Theoretical analysis for monitoring the runway pavement texture quality

a thesis by

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heijmans

Schiphol

Theoretical development of sampling analysis for the monitoring of pavement quality

by

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Preface

This Thesis represents the last step of my academical career at TU Delft. I would like to thank the University for giving me the opportunity to conclude my studies at a top educational level and in this nice country. The experience collected in my rst two years is the base of this report. I would also like to thank the member of the committee for guiding me during this research. In particular I would like to thank Lambert for this assistance with the double degree paperwork. It was a complicated procedure that would have been more complex without his help.

As well, I would like to thank two companies: Heijmans and Schiphol. They gave me chance to work every day at Schiphol Airport and to assist at maintenance activities on the runways. These are unique experiences that I will never forget. In particular, I would like to thank my daily supervisors Arjan and John for the patience they had in these 12 months and for the considerable amount of knowledge and experience they taught me. Although it was not possible to meet often, I would also thank Maarten for the opportunity he gave me last year and for supporting me whenever I needed him in the research process.

In these years far from home I have also learned the importance of family and friends. For this reason there are several people I want to mention.

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Last but not least, Juan Camillo Laguado Lancheros De Castillia. It took me more time to learn your entire name than you. Your help and friendship has been really important.

Abstract

Schiphol Airport and Heijmans are working together on the renewal of the Schiphol runways pavements. Currently the top layer is covered with a synthetic antiskid material called ASK. But the strong weather limitations for the installation of this material have opened the door for alternatives. Heijmans has proposed an innovative asphalt mixture that is able to provide similar and in some cases better surface performances compared with the ASK.

This asphalt mixture is called Flightflex® and is a stone matrix asphalt. Consequently it is affected by the variability of the construction process. This thesis project focuses on the analysis of the best quality control procedure for this asphalt. The pavement surface needs to meet specific requirements and it is of interest to define a sampling methodology for the evaluation of the Texture Depth (TD). In particular the research aims to define **the minimum number of samples that provides the highest reliability for the definition of the Mean Texture Depth (MTD) of the surface.**

To achieve this goal a theoretical approach is adopted. Starting from the collection of a consistent number of samples, the properties of the surface are analysed. In this process it is of interest to define the influence of the construction process on the surface quality. The information obtained are used to simulate bigger surfaces on which different sampling methodologies are tested. In particular three different methodologies are analysed: the current methodology called CROW, a Uniform methodology and a random methodology called Hammersley methodology. Thorough testing these sampling methodologies on the simulated surfaces it is possible to evaluate the relative error between the MTD of the simulated surfaces and the MTD of the samples taken. A Monte Carlo type of approach helps to define precisely which methodology performs better. The one with the lowest relative error and minimum required number of samples will be considered the most efficient.

The simulation of the surfaces and the analysis of the sampling process highlights a correlation between the manufacturing signature and some sampling methodologies. In case of a correlation the reliability of the methodology decreases. In particular the CROW and the Uniform methodology present a form of correlation and thus have a lower reliability. The Hammersley methodology aims to simulate a random selection of samples and for this reason it does not enter in correlation with the surface patterns. The three aforementioned methodologies are in the last part of the research applied on a 500 m long section of the runway Polderbaan at Schiphol Airport.

Although the Uniform methodology is less reliable it provides a 1% of relative error with only 70 samples. The Hammersley instead needs 180 samples to reach the same relative error but with a higher reliability. The CROW is the least performing. In fact it has a lower reliability than the Uniform strategy and it needs 170 samples to reach 1% relative error.

The research helps highlighting the correlation between the manufacturing signature left by the construction process and the sampling strategy adopted. It also highlights the fact that a random distribution escapes this correlation and provides more reliable results.

To conclude, the companies are suggested to use the Uniform methodology in case of short time available for the quality control measurements. This comes with a lowest reliability that has to be accepted. But in case a high reliability is required and sufficient time is available, the Hammersley strategy is considered more appropriate.

CHAPTER 1

Introduction

According to the 2017 Airport Traffic Report, Schiphol Airport is one of the busiest airports in the world. Currently it is ranked 11th for passenger traffic volume with a growth rate of 7.7%, the highest in Europe [19]. Also the freight movements have an important impact with 1,960,328 tons transported, the 20th highest value in the world [19].

As can be seen in figure 1.1 Schiphol Airport has a 6 runway system but currently only 5 are actively used for regular operations[3]. With the exception of the runway 36L-18R that was built in 2003, all the other runways are quite old and will need maintenance operations in the following years.

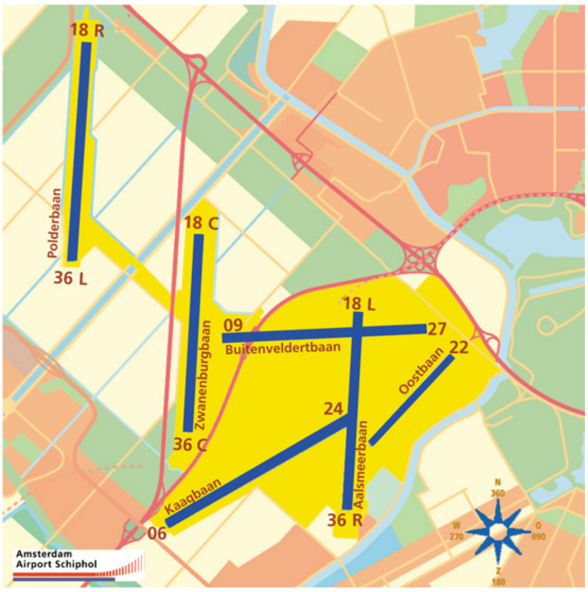


Figure 1.1: Runways configuration Schiphol Airport

In 2017 Schiphol Airport had a traffic volume of 68,515,425 passengers. Compared to the 78,047,278 passengers of Heathrow this is a lower value but the airport of London has a growth factor of only 3.04% [20]. From a prospective point of view the Dutch airport is then expected to increase its passengers volume faster. Keeping this trend Schiphol could reach in a few years a similar passengers volume of Heathrow. The lower growth rate of the English airport is due to the fact that it is currently operating at 98% of its capacity [12]. For this reason the only possible growth is achieved by increasing the share of aircrafts with higher passenger capacity.

The growth percentage of Schiphol, as said previously, is 7.7%. This means that the capacity of the runway system is expected to be maximised as much as possible, and for this reason a night maintenance strategy is a valuable option to be considered. Currently Heijmans is the contractor in charge of asset maintenance activities and is highly involved in the planning of this new maintenance strategy.

One of the main concerns for Heijmans is to meet the high quality standard required by Schiphol. This has been done developing a new asphalt mixture called Flightflex® (FFX). Currently the texture properties are ensured by an anti-skid layer (ASK). Although the final performances are good, its installation requires specific weather conditions, such a: maximum level of relative humidity of 80% and a minimum temperature of 4°C during the construction process. To overcome these problems the engineers from Heijmans have proposed the Flightflex® mixture which would be more suitable for construction under adverse weather conditions and should guarantee the pavement performances required by the client.

The quality of runway pavements is, in fact, one of the main concerns in the asset management department at Schiphol Airport. For safety and regulatory reasons the European Aviation Safety Agency (EASA) has imposed a minimum Mean Texture Depth (MTD) value for runway pavements. This threshold guarantees a proper water storage and reduces the risk of aquaplaning that could lead to a huge number of fatalities in case of an accident. For this reason a surface quality evaluation procedure of the runway pavement surface is required. This is valid for any type of surface and Schiphol has verified both ASK and FFX. Currently the sampling process is executed with a laser machine that has a sampling dimension of 400 cm^2. Compared to the dimension of a runway or a road surface this sampling area is not large enough to enable the measurement of the total surface. Specific points have to be selected and measured but its amount and location need to be defined with a clear methodology.

The regulation imposes a specific minimum MTD value, but it does not specify the location of texture depth measurements and the the required number of samples per area. The regulation is limited to the following sentence[10]:

"The average surface texture depth of a new surface should be not less than 1.0 mm"

A similar regulation approach is also present in the road and highway pavement industry. Schiphol and the contractor Heijmans need to define a precise quality control methodology to include in the project contract. The design of such methodology is the result of a scientific analysis of the correlation between the manufacturing process of the asphalt, its physical properties and the sampling techniques needed to measure the surface texture.

The goal of this thesis research is to bring an academic and thus a more theoretical approach on the definition of such a methodology. This should produce a series of scientific evidences on the relationships between the asphalt quality and the sampling technique adopted. This will be an added information for Schiphol Group and Heijmans to agree on which sampling methodology to adopt.

The research will go through the definition of the most important sampling techniques and the simulation of representative surfaces. These two elements will be combined and the simulated surfaces will be used to try out the different sampling methodologies. An extensive statistical analysis will then be executed to interpret the results and define how the sampling methodologies behave in different situations. From this outcome a series of measurements will be executed in the field in order to define a correspondence between the theoretical analysis and the field results.

In the next chapters the research topic will be described in detail before presenting the literature review. Information regarding sampling methodologies and pavement surfaces will be searched in papers obtained on Google Scholar, Scopus and TU Delft library. Once the background and current state of art of these topics are clear, the analysis and simulation of the surfaces will take place. It will be necessary to simulate on Python a series of asphalt surfaces containing the surface characteristics left by the construction process and to define the algorithms representing the sampling methodologies. The third part will be dedicated to the analysis and interpretation of the results. The fourth will focus on defining which methodology provides, with a sufficient reliability, the minimum number of samples for the calculation of the mean of the entire surface. After this theoretical analysis there will be the possibility to try the different methodologies in the field to ensure consistency and validation of the theoretical and simulation results. The final part of the research will be dedicated to present the outcome of the analysis and provide some practical recommendations to both Heijmans and Schiphol Group.

Chapter 2

Case study

As mentioned in the introduction, the EASA regulation does not propose a sampling guidance for quality control of runway surfaces. This then became a topic of discussion between contractors and clients on the procedure to adopt to verify the pavement's qualities. This practical issue has called for a more academical study on the effect of sampling methodologies on runway surfaces.

2.1 AntiSkid Layer (ASK)

Figure 2.1: ASK installation proces

In this chapter the surface properties, the sampling materials and the current sampling methodology adopted will be described. The first part will be used to describe the types of pavement surfaces that are currently present at Schiphol. The second part will be dedicated to describe the methods available for the Texture Depth measurement. The last section will present the sampling strategy that is currently used by Schiphol. The proposition of the alternatives strategies and their effects will be the core of the research described in the next chapters.

2.1.1 Type of pavement surfaces

There are two types of runway surfaces at Schiphol Airport: the ASK surfaces and the Flightflex® surfaces. The first type is used since 1967 and currently is present in almost the totality of the runway pavements. The second is an innovation proposed by Heijmans and currently has been installed only in few areas of the runways.

Currently all the runways at Schiphol Airport are characterised by the presence of an antiskid layer on top of their surfaces. It is called Possehl Antiskid and is produced by a German company, Possehl Spezialbau [11]. This product is a two-component epoxy-resin coated with a basalt grit mixture. This makes the surface of ASK similar to a coarse sandpaper.

This material creates a thin high friction surface that fulfils the requirements imposed by the ICAO[1] regulation under the "design objective coefficient for new runway"[11]. The company claims a series of benefits from the application of this material: reduction of aquaplaning, resistance against aircraft fuel and pollutants, improved grip and stability of the aircraft in adverse wind situation and high water storage capacity. The minimum thickness requirement is 4 mm but Schiphol preferred to adopt a 5 mm layer. This provides an expected durability of 5 years.

Until the quality of the ASK is high and the degradation has not started it provides high performances of the surface and simultaneously protects the underneath layers of asphalt. The company affirms that this last property of the ASK is important in increasing the lifetime of the asphalt by reducing the need of maintenance.

One of the main disadvantages of this material, beside the high costs, is the strict weather conditions required for the installation. Under a temperature lower then 10°C and humidity higher than 80% the ASK layer is not applicable. Moreover total absence of rain is needed. These requirements strictly limit the installation phases. In fact during the winter period and night shifts it will not be possible to install this material. This forces some limitation on the maintenance strategy of Schiphol. As an example an overnight maintenance strategy could not be planned with this kind of procedure, not even in the summer period.

Another important disadvantage is the degradation phase at the end of the material lifetime. After 4-5 years the ASK starts degrading and entire areas get consumed. These areas loose the basalt mixture and uncover the underneath asphalt reducing the overall performance of the pavement. To conclude, it is important to highlight that the high costs of this product were one of the main reason for evaluating a more economical alternative.

As mentioned this material is made by a synthetic glue and a homogeneous basalt mixture. These elements define a surface that is highly homogeneous and require a limited number of Texture Depth measurements. A different scenario is present with an asphalt mixture. The variance of aggregates, quantity of bitumen and construction process influence the uniformity of the mixture and the final properties of the surface. This requires a specific methodology for quality control, able to determine the MTD of the surface with a limited number of samples and an acceptable accuracy.

2.1.2 Flightflex®

Schiphol Airport is constantly increasing its capacity and is looking at maintenance strategies that could help achieving this goal. For this reason the evaluation of an overnight maintenance strategy is under analysis. The night maintenance operation could increase the capacity of the airport but it would be complicated to place the ASK during the night. To face this problem Schiphol is looking for an alternative. Heijmans has proposed a new asphalt mixture called Flightflex® that aims to provide all the surface performances required by Schiphol.

Advantages of Flightflex®

This mixture has a higher flexibility for the construction process allowing the construction at any humidity condition and also with light rain. Moreover the minimum temperature required is 6°C. These factors would allow the construction also during the night shift in the summer period.

[1]ICAO= International Civil Aviation Organisation. It is an agency of the United Nations that defines codes and regulation to ensure safety in the international air transport.

In general the time window available during the year where the maintenance can be executed is larger for the Flightflex® than the ASK as figure 2.2 shows.

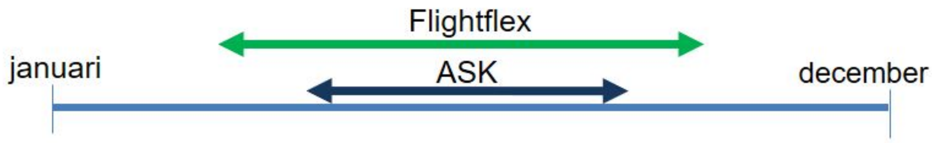


Figure 2.2: Period of the year available for the installation of FFX and ASK

The adoption of Flightflex® during night maintenance is also expected to help reduce the Total Cost of Ownership (TCO) and optimise the use of runways. Also during the construction phase several advantages are present. The installation process is faster and easier reducing the risk of failure or delay during the construction phase. The final performances of the Flightflex® are expected to meet the Schiphol and EASA requirements and be comparable with the ASK performances.

Flightflex® characteristics

Heijmans started the development of Flightflex® at the end of 2013. The development process lasted from December 2013 to August 2014. There were two leading parameters for the mixture design, namely the texture depth and the skid resistance. The requirements values for this parameters are:

- Minimum texture depth 1.3 mm (EASA requirement is 1) [3]
- Minimum skid resistance of μ=0.74 as the EASA requirement. This value is required to be measured at 95 km/h [3].

Flightflex® is a stone matrix asphalt, this means the aggregates play an important role in the performances of the final product. This category of mixtures is characterised by high bearing capacity provided by the contact between the aggregates [23]. The downside of this mixture design is the fact that the final asphalt is more subject to ravelling damages. This negative aspect can be reduced by the use of synthetic additives that also increase the cost of the final product.

The aggregates also play an important role on the texture properties of the surface. From the micro-texture point of view they have to be rough enough for the skid resistance of the surface. From the macro-texture point of view the shape and dimension will influence the Texture Depth. This last value will be the main aspect of analysis during this thesis project.

Due to the importance of the aggregate, Heijmans has tested three different types of aggregates in order to evaluate the most suitable for a runway pavement. In table 2.1 the type of tests and results are presented.

The laboratory analysis lead to three suitable stone types: EO slags, Grauwacke and BeStone. Samples created from these aggregates have been tested for friction, texture depth, splitting strength, tear resistance and stone losses.

The aggregate type was considered the most appropriate to meet the Schiphol requirements was the Grauwacke. This provided the best results in terms of texture depth (1.92 mm) and high values in term of skid resistance. The value of the FAP (Friction After Polishing) is also the one of the best with 75.4 μ. In some categories (as the Splitting strength) the Grauwacke was not the most performing aggregate type but these categories were less important to meet the final requirement of Schiphol. Please note that in general the quality reached is very high although the

Test type	EOS	BeStone	Grauwacke
FAP (Friction After Polishing)			
C90 without removing bitumen	0.224	0.310	0.247
C90 removing bitumen by sanding	0.377	0.402	0.299
C90 removing bitumen by water jetting	0.553	0.506	0.583
SRT (skid resistance)[μ]			
Before FAP test	65.4	66.6	65.4
after FAP test	75.8	76.0	75.4
Before RSAT test	71.6	72.2	80.1
After RSAT test	57.9	69.7	72.2
Texture depth [mm]	1.78	1.71	1.92
Splitting strength [MPa]			
Average	3.55	2.55	2.55
Minimum	3.45	2.40	2.45
Tear resistance [N/mm]			
Average	21.9	25.9	27.3
Minimum	21.3	25.0	25.4
RSAT [g]			
Before aging	12.27	19.97	16.33
After aging	3.30	12.30	9.43
ITSR [%]	103	87	94
Hollow space [%]	7.5	7	7
Bitumen content [% by mass]	8	8	8

Table 2.1: Test of different aggregate mixture [21]

values were lower than the other aggregates. After these tests the Grauwacke has been selected for the realisation of the FlighFlex.

To ensure the proper binding properties of these aggregates a 8% [m/m] of bitumen content is required. The negative effect of this high quantity of bitumen is the reduction of texture depth on the surface. To face this problem Heijmans has decided to implement a water-blasting process after the compaction phase. A blast of water at high pressure (around 2000 bar) removes part of the bitumen from the surface and consequently increases the final Texture Depth. A comparison of the surface before and after the treatment is shown in figure 2.3

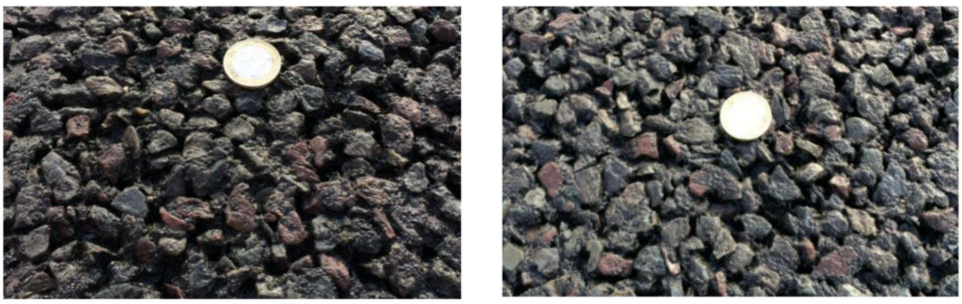


Figure 2.3: Asphalt texture before and after waterjetting

Several tests have suggested Heijmans to define a water-jetting procedure to reach proper results. In fact it has been observed that if the temperature of the asphalt was too high during this treatment the bitumen was not detaching from the aggregates but was just sliding and redistributing on the surface. The texture depth then was not increased, moreover the micro-texture was reduced due to this sliding behaviour of the bitumen. Better results can be achieved when a minimum waiting period of 48 hours (between the start of water-jetting and the finalisation of compaction) is adopted. During that waiting period the surface temperature of the asphalt must have been lower than 20°C. In this conditions the bitumen has a more solid consistency and it detaches from the aggregates.

Figure 2.4: ASK (on the left) and Flightflex®(on the right)

2.2 Quality control

The two type of surfaces presented previously are both used at Schiphol Airport. As mentioned in the previous section, the quality of the surface of any type of pavement has to be verified. Currently this process is performed with two different methodologies: The sand Patch Method and the Laser Measurements. Both methodologies will be analysed in order to present their advantages and disadvantages. The section will conclude with a description of the actual sampling strategy adopted.

2.2.1 Type of sampling methodologies

As mentioned the methodologies currently used for the Texture Depth Measurement are two: the Sand patch Method and the Laser Method.

Sand Patch Method

The first one is the Sand Patch Method. It is the most traditional methodology for the texture depth measurements. This methodology consists in distributing a specific volume (V) of a standard sand on the surface. The sand is spread creating a circle that is enlarged until the sand is completely distributed into the surface. When the level of the sand is the same as that of the surface, the diameter of the circle obtained is measured. Different measurements of the circle's diameter are collected and an average is calculated (defining a value D). With D and V it is possible to calculate the texture depth using the following equation:

$$T = \frac{4V}{\pi D^2} \tag{2.1}$$

with:

- T= Texture depth [mm]
- V= Volume of the cylinder containing the sand [mm]
- D= Average diameter of the sand patch [mm]

Figure 2.5: Sand Patch measurement

This methodology is proposed in the ASTM standards in the TP763 clause [6]. From an execution point of view this methodology presents a series of disadvantages: first of all with high wind and rain it is not possible to execute the test. Moreover when the conditions are suitable for the test execution it takes 3-5 minutes to execute it. The duration is also dependent on the experience of the operator. Besides these negative factors there is also the good reliability of the results. With this methodology the accuracy of the measurement is high due to the possibility of the sand to fill all the holes of the pavement structure. The sand is pushed in the structure and can also occupy the voids present below some aggregates. Figure 2.6 shows this.

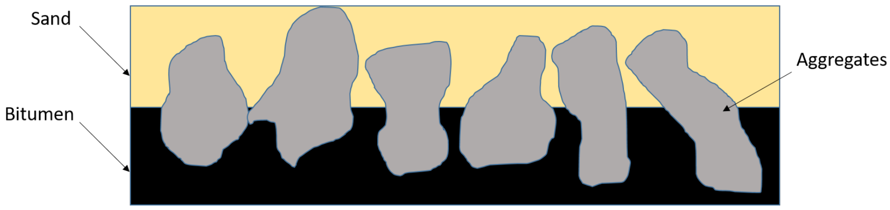


Figure 2.6: Sand Patch measurement holes detection

Laser method

The second methodology available to measure the Texture Depth is the laser technique. The tool used at Schiphol Airport is the ELAtextur machine that is shown in figure 2.8.

The Texture Depth is measured by a rotating laser that scans 2000 points per measurement and calculates the texture depth area under the machine. In this case the sample dimension remains fixed and the exact area is represented by a circle with a diameter of 400 mm. This machine measures the Texture Depth in accordance with the EN ISO 13473-1 and ASTM E1845-09 regulations.

Figure 2.7: ELAtextur machine

The most important advantage of this methodology is the short duration of execution. It takes 12 seconds, including the saving data time, to take a measurement. It is faster than the sand patch method. For this reason it is preferred in case of a high amount of measurements needed. The limit of this technique arises from the nature of the laser technique. During the measurement process the laser line remains straight and cannot bend under the aggregates, some spaces remain then undetected and are not calculated by the machine (see figure **??**). The Texture depth can, for this reason, be lower than the real one. The reliability of the laser method with the ELATextur machine needs to be analysed during this thesis to ensure that the methodologies can provide reliable results for the calculation of the Mean Texture Depth (MTD).

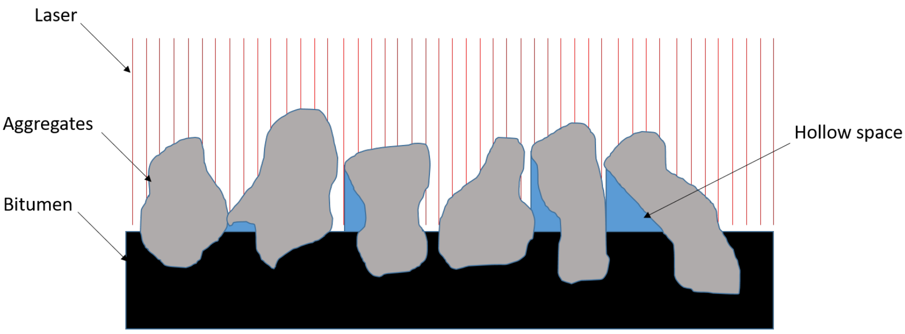


Figure 2.8: Laser limitation for detection during texture depth measurement

Both methods for measuring the texture depth have a very limited sampling dimension and for this reason a consistent number of samples is needed to define the MTD of the surface. In this case the surface analysed is a runway. In particular, the runway used to test the different methodologies is the Polderbaan that has a dimension of 3500 m length and 60 meter width. But the test area has a dimension of 500 meters length and 60 m width. This area has been renovated in April 2018 with Flightflex®. The definition of the number of samples and their locations for the Flightflex® surfaces will be based on the dimensions of this test area.

2.2.2 Current sampling strategies

This two sampling methodologies described previously are used in detailed sampling strategies. These define the number and location of samples that have to be taken for a defined area.

In this case study the area used to analyse the different sampling strategies is a rectangle of 500 m length and 60 mt width equal to the test area described previously. Currently there is a proposed sampling strategy based on the CROW regulation. The CROW is a non-profit organisation that has been established to enable the Dutch government and private companies to operate together in the design, construction and maintenance of roads. This organisation has proposed a sampling strategy with the Sand Patch Method to apply on Roads. This methodology starts with the assumption that the runways is divided in longitudinal strips that have a width equal to the paver width. In each strip three transverse measurements are planned and repeated with a specific interval in longitudinal direction. The measurements are not parallel over the strips but are scattered with a fixed length. This concept appears more clear looking at figure 5.1. This strategy was producing a limited number of samples for the test area and was not able to provide a representative analysis of the surface. For this reason this methodology has been adapted by reducing the width of the strips and the longitudinal distance between the measurements.

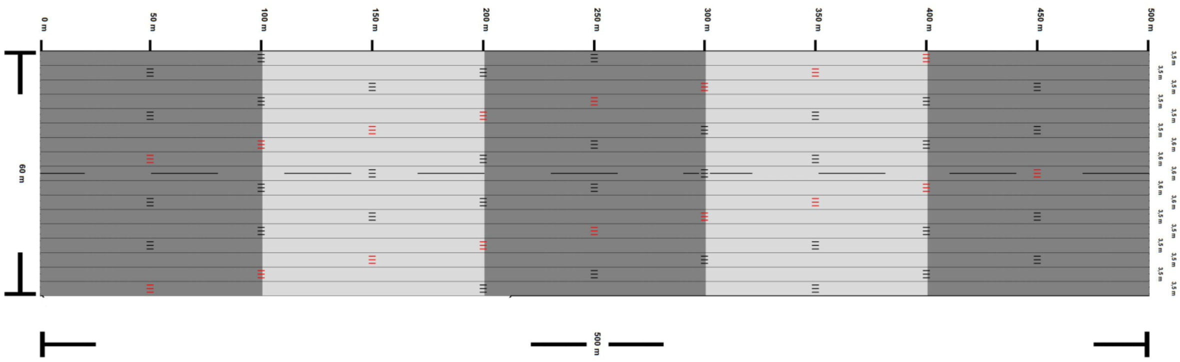


Figure 2.9: Sampling strategy proposed by Heijmans

During this research this sampling strategy will be referred to as the CROW Method. This sampling pattern is a deterministic method that is not influenced by the manufacturing process. The number of samples and their location is fixed and decided without taking into consideration the different phases that characterise the construction process.

At this stage of the research the CROW method was adapted to the runway dimensions and modified from the original version. During this research the characteristics of this and other sampling strategies will be examined: their characteristics, relations with the manufacturing process and reliability will be tested and compared in order to choose the most efficient one for this construction process. Moreover during the analysis of the sampling strategies and the comparison phase it will be possible to derive some theoretical and more academical conclusions on this topic.

Chapter 3

Literature review

From the TU Delft library and online websites as Google scholar and Scopus different articles have been found on the sampling theory and surface texture.

