5.97413966	6	120.17
196.3	52.132037	5.974135	8554	10:44:47	52.1320373	5.97413857	6	120.19
196.3	52.132037	5.974135	8555	10:44:48	52.1320368	5.97413752	6	120.12
196.3	52.132037	5.974135	8556	10:44:49	52.132036	5.97413597	6	120.11
196.3	52.132037	5.974135	8553	10:44:46	52.13204	5.97413691	7	123.14
196.3	52.132037	5.974135	8554	10:44:47	52.1320395	5.97413575	7	123
196.3	52.132037	5.974135	8555	10:44:48	52.132039	5.97413462	7	122.71
196.3	52.132037	5.974135	8556	10:44:49	52.1320382	5.97413311	7	122.59
196.1	52.130939	5.971822	10182	11:11:56	52.1309391	5.97182671	6	125.16
196.1	52.130939	5.971822	10183	11:11:57	52.1309386	5.97182561	6	125.05
196.1	52.130939	5.971822	10184	11:11:58	52.130938	5.9718245	6	124.86
196.1	52.130939	5.971822	10185	11:11:59	52.1309372	5.97182273	6	124.59
196.1	52.130939	5.971822	10181	11:11:55	52.1309421	5.97182558	7	125.99
196.1	52.130939	5.971822	10182	11:11:56	52.1309413	5.971824	7	125.89
196.1	52.130939	5.971822	10183	11:11:57	52.1309408	5.97182282	7	125.85
196.1	52.130939	5.971822	10184	11:11:58	52.1309403	5.97182164	7	125.64
196.1	52.130939	5.971822	10185	11:11:59	52.1309394	5.97181995	7	125.53
195.9	52.129852	5.969497	11745	11:39:05	52.1298521	5.96950191	6	128.16
195.9	52.129852	5.969497	11746	11:39:06	52.1298516	5.9695008	6	128.26
195.9	52.129852	5.969497	11747	11:39:07	52.1298508	5.96949927	6	128.32
195.9	52.129852	5.969497	11748	11:39:08	52.1298502	5.96949797	6	128.31
195.9	52.129852	5.969497	11745	11:39:05	52.1298543	5.9694992	7	126.55
195.9	52.129852	5.969497	11746	11:39:06	52.1298538	5.96949801	7	126.75
195.9	52.129852	5.969497	11747	11:39:07	52.1298531	5.96949651	7	126.87
195.9	52.129852	5.969497	11748	11:39:08	52.1298525	5.96949518	7	127.05
195.7	52.12877	5.967152	13379	12:06:21	52.1287691	5.96715644	5	131.44
195.7	52.12877	5.967152	13380	12:06:22	52.1287682	5.96715449	5	131.15
195.7	52.12877	5.967152	13377	12:06:19	52.1287724	5.96715595	6	131.29
195.7	52.12877	5.967152	13378	12:06:20	52.1287718	5.96715468	6	131.52
195.7	52.12877	5.967152	13379	12:06:21	52.1287713	5.96715361	6	131.63
195.7	52.12877	5.967152	13380	12:06:22	52.1287704	5.96715175	6	131.38
195.7	52.12877	5.967152	13381	12:06:23	52.1287698	5.96715031	6	131.64
195.5	52.127672	5.964724	15056	12:34:20	52.1276737	5.9647295	6	136.56
195.5	52.127672	5.964724	15057	12:34:21	52.1276728	5.96472759	6	136.43
195.5	52.127672	5.964724	15058	12:34:22	52.127672	5.96472584	6	136.41
195.5	52.127672	5.964724	15059	12:34:23	52.1276713	5.96472424	6	136.43
195.5	52.127672	5.964724	15060	12:34:24	52.1276708	5.96472318	6	136.26
195.5	52.127672	5.964724	15057	12:34:21	52.127675	5.96472488	7	135.64
195.5	52.127672	5.964724	15058	12:34:22	52.1276743	5.9647232	7	135.53
195.5	52.127672	5.964724	15059	12:34:23	52.1276736	5.96472164	7	135.5

TABLE 5: Radius 30 *cm* data (continuation of the previous table)

