Predicting asphalt temperature for construction

A contribution to the analysis of the cooling rate of asphalt during construction process

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Cover image: Roller machine in asphalt process (AsphaltPro, 2022)

Preface

The report made during my bachelor thesis is entitled "Predicting asphalt temperature for construction". This thesis was carried out to improve the prediction of the asphalt cooling rate during construction, in order to improve the final quality of the asphalt. This work has been written as part of the graduation requirements for the degree in Civil Engineering at the University of Twente. The period of research and writing of this bachelor thesis lasted from May to July 2022.

The project was carried out with the Asphalt Pavement Research and Innovation (ASPARi) group, a research collaboration between the University of Twente and infrastructure contractors, and the Roelofs company. On behalf of the university and ASPARi, my supervisor was Dr. Seirgei Miller, whom I would like to thank for allowing me to conduct this research at ASPARi, as well as for all the help, excellent guidance, and support provided throughout the process. Moreover, I would like to thank my supervisor Inga Maria for her help and tips during the research and writing process, also for the support in preparing the necessary equipment and collecting the data. Thirdly, I would like to thank Mr. Hans Siedenburg, my external supervisor, for all the feedback provided for better development of the thesis. Also, I would like to thank all the companies and people that allowed me to take the measurements during road construction.

Apart from academics, I want to thank the Government of my country Ecuador for giving me the scholarship which allowed me to study abroad. Also to my friends and family for the support they always gave me. Finally, a special thanks to my parents for all their love, advice, and unconditional support.

I hope you enjoy reading.

Kelvin Ayuquina

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Key Terminology

Word	Definition
ASPARi	Asphalt Paving Research & Innovation, it is network of companies and the University of Twente that jointly work for an improvement in the asphalting process.
HMA	Hot Mix Asphalt mixture.
PQi	The Process Quality improvement method is based on monitoring the asphalting process using technologies and sensors.
Compaction	Exertion of force on something to become more dense.
Cooling	Removal of heat, usually resulting in a lower temperature.
AC	The first mixture, Asphalt Concrete, is composed mainly of asphalt bitumen and aggregates, making it resistant to abrasion.
PA	Porous Asphalt is a mixture widely used in The Netherlands, it helps keeping the surface dry avoiding splash.
SMA-NL	Stone Mastic Asphalt is a mixture with an essential percentage of material of 2mm and the spaces are filled with mastic (sand, filler, bitumen).
TAC	It is the time available that the operator has to compact the asphalt layer, and thus obtain a better quality.
MLP	A Multi-Layer Perceptron Algorithm is the union of several perceptron connected and ordered one next to another, inspired by the connections of the brain.
ASPARiCool	A software created by ASPARi based on machine learning. It uses historical data to have more accurate cooling rate predictions inside the Netherlands.
RSME	The Root Mean Square Error (RMSE) is the standard deviation of the prediction errors (residuals). It compares the error between the predicted values and data obtained in field.

Abstract (English)

The Netherlands is a country that has one of the largest road networks, therefore the quality of the roads is essential. An important factor during road construction is the compaction of the Hot Mix Asphalt which needs to be done in a specific time and temperature window in order to obtain a better quality. However, the cooling rate of asphalt cannot be easily calculated since it is influenced by factors such as types of mixture, thickness of the layer, underlying layer, underlying temperature, initial temperature, wind speed, outside temperature, weather conditions, and rain.

To solve this problem, a tool named ASPARiCool is being developed, which is a Dutch application that aims to predict the cooling rate using empirical measurements based on Machine Learning. However, the main drawback of a previous version is that it provides inaccurate cooling rate prediction due to the limited data obtained in field measurements.

In this study, the ASPARiCool tool was studied to better understand its operation. This software works using the Multi-layer perceptron. This model is based on training the program with historical data and then making predictions. To determine if using more data improves accuracy, during the months of the study, data was obtained from projects carried out in the Twente region.

The first results showed an increase in accuracy compared to when the amount of historical data was less. However, the RSME was still significant. To increase the accuracy of ASPARiCool, a sensitivity analysis of each parameter with which the MLP works was performed. In addition, a calibration of the program was then made to find the best performance. The predictions obtained using the new parameter values were better than the results using the default values by 65%.

Abstract (Dutch)

Nederland is een land met een van de grootste wegennetwerken, daarom is de kwaliteit van de wegen essentieel. Een belangrijke factor tijdens de wegenbouw is de verdichting van het Hot Mix Asphalt die in een bepaald tijd- en temperatuurvenster moet gebeuren om een betere kwaliteit te verkrijgen. De afkoelsnelheid van asfalt is echter niet eenvoudig te berekenen, omdat deze wordt beïnvloed door factoren als mengselsoorten, laagdikte, onderliggende laag, onderliggende temperatuur, begintemperatuur, windsnelheid, buitentemperatuur, weersomstandigheden en regen.