3.1 Categories of sampling techniques

Currently the literature is poor of research on the sampling techniques to adopt with asphalt surfaces. Colosimo et al. define three main general sampling approaches [8]: blind, adaptive and process based strategies. Their studies are based on the definition of sampling techniques for the quality control of industrial products.

The first category requires only geometrical information about the surfaces that need to be analysed, some measurement tolerance and no information regarding the manufacturing process. The scarcity of information can lead to choose this methodology implementing a standardised procedure and a fixed number of measurements. Normally a uniform spatial measurement is considered the most appropriate to provide robustness to this kind of processes. The negative aspect of this methodology is the fact that for large surfaces many samples are required in order to provide a proper level of analysis reliability [8]. Some, like Lee et al, have defined a specific segmentation procedure to divide the area that needs to be analysed and provide a series of regions where the texture properties are homogeneous [15]. This approach is typical of image analysis and could find application difficulties with in-homogeneous surfaces such as pavements.

Different is the situation with the adaptive strategies, where the sampling proceeds by adapting to the data features. Initially a certain amount of samples are taken, to their analysis new samples are added by trying to meet a pre-defined criterion. Often the analysis proceeds by searching for those points that present the higher deviation from the mean. Important with this methodology is the definition of the analysis criterion, this can be a maximum number of samples analysed or a property of the analysis (i.e. the geometric deviation does not vary substantially from the mean). The main drawback is the number of samples needed to achieve the criterion established, in case of very in-homogeneous and varying surfaces it could take an excessive number of samples to have a suitable set of results or, in case of a limited number of samples allowed, a non-representative description of the surface [18].

Affan Badar et al. have developed a search based algorithm sampling technique that enables the operator to reduce the number of samples needed to have an accurate representation of the surface's property. From a defined number of starting points it is then possible to move forward in a precise direction in order to find the most significant points of the surface [2]. Although this methodology reduces the number of samples needed, if the texture is highly irregular a large number of measurements will still be needed.

The third and last category is based on particular information provided by the manufacturing process. Knowing some properties or aspects of the surface and the production process, it is then possible to reduce the number of samples required and focus only on the element that still presents a high value of variability. This can be as an example integrated with the blind strategy by reducing the area that needs to be analysed or just focus on one aspect of the surface. The main disadvantage of this technique is the fact that it is based on a specific manufacturing process and surface type, for this reason it cannot be generalised to other fields or materials [8, 18].

3.2 Surface properties and manufacturing process signatures

In order to understand which sampling techniques perform better it is important to study the surface properties and their relation with the manufacturing process.

The process of raw data modelling has been extensively described by Colosimo et al. in a second paper where they defined the extreme point selection Method (EPS). They assert that if there is a signature in the manufacturing process, then with this methodology it will be found more or less in the same surface location. In contrast with the random or predefined selection of sample locations this methodology defines the exact locations based on the manufacturing process, but if this changes, also the locations change, so with process uncertainty this methodology appears less suitable [16]

Stefano Pertò in his doctorate thesis presented a series of models aimed to describe the manufacturing signature [18]. The two main categories are: Ordinary Least Squares Model and Spatial Error Model. The first one is basically a linear regression model, the second a model based on the property per location. More specifically a method called Lattice model has been defined that could suit the asphalt manufacturing process. Each sampled point represents a certain area that is then modelled through a Spatial Auto-regressive Model. This model is mathematically complex and long, for this reason it will not be explained in this section but will be used if necessary in the pavement analysis.

Another alternative is the application of a manufacturing signature model. There is very limited literature regarding signature sampling modelling, in particular nothing has been found for asphalt compaction and manufacturing. Some mathematical and statistical models are frequently used, in particular Corrado et al. defined a signature modelling for tolerance analysis of rigid parts which proved to be a reliable analysis [9]. The asphalt mixture is anyway influenced by many variables and it would be difficult to define a mathematical model. Colosimo et al. also present the opportunity to determine this model experimentally [8], in cases with high variability this would be the preferred option but to define the signature a high number of samples is needed so a simulation based approach can also be used.

3.3 Definition of a sampling strategy

Once the manufacturing signature model is ready or a proper number of raw data is given it is possible to define the sampling strategy. Moroni et al. proposed a procedure called "Minimum U" that is based on the ISO regulations. They defined an uncertainty variable (U) and elaborated a procedure in order to minimise and stabilise its value as much as possible [17].

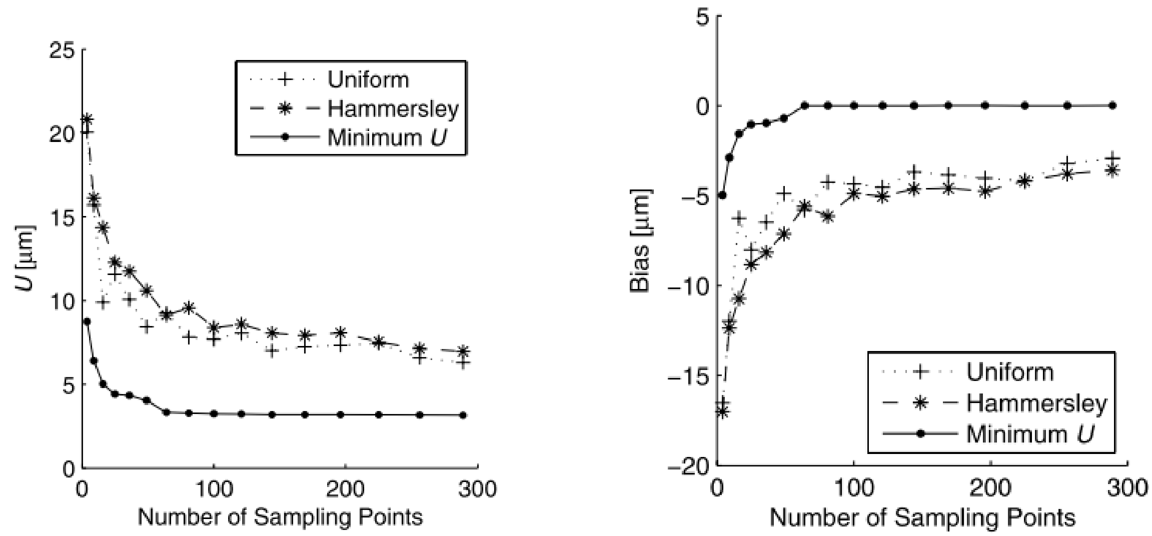
$$U = k\sqrt{u_{cal}^2 + u_p^2 + u_w^2} + |b| \tag{3.1}$$

Where:

- k is the expansion factor
- b is a compensation factor
- u_w is the variability of production and is suggested to be set as 0
- u_p uncertainty of measurements
- u_{cal} is the calibration uncertainty

This formula and all the different factors are calculated according to the ISO/IEC guide98-3 [1] and ISO/IEC guide99:2007(E/F) [13].

The solution of this problem can be reached by defining a sampling strategy that minimises the U function as much as possible. If the methodology is effective then the U value will have a lower value and the sampling points will represent the areas with the higher deviations from the mean. Colosimo et al. proposed to transform this strategy selection in an optimisation process and look for genetic algorithms. Still in the same paper a comparison of a uniform, a random called Hammersley and minimum U strategy selection has been presented in terms of an U function. Figure 3.1 shows that the minimum U strategy has proven to be the best.



(a) U value with different strategies

(b) Bias for different strategies

Figure 3.1: U comparison with other sampling methodologies

3.4 Literature conclusions

The papers of Colosimo and Petrò will be taken in consideration because they provide a wide overview of the different methodologies. They also insist on the sampling methodologies and the dependency on the manufacturing process proposing mathematical tools to analyse it. Meanwhile being restricted to the laser machine, the image approach proposed by Lee et al. cannot be applied to this case study and analysis. At the moment the quality of the surface is analysed only with the two methodologies presented in chapter 2. The evaluation of the quality with pictures has not been implemented yet. Also the mathematical approach proposed by Assan and Badar will be of great importance due to the necessity to reduce as much as possible the number of samples needed.

Finally it will be complicated to implement the exact U function as proposed by Moroni et al. because this function was applied to the manufacturing process of mechanical parts. In this field the construction is automatised and the level of precision is very high. It is thus possible to define the parameters needed to apply the formula presented previously.

In the pavement industry the level of uncertainty is higher and the precision of the manufacturing process is lower. The strict application of the U function becomes complicated, but the idea to define an analytical and graphical way of comparing the different methodologies will be implemented. The desired final outcome will be to have curves similar to those shown in figure 3.1 and see which one decreases fastest.

Chapter 4

Research question and research methodology

In this chapter the research question that will guide the thesis and the research approach presented.

4.1 Goal and Research Question

The construction process of asphalt pavements influences the final quality of the surface. A non homogeneous mixture, a wrong compaction procedure and other external factors can generate areas with higher or lower texture depth and skid resistance. Being unrealistic to have a perfect construction process, an asphalt surface will have high chances to be influenced by the manufacturing process.

As described in the introduction, the industry lacks a scientific basis for the definition of a proper sampling methodology for runway textures evaluation. This research aims to provide this support by defining the theoretical relations between the surface properties and the sampling methodologies. Different intermediate steps as the definition of the simulations, the virtual representation of the surfaces, the influence of the manufacturing process will be part of the research and help during the different operational phases.

To achieve the goal the main guiding research question is:

"Given a surface characterised by a predefined manufacturing process, which minimum number of samples and at which locations provide the lowest relative error between the real mean of the surface and the mean texture depth of the samples collected?"

This is the main question of this research but some specific sub-questions will also guide the different steps needed. The main sub questions are:

- How does the manufacturing process affect the properties of the surface?
- Can the surface be consistently represented with a matrix of values?
- How do the different sampling methodologies behave with the simulated surfaces?

These sub questions assume relevance during the different phases of the process because they will provide consistency and preserve the scientific approach of the research. The simulation of the sampling methodologies cannot take place if it is not clear how the surface is characterised by the manufacturing process. The same applies if there is no consistency in the representation of the surface during the simulation. To conclude, it is clear that to evaluate which sampling methodology is the most efficient, all the proposed ones need to be tried and compared on the same simulated surfaces.

This subject and research question represent the willingness to provide a practical support to the industry by means of a scientific analysis. The academic approach is introduced to provide a conclusive and reliable analysis to the industry. Interested companies can then rely on the outcome of this analysis and take decisions to reduce their risks on specific projects. The feasibility of this research will strongly depend on the quality of data obtained during the field measurements.

4.2 Research approach

The main characteristic of this research process is the presence and delicate combination of different research approaches. Several data and information need to be meticulously collected and carefully analysed during the research. Field tests are essential to analyse the MTD distribution on the surface, more precisely they will provide the information on the manufacturing process effects on the surface.

Data collection from the field

A consistent number of samples are needed to reach the aforementioned goal, and this sampling process requires at least 5/6 hours on the field. Although this research is in co-participation with Heijmans and Schiphol Airport, obtaining the authorisation to stay on the runway during the time required is part of a complicate bureaucratic process. The only opportunities will be during regular night maintenance that is planned once a month and during the full closure of the runway for 20 days in March and April 2018.

Definition of the sampling techniques

Alongside this data collection, the sampling techniques for the simulation have to be analysed and precisely defined in order to be correctly applied. This process is based on three main steps:

1. Define in detail the distribution of the samples according to the CROW regulation. This is a blind technique that partially takes into account the whole manufacturing process.

2. Define a methodology for the simulation of a random sampling technique. In this case it will be necessary to simulate a sampling process that is not related with the manufacturing process and the characteristics of the asphalt. In the literature review it has been shown that Colosimo et al. have defined the Hammersley distribution the most appropriate to simulate a random sampling process[8]. For this reason the Hammersley methodology will be adapted and used also in this research.

3. Define the manufacturing properties of the asphalt construction process. In this case the design phase is more complex because finding a manufacturing signature for this kind of process appears to be a challenging operation. Two approaches will be applied and the best one will be selected:

   - A stochastic manufacturing signature by sampling a little area (1 m^2) with a high number of measurements (more than 1000). In accordance with Colosimo et al. this process would be long and time consuming but should provide a proper representation of the signature model.

- The implementation of the Lattice model proposed by Pertò in his doctorate thesis[16]. This model has never been applied to asphalt surfaces and, although it appears challenging, it could lead to a suitable representation of the manufacturing signature.

Once the manufacturing signature is identified it will be possible to implement the U function and implement the genetic algorithms to minimise the number of samples as much as possible. The algorithm has not been defined yet and will be part of the analysis process.

Simulation process

Knowing the characteristics of the pavement and having developed different sampling techniques, the simulation process can take place. This process will be executed with computer simulations. The simulation will be set and programmed with Python, the development of the code will be totally made from the beginning and tailored on the data and findings provided in the previous steps. The program will take the samples obtained in the field, then it will extract the statistical properties as Mean, Variance and Covariance. From this information it will be possible to simulate entire runways surfaces containing those properties and being representative of the real ones. The algorithms will simulate them hundreds and thousands times, testing on each surface the sampling techniques and recording the MTD of each technique used. Each time a surface is simulated it is possible to know its real MTD, this enables to calculate the relative error with the MTD of the samples taken. Each simulation cycle will present a comparison of the relative error of each sampling methodology.

Results analysis

A challenge will be to define how to evaluate the results of the simulation. Two main approaches are possible. The first one is to choose which sampling methodology provides the lowest relative error without caring about the number of samples. This could be positive to increase the reliability of the measurements but could also produce a too high number of samples, that could not be measured in practice.

The second possibility is to direct the analysis towards the minimisation of the samples number, this would be preferred for field operations. In this case the algorithm will look for the sampling methodology that provides the minimum number of samples, but imposing a threshold for the relative error.

In the first case the analysis will be more consistent and rigorous from the academical point of view, presenting a precise and clear relation between the manufacturing process of the surface and the sampling techniques used. But this will not answer the research question where it is specified that the minimum number of samples is required. The second approach could provide a series of conclusions and recommendations applicable on the field in the form of regulations. But the negative aspect of this strategy is the definition of the relative error threshold value to impose on the analysis. This should be chosen in order to provide consistency with analysis and real data and provide the company with an applicable methodology.

Validation and testing

The final part of the research will be based on a practical sampling process in the field. The measurement results will also be used to validate the surface simulation process. The three methodologies defined in the research will be tested in order to evaluate the results and verify if they correspond to those obtained with the computer simulations.

All this phases will be part of the research and are schematised in figure 4.1.

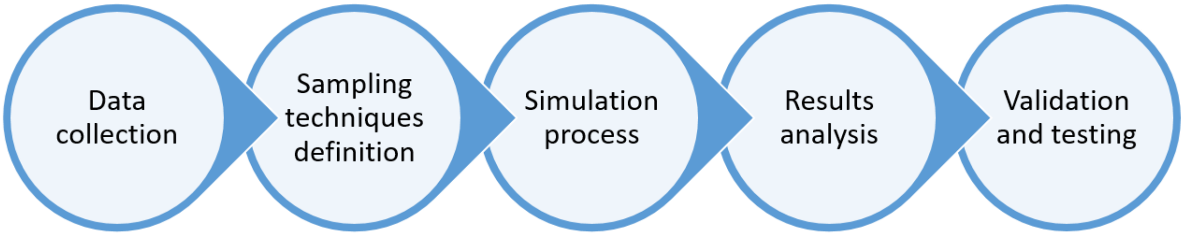


Figure 4.1: Research's process overview

CHAPTER 5

Sampling and simulation modelling

In this chapter the models of the sampling methodologies and the surfaces will be defined. From this information it will be possible to start the simulations and compare the results in order to evaluate the best sampling techniques.

5.1 Sampling techniques

Here three sampling techniques will be defined and analysed for the application on the simulated and real surfaces: Uniform sampling technique, Hammersley sampling technique and CROW sampling technique.

5.1.1 CROW sampling Technique

The first sampling strategy analysed is the one proposed by the CROW regulation. As briefly described in chapter 2 the CROW is a no profit organisation that proposes a series of regulations to ease the collaboration between highway agencies and private companies for the design, maintenance and construction of highways.

This sampling methodology is a deterministic planning of locations where the texture depth measurements have to be collected. These locations are not adapted nor influenced by the manufacturing process. The only relation with the construction process is the fact that the width of the longitudinal strips can be the same as the pavers width. The reason behind this particularity is the fact that the CROW methodology was mostly intended to verify the quality of the paving and compaction process. In each longitudinal strip a series of three measurements in transverse direction are defined. Two at the extreme of the strip in transverse direction and one in the middle. This distribution is aimed to analyse the homogeneity of the texture depth on the width of the paver. During the paving process it can happen that the asphalt is not homogeneously distributed by the paver, for this reason the final texture depth can be slightly different. This sampling process was aimed to verify this aspect of the construction process.

It has been proposed to start from the CROW regulation and apply some modifications to adapt it to the runway dimensions. The Polderbaan is used as main reference for the runway dimensions. This runway has a length of 3800 m and width of 60 m [14]. The proposal was to divide the width in 3 m wide strips. In each strip 3 measurements are set with an interval of 150 m in the longitudinal direction. The location of the measurements in the other strip is scattered with 50 m distance. A clear representation of the sampling strategy is shown in figure 5.1.

The total number of measurements with this strategy for a 500 m longitudinal length is 102. It has been decided to take a 500 m length unit because Schiphol and Heijmans have decided to

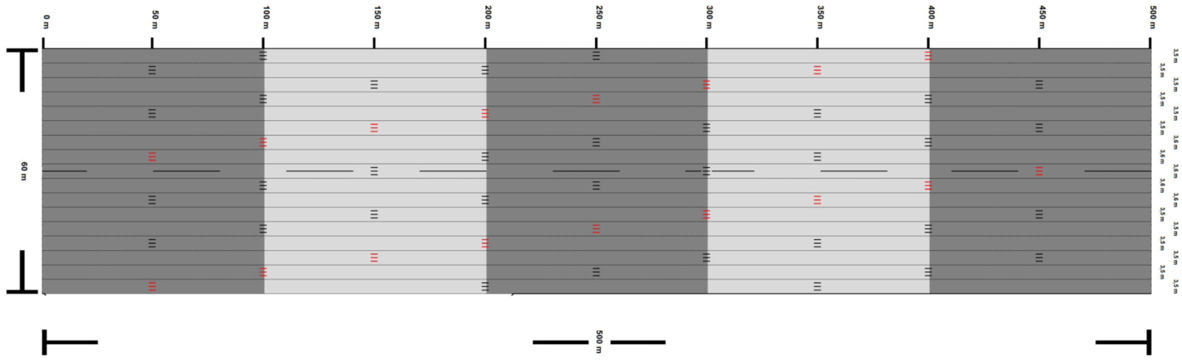


Figure 5.1: Sampling strategy proposed by Heijmans

renovate a Polderbaan stretch with the same dimension. This work was planned in order to test the performances of FFX on a bigger area compared to the previous test stretches. But during the simulation this methodology needs more flexibility in order to enable an increase and decrease of number of samples for the same runway length. This will be done by creating an algorithm that varies the longitudinal distance between the measurements in the same longitudinal column. In this way the main properties of the methodology are maintained with a lower number of samples. The disadvantage of this algorithm is the constraints in the increment of the number of samples collected. With this strategy it is not possible to increase the few independent samples but an entire transverse row is inserted. This because the longitudinal distance between the rows change and in 500 m more lines of samples can be inserted.

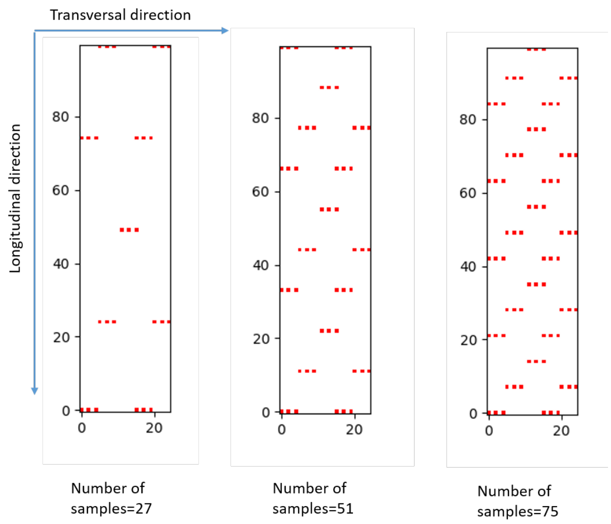


Figure 5.2: Example of increase of samples with CROW method (own creation). Axis labels represent the number of surface squares

As explained in section 2.2.2 the CROW procedure has been adapted to this case study. The interval between two subsequent measurements has been reduced to 150 m instead of 500 m. Moreover the strip width has been reduced to 3.5 m instead of the 4 m of the paver. This was necessary to increase the number of samples in the test stretch and provide the necessary information of the pavement quality. With the original method the number of samples would have been limited and the information on the surface would have not been sufficient. In figure

5.2 it is possible to see how the increment of points works for the same surface. This increment procedure will be useful to analyse how the relative error reacts to this variation. It is in fact expected that the relative error decreases by increasing the number of samples as described by Colosimo in figure 9.1.

5.1.2 Uniform Sampling technique

As proposed by Colosimo it is worthy to insert the uniform sampling technique in this study because it is easy to vary the number of samples proportionally and have a clear location of the sampling points [8]. The uniform sampling distribution is developed by dividing the surface in an proportional number of rows and columns. In this case the width of the rows and columns will be chosen as the dimension of the sampling area. In this case study the sampling area is determined by the dimension of the ELATextur machine. The sampling circle has a circumference of 400 mm and a diameter of 127 mm. The machine though has bigger dimensions and for this reason a diameter of 150 mm has been considered. In order to take into account human mistakes during the measurement phase a square of 250 mm has been considered. That determine a sampling area of 62500 mm^2. Figure 5.3 clearly show that the sampling circle is contained inside the sampling square and has a tolerance in all directions.

Figure 5.3: ELAtextur machine and consequent sampling dimension

From this sampling dimension it is possible to divide the surface in rows and columns. When this process is concluded, it is possible to design an algorithm for the increase and decrease of sampling points. The main constraint was to maintain a proportion between the location of the sampling points and the number of rows and columns defined before. The complete algorithm can be found in the Appendix.

In figure 5.4 the increment of the number of sampling points is shown as an example. Please note that this is only an example surface aimed to show how the location of the sampling points changes when the number of samples is increased.

With this sampling methodology it is possible to have a better overview of the texture depth values and their locations. This will enable a clearer understanding of the locations with lower or higher TD. The previous definition of the uniform sampling methodology shows that it has no relation with the manufacturing process nor is influenced by it. This methodology is then categorised as a blind technique that has a practical advantage during the measurement phase. Having an entire runway to measure, for the operator it is easier to define a grid of the points to measure. Meanwhile the CROW methodology has specific locations that are not contained in a regular grid. This make the process longer and increases the possibility of wrong measurement

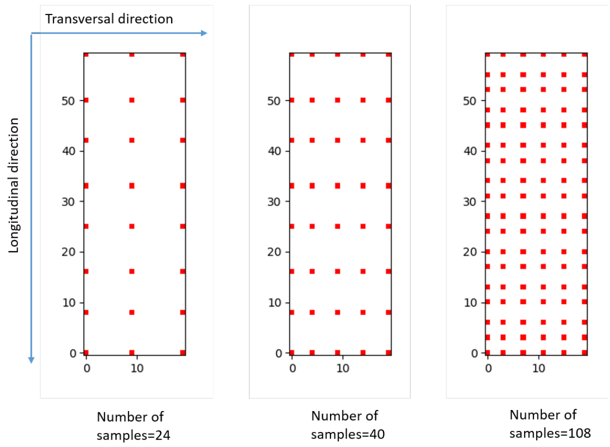


Figure 5.4: Example of increase of samples with Uniform method (own creation). Axis labels represent the number of surface squares

locations.

5.1.3 Hammersley Sampling Technique

The Hammersley Method is also a blind technique because it is not related to the construction process nor the dimensions of the surface. It has been developed with the aim of simulating a random selection of points on a surface. In this case study it is applied because there is the need to evaluate the precision of the MTD with a random points selection. This will be compared with the other methodologies to see if a total detachment from predefined rules and relations with the manufacturing process can increase the precision of the MTD.

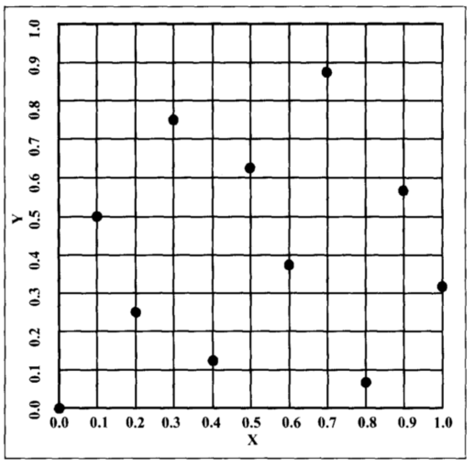


Figure 5.5: Example of Hammersley location of 10 sampling points [22]. Axis labels represent the number of surface squares

A random selection of points can, in theory, determine a group of points that are concentrated in a specific part of the surface, leaving another part totally unmeasured. The necessity is to define a sequence of locations that can be assumed as random selection but maintaining uniformity on the surface.

This methodology is based on a low discrepancy sequence firstly elaborated by Van der Corput [22]. Hammersley had the merit to develop this mathematical tool to N dimensions. In this case study only a 2 dimension sequence is needed. The main functions that governs this sequence of points are[22]:

$$Y_i = \frac{iW}{N} \tag{5.1}$$

$$X_i = \sum_{j=0}^{k-1} b_{ij} 2^{-j-i} \tag{5.2}$$

where:

- X_i is the point coordinate in the transverse direction of the surface (of the runway if we consider the case study)
- Y_i is the coordinate in the longitudinal direction of the surface
- N is the total number of samples
- W is the total width of the runway
- b_{ij} is the binary representation of the index i

As an example: if 15 samples need to be located on a surface the distribution will be the first in figure 5.5

As it can be seen in figure 5.5 this sampling strategy works for squared sections. In order to adapt to this case study it has been decided to create a repetitive series of squares that present the same Hammersley distribution. The number of samples is increased just by increasing the number N in the previous equations. The complete code for this strategy can be found in the Appendix.

An example of the increment and change of location of the number of sampling points is presented in figure 5.6

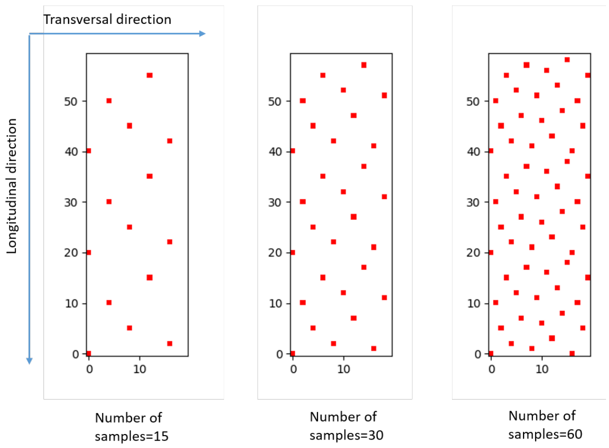


Figure 5.6: Example of increase of samples with Hammersley method (own creation). Axis labels represent the number of surface squares

5.2 Surface simulation

Once that the three selected sampling methodologies are coded and defined it is possible to work on the surface texture depth measurements simulation. In order to apply the different sampling technique a surface that has the same properties as the runway is needed. The most complex part in this process is to work on the properties of the real pavement, more specifically try to understand how those are determined and influenced by the manufacturing process. As it has been described in chapter 2 the properties of the asphalt mixture are dependent on the components of the mixture but also on the construction process. For instance, a wrong execution of the waterjetting process can improve the properties of the surface but also decrease them.