Section	Pass_Roller1	Pass_Roller2	Pass_Roller3	Pass_All	numOfPassAbove	numOfPassBelow	numOfPassIn	ID
4	0	1	1	2	0	0	2	84541
4	0	1	1	2	0	0	2	84542
4	0	1	1	2	0	0	2	84543
4	0	1	1	2	0	0	2	84544
4	0	1	1	2	0	0	2	84545
6	0	2	2	4	0	1	3	106442
6	0	2	1	3	0	1	2	106443
6	0	2	2	4	0	1	3	126669
6	0	2	2	4	0	1	3	126670
6	0	3	2	5	0	1	4	126671
6	0	3	1	4	0	1	3	126672
6	0	3	1	4	0	1	3	126673
8	0	4	5	9	0	0	9	128298
8	0	3	5	8	0	0	8	128299
8	0	3	4	7	0	0	7	128300
8	0	2	4	6	0	0	6	128301
8	0	1	3	4	0	0	4	128302
8	0	5	4	9	0	0	9	148528
8	0	5	3	8	0	0	8	148529
8	0	5	3	8	0	0	8	148530
10	0	2	0	2	0	1	1	109697
10	0	4	0	4	0	1	3	109698
10	0	4	0	4	0	1	3	109699
10	0	3	0	3	0	1	2	109700
10	0	6	0	6	0	1	5	129926
10	0	8	0	8	0	1	7	129927
10	0	7	0	7	0	1	6	129928
10	0	5	0	5	0	1	4	129929
12	0	3	1	4	0	0	4	111326
12	0	3	1	4	0	0	4	111327
12	0	2	1	3	0	0	3	111328
12	0	1	2	3	0	0	3	111329
12	0	4	1	5	0	0	5	131554
12	0	5	1	6	0	0	6	131555
12	0	3	1	4	0	0	4	131556
12	0	3	1	4	0	0	4	131557
12	0	3	1	4	0	0	4	131558
14	0	2	1	3	0	0	3	112889
14	0	3	1	4	0	0	4	112890
14	0	3	2	5	0	1	4	112891
14	0	2	2	4	0	0	4	112892
14	0	2	0	2	0	0	2	133118
14	0	3	0	3	0	0	3	133119
14	0	3	2	5	0	1	4	133120
14	0	3	2	5	0	1	4	133121
16	0	3	1	4	0	1	3	94294
16	0	2	1	3	0	0	3	94295
16	0	3	1	4	0	2	2	114521
16	0	3	1	4	0	2	2	114522
16	0	3	1	4	0	2	2	114523
16	0	3	1	4	0	1	3	114524
16	0	3	1	4	0	1	3	114525
19	0	1	4	5	0	0	5	116200
19	0	1	4	5	0	0	5	116201
19	0	1	2	3	0	0	3	116202
19	0	0	2	2	0	0	2	116203
19	0	0	1	1	0	0	1	116204
19	0	3	5	8	0	1	7	136430
19	0	1	4	5	0	0	5	136431
19	0	1	3	4	0	0	4	136432

7.3 Appendix C: Density progress

The following diagram shows how the density was obtained from the PQi ASPARi report.

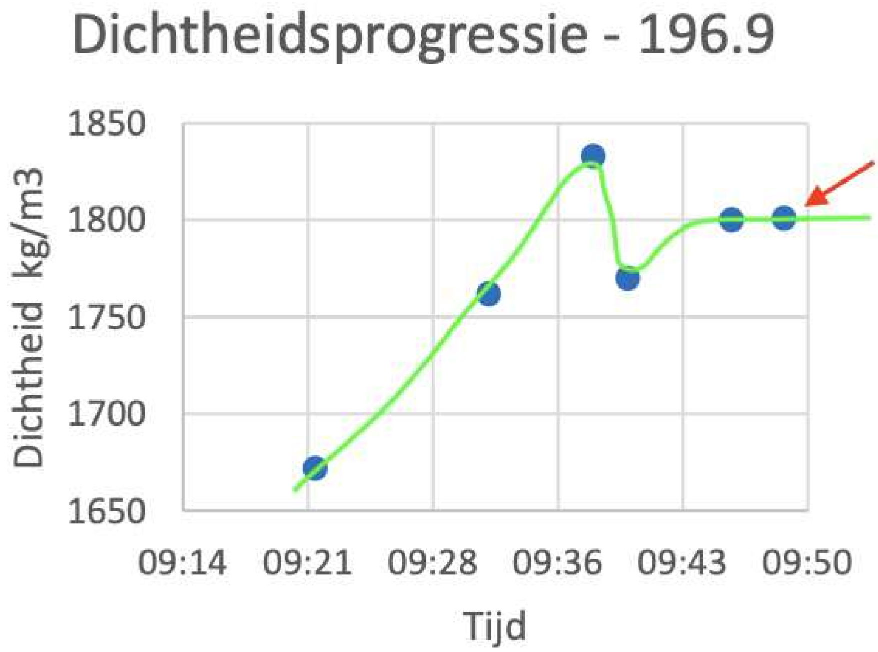

FIGURE 14: Density progress at hectometer 196.9 (Shen and Miller, 2022)