The pattern and characteristics of the construction process thus became an important aspect for the determination of the surface properties. It is necessary to identify those characteristics and represent them on the simulated surfaces. This is possible by collecting a large number of samples in a limited surface. This determines a high density of the points and ensures a highly correct representation of the real surface properties. The surface has to be divided in rows and columns with a width equal to the sample square. Then the Texture Depth is measured in all the cells.

To have a clear visualisation of the measurements results a program in python has been coded to export the data from the Elatextur machine and locate the value of the measurements in a matrix. These data are then plotted in the surface with a different colour representing the value of the Texture Depth. In figure 5.7 we can clearly see how the points are plotted and areas with different values are independent.

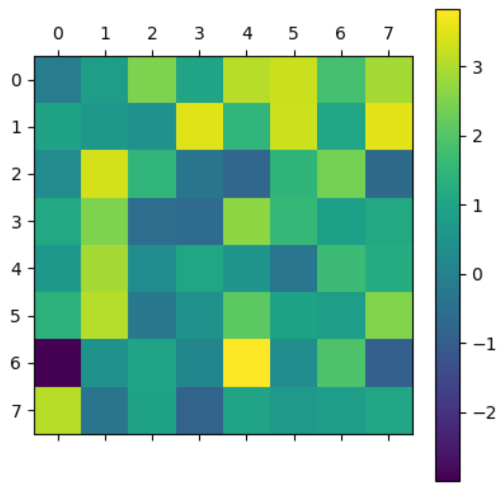


Figure 5.7: Example of Surface simulation. Axis labels represent the number of surface squares

This example matrix is plotted with random values but it is possible to identify different areas where values are lower and higher. In the next phase an analysis of these surfaces to obtain statistic outputs is carried out. The scope of this part is to find the most important properties of the surface in order to generalise them and create entire simulated runways.

Not only the numerical values of the Texture Depth are important but also the location of those measurements. It can happen that a certain part of the manufacturing process determines a repetition of areas with different MTD. The identification of such zones is important because it represents a feature of the manufacturing process and has to be identified and repeated in the simulated surfaces.

The representative surface will be created multiple times and each time all the sampling methodologies will be tested. The real value of the MTD will be known because the matrix will be created manually and it will be possible to compare it with the MTD calculated from the collected samples. The technique with the lowest relative error for the minimum number of samples will be the most reliable from a theoretical point of view but also other considerations will be made.

5.2.1 Defining Surface Properties

The first information that has to be collected from the surface is the value distributions of the TD values present in all the cells. This can be done by fitting the TD values with different distribution and searching for the one that approximates the best. This fitting process is based on the least squared method.

This method consists in proposing a curve drawn from the data parameter. As an example, if the normal distribution has to be fitted on the data the parameters used will be the Mean and the Variance. Once the fitted curve is drawn it is possible to calculate the fitting accuracy by calculating for each point of the distribution its distance from the fitted curve. In figure 5.8 the points of the distribution and the fitted curves can be seen. Each point has a distance Y_i to the curve. By taking this distance squared for each point it is possible to have a final value that has to be compared with all the other fitting curves.

$$S_{normaldistribution} = \sum_{i=1}^{N} Y_i^2 \tag{5.3}$$

with:

- Y_i = distance of single point i from the fitted curve
- N = number of points collected

The distance is squared and summed with the ones of all the other points. The fitting curve that provides the minimum sum is the best fitting curve.

To check the best curve fitting the program has be set to evaluate the fitting process with all the curves available in the mathematical Python library. This produces the outcome as shown in figure 5.9a. At first sight the figure appears confusing but it is possible to see in the background the distribution of TD values and above it all the possible curves representing the distribution.

The program will calculate with the minimum least square method which curve best represent the distribution of points. The output will be a single curve that will be plotted in the same TD value histogram.

The selected distribution in this case is very specific and not common in basic statistic analyses. This is due to the fact that the program searches for the best curve possible. If the number of samples is limited and not representing the majority of the surface this fitting process can be misleading. A limited number of samples could be characterised by particular aspects that are not

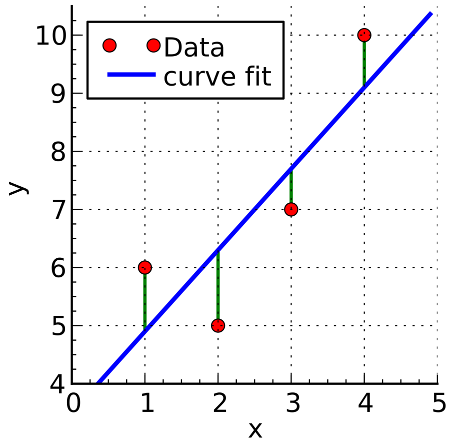
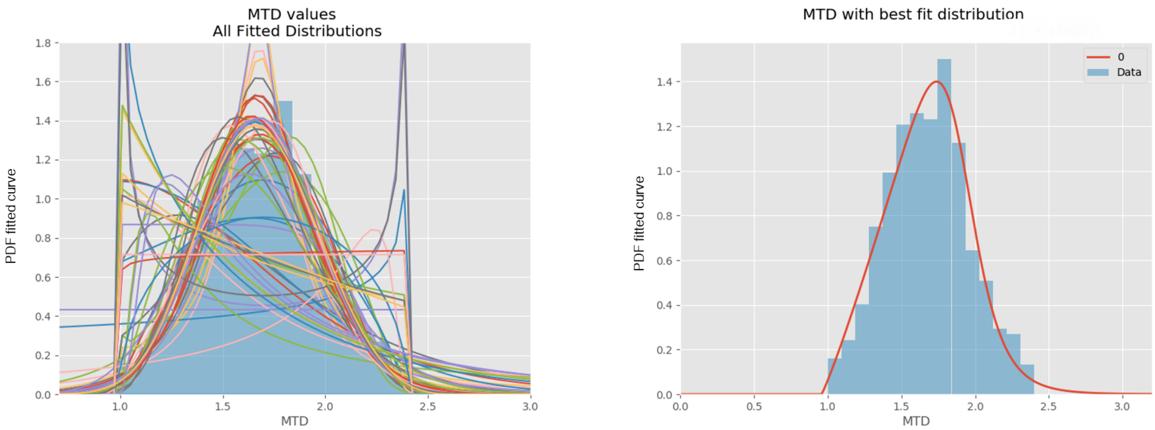


Figure 5.8: Example of distance between fitted curve and data points

recurrent in the whole surface. The final fitting curve could be the most representative for these samples, but not for the total surface. This imprecise interpretation of the results is also known as Overfitting[7]. This word refers to the practice to create a model based on a limited number of values and apply it on another group of data[7]. The model is not able to provide reliable results in different applications. In case of a limited number of data the solution is to fit those data with more generic curves. The fitting process with normal distribution, from a mathematical point of view, is not the most precise but provides reliable results in case of more general data. The distributions usually used in this cases are the Normal or Log-normal distribution.



(a) Fitting process of all the curves

(b) Best curve selected

Figure 5.9: Fitting process and selection of the best curve

In this research an initial fitting of all the curves has been used to extrapolate the features of the asphalt. But due to the limited number of data available it has been decided to fit only the normal distribution in order to have a more conservative approach for the generalisation of those properties during the simulation of the entire runway.

5.2.2 Normal Probability distribution

The normal probability distribution is the most used in statistical analyses[5]. It has a probability distribution curve that is shaped as a symmetric bell, for this reason it is also called Bell curve (Figure 5.10).

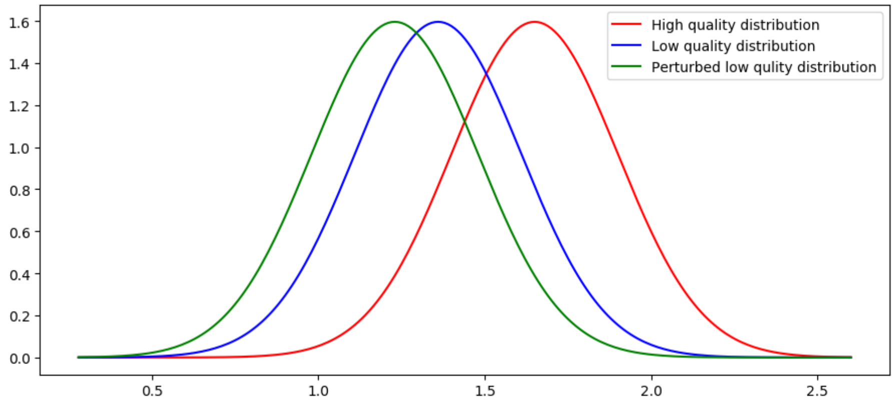


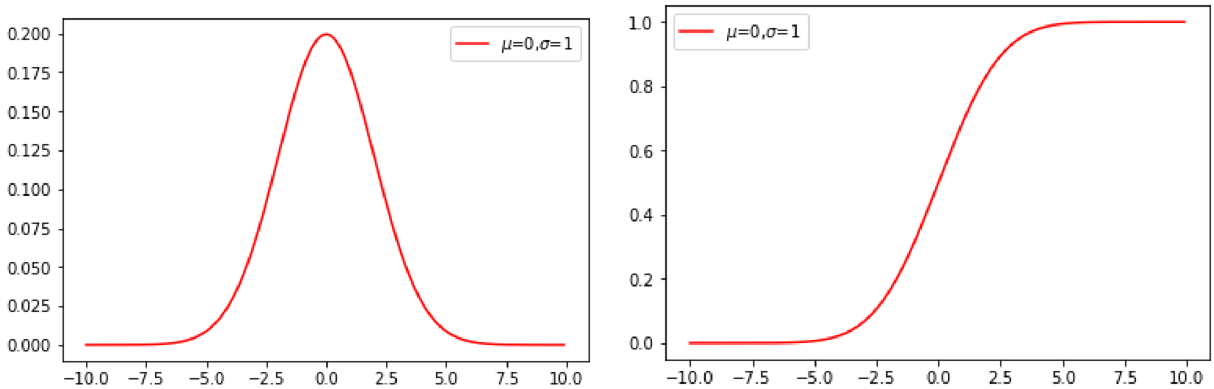
Figure 5.10: Example of three different Probability density curves for a normal distribution with different mean value but the same standard deviation

Its probability density curve is characterised by the following equation:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{5.4}$$

With:

- $\sigma=$ standard deviation
- $\mu=$ Mean, called also median
- $\sigma^2=$ Variance



(a) Probability distribution function (b) Cumulative distribution function

Figure 5.11: CDF and PDF for the same normal distribution

During the fitting process the Mean and Standard deviation are defined. They will be used as parameters for the creation of the cumulative distribution function (CFD).

Figure 5.11 shows the Cumulative distribution function and the Probability Distribution Function of a normal distribution can be seen. The Cumulative Distribution Function is defined as the inverse of the Probability Distribution Function. Providing an input probability, defined as a number between 0 and 1, in the CDF will give the corresponding value.

The cumulative distribution function will be very useful during the analysis because a uniform distribution of values between 0 and 1 will generate a percentage to insert in the CDF to determine TD values. These values will then be used to create simulated surfaces with a MTD probability corresponding to the PDF obtained from the fitting process describe above.

Figure 5.12 shows a more clear description of the steps and the corresponding graphs.

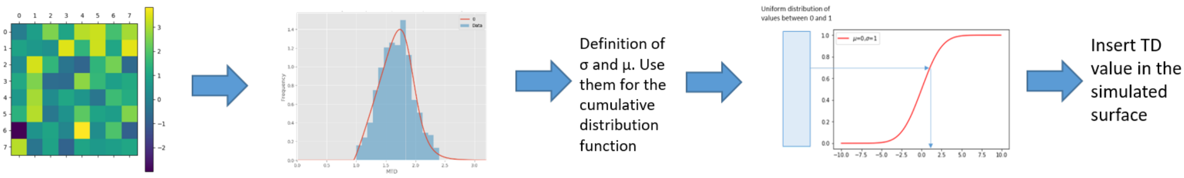


Figure 5.12: Summary of fitting process and determination of simulated texture values

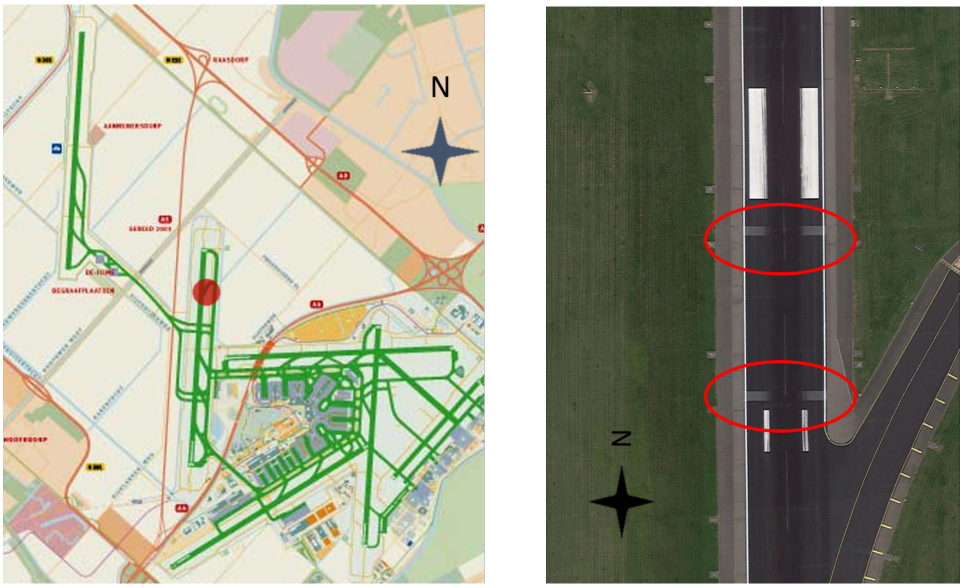
Chapter 6

Real data analysis and surface simulation

In the previous chapter a description of the sampling techniques, enriched with theoretical notions, has been proposed to ease the understanding of the whole analysis presented in this chapter. Here the description of the data collection is presented, followed by the extrapolation of the manufacturing features. These information are used in the last part of the chapter for the construction of the entire surface.

6.1 Data Collection from the field

The Flightflex® has been placed on the Touch Down Zone of the 18C runway in 2014. It was interesting then to measure the Texture Depth on this area because it is the most damaged from the landing of aircraft.



(a) Runway Location (b) Flightflex® strips

Figure 6.1: Location of Flightflex® strips

The first opportunity to take measurements was during the night between 19-02-18 and 20-02-18 because of regular maintenance on the Zwanenburg runway. In figure 6.1 the locations of the runways and the specific areas built with Flightflex® are shown with red markings.

The authorisation to take measurements was from 22:30 PM to 4:30 AM. In this time window three groups of measurements were taken.

- In the lower strip in figure 6.1b a square of 25 m^2 is used to take 400 measurements.
- In the upper FFX strip in figure 6.1b the whole area is measured with 105 sampling points using a uniform distribution.
- A short strip with 100 samples will also be analysed for the ASK.

The idea behind the first group of measurements was to get a real mean and variation of a FFX area. Measuring 400 points in a 25 m^2 area means that the exact Mean and Standard Deviation are calculated. To avoid overfitting though, the mean and variance will be based on a normal distribution fitting.

Figure 5.3 shows the sampling unit is assumed to be a square of 250 mm side length. This is bigger than the diameter of the ELATexture machine but it helps to take into account tolerances for imprecision during the measurements. Knowing that, one main assumption is made:

In all the sampling units, represented by a square of 250 mm side, the Texture Depth is assumed to be equal to the value provided by the ELATextur machine.

6.1.1 Dense measurements

The first part analysed was a square area of 5 m side located in the first strip of figure 6.1b. The exact location was the red Square shown in figure 6.2. The area was divided in 20 column and 20 rows for a total of 400 samples.

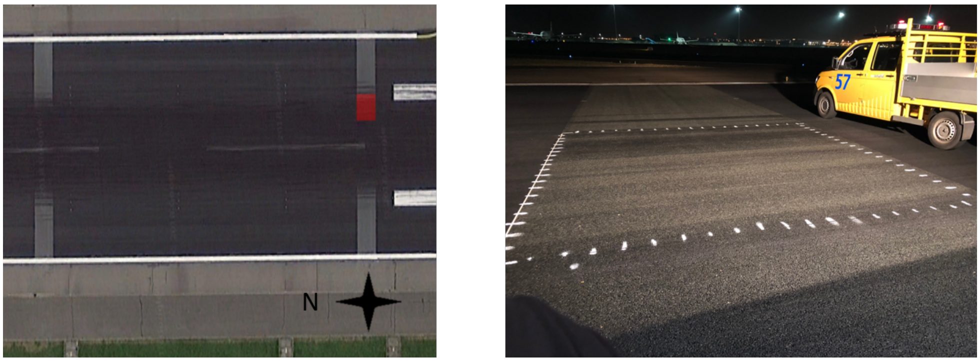


Figure 6.2: Square area for dense measurements with division in rows and columns

The measurement process took 2 hours and 26 minutes excluding the time needed to make the grid and remove the markings.

The Texture Depth values were then inserted in the plotting program and the outcome obtained is the one in figure 6.3. The plotting process really helps to have a quick overview of the surface properties.

At first sight it is possible to see that the average value is quite high. In fact the scale of values starts from 1, this means that there are no lower values. The EASA regulation of a minimum value of 1 mm for the MTD would be respected because the mean of values that are all above 1mm will be above 1 mm too. In order to see if the same can be said for the Schiphol requirement of 1.3 mm MTD, the average of the values will be computed.

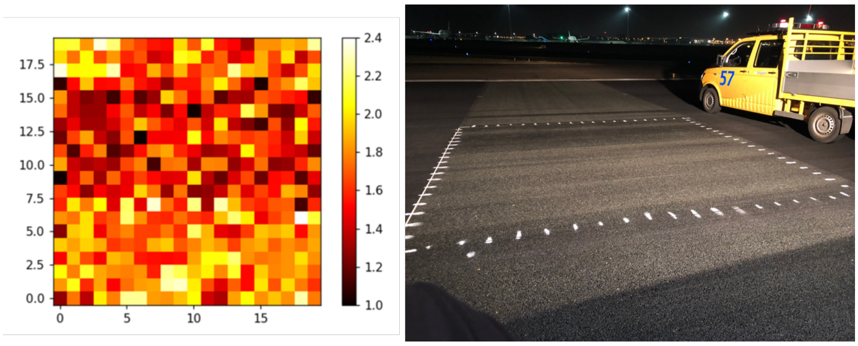


Figure 6.3: Square area for dense measurements and plot of the TD values. Axis labels represent the number of surface squares

The average of these 400 values is 1.67 mm so also the Schiphol requirement is met.

The surface is characterised by two distinct areas. One with yellow squares and high texture quality, and a second with lower TD values and darker colours. The main characteristics is that the lower quality strip affect all the transverse width of the square. Figure 6.3 shows that a darker strips is present of the asphalt. This strip is determined by rubber deposition. The location of the dark strip and the low quality area have been verified and it has been confirmed that they do not match. The conclusion is that this lower quality is determined by the construction process (asphalt mixture, paving, compacting or waterjetting). A confirmation comes from the second strip where a lower area can be found in an area far from the rubber deposition strips.

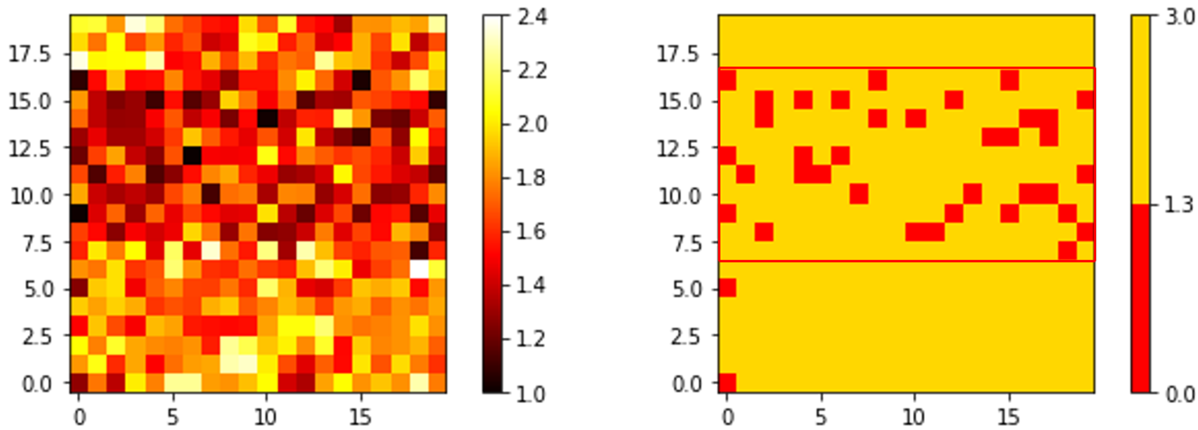


Figure 6.4: Highlighted values below and above 1.3 mm. Axis labels represent the number of surface squares

Figure 6.4 highlights the low quality area of the surface, from which the TD values have been isolated and the MTD of this area is equal to 1.52 mm. The Schiphol requirement is also met here.

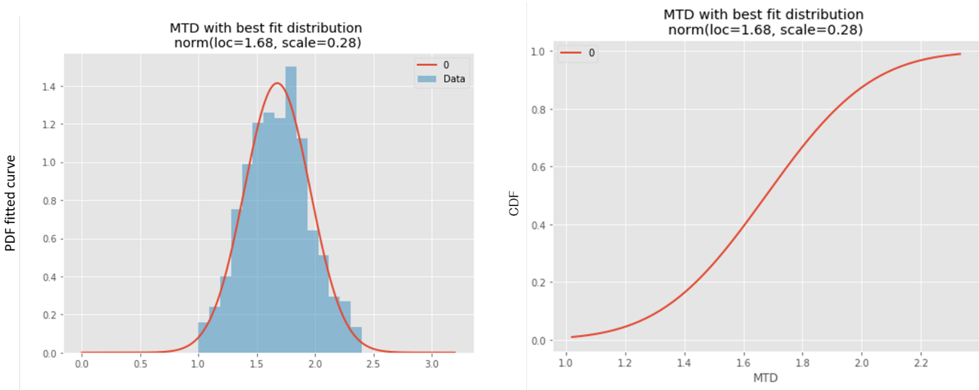
At this point it is known that:

- The surface on average meets the EASA and Schiphol MTD requirements.
- There can be a good quality surface and a lower quality surface area, but both fulfil the Schiphol requirements.

- The low quality area is a rectangle that covers the whole width of the square and part of the length.

As described in chapter 5 the next step is to fit the TD values with a normal distribution in order to get a graphical overview of the numerical results and define the curve parameters.

First all the 400 values have been fit with a normal distribution curve as we can see in figure 6.5. The mean μ is 1.68 mm and St.Deviation σ is 0.28 mm. The latter value describes how all the values are distributed around the mean. In this case it is quite low, which means that the values are very close the average.



(a) Probability distribution function (b) Cumulative distribution function

Figure 6.5: Result of the fitting process; loc= Mean, scale= St.Deviation

A better understanding of this numerical data is provided by figure 6.6. Here it becomes clear that a limited area of the surface has TD values below 1.3 mm, and the corresponding percentage is 9.11%. This means that using this curve parameter for the simulation of surfaces there will be a chance to have values lower than 1.3 mm equal to 9.11%.

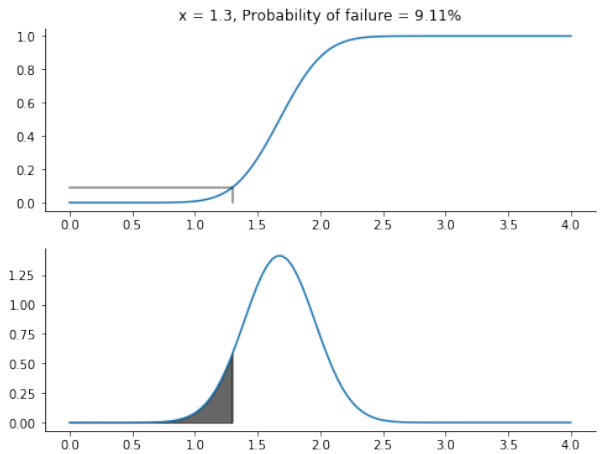


Figure 6.6: Percentage of values below 1.3 mm

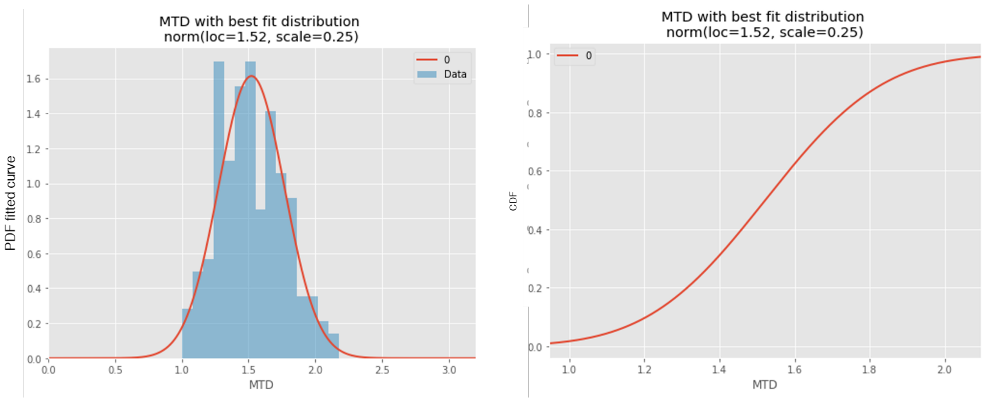
A more accurate evaluation of the information is executed by not considering the fitting process on all the 400 sampling points but by fitting the normal curves to the two different areas defined in the previous phases: the good quality area and the lower quality areas. Figure 6.4 shows the two areas. The red square defines the low quality area while the remaining area represents the high quality values.

Low quality area

The low quality area TD values have been fitted with a normal distribution and the parameters obtained are:

- μ=1.52 mm
- σ=0.25 mm

The corresponding graphs are shown in figure 6.7.



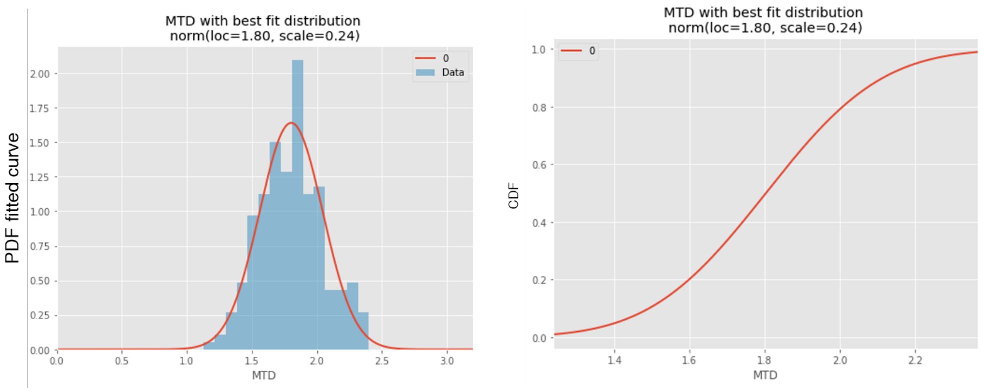
(a) Probability distribution function (b) Cumulative distribution function

Figure 6.7: Result of the fitting process; loc= Mean, scale= St.Deviation

High quality area

The same applies for the high quality area where the values are:

- μ=1.80 mm
- σ=0.24 mm



(a) Probability distribution function (b) Cumulative distribution function

Figure 6.8: Result of the fitting process; loc= Mean, scale= St.Deviation

6.1.2 Uniform measurement

The second group of measurements took place on the first FFX strip. In this case the measurements were not dense because the surface analysed was bigger (60 m x 5 m) and the number of samples was considerably lower (105 samples).

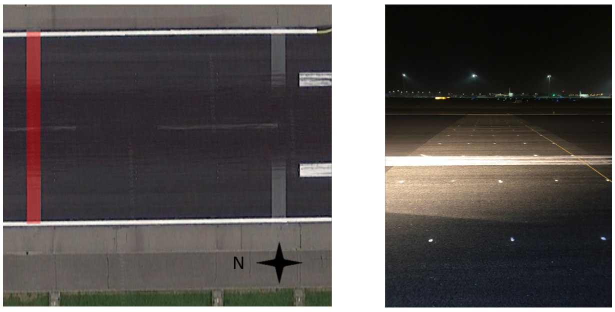


Figure 6.9: Location of the first strip

The total surface was divided in 5 transverse strips and 11 longitudinal strips for a total of 105 squares of 1 m^2. In this case it is assumed that the measurements of the ELATextur Machine represent the uniform TD of the entire square. In the first case this assumption was coherent due to the close dimension of the sampling machine and sampling unit. In this scenario this assumption is weaker due to the high difference between the sampling unit and the actual area measured. But the scope in this case is not to detect the behaviour of the surface properties in detail, but to understand if the properties of the surface are detectable in a large area. This is possible accepting a lower level of precision.

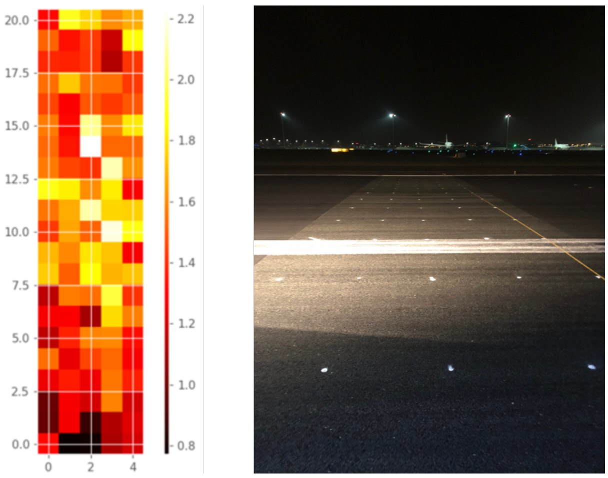


Figure 6.10: Uniform distribution of points. Axis labels represent the number of surface squares

Although the preparation and dismissal took more time due to the large area of analysis, the measurement session in this case was shorter (around 1 hour). Figure 6.10 shows how the measurements have been performed and what the outcome was.

Also in this case it is possible to find an area that had a better quality and another with a concentration of low TD values. The low quality area is present over the whole width of the strip with a behaviour that is similar to the one on the square measured previously. It is also possible in this case to separate the two areas as shown in figure 6.11.

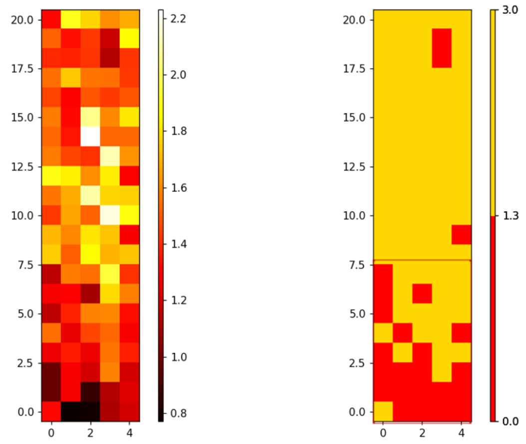


Figure 6.11: Identification of good and low quality area. Axis labels represent the number of surface squares

This shows that the manufacturing process affects the surface with similar patterns. The paving of this two strips was executed with one paver, this means that the influence affects the entire width of the paving machine. Also the waterjetting process affects the quality of the surface but in this case the width of the machine is only 2 meters and the influence is less homogeneous. This suggests that the different areas are more likely determined by the paver than the waterjetting process.

Fitting process

Also for this stretch the values will be fitted with a normal distribution. The outcome is shown in figure 6.12. It is possible to notice that in this case the lower value of the distribution is less than 1 mm, but the average is still above the Schiphol requirements. In fact the Mean μ is 1.50 mm and the St.Deviation σ is 0.28 mm.
Compared to the dense area measured previously, the quality overall is lower but the St.Deviation is still the same. This means that in general the surface has a lower MTD but the values are distributed around the mean similarly. The distribution of the quality of the surface remains the same in general.

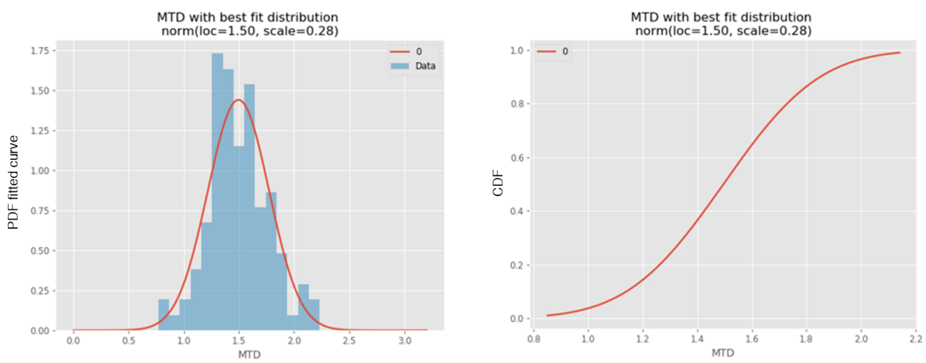


Figure 6.12: Probability distribution function and cumulative distribution function; loc= Mean, scale= St.Deviation

Also in this case it is possible to fit the two different areas identified in figure 6.11. Figure 6.13 shows that in the low quality area the Mean is 1.36 mm and this still fulfils the Schiphol requirements. The same, consequently, can be said for the high quality area were the surface has a MTD of 1.65 mm.

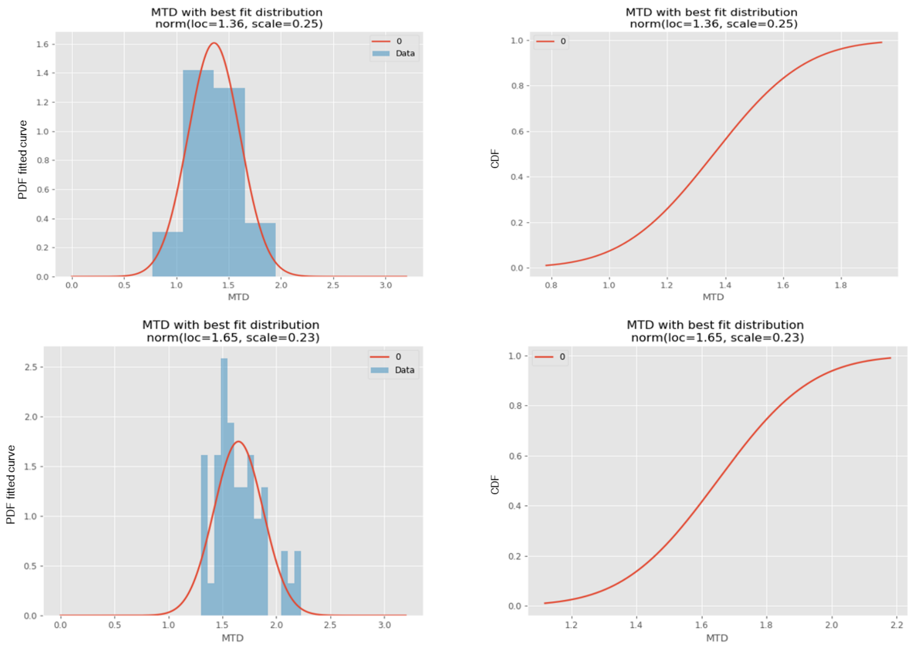


Figure 6.13: Fitting process of low (top) and high (bottom) quality pavement; loc= Mean, scale= St.Deviation

In both cases the St.Deviation remains around 0.25 mm that is in accordance with the high density measurements. This testifies how the Flightflex® manufacturing process provides a certain value of homogeneity to the surface.

6.1.3 ASK Measurements

In the last hours available that night it has been possible to take 100 measurements from the ASK strip identified in figure 6.14.

The number of samples were 100 with a Mean μ of 1.54 mm and a St.Deviation σ of 0.12. The results are plotted in figure 6.15.

It can be observed that the ASK fulfils the requirements imposed by Schiphol and the EASA regulation but the mean is lower than that of the FFX surface. But the most important feature of the ASK layer is its very low St.Deviation. In fact this is 50% lower than that of FFX. The homogeneity of this material is very high, this is due to its manufacturing process. As explained in chapter 2 the production process of the ASK gives less room for variance and uncertainty. The glue is laid and being a synthetic material this has a high homogeneity. Moreover the basalt grit

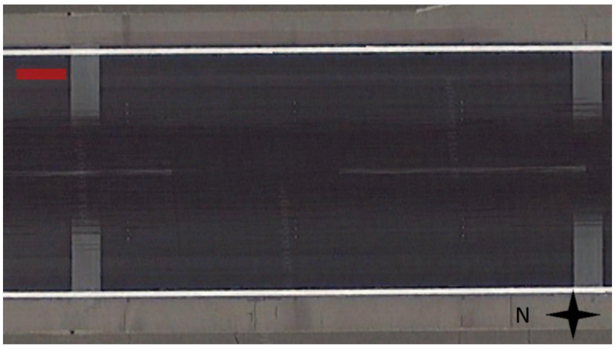


Figure 6.14: Location of ASK Measurements

mixture used to provide texture and friction is the result of a though and severe selection process that guarantees a high homogeneity level of the aggregates.

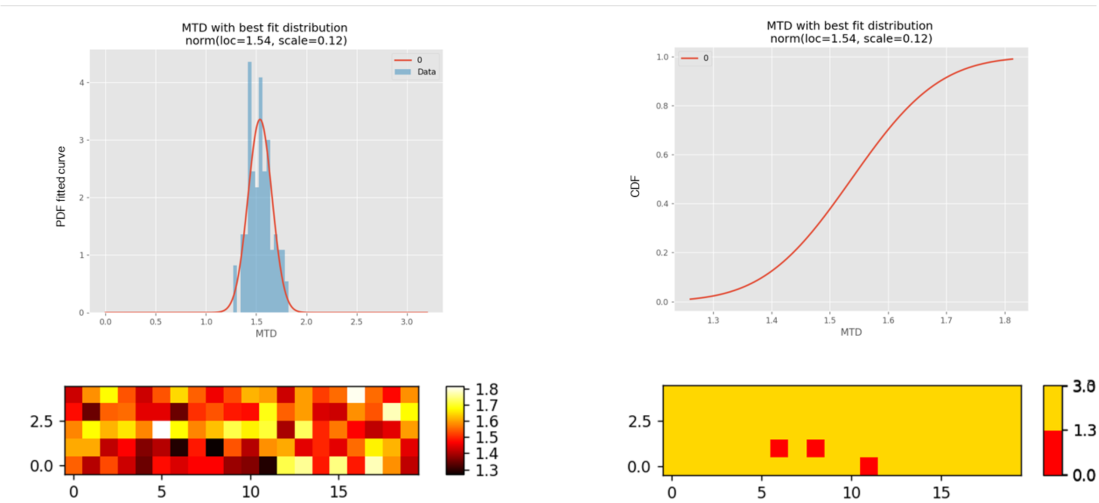


Figure 6.15: Results of ASK measurements analysis. Axis labels represent the number of surface squares; loc= Mean, scale= St.Deviation

6.1.4 Conclusion of the measurement process

Table 6.1 presents an overview of the results obtained from the measurements.

	Mean[mm]	**St.Deviation [mm]**	**Variance [mm]**	**N.Samples**
Dense Matrix	**1.68**	**0.28**	**0.08**	**400**
High quality group	1.8	0.24	0.06	220
Low quality area	1.52	0.25	0.06	180
Uniform sampling	**1.5**	**0.28**	**0.08**	**105**
High Quality Group	1.65	0.23	0.05	50
Low Quality Group	1.36	0.25	0.06	55

Table 6.1: Overview Results of Measurements Phase

The quality of the Flightflex® pavement surface is high and fulfils both Schiphol and EASA requirements. It can also be observed that in both strips there are low and high quality areas. The low quality areas have a lower TD than the average but maintain the same variance. This means that, although the quality of the surface decreases or increases, the homogeneity remains almost constant. This is the effect of the manufacturing process. If the homogeneity of the asphalt remains the same over the entire width of the strip, this suggest that the mixture was homogeneous but the paving or compaction process could have influenced the final results.

Compared to the ASK measurement, the higher variance of the FFX measurements and the presence of a high and low quality surface testifies the need of a tailored sampling methodology. The ASK does not present different quality areas and has a low Variance. This would suggest that the TD on the surface is uniform. With the FFX there is the risk of having a low or high quality area and this needs to be taken into account in the sampling process. In particular it has to be avoided to measure only one type of surface quality because the resulting MTD would not be correct.

In the next chapter the information will be used to simulate the surface and make them more similar as possible to the real ones.

6.2 Surface simulation

In this section the simulation process of the surfaces will be described. To simulate the process in python a series of rules and boundary conditions have to be established. The two strips in figure 6.1 have the width dimension of the strips that are built during the construction process. They can be used as surface units that will be repeated for the creation of the final surface. For this reason some patterns of the surface have to be identified and will be part of all the surface units determined in the next phases of this research.

From the analysis of the measurements obtained, the following rules have been imposed for a strip of FFX:

- A surface strip is characterised by a percentage of low quality texture. This is represented by a normal distribution with Mean 1.36 mm and St.Deviation 0.25 mm. Those values are taken from the fitting process of the low quality area of the dense measurements. But the values can be changed to increase or decrease the quality of this patch.

- The lower quality areas cover the entire width of a simulated strip. The width dimension is the same as the paver width: 4 m.

- The real runway surface will be made by a sequence of strips with the same manufacturing process.

- The distribution of the dense area (400 samples) needs to be perturbed in order to take into account a lower quality mixture. It has been seen in the second group of measurements that the minimum value was lower than 1 mm. The simulated surface can be represented then with lower values to take into account defects in the production process.

- The variance of the high and low quality surface should be similar.

- The percentage of low quality areas should vary to take into account different manufacturing process influences.

These main guidelines and rules are the basis in the construction of the artificial surface.

The measurements presented previously are based on strips with a width of 5 m, but the surface needed is 60 m wide and 500 m long. To obtain a surface of such dimensions a specific construction process needs to be created. The main concept is to add a sequence of strips and create the final surface. This is in accordance with the manufacturing process because the paver normally works with a width of 4 m and the strips are paved in sequence.

Here a remark is needed. There are two types of maintenance process:

- Continuous maintenance process: in this case the strips paved are continuous and long, reaching also a distance of 500 m. The scope is to reduce as much as possible the number of transverse joints. In this process some areas of different quality are still present due to stops, pauses, loading of new asphalt, and variation in the asphalt mixture due to waiting time of the truck or production imperfections.
- Clustered maintenance process: this process it typical for night maintenance operations. It consists in dividing the surface in short transverse sections and pave each one completely before to advance the next one. In this case the strips are shorter with a distance of 100-120 m and for this reason more transverse joints are present in the final surface. The number of strips in the transverse direction remains constant though.

During the construction process the paver lays the asphalt in parallel strips. To ease the simulation process it has been assumed that the width of a strip is equal to the width of the paver and that the length of a strip is 60 m. The latter dimension has been assumed taking into account the uniform measurements. In that case a percentage of the longitudinal dimension of the strip was characterised by low quality asphalt. The consequence of this assumption is that to have a total strip with a length of 500 m, 10 strip units have to be added in longitudinal direction.

The procedure for the creation of the surface will be the following:

- Define the dimension of a single strip.
- Define a percentage of low quality surface for each strip. To increase the variability and make the surface more realistic a normal distribution of the percentage will be used.
- From the dense matrix measurements define the best fit distribution of the low quality and high quality areas are taken.
- Take the inverse of the cumulative distributions and give as input values from a normal distribution between 0 and 1. This defines a series of TD values.
- Insert the values in the matrix taking into account the different areas.
- Vary the position of the low quality area in each strip.
- Add the strips in transverse and longitudinal direction to create the final matrix.

The assumptions made in this case are aimed to define a patch unit that is multiplied in longitudinal and transverse direction to form the total surface. Each strip will follow the rules described previously. Figure 6.17 describes the assembly process.

The final matrix is then influenced by the nature of each strip unit. It has to be noted that each strip is generated from the sequence of rules defined in the previous section. Each strip being generated by the inverse of the cumulative distribution will follow the imposed distribution but it

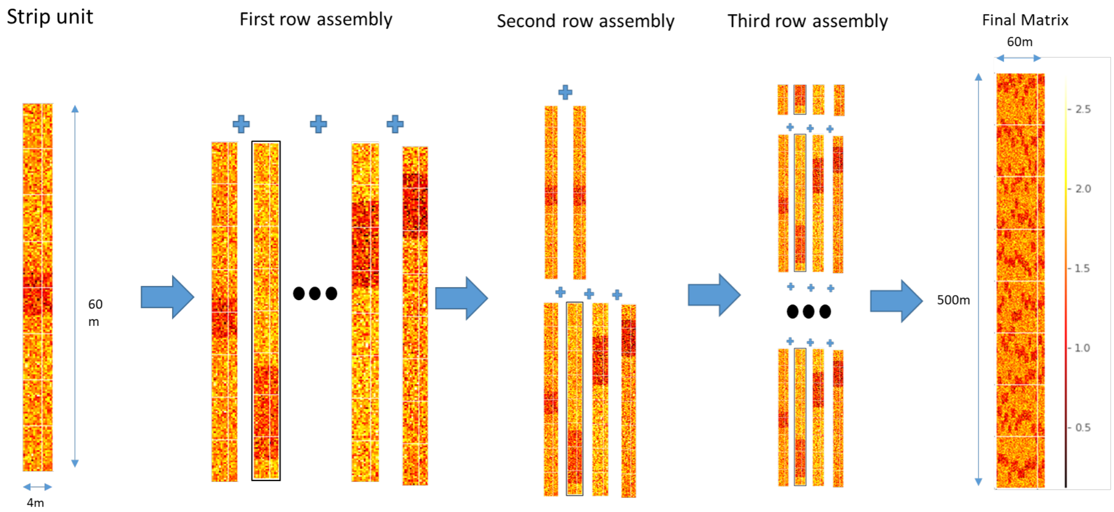


Figure 6.16: Assembly procedure of simulated surface

will also make each strip unique. This way of building the matrix is based on the manufacturing process and is aimed to simulate the real surface as much as possible. Each construction process is different because influencing events may occur. This simulation process is aimed to represent the main features of the construction process.

One of the main features of this simulation model is its flexibility. By changing some parameters, such as the percentage of low quality area per strip, or the means and variance of the distribution it is possible to obtain slightly different strips. This will be very useful during the simulation of the sampling methodologies performances. It will be possible to verify which sampling methodology behaves better when the surface quality changes to an overall better or lower quality.

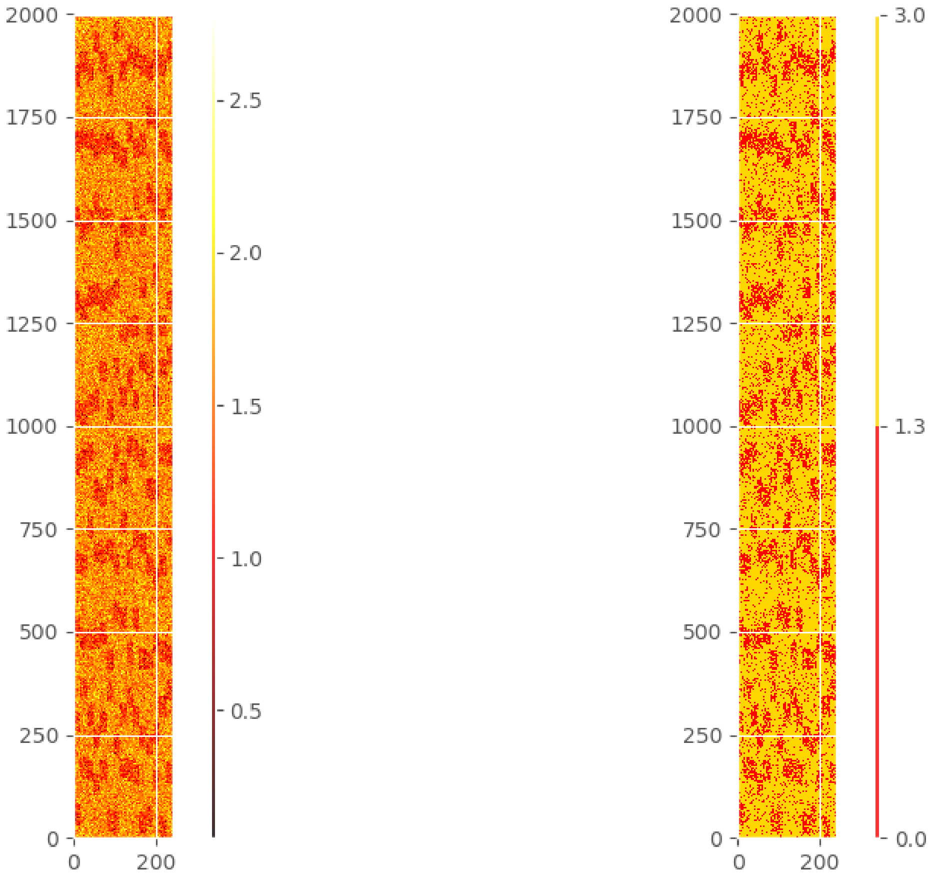


Figure 6.17: Final Surface Simulated. Axis labels represent the number of surface squares

CHAPTER 7

Analysis methodology and results

Now that the surface simulation process is completes it is possible to test the different sampling methodologies and observe how they behave.

The runway surface is entirely simulated with python. Inside the simulations all the TD values are known and consequently also the exact MTD is known. With this value it is possible to calculate the relative error between the real MTD and the mean of the TD values measured with the sampling methodologies.

The relative error is defined as:

$$\epsilon = \frac{MTD_r - MTD_s}{MTD_r}$$

with:

- MTD_r = Real Mean Texture Depth for the surface. This is the Average of the Texture Depth values of all the sample units composing the surface

- MTD_s = Mean Texture Depth of the samples collected.

Two methodologies are proposed for the performance simulation:

1. The first one is based on an iterative process. Having set a maximum threshold for the relative error as a requirement, the process starts by defining a minimum number of samples for each technique. This minimum number of samples is applied to the surface, then the relative error is calculated. If this value is lower than the threshold, the simulation stops and the minimum number of samples is defined. In case the relative error is higher the number of samples is increased and the process restarts. The cycle will stop when the requirement is met.

2. The second one is similar but consists in defining in advance the number of samples for each technique and verifies the relative error for each group of samples. Then the lowest number of samples that guarantees the required minimum relative error is selected. This way of proceeding impose to verify different numbers of samples and provides a wider overview of the behaviour of the surface. In the previous simulation strategy this was not possible. As an example, if the minimum ϵ is met with the minimum number of samples it will be impossible to evaluate how the sampling methodology behaves with a larger number of samples.

7.1 First sampling methodology

This simulation strategy is based on an iterative algorithm that is meant to stop when the minimum relative error is reached. In figure 7.1 the exact algorithm is represented.

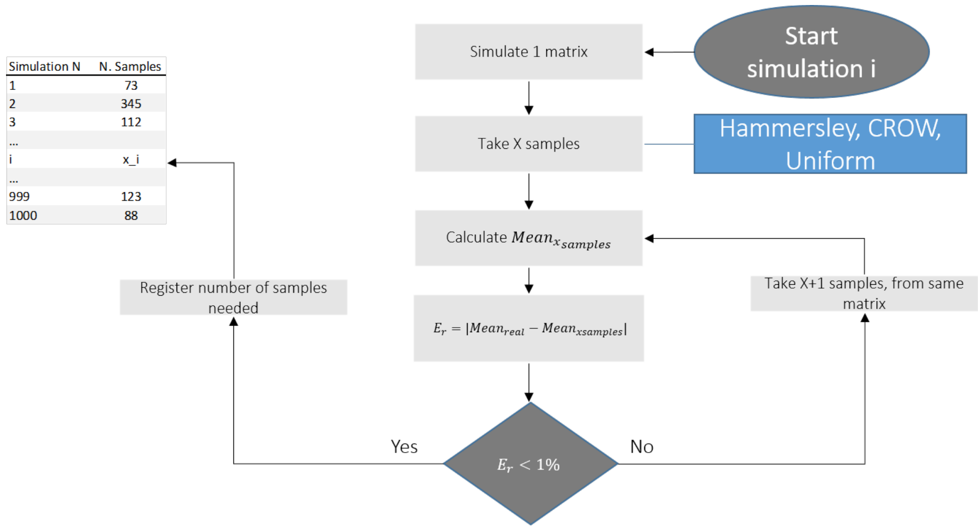


Figure 7.1: Flowchart of simulation algorithm for the first methodology proposed

The starting point is the simulation of one entire surface. When the surface is ready it is possible to calculate its real MTD that will be used for the Relative Error calculation. At this point the minimum number of samples X is used on the simulated surface and the mean of the TD values obtained is compared with the real MTD. If the requirement is met the simulation stops, if not the number of samples is increased and the procedure restarts. The cycle is executed for each sampling methodology.

When the simulation stops the number of samples that meets the requirement is registered in a matrix. At this point another surface matrix is simulated and the process is restarted. When 1000 values are stored in the matrix the total simulation process stops. This means that the surface is simulated 1000 times and the procedure above is executed from the beginning every time. All this tasks are executed for the three sampling methodologies and the data restored and compared.

This way of proceeding is an adaptation of a Monte Carlo simulation. The Monte Carlo method has wide application in different fields. In general it is based on the repetitive simulation of a process or a series of calculations using as input (controlled) random values for the system variables. The results of all the processes are then collected and outcomes based on statistical analysis are provided.

This also applies for this case study because each time a unique surface is simulated and then a mathematical process is applied. The results of all the simulations are collected in the final matrix and for each sampling methodology the mean is calculated.

Table 7.1 shows the results of the simulation for each sampling methodology. As already mentioned for each simulation the minimum value is stored and after 1000 simulations the mean is calculated. In this case the relative error threshold was fixed at 1%. This threshold is selected as the maximum acceptable relative error between samples mean and real MTD. In table 7.1 it can be seen that the methodology that provided the minimum relative error with the lowest number of samples is the CROW methodology.

Uniform		Hammersley		CROW	
Simulation No	**Min No samples**	**Simulation No**	**Min No samples**	**Simulation No**	**Min No samples**
1	73	1	145	1	85
2	345	2	273	2	195
3	112	3	68	3	15
...		...		...	
999	123	999	225	999	420
1000	88	1000	187	1000	362
Mean	144	**Mean**	165	**Mean**	99

Table 7.1: Paired t-test of most common TF families for Pearson Correlations

7.1.1 Robustness of the methodology

For the validation of the robustness and consistency of this methodology different cycles of 1000 simulations have been executed. Table 7.2 shows the results of three different cycles. It can be observed that the three cycles have different outputs. This shows that the process lacks robustness and needs more verification.

Simulations	Uniform	Hammersley	CROW
first cycle	144	165	99
second cycle	102	158	76
third cycle	132	189	102

Table 7.2: Simulations results or different cycles

To define and explain such behaviour more simulations are run. In this case it is decided to simulate only one surface and regularly increase the number of samples until they are 8000. For each number of samples the relative error is calculated, then the number of samples is increased and the same does the news relative error calculated and so on.