7.4 Appendix D: Air void ratio prediction in the hectometers 196.9 to 195.5

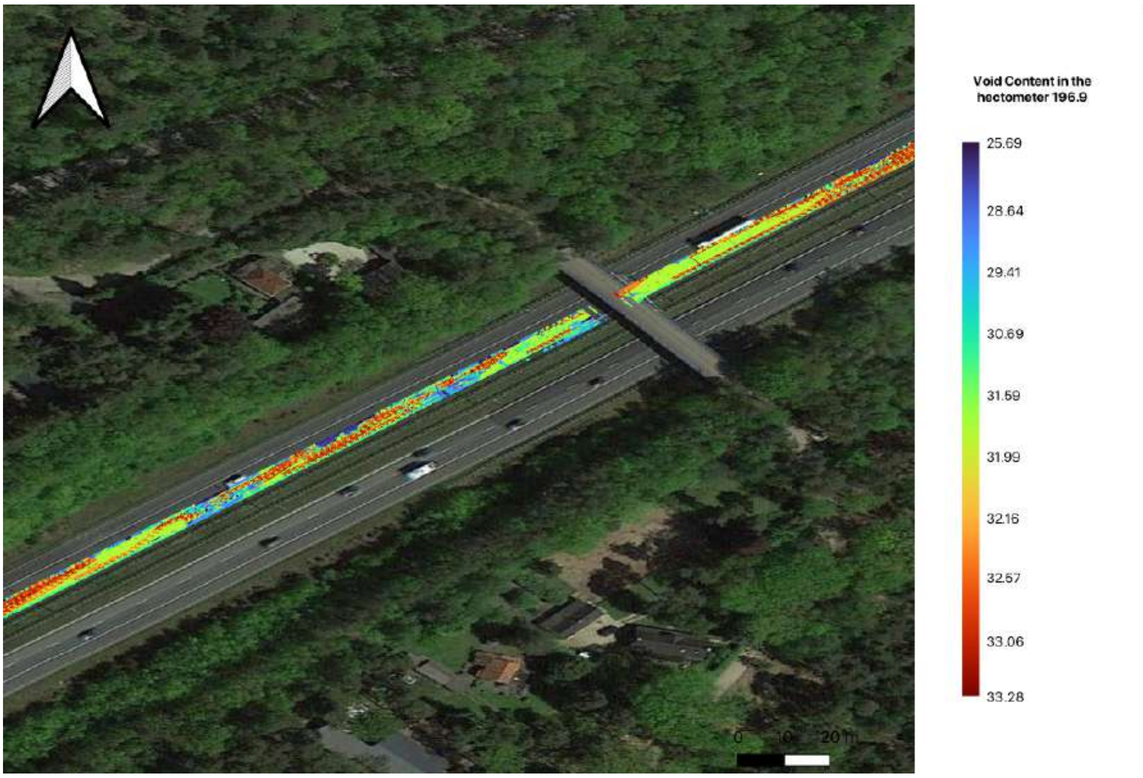

FIGURE 15: Air void ratio prediction in the hectometer 196.9

FIGURE 16: Air void ratio prediction in the hectometer 196.7

FIGURE 17: Air void ratio prediction in the hectometer 196.5

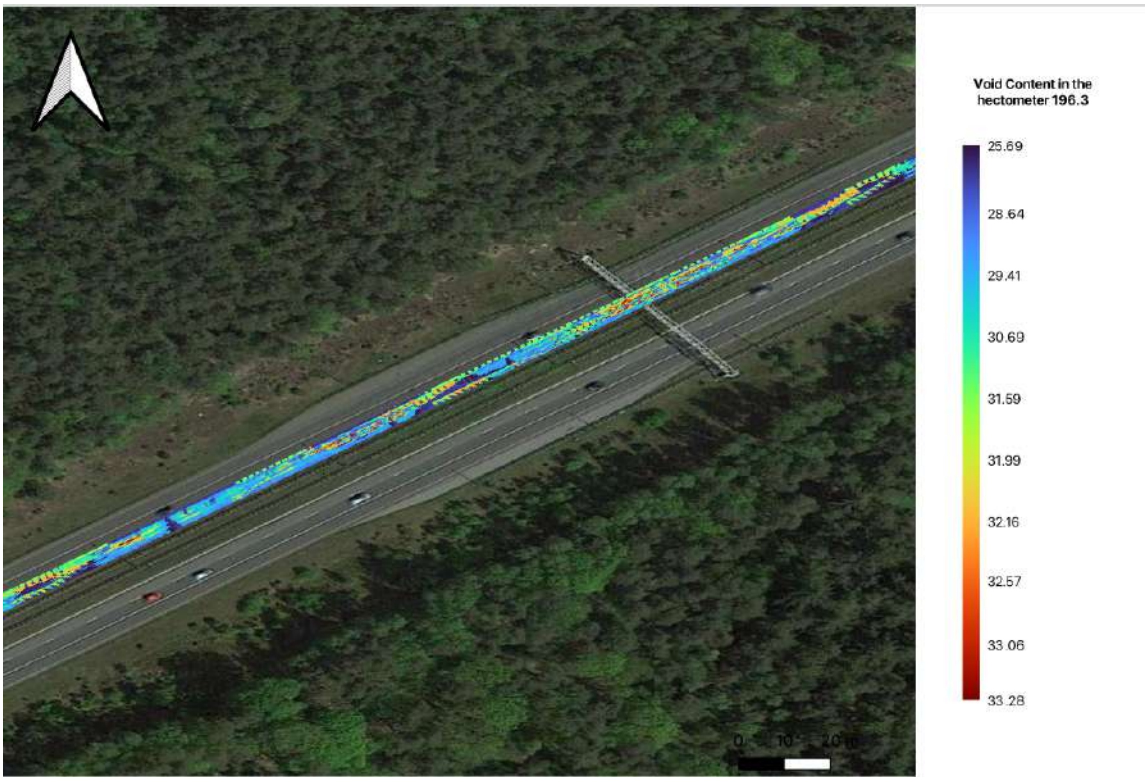