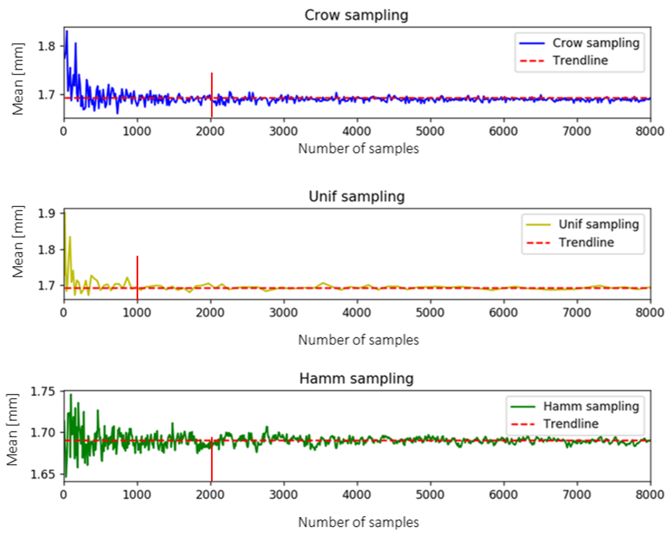


Figure 7.2: Verification of mean behaviour related to the variation of number of samples

The scope of these procedure is to have an overview of the relative error behaviour with different numbers of samples. Similarly for each number of samples it is possible to calculate the MTD_s and verify how it behaves with different number of samples. The outcome is expected to be similar because it only represents a second point of view of the same mathematical problem.

Figure 7.2 shows that for less than 1000 samples the mean remains unstable with the uniform sampling methodology. The Hammersley and CROW methodology take longer to stabilise but after 2000 samples the asymptotic line is reached. For this reason the first simulation methodology was providing different results: the minimum relative error requirement is met with a very low number of samples and the probability to go beyond the 1000 samples is extremely low.

From a practical point of view and to facilitate the understanding also the evaluation of the relative error related to the number of samples is presented. Figure 7.3 shows that in terms of relative error the curve behaviour is similar to that of the mean TD. In this case it is observed that the relative error has a high variation until 1000 samples for the Uniform distribution, and until 2000 for the Hammersley and CROW distribution.

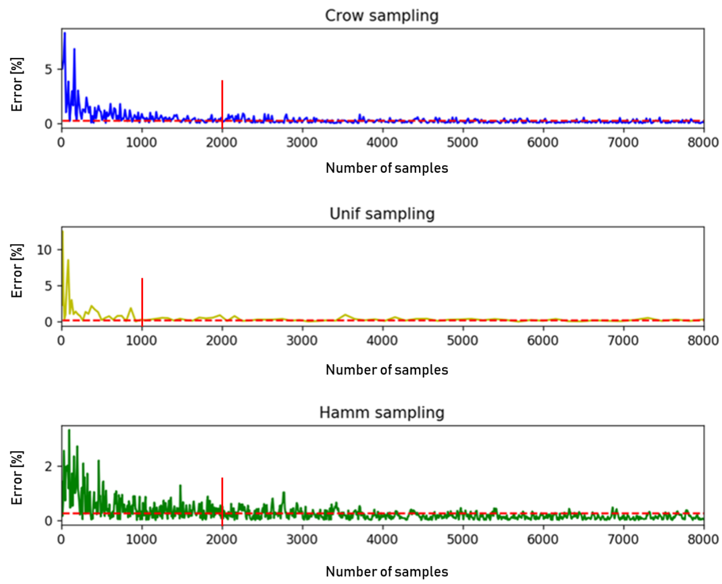


Figure 7.3: Verification of Relative Error behaviour related to the variation of number of samples

This last Analysis has highlighted the limits of the first simulation methodology due to high variability of the surface texture. To reach a stable behaviour of the relative error and a high lever of robustness it is necessary to work with more than 1000-2000 samples. In practice such an amount of samples cannot be measured during a quality control session. As described in chapter 2 the measurements are taken with the ELAtexture machine that reduces the measurement time. But still the time available for the measurements is limited and measuring 1000 locations would take more than 8 hours. Time that is not compatible with Schiphol's operational schedules.

With the second simulation methodology it will be analysed whether it is possible to achieve a high consistency and robustness with a lower number of samples.

7.2 Second sampling methodology

For the second sampling methodology the procedure changes. The first step is to identify for each sampling methodology different number of samples. The goal of this simulation methodology is to use these limited number of samples and analyse their average relative error with 1000 different surfaces. This prospective is different from the previous simulation methodology. In the previous case the simulation stopped if the threshold requirement was reached with a limited number of samples. Thus the behaviour of the relative error related to more samples, for that single simulation, remains unknown.

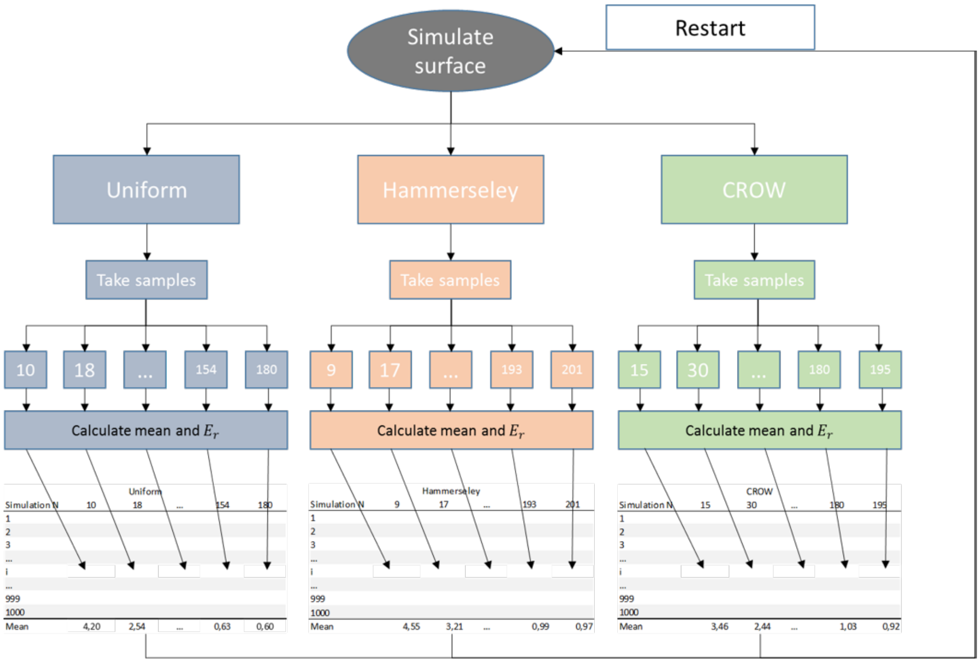


Figure 7.4: Flowchart of second simulation methodology

With this methodology the number of samples are fixed and they are all used on the same surface. There is no loss of information, but there is a downside: if none of the defined numbers of samples meets the error threshold value, then more samples need to be planned and the simulation runs from the beginning. Moreover, to ensure consistency of this process, all the sample methodologies are applied on the same simulated surface. This enables to understand not only how these methodologies behave on average but also how they relate to the same surface.

Also for this simulation methodology a specific algorithm is defined in Python. The flowchart in figure 7.4 provides an overview of the steps that constitute the simulation process. The main tasks are:

1. Define and list the number of samples for each sampling methodology. To better understand, the number of samples selected for this case study are given in table 7.3. The increment rules for each sampling methodology are based on the rules defined in chapter 5.

2. Simulate one entire surface as it has been defined in chapter 6

3. For each sampling methodology try all the numbers of samples set at point 1

4. Calculate the relative error for each number of samples of each methodology

5. Store these values inside a matrix
6. Simulate another surface and restart the process
7. Stop when 1000 surfaces are simulated
8. Calculate the average of the relative error for each sampling number for each methodology

Sampling methodology																								
Hammersley	9	17	26	34	43	51	59	67	76	84	93	101	110	118	126	134	143	151	160	168	177	185	193	201
CROW	15	30	45	60	75	90	105	120	135	150	165	180	195											
Uniform	10	18	28	40	54	70	88	108	130	154	180													

Table 7.3: Selection of the number of samples for each methodology

Standare Deviation of the simulated surface

In section 6.2 the flexibility of the surface simulator was mentioned. This property proves to be useful during this simulation, because it is of interest to understand how the sampling methodologies behave when the configuration of the surface properties vary.

Four factors can be modified to influence the surface property:

- The uniform distribution's Mean of the high quality area.
- The uniform distribution's Mean of the low quality area.
- The percentage of low quality area on a single strip.
- The noise factor of the low quality area distribution values.

The last may seem confusing, for this reason it has to be explained in detail. As described in chapter 6 the surface is characterised by two normal distribution functions, one for the high quality values and one for the low quality values. Figure 7.5 shows the two distribution curves. Their Mean can be changed or influenced as shown before. But for this case study the values obtained from chapter 6 are used. Moreover the Standard Deviation was close to 0.25 mm in almost all configurations and for this reason it has been kept fixed for all the simulations.

In mathematics the representation of an unexpected variation on a distribution is expressed by a factor called "noise" [4]. This can be obtained by adding or removing to the original distribution a secondary distribution that in general has μ=0 and a specific Standard Deviation. In this case the need is to evaluate a decrease of the surface quality so the worst scenario is simulated by subtracting the noise from the distribution of the low quality area distribution.

Figure 7.5 shows the effect of the noise. The blue curve is shifted to the left side due to the subtraction of the noise from the original distribution. The shift is a pure translation to the left due to the fact that each value of the original probability distribution function is reduced by the noise. The final low quality distribution curve became the green one.

Using the input values from the measurements and changing some of the parameters, it is possible to simulate the surface in different conditions. The main concept of this simulation process is to be able to have different configurations of the surface and see how the different sampling methodologies perform.

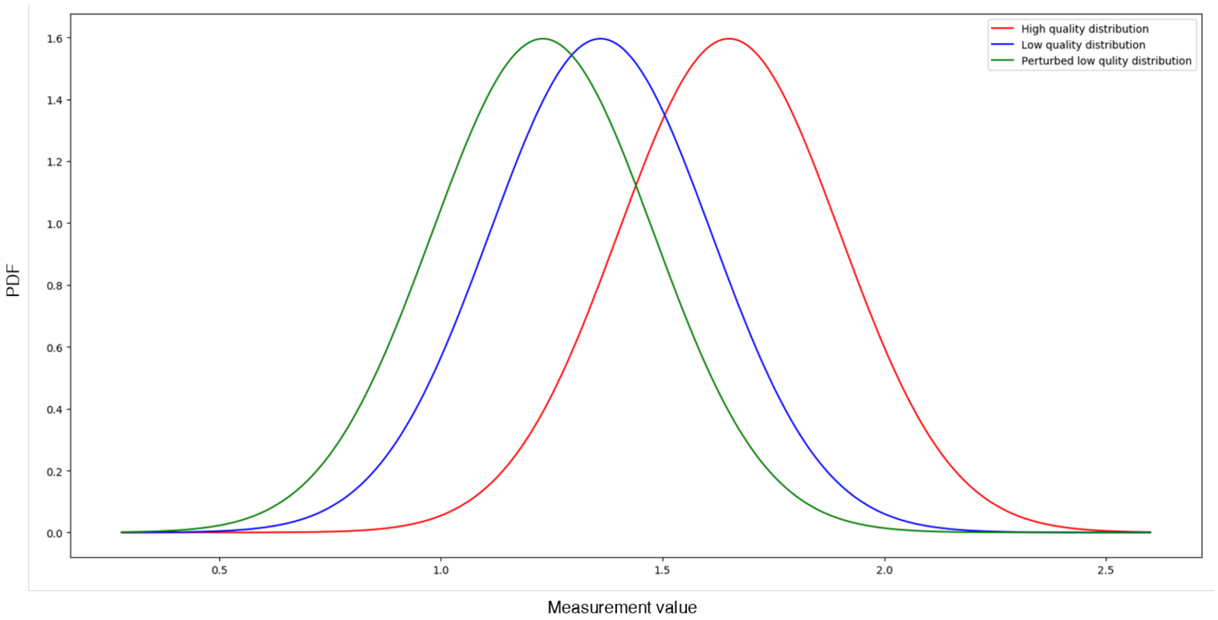


Figure 7.5: Representation of distribution curves and perturbing effect

In order to avoid misunderstandings regarding this simulation it is very important to remember that the scope of this procedure:

It is not to simulate a surface that meets the Schiphol or EASA requirements. But to simulate a surface that presents the manufacturing process patterns and evaluates which sampling methodology performs better in the identification of the real MTD

Having this concept in mind it is legit to consider the simulation of surfaces that present a lower quality than the real ones. If the sampling process proves to be effective it will be able to detect this lower quality.

It has already been mentioned that the Mean of both high and low quality distributions have been taken from the results of chapter 6 and will be kept fixed during the simulations. This means that the two variables that will be allowed to change are: the percentage of low quality area per strip and the intensity of the noise. These two parameters will allow to simulate surfaces with lower quality than the real ones. The goal is to verify the efficiency of the methodology in case of very low quality surfaces.

7.2.1 Results of the simulations

Having a clear understanding of how the simulation works, it is possible to describe which parameters have been used for the simulations and the related results.

In all the simulations the following inputs have been used:

- μ= 1.65 mm, σ = 0.23 mm for the high quality surface values
- μ= 1.36 mm, σ= 0.25 mm for the low quality surface values

Overview of all the simulation methodologies

For the simulations the noise and percentage of low quality have been defined as follow:

- The noise factor has been set as a value taken from a uniform distribution of values between 0 and 0.3. This means that for each surface simulation the noise was slightly different. This simulates a manufacturing process that contains imperfections.
- For the percentage of low quality area per strip it has been decided to create different categories. Each category represents a uniform distribution with a value between 0, 0.1, 0.2, 0.3, 0.4, 0.5. For each category of values 1000 surfaces have been simulated.

Table 7.4 shows an overview of the results of this simulation. The different surfaces are represented by the two parameters mentioned above. The two values used to represent the different surfaces are shown in the first column of each table. More specifically:

- The first is related to the percentage of the low quality area on each strip. The value represents the extreme of the uniform distribution (i.e. 0.2 represents the extreme of a uniform distribution between 0 and 0.2).
- The second represent the intensity of the noise. Also this value is represented as the extreme of an uniform distribution.

As an example "0.3_0.2" represents a surface with a a noise that come from a uniform distribution of values between 0 and 0.3 and a percentage of low quality area that can have a value between 0 and 0.2.

CROW

Type of surface	15	30	45	60	...	90	105	120	135	180	195
0.0_0.0	3,46	2,44	1,96	1,79	...	1,42	1,33	1,16	1,16	1,03	0,92
0.3_0.1	3,76	3,21	2,99	1,84	...	2,82	1,38	1,29	1,21	1,01	0,99
0.3_0.2	4,07	3,38	3,29	2,05	...	3,12	1,50	1,32	1,22	1,05	1,02
0.3_0.3	3,95	3,49	3,36	1,94	...	3,22	1,52	1,39	1,29	1,07	1,06
0.3_0.4	4,44	3,94	3,79	2,10	...	3,55	1,64	1,43	1,29	1,17	1,11
0.3_0.5	4,26	3,97	3,83	2,06	...	3,68	1,63	1,45	1,37	1,16	1,12

Hammerseley

Type of surface	9	17	26	34	...	160	168	177	185	193	201
0.0_0.0	4,55	3,21	2,58	2,28	...	1,04	1,01	1,02	1,01	0,99	0,97
0.3_0.1	3,85	2,93	2,31	2,05	...	0,95	0,93	0,89	0,87	0,84	0,84
0.3_0.2	3,96	2,87	2,41	2,08	...	0,94	0,92	0,93	0,89	0,88	0,87
0.3_0.3	4,11	2,90	2,41	2,06	...	0,96	0,95	0,93	0,92	0,90	0,88
0.3_0.4	4,14	3,16	2,50	2,20	...	1,02	1,00	0,95	0,96	0,92	0,90
0.3_0.5	4,29	3,25	2,49	2,20	...	1,01	0,98	0,98	0,95	0,92	0,91

Uniform

Type of surface	10	18	28	40	54	70	88	108	130	154	180
0.0_0.0	4,20	2,54	1,89	1,41	1,22	1,04	0,88	0,77	0,70	0,63	0,60
0.3_0.1	3,88	2,33	1,61	1,28	1,46	0,84	0,78	0,70	0,58	0,58	0,48
0.3_0.2	3,87	2,37	1,68	1,26	1,45	0,90	0,79	0,65	0,60	0,59	0,50
0.3_0.3	4,10	2,40	1,67	1,36	1,59	0,92	0,80	0,68	0,62	0,60	0,50
0.3_0.4	3,91	2,43	1,81	1,38	1,65	0,95	0,80	0,69	0,64	0,62	0,50
0.3_0.5	3,95	2,51	1,84	1,42	1,69	0,93	0,81	0,69	0,63	0,62	0,49

Table 7.4: Results of sampling simulation

All the tables present in the first row a type of surface with 0 percentage of low quality and 0 noise (type of surface 0.0_0.0). This means that this surface is considered as a uniform surface without any low quality area. This would represent a surface with a perfect construction process without any influence of the manufacturing process. An ideal situation that both client and contractor want to achieve.

A graphical representation of the results in table 7.4 is shown in the following sections. Different plots are proposed based on the research scope. The first plot in figure 7.6 presents how the three sampling methodologies perform with ideal surfaces (0.0_0.0).

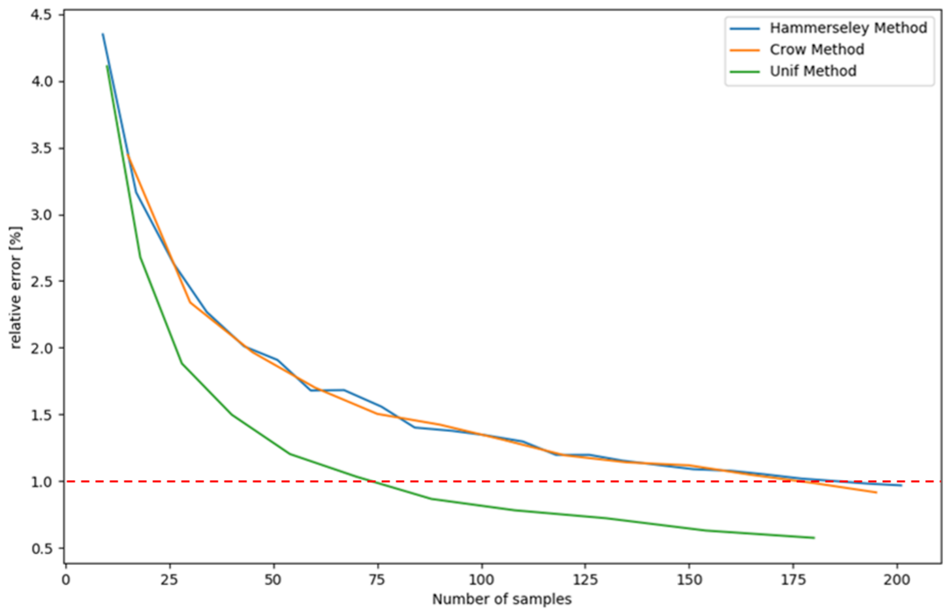


Figure 7.6: Results for each sampling methodology on a surface with no low quality areas.

Figure 7.6 presents a more consistent behaviour with respect to the first simulation methodology. In fact the sampling methodologies all present a decrease of the relative error when the number of samples increases. This is coherent with the U function proposed by the ISO regulations as can be observed in figure 3.1.

Figure 7.6 also shows that all the three sampling methodologies appear to be effective in reaching a relative error lower than 1% within the numbers of samples proposed in table 7.3. This means that no other numbers of samples need to be added. It can be observed that with an ideal surface the Uniform sampling methodology appears to be the most effective in reaching the 1% relative error with the lowest number of samples. With 70 samples a relative error of 1.04% is reached. Meanwhile, with the Hammersley and CROW methodology 160 samples are needed. This is certainly an idealistic situation that will not occur in practice but from a scientific perspective it is important to evaluate the general behaviour of these sampling methodologies with uniform surfaces.

Simulation of Hammersley for different surface types

In this case the focus is on the Hammersley Sampling Methodology. All the different types of surface results are plotted in order to evaluate how this sampling methodology performs with different surfaces.

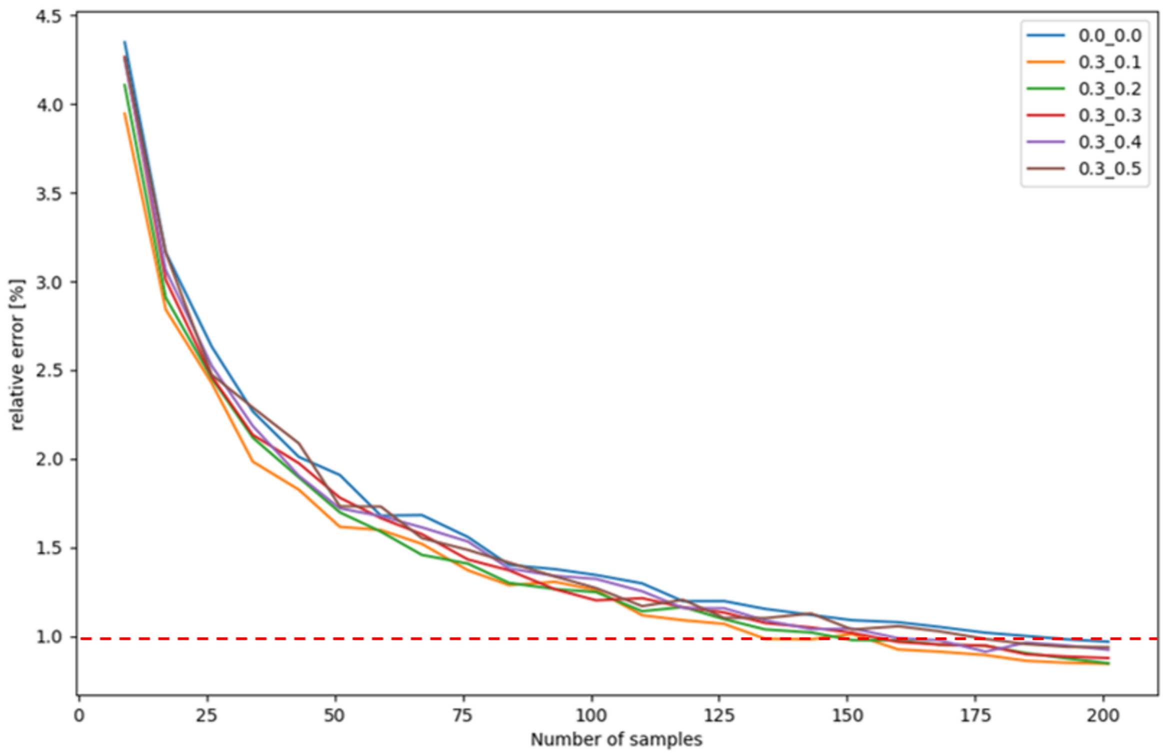


Figure 7.7: Hammersley sampling technique for different surface properties

Figure 7.7 shows that all the curves have the same behaviour. The trend is similar and the distance between the curves is negligible. This means that the Hammersley methodology is not affected by the manufacturing process. The justification is found by the fact that the construction process creates areas of low quality texture with specific patterns but the locations of the Hammersley samples are random and do not follow a fixed structure. The probability of having more sampling locations in the same low quality area is then very low. No relation between the sampling technique and the construction process is then found.

It has to be mentioned that also when the noise of the low quality area is increased the effect on the sampling methodology is negligible. This is a second evidence of the lack of correlation between the sampling methodology and the manufacturing process. The downside of this technique is the fact that 160 samples are required to reach a 0.96% relative error.

Simulation of Uniform for different surfaces types

The sample plotting process has been applied to the group of results of the Uniform Methodology.

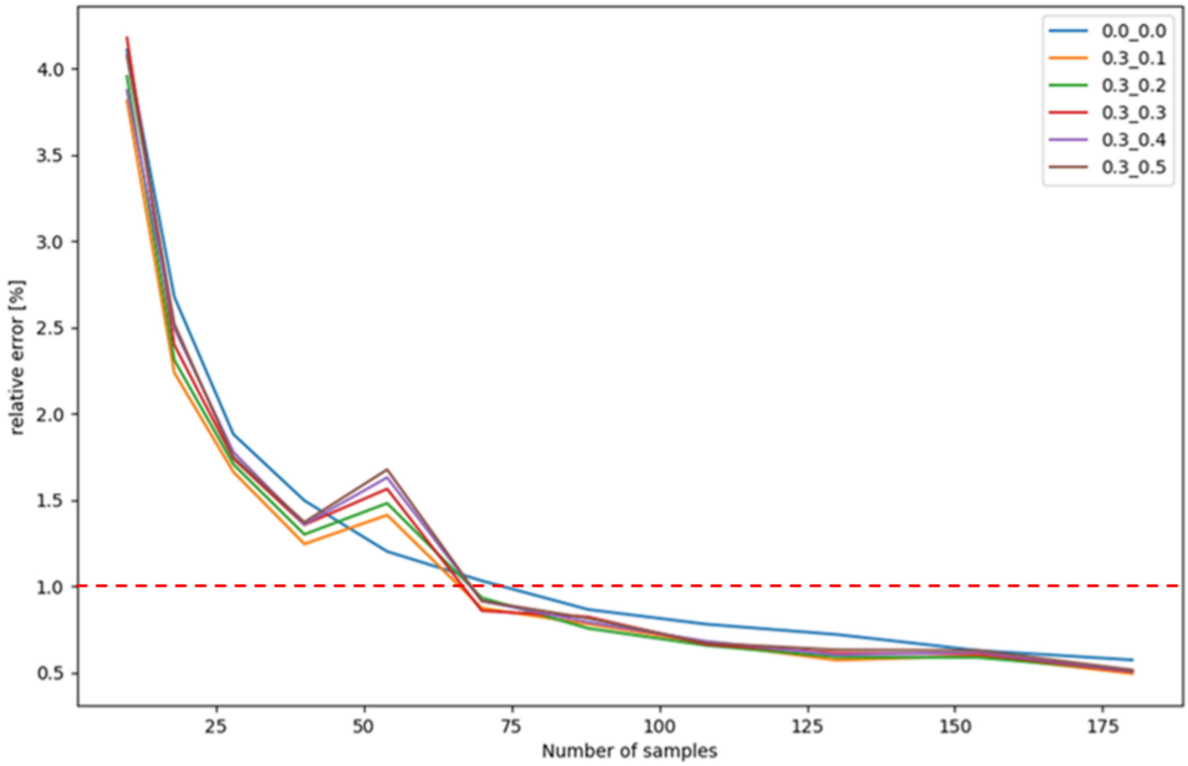


Figure 7.8: Uniform sampling technique for different surface properties

In this case the situation is slightly different because the behaviour of the curves does not follow completely the blue curve that represents the surface with no low quality areas. A trendline representing the other 5 lines would be very similar to the blue line because the overall behaviour of the curve is the same. But it is clear that all the disturbed surfaces present a particular peak when 55 samples are imposed.

This is due to the fact that in this particular sampling configuration a higher percentage of samples are located on the low quality areas of the surface. The simulations create 1000 different surfaces and each surface is different but maintains the same manufacturing signature. Every time it is simulated the surface presents a series of strips with different locations of the low quality area. But the number of strips, the percentage of low quality area and the noise intensity remains the same. This preserves the manufacturing signature. The fact that this peak is present in each simulation testifies that there is a correlation between the sampling methodology and the manufacturing process for this specific number of samples. Another proof of this correlation comes from the fact that the peak is present also when the noise is increased.

This curve behaviour is in accordance with the findings of Colosimo et al. In their researches they obtained similar peaks and a similar configuration of the curves [8].

Simulation of CROW for different surfaces types

The last sampling methodology that has to be plotted is the adapted CROW methodology presented in chapter 2. In this case the sampling methodology is related to the manufacturing process although the original scope of this method was to test the paving quality.

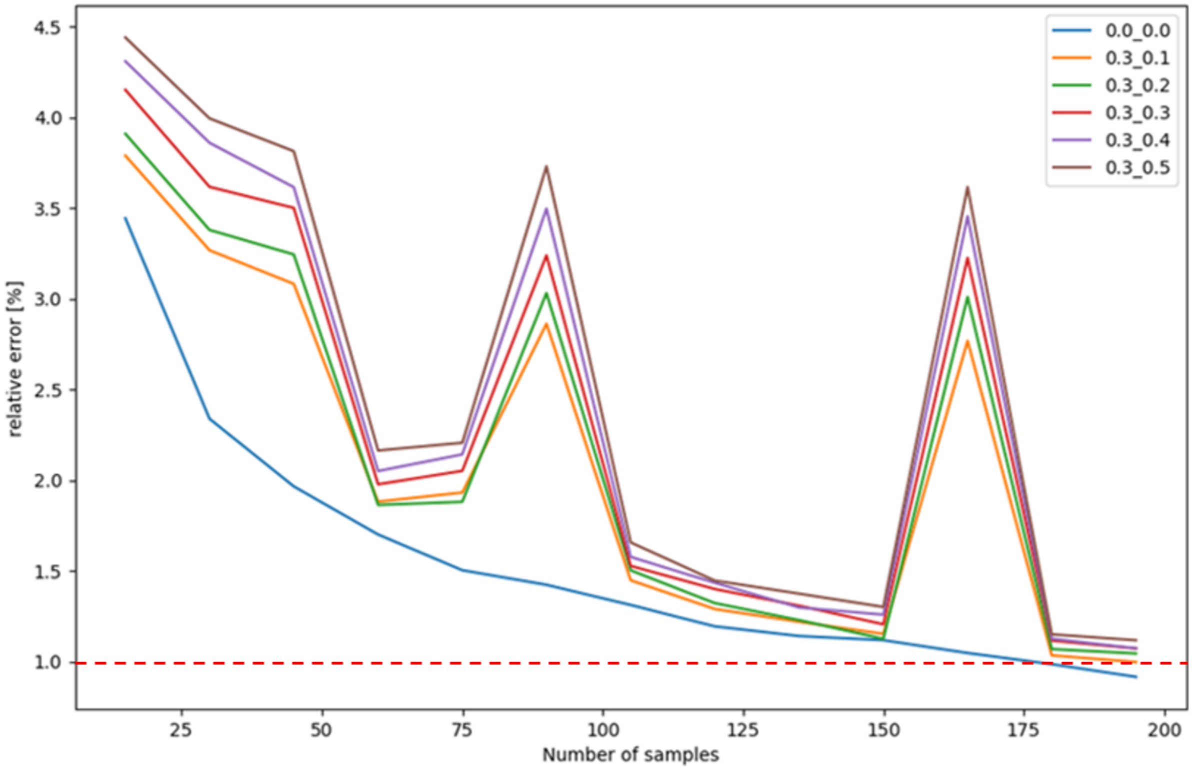


Figure 7.9: CROW sampling technique for different surface properties

The results are slightly different with respect to the previous cases. But it is still possible to say that the general trendline of the curve is maintained. Three main peaks are present and the reason is the same as the one for the Uniform Methodology. The surface signature and the sampling methodology enter in relation and the samples taken are mainly located on the low quality areas of the surface. In this case a sequence of three sampling locations are drawn closer to each other. This sampling distribution was originally meant to check the paving quality at the extremes of the paver and the compactors. For this reason, in this technical context, if one of the three points is located on a low quality strip most likely the two adjacent points will be included in that area too. The probability of having a correlation between the manufacturing pattern and the sampling methodology is higher and determines a major relative error. The three peaks increase when the noise is increased. This is the proof that a higher number of samples is located in the low quality areas. With higher noise the difference between the samples means and the real mean of the surface is greater.

Please note that the scale of this graph is very low. The vertical axis has a maximum value of 4.5% relative error. If the scale would have reached 100% then those peaks would have not been detectable. From a scientific perspective an error of 3-4% is considerable and is object of investigation, in particular for the mechanical production industry. In pavement construction industry an error of 4% could still be considered acceptable. This is because for a runway strip of 500 m length and 60 m width there are 480,000 sample units and at the first peaks with 90 samples a real estimation of the MTD with an error of 3.5% is obtained. So with 0.019% of the total sample units it is possible to estimate the MTD value of the surface with an accuracy of 96.5%.

7.3 Overview of the results

The three sampling methodology techniques have been analysed with different simulation techniques. The first simulation technique has proven to not be consistent and robust because during the simulation process part of the information was lost. The iterations were forced to stop when the relative error requirement was met. For this reason it was not possible to evaluate the behaviour of the methodology with a large number of samples. It has been proven that the stability of the relative error was reached only when 1000-2000 of samples were used and this justifies the inconsistency of the first simulation technique. But to understand the intensity of the error committed by taking a lower number of samples the second simulation methodology was adopted.

More stability and coherence is brought with the second simulation strategy. A series of number of samples is selected and the behaviour of all the numbers of samples on the list is tested. It is proven that the results are coherent with the ISO regulation introduced in the literature review. Among the three sampling techniques the Hammersley is the only one that is not affected by the manufacturing process. Due to his structural nature there is no correlation between the sampling methodology and the patterns determined by the construction process. The situation with the Uniform and the CROW methodology is different. They are both influenced by the manufacturing process. The Uniform methodology is sensible when 55 samples are used, this is why a Peak is present in the graph. The CROW methodology is more sensible to the manufacturing process. The reason is that groups of three samples are taken and there is more probability to have a high concentration of samples in the low quality areas. This is also testified by the fact that the peaks increase when the noise is increased. The peaks present with the CROW and the Uniform methodology testifies the lower **reliability** of these methodologies. The presence of the peaks testifies a deviation from the general behaviour of the curves and thus represents measurement values that have a higher relative error than expected. These measurement techniques will have the risk to provide a MTD value lower than the real one.

	Number of samples	**Relative error**	**Type of surface**
Hammersley	160	0.96 %	0.3-0.3
Uniform	70	0.96 %	0.3-0.3
CROW	180	1%	0.3-0.3

Table 7.5: Presentation of number of samples corresponding to 1% or lower relative error

From the results it can be said that if the real MTD needs to be measured with a high reliability the Hammersley methodology is the most appropriate one. Because it is independent on the sampling technique, but compared to the other two strategies this requires more samples to obtain a relative error lower than 1%. Table 7.5 shows how quickly the methodology reaches a proper relative error. The Uniform method is the quickest but is also less reliable. In case of an ideal surface with no lower quality areas the Uniform is the most reliable and requires the least number of samples. The same behaviour is present also with the undisturbed surfaces (0.0_0.0). This proves that the performance of the different sampling techniques are similar in all the surface condition when the lower number of samples is required.

Chapter 8

Validation and Test

In this chapter the field experience will be described and the results presented. This will lead to a series of conclusions and comparisons with the simulation proposed previously. The field experience was aimed to enrich and validate the theoretical notions and the results from the simulations.

This part was divided in different phases:

- Analysis of the correlation between laser MTD measurement and Sand Patch Method
- Analysis of the effects of waterjetting on MTD
- Testing of sampling methodologies

8.1 Correlation between Elatextur and Sand Patch Method

As described in section 2.2, two methods are used by Schiphol and Heijmans for the TD measurements. The first one presented was the Sand Patch method and the second the laser method. The first is the older and more precise methodology and is able to measure also the hidden holes that are present underneath the aggregates. During this analysis the Sand Patch results will be considered the most precise and it will be calculated how much the Laser Method results differ from them.

The drawback of the sand patch method is the fact that it takes 3-4 minutes per measurement, while an ELAtextur measurement takes 12 seconds. The analysis with the laser methodology is different. This is executed with the ELATextur machine and it is considered less precise because the laser is not able to measure the hidden holes underneath the aggregates. The scope of this paragraph is to evaluate how much the two methodologies differ and to define if the ELATexture machine is a reliable tool for the quality control.

8.1.1 Correlation between the techniques

To answer this question 33 measurements have been taken with both techniques at exactly the same locations. The results are presented in table 8.1. The data shows that there is an important difference between the mean of the two values. The correlation between two sets of data is expressed by a factor called correlation factor defined as

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}$$

with:

- Cov(X,Y) as the covariance between the variable X and σ_Y
- σ_X as the standard deviation of X

- σ_Y as the standard deviation of Y

In table 8.1 the value of the correlation factor are shown.

Measurement	Sand patch	electronic	Rel.error
1	1.52	1.58	0.04
2	1.55	1.33	0.14
3	1.61	1.24	0.23
4	1.6	1.35	0.16
5	1.76	1.5	0.15
6	1.6	1.28	0.20
7	1.77	1.88	0.06
8	1.55	1.49	0.04
9	1.52	1.33	0.13
10	1.69	1.58	0.07
11	1.66	1.27	0.23
12	1.73	1.5	0.13
13	1.73	1.36	0.21
14	1.73	1.72	0.01
15	1.98	1.88	0.05
16	1.52	1.51	0.01
17	1.69	1.81	0.07
18	1.5	1.34	0.11
19	1.63	1.46	0.10
20	1.57	1.29	0.18
21	1.69	1.71	0.01
22	1.63	1.75	0.07
23	1.44	1.28	0.11
24	1.66	1.42	0.14
25	1.63	1.3	0.20
26	1.66	1.62	0.02
27	1.55	1.29	0.17
28	1.63	1.71	0.05
29	1.6	1.46	0.09
30	1.44	1.38	0.04
31	1.83	1.41	0.23
32	1.94	1.5	0.23
33	1.49	1.52	0.02
Mean	**1.64**	**1.49**	**0.11**

Table 8.1: Results values from Sand Patch and ELAtextur measurements

To try to understand the exact distribution of those values, the plot in figure 8.1 shows the scatter distribution of the measurement values and the trend that can be seen as a graphical interpretation of the correlation factor. **The correlation factor is 0,48 so partially correlated values**. The graph is characterised by the thick 45 degree line that represents the perfect correlation between the two variables. The closer the points are to this line, the higher is the correlation factor. **The fact that the points are located above the blue line means, in general, that the measurements are more conservative for the ELAtextur with the values below 1.5 mm. Above 1.5 mm the Sand Patch method appears to be more conservative but the number of measurements in this region is considerably low**

To validate this observation the relative error between the measurements for the ELAtextur data below 1.5 mm and above 1.5 mm are calculated for each pair of data. Finally the average is provided. Looking at table 8.2 it can be observed that for values below 1.5 mm the conservative error committed using the ELAtextur machine is around 15% meanwhile for values above 1.5 mm is 4%.

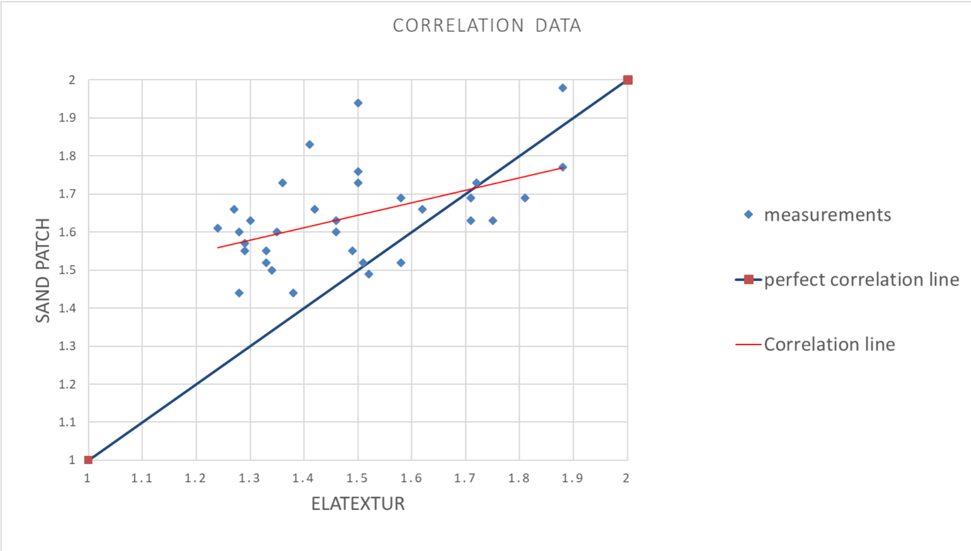


Figure 8.1: Measurements distribution and correlation

Measurement	Sand patch	electronic	Rel.error
1	1.33	1.55	0.14
2	1.24	1.61	0.23
3	1.35	1.6	0.16
4	1.5	1.76	0.15
5	1.28	1.6	0.20
6	1.49	1.55	0.04
7	1.33	1.52	0.13
8	1.27	1.66	0.23
9	1.5	1.73	0.13
10	1.36	1.73	0.21
11	1.34	1.5	0.11
12	1.46	1.63	0.10
13	1.29	1.57	0.18
14	1.28	1.44	0.11
15	1.42	1.66	0.14
16	1.3	1.63	0.20
17	1.29	1.55	0.17
18	1.46	1.6	0.09
19	1.38	1.44	0.04
20	1.41	1.83	0.23
21	1.5	1.94	0.23
Mean	**1.37**	**1.62**	**0.15**

(a) Values Below 1.5 mm

Measurement	Sand patch	electronic	Rel.error
1	1.58	1.52	0.04
2	1.88	1.77	0.06
3	1.58	1.69	0.07
4	1.72	1.73	0.01
5	1.88	1.98	0.05
6	1.51	1.52	0.01
7	1.81	1.69	0.07
8	1.71	1.69	0.01
9	1.75	1.63	0.07
10	1.62	1.66	0.02
11	1.71	1.63	0.05
12	1.52	1.49	0.02
Mean	**1.69**	**1.67**	**0.03**

(b) values above 1.5 mm

Table 8.2: Result of fitting process

8.1.2 Conclusion ad Recommendation

Although from a statistical point of view the amount of analysed data is considered too low for a complete analysis, it is possible to say that between the two methods of measurements there is a partial correlation (almost 0.5) but for ELAtextur values below 1.5 mm the average value is 15% lower than the Sand Patch value. The same error for values above 1.5 mm is considerably lower. But this means that the ELATextur results can be used because the error is conservative. The results proposed by the laser in the worst scenario will be lower than the real one. This means that if the ELATextur results already meet the Schiphol requirement then also the real MTD will do so.

Due to the large surface available and the need to have a proper evaluation of the MTD, the

ELAtextur method is considered more convenient and fast. But the previous analysis highlights the conservative nature of the results with a MTD value below 1.5 mm. For this reason, due to high requirement set by Schiphol, it could be taken into consideration to increase the values below 1.5 mm obtained with the machine with 10 to 15%. This way of proceeding, according with the results proposed would allow to increase the reliability of the ELAtextur and preserve operational time. This only in case more precision is needed. But as mentioned the error is conservative and there is no need if the results already meet the requirements.

Please note that these results and analyses are referring to Flightflex® surfaces.

8.2 Field Measurements

From the 27th to the 14th of April 2018, the Polderbaan (18R-36L runway) has undergone a maintenance process where a pavement section has been renewed with Flightflex®. Figure 8.2 presents the exact location of the construction site.

Figure 8.2: Location of the maintenance works on the Polderbaan

During the construction process it has been possible to measure the asphalt surface in the different phases of the process: after compaction and after the waterjetting process. The scope was to analyse the performance of the asphalt from the MTD point of view in the different phases to see if and how the manufacturing process influences the surface quality. This helps to verify if the properties of the simulated surfaces are reliable. In fact a full validation process is only possible if all the locations of the runway are measured and this would mean measuring 480,000 locations. The time available for the measurements was limited to a few hours. To obtain that amount of measurements, several weeks are necessary. This is not a possibility. For this reason during the maintenance process the goal was to take as much measurements as possible.

Unfortunately due to weather conditions and few delays, it was not possible to have a full time slot to execute the measurements. Most of the measurements were taken with the machinery still working on the construction site. For this reason the number of measurements is limited and it was not always possible to try all the sampling strategies.

8.3 Measurements on Taxiway

The first measurements were taken on the taxiway because the maintenance process started at this location. After the compaction of Flightflex® some measurements were taken with a uniform distribution as seen in figure 8.3. Green points represent TD values above 1.3 mm, yellow between 1 mm and 1.3 mm and red for values below 1 mm. First a group of measurements was taken from a straight line cutting the pavement in the transverse direction.

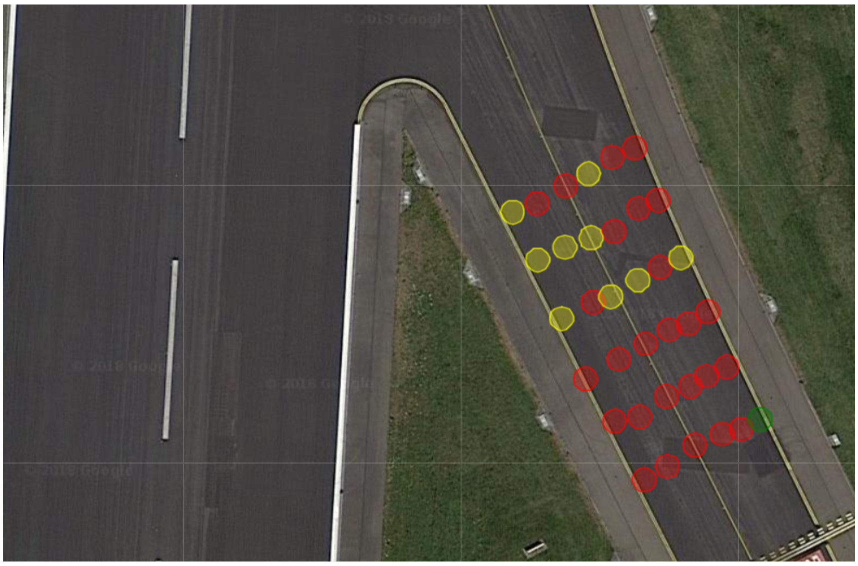
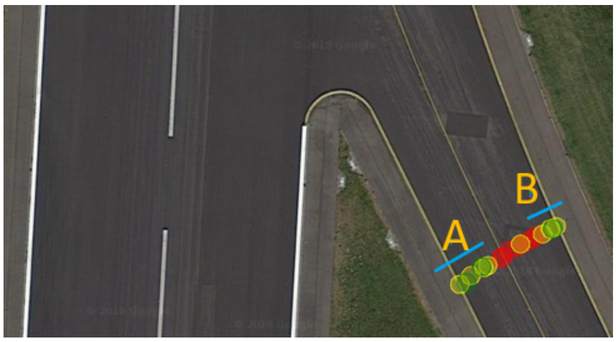


Figure 8.3: Uniform distribution in the taxiway

The samples were obtained before waterjetting and also after the shoulders of the runway was treated. Figure 8.4 shows that the treated shoulder presents a higher MTD but this is still not enough to reach the requested value of 1,3 mm set by Schiphol. The middle part, untreated, remains the same, below 1 mm in average. To facilitate the understanding, the two different edges of the investigated area have been called with the letter A and B. A for the one closer to the runway and B for the other.

(a) Surface before waterjetting



(b) Surface after waterjetting

Figure 8.4: Comparison of surfaces before and after waterjetting

The calculation presented in figure 8.5 shows an MTD increase due to waterjetting of 23% in the A part and 18% in the B part.

BEFORE WATERJETTING

	MTD		
0	0,99		
1	0,83	Mean	1,04
2	1,26		
3	1,13		
4	1		
5	0,9		
6	0,89		
7	0,73		
8	0,97	Mean	0,93
9	0,76		
10	0,99		
11	1,24		
12	0,84		
13	0,73		
14	0,97		
15	0,93	Mean	0,91
16	1,07		
Tot Mean	0,95		

+ 23%

+ 18%

AFTER WATERJETTING

	MTD		
0	1,03		
1	1,44	Mean	1,28
2	1,11		
3	1,74		
4	1,09		
5	1,18		
6	0,93		
7	0,86		
8	0,92	Mean	0,96
9	0,86		
10	1,17		
11	0,83		
12	0,91		
13	0,82		
14	1,12		
15	1,15	Mean	1,07
16	1,36		
Tot Mean	1,09		

Figure 8.5: Results of analysis taxiway surface

Some characteristics of the performance of the asphalt and the manufacturing process already arise. First, it can be see that after the compaction process the central part has a lower quality than the shoulders. The average value is 0.95 mm, lower than the EASA regulation requirement. The same appears from the uniform sampling where the mean MTD is 0.94 mm.

At the same time the waterjetting process proved to increase this characteristic of the asphalt by 20% from the original value. But compared to the measurements of March the overall values are lower. The reason for this is still under investigation and will help to understand how to improve the performance of the asphalt.

8.4 Measurements on the Runway

The second and more consistent number of measurements came from the runway. There, four main sets of measurements have been executed. The goal was to obtain an overview of the spread of the MTD on a major surface area.

8.4.1 Measurements on untreated surface

The first series of measurements are clearly seen in figure 8.6. We could consider this method as a semi-random one. The three lines have been taken in compacted strips in order to analyse the variation of MTD due to the compaction process. It was not possible to choose the location of the strips because the construction process was still ongoing and part of the runway was not paved yet.

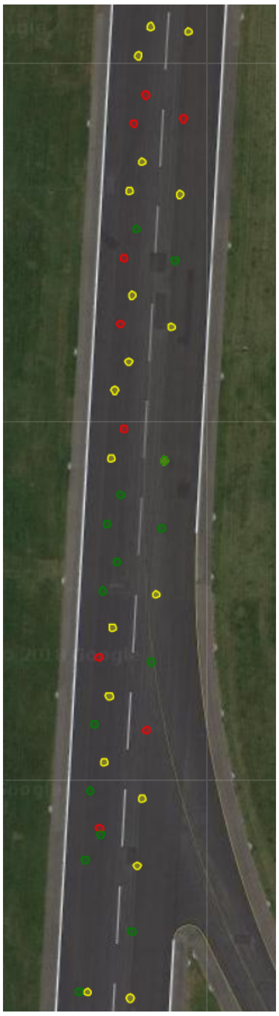


Figure 8.6: Measurement on untreated area

The data analysis provides the following output:

- Mean = 1.19 mm
- St.Deviation = 0.06 mm

From these data it can be said that the performance of the runway's pavement is superior compared to the taxiway. This is testified by the green circles in the central part of the runway. Moreover it is possible to recognise different quality areas. On the northern part of the runway a concentration of yellow and red spots is observed that represent a lower quality surface. Also can be seen that there are groups of three dots that allow to easily recognise the lower quality areas. The centre is characterised by the presence of some high quality areas. This means that during the compaction process, in some locations, the MTD already meets the Schiphol requirements. But uniformity is not achieved.

8.4.2 Measurement on semi treated surface

Due to time constraints and delay during the compaction process it was not possible to have a total evaluation of the runway before waterjetting and post waterjetting. For this reason it has been decided to take samples according to the monitoring plan when the waterjetting process was not totally completed.

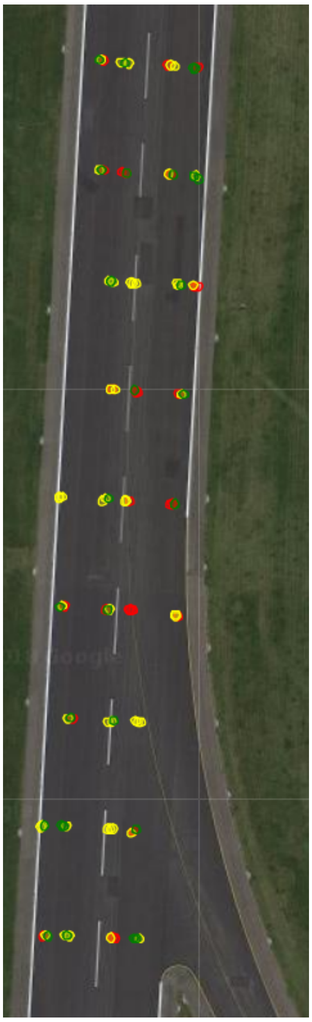


Figure 8.7: Measurement according to the monitoring plan

The sampling methodology applied in this case was the modified CROW proposed by Heijmans. In figure 8.7 all the points required are plotted but it is difficult to see each point separately due to the fact that they are very close on the surface. For this reason in figure 8.9 three different images can be distinguished, each one with one quality of values. Please note that the green values represent values above 1.3 mm, yellow those between 1 mm and 1.3 mm and the red ones those below 1 mm.

The number of samples amounted is 112 with:

- Mean = 1.17 mm
- St.Deviation = 0.06 mm

Paying attention to the second image in figure 8.9 it is possible to notice that the waterjetting process presents a specific pattern and does not remove the mastic uniformly. The waterjetting process was more complex than the other tasks of the maintenance process. Several factors affect the quality of the waterjetting process such as the speed of the truck and the pressure of the water. When the speed of the waterjetting machine was too high the bitumen was not properly removed, the same results were obtained when the pressure was not high enough. But also a too high pressure is not recommended, because in that case too much bitumen is removed and the pavement life expectation is reduced.

It was also observed that one waterjetting treatment was not enough to reach a proper Texture Depth. To solve this problem a second treatment was planned. With a double treatment the process has proven to be enough efficent as it will be shown in the next sections.

This methodology was taking three points with a fixed distance of 1.75 m between two measurements. This would allow to evaluate the quality of the compaction process. But as we can see from figure 8.8 the waterjetting machine has a width not bigger than 1.5 m. The waterjetting process itself was not uniform as we can see in figure 8.8 and the quality changes from strip to strip. This is the reason why a location with three points may have three totally different values. Figure 8.8 shows that the left part has a proper bitumen removal while the other part has a lower visual texture depth. The manufacturing process, in particular the waterjetting, apparently strongly affects the quality of the pavement in term of TD.

Figure 8.8: Waterjetting process and heterogeneity of TD surface

To have an easier comprehension of the MTD distribution figure 8.9 shows the distribution of the red, yellow and green points on the surface. Some areas appear to have a lower MTD value but the general picture is a homogeneous distribution on the entire surface.

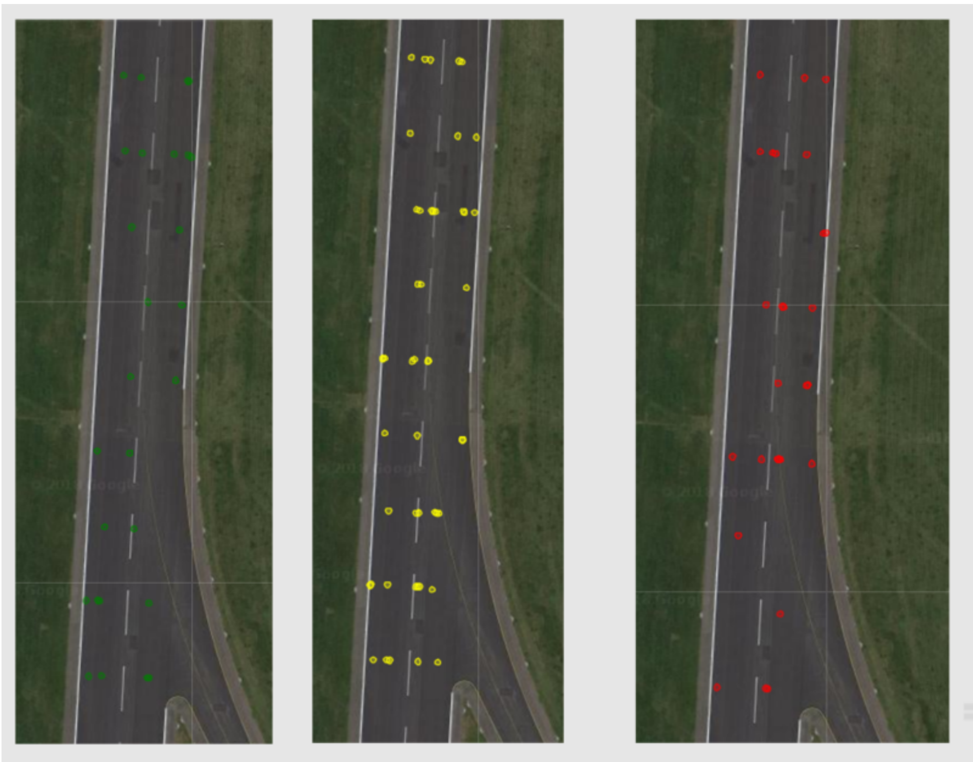


Figure 8.9: Distribution of MTD values on the surface

8.4.3 Homogeneous distribution

Once the paving process was completed and the surface was treated, at least one time the uniform sampling strategy was used. In total 39 measurements were planned as it can be seen in figure 8.10.