FIGURE 18: Air void ratio prediction in the hectometer 196.3

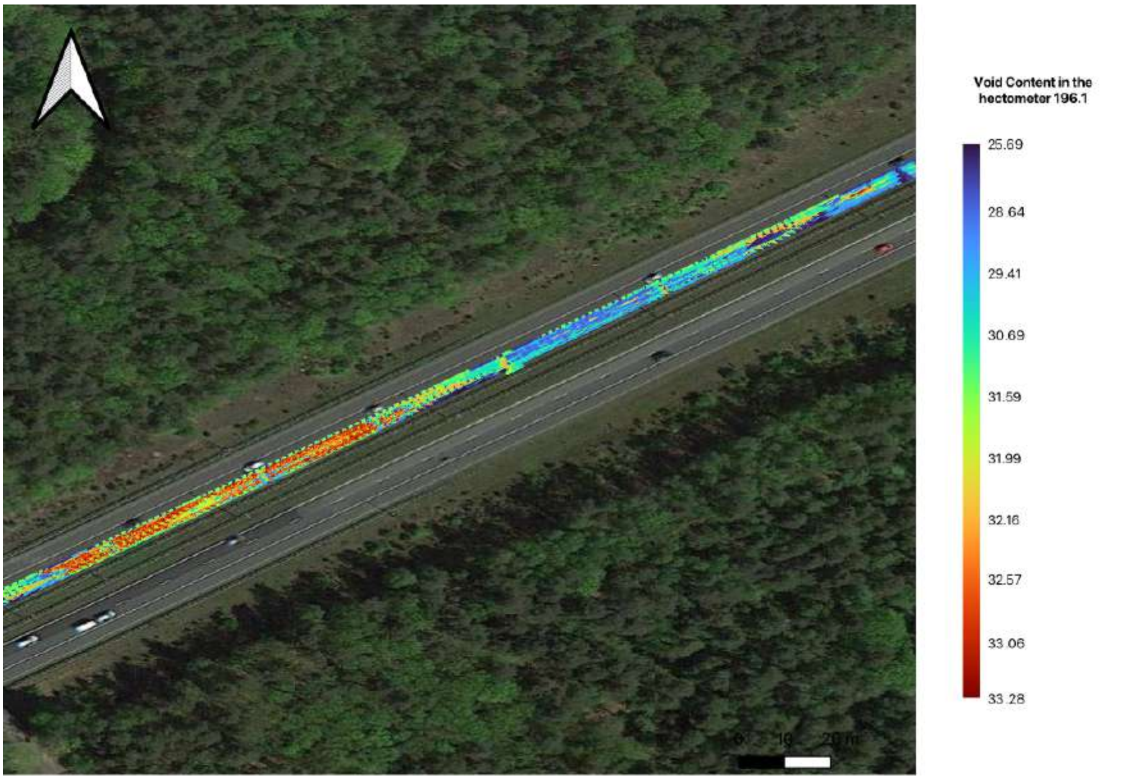

FIGURE 19: Air void ratio prediction in the hectometer 196.1

FIGURE 20: Air void ratio prediction in the hectometer 195.9

FIGURE 21: Air void ratio prediction in the hectometer 195.7

FIGURE 22: Air void ratio prediction in the hectometer 195.5