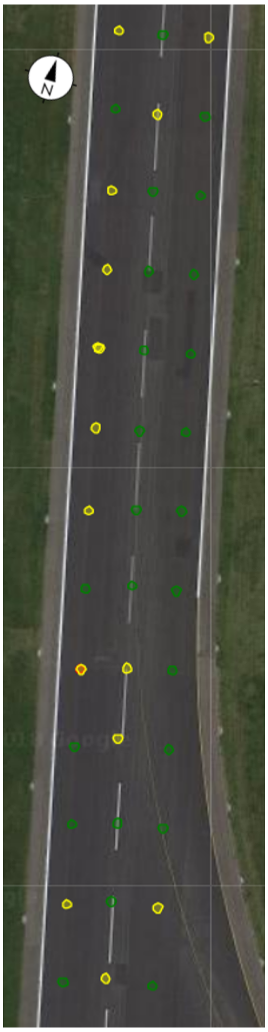


Figure 8.10: Application of uniform strategy

Compared to the previous plotting the surface presented a higher total quality due to the fact that the waterjetting process was already executed at least once. Some areas as the two external strips were waterjetted already twice.

Please observe the left strip that presents in the upper part a concentration of lower quality points. In this area the EASA requirement is met but not the one imposed by Schiphol. This representation of the points comes from the GPS coordinates and allows a quick and easy understanding of the surface's quality in different locations.

The analysis of the sample values confirms the previous visual interpretation because:

- Mean = 1.45 mm
- St.Deviation = 0.1 mm

The Mean is consistently higher than in the previous case. i.e. an increase of MTD of 23%. This value is indeed coherent with the test previously executed in the taxiway.

8.4.4 Final Measurements

When the works were totally completed some engineers from Heijmans had the chance to take some final measurements.

Exactly 33 locations were measured in accordance to the correlation test with the sand patch method. The data presented in section 8.1.1 come from this group of measurements. The plot in figure 8.11 shows the disposition and intensity of these values. In this case the numerical results are the following:

- Mean = 1.48 mm
- St.Deviation = 0.01 mm

Also in this case the Mean is considerably higher than that on the untreated surface. In this specific case the MTD compared to the first group of measurements has increased by 25%, also this value is in accordance with the test in the taxiway. The second waterjetting process has lightly increased the MTD but has strongly reduced the variance. Thus the surface is more uniform and the overall quality is increased. It is still possible to find lower quality areas as in the bottom part, but in general there are no values below 1 mm in accordance with the first group of dense measurements from February 2018.

Figure 8.11: Last group of measurements

8.5 Conclusion of measurements process

During this measuring process the difficulties caused by delays and defects on the waterjetting process have forced to adapt the measurements strategy. It was not possible to try exactly all the three sampling methodologies but this is not considered a main issue because without knowing the exact value of all the surface locations it would have been not possible to define the exact evaluation of the performances.

The focus was more on the analysis of the construction process and its influence on the surface quality. It has been highlighted that the compaction process itself already influences the pavement's properties. In some areas the MTD already satisfies the Schiphol requirements as it has been seen in figure 8.6. The general mean of an untreated surface remains low and increases when it is treated with high pressurised water. If this process is executed correctly the proper amount of bitumen is removed from the surface, increasing the MTD approximately by 25% (figure 8.12). Moreover this procedure will also increase the skid resistance properties of the surfaces because the removal of the bitumen will uncover the micro-texuter of the aggregates.

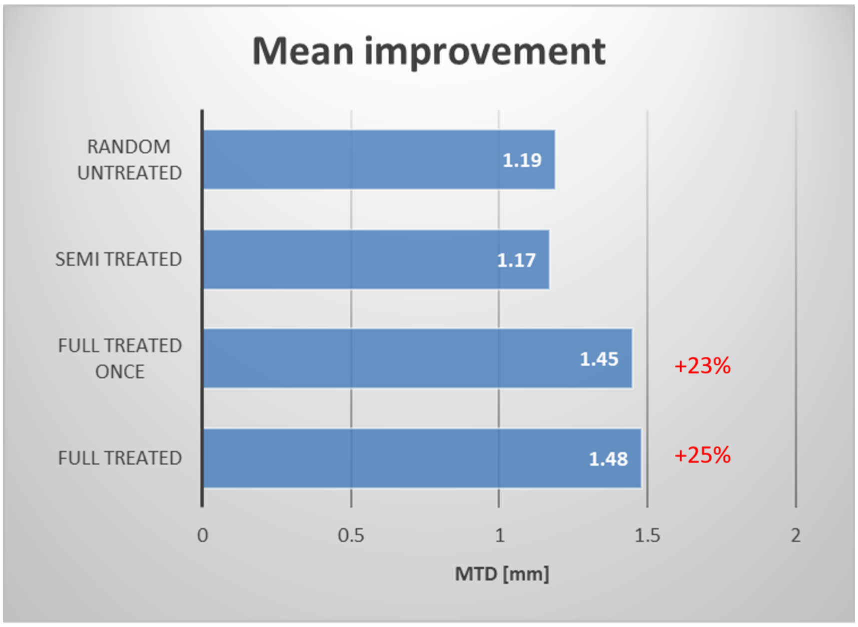


Figure 8.12: Effect of Waterjetting on MTD

It has been observed that the waterjetting process needs attention and supervision to obtain an homogeneous surface. In particular the machine is characterised by two brushes that are supposed to help remove the bitumen. The quality of the two parallel brushes is hardly the same thus the quantity of bitumen removed is not the same. This could create a series of strips with very different texture depth. The consequence is that during the measurement process it is very easy to only measure a series of locations in a good or a better strip. The Uniform sampling methodology could, as an example, have an entire column of measurements on a high quality or low quality strip. The final quality of the waterjetting process can be improved by controlling that the speed of the waterjetting machine is kept constant and the brushes regularly changed.

In case this pattern of high and low quality strips is present a second waterjetting process is planned. The process becomes in this case however more delicate because an excess of pressure or passes could remove more bitumen than necessary. In the worst circumstances the surface could face damages that reduce the expected lifetime. In the last group of measurements this second post-process has proven to not increase sensibly the MTD but to strongly reduce the variance of the data. The MTD from the Homogeneous distribution of samples to the final measurement has a difference of 0.03 mm. The Standard Deviation instead has reduced 10 times in value from 0.1 to 0.01. This means that the final quality of the surface is ten times more homogeneous. The second waterjetting process has proven to be effective for the increase of the total quality of the surface.

In general it can be said that both paving and waterjetting influence the MTD. The last process in particular has proven to sensibly increase the texture depth by 25%. This values are coherent with the measurements obtained in the taxiways and an overview of the final results can be found in figure 8.12

CHAPTER 9

Conclusions and recommendations

In this chapter the final conclusions of the research question will be described. Starting from the research question the final outcomes of the thesis are presented. This part will lead to some recommendations for Schiphol and Heijmans. Finally some recommendations for future researches will be proposed.

9.1 Conclusions

The starting point for this thesis was the following research question:

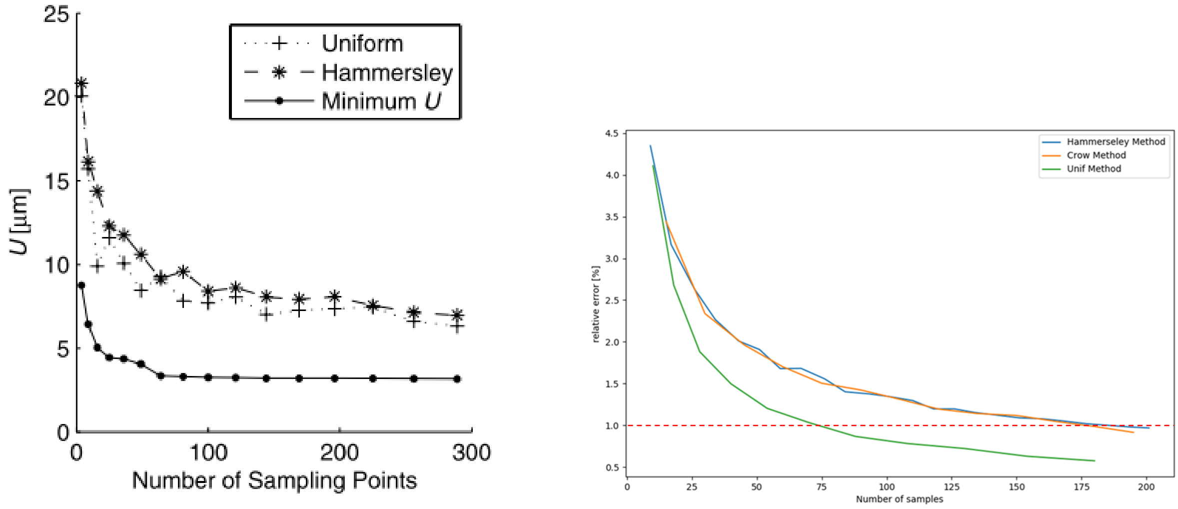
"Given a surface characterised by a predefined manufacturing process, which minimum number of samples and at which locations provide the lowest relative error between the real mean of the surface and the mean texture depth of the samples collected?"

In the definition of the research boundaries three main sampling techniques have been selected: Modified CROW, Uniform, Hammersley. But to investigate which technique could guarantee the best MTD evaluation some surfaces have been simulated with Python scripts. This methodology was based on an adapted Monte Carlo simulation, where the surfaces were repetitively simulated and the different techniques were applied. A first simulation technique based on an iteration process proved to be unreliable due to the high variability of the surface texture depth values. It has been in fact proven that the relative error stabilised to acceptable values only after 1000-2000 samples were used. But a better bench of results was obtained with the second simulation methodology. In this case a number of samples per sampling methodology is imposed to the same surface repetitively for 1000 times.

In this case the results are consistent and coherent with the analysis proposed by Colosimo et al. [8]. As for their analysis it has been possible to represent the decrease of the relative error by increasing the number of samples. This is in accordance with the behaviour of the U function presented in the ISO regulations [13]. Figure 9.1 shows the similarity of the curves proposed by Colosimo and the ones obtained from the simulations.

The results highlighted the fact that the behaviour is regular for all the three methodologies in the case of a homogeneous surface without low quality areas. Moreover the best performing methodology in this ideal situation would be the uniform methodology because it is able to provide a relative error lower than 1% with only 70 samples.

The situation is slightly different when low quality areas are present. The Hammersley sampling methodology is absolutely not affected by the different types of surface resulting in a smooth behaviour in all circumstances. Different is the situation with the CROW and the



(a) U value with different strategies

(b) Results from Simulation

Figure 9.1: Comparison Colosimo Results and Own results

Uniform methodology. The latter one is only slightly disturbed with 55 samples but the first one gives several peaks in the curves. This is due to the fact that these two methodologies can relate in some cases with the manufacturing process and consequently the reliability of the measurements decreases.

The main conclusion that arises from the simulation analysis is that a random selection of sampling points (Hammersley methodology) appears to be the most reliable because it is not possible to establish a relation with the manufacturing process with any number of samples. But the downside of this methodology is the fact that to reach a relative error lower than 1% a high number of samples is required. In the order of 160 samples for a runway strip of 500 m length and 60 m width. The uniform methodology from this point of view appears to be the most accurate with the lowest number of samples because it can reach a low relative error with only 70-80 samples but there is the risk of having a synchronisation with the pattern left by the construction process and underestimating the real MTD. From this point of view the CROW methodology is considered the most inefficient because it requires almost the same number of samples as the Hammersley methodology to reach a lower relative error and it is less reliable than the Uniform strategy. For these reasons, from a mathematical point of view, the CROW strategy is not considered suitable for this kind of measurements.

The number of samples required for each methodology are referred to the test area of 500 m length in the Polderbaan were the FFX has been placed. If it is of interest to know the number of samples required for a different area it is necessary to make a proportion with the test area. As an examples: the number of samples required for the entire Polderbaan, which has a lenght of 3500 m is 7 times the number of the test area. This means that for the entire runway 1260 measurements are requested for the Hammersley strategy and 490 for the Uniform ones.

In future researches it would be of interest to run the same simulation proposed in this research using as reference area not the test stretch but the entire runway. This would define a more accurate result compared to a simple proportional calculation. In this research this process has not been included because of software and hardware limits. The simulation of the entire runway requires a high calculation power to be executed in a limited number of hours.

The field experience has proven that the combination of paving, compacting and the mixture properties on one side and the waterjetting process on the other side, affect the properties of the surface. In particular the mixture aggregates and the paving process create different macro areas with different surface properties. The surface is then again influenced by the waterjetting process that may lead to specific patterns. These are due to the machinery properties and the water pressure. These irregularities are mitigated with a second waterjetting process and this is proven by a reduction of the variance in the samples distribution. But it also proves that the overall MTD increases with 25% after the second waterjetting process. This confirms the need of this double treatment and its efficiency.

The field experience has proven that unexpected events, such as as problems with the production or some machinery, can influence the texture quality of the surface. The main patterns of the construction process have been recorded and translated into parameters that regulate the surface simulation but this process has some limitations. Each construction process will have some main recurrent patterns and a series of variable influences on the surfaces. What arises from this analysis is that a simulation methodology that presents specific patterns may interfere with the manufacturing process and affect the reliability of the results. This discrepancy is however limited to 3-4% relative error, which means that there is still 96% precision with those methodologies.

The main outcome of what has been described is that a pavement surface of SMA presents patterns left by the manufacturing process. The most reliable method to determine the MTD of such surfaces is a random selection of samples that, in this case, is represented by the Hammersley strategy. Other sampling strategies with a fixed and predefined structure are less reliable because they can randomly find a relation with the patterns left by the manufacturing process.

The answer of the research question recalled at the beginning of the chapter is to use 160 samples with a Hammersley distribution. From the results this would ensure a low relative error (<1%) and thus a high reliability of the MTD. The number of samples is higher compared to the Uniform strategy but the reliability is also higher. With this second methodology there would be the risk of a relation between the sampling strategy and the manufacturing signature.

Please note that with this thesis Schiphol and Heijmans will be able to use all the programs created in python. This would furnish them a tool that automatically plots all the samples before in a simulated surface and also on the map with GPS coordinates. This will enable them to see on the maps where the samples have been taken and have an overview of the pavement quality. This could ease the identification of the high and low quality areas and helps the improvement of the maintenance process. Observing the distribution and the characteristics of the low quality area could help the contractor to define which part of the construction process affects most the quality of the pavement surface in terms of texture depth. This would open the doors for mitigation measures and consequently increase the quality of the final product.

9.2 Recommendations for the industry

The outcomes of the analyses, although mainly theoretical, lead to some recommendations for the industry.

Firstly it has to be said that the three methodologies need different measuring times. The Uniform methodology is the fastest to execute due to the simplicity of the grid of samples. The CROW methodology is more complicated but still regular, in particular because in one location three adjacent samples are taken. The most complex methodology is the Hammersley because this algorithm simulates a random distribution. It is more complex to define the map and execute the measurements correctly.

Taking these premises in mind a company has to evaluate the trade off between the time dedicated to the quality control and the level of reliability requested. The most reliable situation would be to measure 180 location (for each 500 m) with the Hammersley methodology. This would ensure a relative error lower than 1% (thus a high accuracy) but it would also require more than 2 hours. Moreover this methodology would be more reliable because there is no risk to have misleading values on the measurements.

In case of a lack of time available it is also possible to sensibly reduce the number of samples and implement the Uniform strategy. With 70 samples there is already a relative error lower than 1% but it has to be taken into account that the reliability is lower. In any case the simulations have proven not to have a relative error higher than 5%. In practice this means that the MTD value obtained risks to be lower than the real one but with a limited error of 5%. The company should be aware of this possibility and could accept a lower reliability of the measurements.

To recapitulate: if the company wants to have the highest reliability of the measurement and simultaneously wants to have a maximum 1% relative error, it is suggested to adopt 180 measurements for each 500 m with the Hammersley methodology. If it is accepted to have a lower reliability of the measurements, 70 samples for each 500 m of runway can be measured with the Uniform distribution. In this case the MTD value obtained is considered to be 5% lower than the real value.

The CROW methodology is not suggested because it still takes a considerable amount of time and samples to have satisfactory results. More important, it is the one that is more sensible to enter in relation with the manufacturing signature.

Moreover a main strategy is proposed:

- Apply the Hammersley strategy right after the completion of the construction process. This will ensure the highest reliability in the definition of the quality of the surface in terms of texture depth.
- For regular monitoring of the quality a Uniform distribution can be implemented. In this case the reliability is lower but it will be faster. This could be interesting for the evaluation of the behaviour of the surface in time. Limited time would be needed and a plot of a regular structure as the Uniform one could facilitate the understanding of which areas are damaged or have lower quality.

It is also suggested to use the plotting tool to visually evaluate if the sampling procedures have been executed correctly.

Overnight maintenance strategy

This research may also be of interest for the quality control during the overnight maintenance strategy. This maintenance strategy refers to maintenance operations executed only during the night. During the daytime the runway is operational and the quality of the pavement needs to meet the EASA requirements.

With this maintenance strategy each night a limited area is renewed because the time available is limited. The quality control in this scenario needs to be fast and produce a sufficient level of reliability. The most appropriate sampling methodology in this case would be the Uniform. This ensures an acceptable reliability and strongly reduces the number of samples required.

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Appendix

```
#EXPORT DATA FROM ELAtextur MACHINE


from pandas import DataFrame
import pandas as pd
import os
import re
import numpy as np
import seaborn as sns
import warnings
import scipy.stats as st
import statsmodels as sm
import matplotlib as mpl
import matplotlib.pyplot as plt
import fuzioni as fz

import random as rd

def get_num(x):
    return float(''.join(ele for ele in x if ele.isdigit() or ele ==
        '.'))


results=[]

folder_path = r'C:\Users\wano2\Desktop\20180608'


for file in sorted(os.listdir(folder_path)):

        path= os.path.join(folder_path,file )

        #print (path)


        with open(path) as f:
            measure=[]
            measure.append(file)

            for line in f:

                if "<mpd>" in line:
                    mpd= get_num(line)/1000
                    measure.append(mpd)
```

```
                if "<etd>" in line:
                    etd=get_num(line)/1000
                    measure.append(etd)

                if "<latitude>" in line:
                    latitude=str(get_num(line))
                    for i in range(len(latitude)):
                        if latitude[i]=='.':
                            splitat_l = i-2
                            risultato_l = float(latitude[:splitat_l])
                               + float(latitude[splitat_l:])/60
                    measure.append(risultato_l)

                if "<longitude>" in line:
                    longitude=str(get_num(line))
                    for i in range(len(longitude)):
                        if longitude[i]=='.':
                            splitat_o = i-2
                            risultato_o = float(longitude[:splitat_o
                               ])+ float(longitude[splitat_o:])/60
                    measure.append(risultato_o)

                if "<time>" in line:
                    time=list(map(str,re.findall("\d+\:\d+", line)))
                    measure.append(time)

        results.append(measure)




#mySubString=myString[myString.find("!")+1:myString.find("@")]
#myfile = open(r'C:\Users\wano2\Desktop\20180205\00001279.ELA')
#C:\\Users\\apple\\Downloads\train.csv
#mytxt = myfile.read()
#mytxt

John_points=pd.DataFrame(data=results, columns=['file','time','MTD','
   ETD','latitude','longitude'])

df=John_points
writer = pd.ExcelWriter('8-6-18.xlsx')
df.to_excel(writer,'Measurements')
writer.save()
\clearpage
```

```
#PLOTTING VALUES ON GOOGLE MAPS IMAGES



from gmplot import gmplot

# Place map
gmap = gmplot.GoogleMapPlotter(52.33813, 4.71003083, 15)

top_attraction_lats_r=[]
top_attraction_lons_r=[]
top_attraction_lats_y=[]
top_attraction_lons_y=[]
top_attraction_lats_g=[]
top_attraction_lons_g=[]


counter=0
for i in df['latitude']:
    if df['MTD'][counter]<1:
        top_attraction_lats_r.append(i)
        counter = counter + 1
    elif df['MTD'][counter]<1.3 and df['MTD'][counter]>=1 :
        top_attraction_lats_y.append(i)
        counter = counter + 1
    elif df['MTD'][counter]>=1.3:
        top_attraction_lats_g.append(i)
        counter = counter + 1

counter=0

for i in df['longitude']:

    if df['MTD'][counter]<1:
        top_attraction_lons_r.append(i)
        counter = counter + 1

    elif df['MTD'][counter]<1.3 and df['MTD'][counter]>=1:
        top_attraction_lons_y.append(i)
        counter = counter + 1

    elif df['MTD'][counter]>=1.3:
        top_attraction_lons_g.append(i)
        counter = counter + 1

gmap.scatter(top_attraction_lats_r, top_attraction_lons_r, 'red',
   size=0.5, marker=False)
gmap.scatter(top_attraction_lats_y, top_attraction_lons_y, 'yellow',
```

```
    size=0.5, marker=False)
gmap.scatter(top_attraction_lats_g, top_attraction_lons_g, 'green',
    size=0.5, marker=False)

# Draw
gmap.draw("provaplot.html")
import webbrowser, os
webbrowser.open("provaplot.html")

\clearpage

#FUNCTION USED DURING THE DIFFERENT ANALYSIS. OWN CREATION





# # Tutte le funzioni che servono per analysis

# ## Generatore matrici

import pandas as pd
import os
import re
#import numpy as np
import seaborn as sns
import warnings
#import numpy as np
import pandas as pd
import scipy.stats as st
import statsmodels as sm
import matplotlib as mpl
import matplotlib.pyplot as plt
import fuzioni as fz
from mpl_toolkits.axes_grid1 import make_axes_locatable
import pandas as pd
import random as rd

def matrice_unif(righe,colonne):
    T=np.random.uniform(0.5,2,[righe,colonne])  # Create an array
        filled with random values
    np.set_printoptions(precision=3)
    return T


# ## Matrice distrib normale

def matrice_norm(righe,colonne):
    T=np.random.normal(1.2,0.8,[righe,colonne])
```

```
    np.set_printoptions(precision=3)
    return T


# ## Matrice con disturbo

import numpy as np
def matrice_dist(righe,colonne):



    X=np.random.normal(0,0.32,[righe,colonne])

    Y=np.random.uniform(0.6,2,[righe,colonne])
    T=[]

# iterate through rows
    for i in range(len(X)):
        rig=[]
   # iterate through columns
        for j in range(len(X[0])):
            val= (X[i][j]+Y[i][j])
            rig.append(val)
        T.append(rig)

    return T


# ## Matrice Composta


#var1, var2 = input("enter two numbers:").split(' ')
#print(var1,var2)


# ## Generatore matrice da distribuzione


import pandas as pd


def simulated_pavement(distribution,param,raw,column):
    "return the matrix representing the surface as DataFrame, the
       array with all the value for the statistic "
    T=[]
    values=[]

    arg = param[:-2]
    loc = param[-2]
```

```
    scale = param[-1]


    for i in range(raw):
        riga=[]
        for j in range(column):
            x=distribution.ppf(np.random.uniform(),loc=loc, scale=
                scale, *arg)
            riga.append(x)
        T.append(riga)

    for i in range(raw):
        for j in range(column):
            x=T[i][j]
            values.append(x)


# ## Generali info Matrice

import numpy as np
#from statistics import mean

import scipy as si
#creazione diversi tipi di vettori


def info_gen(matrix):
    #"""this function return the statistic value of a matrix, in
       order:mean, standard deviation and variance"""
     media_g=np.mean(matrix)
     dev_std_g=np.std(matrix)
     varianza_g=np.var(matrix)
     return media_g,dev_std_g,varianza_g


# ## Sampling Techniques


import numpy as np


def crow_seq(matrice,scatter):
    '''lx and ly have to be expressed in m not other measure units'''

    crow=[]
    nx=len(matrice)
    ny=len(matrice[0])
    b=[0,1,2]
    k=0
```

```
#lstrip=ly//10
#xsequence=np.arange(0,nx, 1500)

crowseq=np.linspace(0,nx-1,num=int(scatter),dtype=int)

fysequence=np.arange(8,ny,48)
sysequence=np.arange(8+16,ny,48)
tysequence=np.arange(8+32,ny,48)

a=b*len(crowseq)

for i in crowseq:
    riga=[]
    if a[k]==0:
        for j in fysequence:

            xi=i
            yi=j
            ye=j+4
            yu=j-4
            val1=matrice[xi][yu]
            val2=matrice[xi][yi]
            val3=matrice[xi][ye]
            riga.append(val1)
            riga.append(val2)
            riga.append(val3)
    elif a[k]==1:
        for j in sysequence:

            xi=i
            yi=j
            ye=j+4
            yu=j-4
            val1=matrice[xi][yu]
            val2=matrice[xi][yi]
            val3=matrice[xi][ye]
            riga.append(val1)
            riga.append(val2)
            riga.append(val3)
    elif a[k]==2:
        for j in tysequence:

            xi=i
            yi=j
            ye=j+4
            yu=j-4
            val1=matrice[xi][yu]
            val2=matrice[xi][yi]
```

```
                    val3=matrice[xi][ye]
                    riga.append(val1)
                    riga.append(val2)
                    riga.append(val3)


            k +=1

            crow.append(riga)



        return crow


# ## Draw sampling map


def draw_crow(matrice):

        nx=len(matrice)
        ny=len(matrice[0])
        b=[0,1,2]
        k=0
        dis=np.zeros((nx,ny))






        #lstrip=ly//10
        #xsequence=np.arange(0,nx, 1500)

        crowseq=np.arange(0,nx,500)

        fysequence=np.arange(19,ny,120)
        sysequence=np.arange(19+40,ny,120)
        tysequence=np.arange(19+80,ny,120)

        a=b*len(crowseq)

        for i in crowseq:
            k
            riga=[]
            if a[k]==0:
                for j in fysequence:

                    xi=i
```

```
                yi=j
                ye=j+5
                yu=j-5
                dis[xi][yu] += 1
                dis[xi][yi] += 1
                dis[xi][ye] += 1
        elif a[k]==1:
            for j in sysequence:

                xi=i
                yi=j
                ye=j+5
                yu=j-5
                dis[xi][yu] += 1
                dis[xi][yi] += 1
                dis[xi][ye] += 1
        elif a[k]==2:
            for j in tysequence:

                xi=i
                yi=j
                ye=j+5
                yu=j-5
                dis[xi][yu] += 1
                dis[xi][yi] += 1
                dis[xi][ye] += 1


        k +=1




    for i in range(len(matrice)):
        for j in range(len(matrice[0])):
            x=matrice[i][j]
            values.append(x)

    return dis, values


# ## Uniform deterministic method

def unif_semplice(srighe,scolonne,matrice):
    #'''Return a matrix that represent the sample obtained from a
        quadratic grid on the 2D surface. There is the possiblity to
        increase the numer of raw and colums'''
    un_sempl=[]
```

```
    x=np.linspace(0,len(matrice)-1,num=srighe,dtype = int)
    y=np.linspace(0,len(matrice[0])-1,num=scolonne,dtype = int)
    for i in range(srighe):
        riga=[]
        for j in range(scolonne):
            val=matrice[x[i]][y[j]]
            riga.append(val)
        un_sempl.append(riga)

    values=[]

    for i in range(len(matrice)):
        for j in range(len(matrice[0])):
            x=matrice[i][j]
            values.append(x)
    return un_sempl




def draw_unif_semplice(srighe,scolonne,matrice):
    #'''Return a matrix that represent the sample obtained from a
       quadratic grid on the 2D surface. There is the possiblity to
       increase the numer of raw and colums'''




    x=np.linspace(0,len(matrice)-1,num=srighe,dtype = int)
    y=np.linspace(0,len(matrice[0])-1,num=scolonne,dtype = int)
    for i in range(srighe):
        for j in range(scolonne):
            matrice[x[i]][y[j]]=1



    return  matrice



# ## Hammerseley Method

def Hammerseley_seq(nsamples_xsquare,matrice):
    width=len(matrice[0])
    lenght=len(matrice)
    raw_i=np.arange(0,lenght,width)
    val=[]
```

```
    for i in range(nsamples_xsquare):


        base=2
        vdc, denom = 0,1

        unit=width/nsamples_xsquare


        j=i
        while j:
            denom *= base
            j, remainder = divmod(j, base)
            vdc += remainder / denom
        yi=int(np.arange(0,width+1,unit)[i])
        xi=int(vdc*width)



        for l in raw_i:
            f=xi+l
            if f < lenght:

                valore=matrice[f][yi]
                val.append(valore)
            else:
                pass



    return val

def Big_mama_sim(percentage,nM1,nM0,loc):


    width=6000 #cm
    lenght=50000 #cm
    unit=25 #cm


    strip_w=400 #cm
    strip_l=5000 #cm

    #percentage=120/400
    raws_strip=strip_l/unit
    raws_strip1=raws_strip*percentage
    raws_strip0=raws_strip-raws_strip1
```

```
column_strip=strip_w/unit

number_w=width/strip_w
number_l=lenght/strip_l
number_strips=number_w*number_l

Big_mama=[]
for a in np.arange(int(number_l)):

    Big_raw=[]

    for i in np.arange(int(number_w)):


        Matrice=[]

        x=rd.randint(0, int(raws_strip0)-1)

        for j in np.arange(int(raws_strip)):

            negstrip=np.arange(x,x+raws_strip1)

            if j in negstrip:
                raw=nM1.ppf(np.random.uniform(size=int(
                    column_strip)))-np.random.uniform( low=0,high=
                    loc, size=int(column_strip))


            if j not in negstrip:
                raw=nM0.ppf(np.random.uniform(size=int(
                    column_strip)))

            Matrice.append(raw)


        if i == 0:
            Big_raw=Matrice

        else:
            Big_raw = np.hstack((Big_raw, Matrice))

    if a == 0:
        Big_mama=Big_raw
    else:
        Big_mama = np.vstack((Big_mama, Big_raw))

return  Big_mama
```

```
def Hammerseley_draw(nsamples_xsquare, matrice):
    width=len(matrice[0])
    lenght=len(matrice)
    raw_i=np.arange(0, lenght, width)
    valy=[]
    valx=[]

    for i in range(nsamples_xsquare):

        colonna=[]
        base=2
        vdc, denom = 0,1

        unit=int(width/nsamples_xsquare)


        j=i
        while j:
            denom *= base
            j, remainder = divmod(j, base)
            vdc += remainder / denom
        yi=int(np.arange(0, width+1, unit)[i])
        xi=int(vdc*width)
        valy.append(yi)


        for l in raw_i:
            f=xi+l

            if f < lenght:

                matrice[f][yi]=1
                valx.append(f)
            else:
                pass




    return matrice, valy, valx

# ## Prendere dati da ELATextuur

import pandas as pd
import os
import re
#import numpy as np
import seaborn as sns
```

```
def elatextur_data(pathf):

    def get_num(x):
        return float(''.join(ele for ele in x if ele.isdigit() or ele
            == '.'))


    results=[]




    for file in sorted(os.listdir(pathf)):

            path= os.path.join(pathf,file)

            #print (path)


            with open(path) as strada:
                measure=[]
                measure.append(file)

                for line in strada:

                    if "<mpd>" in line:
                        mpd= get_num(line)/1000
                        measure.append(mpd)

                    if "<etd>" in line:
                        etd=get_num(line)/1000
                        measure.append(etd)

                    if "<latitude>" in line:
                        latitude=get_num(line)
                        measure.append(latitude)

                    if "<longitude>" in line:
                        longitude=get_num(line)
                        measure.append(longitude)

                    #if "<time>" in line:
                        #time=list(map(str,re.findall("\d+\:\d+",
                            line)))
                        #measure.append(time)

            results.append(measure)
```

```
    df=pd.DataFrame(data=results, columns=['file','MTD','ETD','
       latitude','longitude'] )
    #df=pd.DataFrame(data=results, columns=['file','MTD','ETD'] )

    return df



# ## Real representation of surface
import matplotlib
import matplotlib.pyplot as plt

def real_representation(colonne, righe, matrix_col):

    "This works only with column generated from DataFrame structures,
        for others generate another algorithm. Return the first
       matrix as the exhact representation of the surface and the
       second to highlight the values below 1.3"
    counter=0
    #colonne=20
    #righe=20

    F=[]



    for i in range(righe):
        riga=[]
        for j in range(colonne):
            riga.append(matrix_col[counter])
            counter +=1
        F.append(riga)


    counter2=0

    D=[]

    for i in range(righe):
        riga=[]
        for j in range(colonne):

            if matrix_col[counter2] < 1.3:
                riga.append(0)
            else:
                riga.append(matrix_col[counter2])


            counter2 +=1
```

```
    D.append(riga)


fig, (ax1,ax2) = plt.subplots(1,2,figsize=(8, 6))
fig.tight_layout()
plt.subplots_adjust(left=None, bottom=None, right=None, top=None,
    wspace=0.5, hspace=None)

cmap = plt.cm.get_cmap('hot')

img = ax1.imshow(F,interpolation='nearest',
                cmap = cmap,
                origin='lower')
divider1 = make_axes_locatable(ax1)
# Append axes to the right of ax3, with 20% width of ax3
cax1 = divider1.append_axes("right", size="5%", pad=0.25)

cb=plt.colorbar(img,cax=cax1)



cmap2 = mpl.colors.ListedColormap(['red','gold'])
bounds=[0,1.3,3]


img = ax2.imshow(D,interpolation='nearest',
                cmap = cmap2,
                origin='lower')


divider2 = make_axes_locatable(ax2)
# Append axes to the right of ax3, with 20% width of ax3
cax2 = divider2.append_axes("right", size="5%", pad=0.25)

cb=plt.colorbar(img,cax=cax2,boundaries=bounds)

#cb2=plt.colorbar(img,cmap=cmap2,boundaries=bounds)


cmap2 = mpl.colors.ListedColormap(['red','gold'])
bounds=[0,1.3,3.3]

#ax2.grid(color='b', linestyle='-', linewidth=1)


img = ax2.imshow(D,interpolation='nearest',
                cmap = cmap2,
                origin='lower')
```

```
    divider2 = make_axes_locatable(ax2)
    # Append axes to the right of ax3, with 20% width of ax3
    cax2 = divider2.append_axes("right", size="5%", pad=0.2)

    cb=plt.colorbar(img,cax=cax2,boundaries=bounds)
    #plt.show()

    return F, D




def make_cdf(dist, params, size=1000):
        """Generate distributions's Propbability Distribution
           Function """

        # Separate parts of parameters
        arg = params[:-2]
        loc = params[-2]
        scale = params[-1]

        # Get sane start and end points of distribution
        start = dist.ppf(0.0000001, *arg, loc=loc, scale=scale) if
           arg else dist.ppf(0.01, loc=loc, scale=scale)
        end = dist.ppf(0.999, *arg, loc=loc, scale=scale) if arg else
            dist.ppf(0.99,  loc=loc, scale=scale)

        # Build PDF and turn into pandas Series
        x = np.linspace(start, end, size)
        y = dist.cdf(x, loc=loc, scale=scale, *arg)
        cdf = pd.DataFrame(y, x)
        n= dist(loc=loc, scale=scale, *arg)

        return cdf,n

# Create models from data
def best_fit_distribution(data, bins=200, ax=None):
    """Model data by finding best fit distribution to data"""
    # Get histogram of original data
    y, x = np.histogram(data, bins=bins, density=True)
    x = (x + np.roll(x, -1))[:-1] / 2.0
    z = np.linspace(0,4,100)

    KSframe=pd.DataFrame(columns=['distribution','arg','loc','scale
        ','pvalue'])

    # Distributions to check
    DISTRIBUTIONS = [
```

```
    st.alpha,st.anglit,st.arcsine,st.beta,st.betaprime,st.
        bradford,st.cauchy,st.chi,st.chi2,st.cosine,
    st.erlang,st.expon,st.exponnorm,st.exponweib,st.exponpow,st.f
        ,st.fatiguelife,st.fisk,
    st.foldcauchy,st.frechet_r,st.frechet_l,st.genlogistic,st.
        genpareto,st.gennorm,st.genexpon,
    st.genextreme,st.gausshyper,st.gamma,st.gengamma,st.
        genhalflogistic,st.gilbrat,st.gompertz,st.gumbel_r,
    st.gumbel_l,st.halfcauchy,st.halflogistic,st.halfnorm,st.
        halfgennorm,st.hypsecant,st.invgamma,st.invgauss,
    st.invweibull,st.johnsonsb,st.johnsonsu,st.ksone,st.kstwobign
        ,st.laplace,st.levy,st.levy_l,st.levy_stable,
    st.logistic,st.loggamma,st.loglaplace,st.lognorm,st.lomax,st.
        maxwell,st.mielke,st.nakagami,st.ncx2,st.ncf,
    st.nct,st.norm,st.pareto,st.pearson3,st.powerlaw,st.
        powerlognorm,st.powernorm,st.rdist,st.reciprocal,
    st.rayleigh,st.rice,st.recipinvgauss,st.semicircular,st.t,st.
        truncexpon,st.truncnorm,st.tukeylambda,
    st.uniform,st.vonmises,st.vonmises_line,st.wald,st.
        weibull_min,st.weibull_max,st.wrapcauchy
]
#,st.dweibull ,st.foldnorm st.burr,st.dgamma,st.triang
# Best holders
best_distribution = st.norm
best_params = (0.0, 1.0)
best_sse = np.inf

# Estimate distribution parameters from data
for distribution in DISTRIBUTIONS:

    # Try to fit the distribution
    try:
        # Ignore warnings from data that can't be fit
        with warnings.catch_warnings():
            warnings.filterwarnings('ignore')

            # fit dist to data
            params = distribution.fit(data)

            # Separate parts of parameters
            arg = params[:-2]
            loc = params[-2]
            scale = params[-1]

            # Calculate fitted PDF and error with fit in
                distribution
            pdf = distribution.pdf(x, loc=loc, scale=scale, *arg)
            sse = np.sum(np.power(y - pdf, 2.0))
            pdf2= distribution.pdf(z, loc=loc, scale=scale, *arg)
```

```
                #n= distribution(loc=loc, scale=scale, *arg)



                #Kolmogorov-Smirnov Test

                #s,p=kstest(df['MTD'],n.cdf)

                #Create matrix of kstest results

                #df2 = pd.DataFrame([distribution.name,arg,loc,scale,
                    p], columns=['distribution','arg','loc','scale','
                    pvalue'])


                #KSframe.append(df2, ignore_index=True)



                # if axis pass in add to plot
                try:
                    if ax:
                        pd.Series(pdf2,z).plot(ax=ax)
                    end
                except Exception:
                    pass

                # identify if this distribution is better
                if best_sse > sse > 0:
                    best_distribution = distribution
                    best_params = params
                    best_sse = sse

        except Exception:
            pass

    #finale=KSframe.sort_values(by=['pvalue'])
    return best_distribution.name, best_params

def make_pdf(dist, params, size=1000):
    """Generate distributions's Propbability Distribution Function
        """

    # Separate parts of parameters
    arg = params[:-2]
    loc = params[-2]
    scale = params[-1]

    # Get sane start and end points of distribution
```

```
    start = dist.ppf(0.0001, *arg, loc=loc, scale=scale) if arg else
        dist.ppf(0.01, loc=loc, scale=scale)
    end = dist.ppf(0.999, *arg, loc=loc, scale=scale) if arg else
        dist.ppf(0.99, loc=loc, scale=scale)

    # Build PDF and turn into pandas Series
    x = np.linspace(0, 3.2, size)
    y = dist.pdf(x, loc=loc, scale=scale, *arg)
    pdf = pd.DataFrame(y, x)

    return pdf




def best_curv_fit(data, binss):

    matplotlib.rcParams['figure.figsize'] = (8, 6)
    matplotlib.style.use('ggplot')

    #Find and plot best fit
    # Load data from statsmodels datasets
    #data = df["MTD"]

    #binss=25

    # Plot for comparison
    fig, ax = plt.subplots()
    ax = data.plot(kind='hist', bins=binss, normed=True, alpha=0.5,
        color=plt.rcParams['axes.color_cycle'][1])
    # Save plot limits
    #dataYLim = ax.get_ylim()

    # Find best fit distribution
    best_fit_name, best_fir_paramms = best_fit_distribution(data,
        binss, ax) #, KSresults
    best_dist = getattr(st, best_fit_name)

    # Update plots
    ax.set_ylim((0, 1.8))
    ax.set_xlim((0.7, 3))
    #ax.set_ylim(dataYLim)
    ax.set_title(u'MTD values \n All Fitted Distributions')
    ax.set_xlabel(u'MTD')
    ax.set_ylabel('Frequency')

    # Make PDF
    pdf = make_pdf(best_dist, best_fir_paramms)
```

```
    # Make CDF
    cdf,n = make_cdf(best_dist, best_fir_paramms)


    # Display

    #fig, (ax1,ax2) = plt.subplots(1,2,figsize=(8, 6))

    sfondo1 = pdf.plot(lw=2, label='PDF', legend=True)
    ax1=data.plot(kind='hist', bins=binss, normed=True, alpha=0.5,
        label='Data', legend=True, ax=sfondo1)

    param_names = (best_dist.shapes + ', loc, scale').split(', ') if
        best_dist.shapes else ['loc', 'scale']
    param_str = ', '.join(['{}={:0.2f}'.format(k,v) for k,v in zip(
        param_names, best_fir_paramms)])
    dist_str = '{}({})'.format(best_fit_name, param_str)

    ax1.set_title(u'MTD with best fit distribution \n' + dist_str)
    ax1.set_xlabel(u'MTD')
    ax1.set_ylabel('Frequency')


    # Display
    ax2 = cdf.plot(lw=2, label='CDF', legend=True)

    param_names = (best_dist.shapes + ', loc, scale').split(', ') if
        best_dist.shapes else ['loc', 'scale']
    param_str = ', '.join(['{}={:0.2f}'.format(k,v) for k,v in zip(
        param_names, best_fir_paramms)])
    dist_str = '{}({})'.format(best_fit_name, param_str)

    ax2.set_title(u'MTD with best fit distribution \n' + dist_str)
    ax2.set_xlabel(u'MTD')
    ax2.set_ylabel('Frequency')


    stat, pvalue=st.kstest(data,n.cdf)
    print('The Kolmogorov-Smirnov Test produced a P-Value of',pvalue)

    return best_fir_paramms, best_dist,n

def best_curv_fit_norm(data, binss):

    matplotlib.rcParams['figure.figsize'] = (8, 6)
    matplotlib.style.use('ggplot')
```

```
#Find and plot best fit
#Load data from statsmodels datasets
#data = df["MTD"]

#binss=25

# Plot for comparison
#fig, ax = plt.subplots()
#ax = data.plot(kind='hist', bins=binss, normed=True, alpha=0.5,
    color=plt.rcParams['axes.color_cycle'][1])
# Save plot limits
#dataYLim = ax.get_ylim()

# Find best fit distribution
best_dist = st.norm
best_fir_paramms = best_dist.fit(data) #, KSresults
best_dist = getattr(st, best_dist.name)

# Update plots
#ax.set_ylim((0, 1.8))
#ax.set_xlim((0.7, 3))
#ax.set_ylim(dataYLim)
#ax.set_title(u'MTD values \n All Fitted Distributions')
#ax.set_xlabel(u'MTD')
#ax.set_ylabel('Frequency')

# Make PDF
pdf = make_pdf(best_dist, best_fir_paramms)


# Make CDF
cdf,n = make_cdf(best_dist, best_fir_paramms)


# Display

#fig, (ax1,ax2) = plt.subplots(1,2,figsize=(8, 6))

sfondo1 = pdf.plot(lw=2, label='PDF', legend=True)
ax1=data.plot(kind='hist', bins=binss, normed=True, alpha=0.5,
    label='Data', legend=True, ax=sfondo1)

param_names = (best_dist.shapes + ', loc, scale').split(', ') if
    best_dist.shapes else ['loc', 'scale']
param_str = ', '.join(['{}={:0.2f}'.format(k,v) for k,v in zip(
    param_names, best_fir_paramms)])
dist_str = '{}({})'.format(best_dist.name, param_str)

ax1.set_title(u'MTD with best fit distribution \n' + dist_str)
```

```
    ax1.set_xlabel(u'MTD')
    ax1.set_ylabel('Frequency')


    # Display
    ax2 = cdf.plot(lw=2, label='CDF', legend=True)

    param_names = (best_dist.shapes + ', loc, scale').split(', ') if
        best_dist.shapes else ['loc', 'scale']
    param_str = ', '.join(['{}={:0.2f}'.format(k,v) for k,v in zip(
        param_names, best_fir_paramms)])
    dist_str = '{}({})'.format(best_dist.name, param_str)

    ax2.set_title(u'MTD with best fit distribution \n' + dist_str)
    ax2.set_xlabel(u'MTD')
    ax2.set_ylabel('Frequency')


    stat, pvalue=st.kstest(data,n.cdf)
    print('The Kolmogorov-Smirnov Test produced a P-Value of',pvalue)

    return best_fir_paramms, best_dist,n


#Probability of failure with graphs


def prob_fail(best_dist, best_fir_paramms, target):

    z = np.linspace(0,4,100)

    arg = best_fir_paramms[:-2]
    loc = best_fir_paramms[-2]
    scale = best_fir_paramms[-1]

    pdf_values = best_dist.pdf(z,loc=loc, scale=scale, *arg)
    cdf_values = best_dist.cdf(z,loc=loc, scale=scale, *arg)
    fill_color = (0, 0, 0, 0.6)  # Light gray in RGBA format.
    line_color = (0, 0, 0, 0.5)  # Medium gray in RGBA format.
    fig, axes = plt.subplots(2, 1, figsize=(8, 6))

    cdf_ax, pdf_ax = axes[:]
    cdf_ax.plot(z, cdf_values)
    pdf_ax.plot(z, pdf_values)


    # Fill area at and to the left of x.
    pdf_ax.fill_between(z, pdf_values,
                        where=z <= target,
```

```
                         color=fill_color)
    pd = best_dist.pdf(target,loc=loc, scale=scale, *arg)  #
        Probability density at this value.

    # Line showing position of x on x-axis of PDF plot.
    pdf_ax.plot([target, target],
                [0, pd], color=line_color)
    cd = best_dist.cdf(target,loc=loc, scale=scale, *arg)  #
        Cumulative distribution value for this x.f fvf

    # Lines showing x and CDF value on CDF plot.
    x_ax_min = cdf_ax.axis()[0]  # x position of y axis on plot.
    cdf_ax.plot([target, target,0],
                [0, cd, cd], color=line_color)
    cdf_ax.set_title('x = {:.1f}, Probability of failure = {:.2f}%'.
        format(target, cd*100))
    # Hide top and right axis lines and ticks to reduce clutter.
    for ax in (cdf_ax, pdf_ax):
         ax.spines['right'].set_visible(False)
         ax.spines['top'].set_visible(False)
         ax.yaxis.set_ticks_position('left')
         ax.xaxis.set_ticks_position('bottom')


    return cd*100


def best_fit_distribution_2(data, bins=200, ax=None):
    """Model data by finding best fit distribution to data"""
    # Get histogram of original data
    y, x = np.histogram(data, bins=bins, density=True)
    x = (x + np.roll(x, -1))[:-1] / 2.0
    z = np.linspace(0,4,100)



    # Distributions to check
    DISTRIBUTIONS = [st.lognorm,st.norm

    ]
    #,st.dweibull ,st.foldnorm st.burr,st.dgamma,st.triang
    # Best holders
    best_distribution = st.norm
    best_params = (0.0, 1.0)
    best_sse = np.inf

    # Estimate distribution parameters from data
    for distribution in DISTRIBUTIONS:
```

```
        # fit dist to data
        params = distribution.fit(data)

        # Separate parts of parameters
        arg = params[:-2]
        loc = params[-2]
        scale = params[-1]

        # Calculate fitted PDF and error with fit in distribution
        pdf = distribution.pdf(x, loc=loc, scale=scale, *arg)
        sse = np.sum(np.power(y - pdf, 2.0))

        # identify if this distribution is better
        if best_sse > sse > 0:
            best_distribution = distribution
            best_params = params
            best_sse = sse

        else:
            pass


    return best_distribution.name, best_params


def curv_fit_Lognorm(data, binss):

    matplotlib.rcParams['figure.figsize'] = (8, 6)
    matplotlib.style.use('ggplot')

    #Find and plot best fit
    #Load data from statsmodels datasets
    #data = df["MTD"]

    #binss=25

    # Plot for comparison
    #fig, ax = plt.subplots()
    #ax = data.plot(kind='hist', bins=binss, normed=True, alpha=0.5,
        color=plt.rcParams['axes.color_cycle'][1])
    # Save plot limits
    #dataYLim = ax.get_ylim()

    # Find best fit distribution
    best_dist = st.lognorm
    best_fir_paramms = best_dist.fit(data) #, KSresults
```

```
# Update plots
#ax.set_ylim((0, 1.8))
#ax.set_xlim((0.7, 3))
#ax.set_ylim(dataYLim)
#ax.set_title(u'MTD values \n All Fitted Distributions')
#ax.set_xlabel(u'MTD')
#ax.set_ylabel('Frequency')

# Make PDF
pdf = make_pdf(best_dist, best_fir_paramms)


# Make CDF
cdf,n = make_cdf(best_dist, best_fir_paramms)


# Display

#fig, (ax1,ax2) = plt.subplots(1,2,figsize=(8, 6))

sfondo1 = pdf.plot(lw=2, label='PDF', legend=True)
ax1=data.plot(kind='hist', bins=binss, alpha=0.5, label='Data',
    legend=True, ax=sfondo1)

param_names = (best_dist.shapes + ', loc, scale').split(', ') if
    best_dist.shapes else ['loc', 'scale']
param_str = ', '.join(['{}={:0.2f}'.format(k,v) for k,v in zip(
    param_names, best_fir_paramms)])
dist_str = '{}({})'.format(best_dist.name, param_str)

ax1.set_title(u'MTD with best fit distribution \n' + dist_str)
ax1.set_xlabel(u'MTD')
ax1.set_ylabel('Frequency')
ax1.set_ylim(ax1.get_ylim())
ax1.set_xlim(ax1.get_xlim())


ax2 = cdf.plot(lw=2, label='CDF', legend=True)

param_names = (best_dist.shapes + ', loc, scale').split(', ') if
    best_dist.shapes else ['loc', 'scale']
param_str = ', '.join(['{}={:0.2f}'.format(k,v) for k,v in zip(
    param_names, best_fir_paramms)])
dist_str = '{}({})'.format(best_dist.name, param_str)

ax2.set_title(u'MTD with best fit distribution \n' + dist_str)
ax2.set_xlabel(u'MTD')
ax2.set_ylabel('Frequency')
```

```
    stat, pvalue=st.kstest(data,n.cdf)
    print('The Kolmogorov−Smirnov Test produced a P−Value of',pvalue)

    return best_fir_paramms, best_dist,n

\clearpage

#ANALYSIS OF MEASUREMENTS
```

```
#GET DATA FROM ELATEXTUR

df=fz.elatextur_data(r'F:\Documents\Walter\analysis')

#PLOT DATA ON MATRIX

F,D=fz.real_representation(20,20,df['MTD'])

#DEFINE THE BEST CURVE

best_fir_paramms, best_dist, n=fz.best_curv_fit(df['MTD'],15)

#EVALUATION OF FAILURE PROBABILITY

pfail=fz.prob_fail(best_dist, best_fir_paramms, 1.3)

#FIT ONLY NORMAL DISTRIBUTION

distribution = st.norm
params = distribution.fit(df['MTD'])

best_fir_paramms_NORM, best_dist_NORM, n_NORM=fz.best_curv_fit_norm(
    df['MTD'],15)

#IDENTIFY HIGH AND LOW QUALITY AREAS

sequence=np.linspace(0,4,20)

count=0
for i in range(len(F)):
    vlag=0


    for j in range(len(F[0])):
        if F[i][j]<1.3:
            vlag += 1
```

```
                count += 1
            else:
                vlag=vlag
        if vlag >= 0.15*len(F[0]):
            sequence[i]=1
        else:
            sequence[i]=0

M1=[]
M0=[]
indx=0

for i in sequence:
    riga1=[]
    riga0=[]
    if i ==0:
        for j in range(len(F[0])):
            riga0.append(F[indx][j])
        M0.append(riga0)
    else:
        for j in range(len(F[0])):
            riga1.append(F[indx][j])
        M1.append(riga1)

    indx += 1


listM1=[]
listM0=[]

for i in range(len(M1)):
        for j in range(len(M1[0])):
            x=M1[i][j]
            listM1.append(x)

for i in range(len(M0)):
        for j in range(len(M0[0])):
            x=M0[i][j]
            listM0.append(x)

listM0=pd.DataFrame(data=listM0, columns=['MTD'])
listM1=pd.DataFrame(data=listM1, columns=['MTD'])


#GET PARAMETERS FROM THESE AREAS AND PLOT STATISTICAL ANALYSIS

best_fir_parammsM1_NORM, best_distM1_NORM, nM1_NORM=fz.
    best_curv_fit_norm(listM0['MTD'],15)
```

```
#CREATE BIG SURFACE
```

```
def Big_mama_sim(percentage,nM1,nM0,loc):


    width=6000 #cm
    lenght=50000 #cm
    unit=25 #cm


    strip_w=400 #cm
    strip_l=5000 #cm

    #percentage=120/400
    raws_strip=strip_l/unit
    raws_strip1=raws_strip*percentage
    raws_strip0=raws_strip-raws_strip1
    column_strip=strip_w/unit

    number_w=width/strip_w
    number_l=lenght/strip_l
    number_strips=number_w*number_l

    Big_mama=[]
    for a in np.arange(int(number_l)):

        Big_raw=[]

        for i in np.arange(int(number_w)):


            Matrice=[]

            x=rd.randint(0, int(raws_strip0)-1)

            for j in np.arange(int(raws_strip)):

                negstrip=np.arange(x,x+raws_strip1)

                if j in negstrip:
                    raw=nM1.ppf(np.random.uniform(size=int(
                        column_strip)))-np.random.normal( loc=loc,
                        scale=0.07,size=int(column_strip))


                if j not in negstrip:
                    raw=nM0.ppf(np.random.uniform(size=int(
```