Om dit probleem op te lossen, wordt een tool ontwikkeld met de naam ASPARiCool, een Nederlandse applicatie die tot doel heeft de afkoelsnelheid te voorspellen met behulp van empirische metingen op basis van Machine Learning. Het belangrijkste nadeel van deze versie is echter dat deze een onnauwkeurige voorspelling van de koelsnelheid biedt vanwege de beperkte gegevens die zijn verkregen in veldmetingen.

In deze studie werd de ASPARiCool-tool bestudeerd om de werking ervan beter te begrijpen. Deze software werkt met behulp van de Multi-layer perceptron. Dit model is gebaseerd op het trainen van het programma met historische data en vervolgens het doen van voorspellingen. Om te bepalen of het gebruik van meer data de nauwkeurigheid verbetert, zijn gedurende de maanden van het onderzoek data verkregen van projecten uitgevoerd in de regio Twente.

De eerste resultaten toonden een toename in nauwkeurigheid in vergelijking met wanneer de hoeveelheid historische gegevens minder was. De RSME was echter nog steeds aanzienlijk. Om de nauwkeurigheid van ASPARiCool te vergroten, is een gevoeligheidsanalyse uitgevoerd van elke parameter waarmee de MLP werkt. Daarnaast is er vervolgens een kalibratie van het programma uitgevoerd om de beste prestaties te vinden. De voorspellingen die werden verkregen met de nieuwe parameterwaarden waren 65% beter dan de resultaten met de standaardwaarden.

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1. Introduction

1.1. Topic

The development of a country brings new challenges and problems, one of them is the road connections and infrastructures that a country has. With further developments, the quality of roads also has to improve. For this reason, a great concern for the government and contractors is to enhance the features of roads. With this, if the condition of the roads improves, a longer guarantee in terms of lifespan can be given (Arbeider, 2017).

In the process of road construction, there are several steps that must be followed. Compaction is one of them in which the quality is defined. Currently, the compaction process is mainly based on the experience of the machine operators, who decide when is the right time to start compacting (Arbeider, 2017). Nevertheless, this process does not provide sufficient assurance that the characteristics of the road will be optimal. During compaction, the temperature of the asphalt is crucial to obtain a better quality of the road. However, Hot Mix Asphalt mixture cooling rate varies depending on the weather, wind speed, rain and type of asphalt, making it difficult to manage (Huerne, 2017).

Some tools have been developed to estimate the temperature of the asphalt considering the influential parameters, and thereby help operators. One software tool developed is Pavecool, which was elaborated by the University of Minnesota based on theoretical models, however, since it was carried out in the USA, it does not provide accurate results in the Netherlands. Therefore, ASPARiCool, a similar software based on an empirical model is being developed (Miller et al. 2019). This tool works using a Machine Learning algorithm called Multi-Layer Perceptron. However, previous studies show the cooling rate predictions to be inaccurate.

1.2. Company profile

This project, will be hosted by ASPARi and the Roelofs Group. ASPARi is a group of infrastructure contractors and Rijkswaterstaat that jointly work for an improvement in the asphalting process. This network was created in 2006 together with the University of Twente. Currently, it is made up of eleven different companies, which carry out 80% of the asphalting in the Netherlands (ASPARi, n.d.). ASPARi aims to connect technology, education, and machine operators for better project execution. Roelofs is a Dutch company specialized in infrastructure. Among the main areas of work are road construction, mobility, and raw material extraction. In these areas, Roelofs manages projects from design and advice to implementation and maintenance. In the field of paving, it is one of the largest companies with projects in the Netherlands. Roelofs has its own asphalt plant which allows it to distribute asphalt to various plants in the Netherlands and Germany. Asset management by Roelofs is based on historical data, and with this, guidelines are developed to indicate exactly when to carry out maintenance (Roelofs, n.d.).

1.3. Research Framework

1.3.1. Problem statement

Compaction of the Hot Mix Asphalt needs to be done in a specific time and temperature window in order to obtain a better quality for the roads. ASPARiCool is a Dutch application that aims to predict the cooling rate using empirical measurements. However, the main drawback for the current version of the software is that it provides inaccurate cooling rate prediction due to the limited data obtained in field measurements.

1.3.2. Research objective and Research Question

The objective of this research is to *improve the accuracy of the prediction of ASPARiCool tool by obtaining data from field measurements, and to calibrate and validate the model*.

To follow the purpose of this research, a main question was proposed:

- How can the predictions of the cooling rate calculated by the ASPARiCool tool be improved, so that it can be implemented on construction sites?

This main question was answered by using sub-questions:

- How does the cooling rate of the asphalt affect the construction process and the final quality of the asphalt layer?
- What is the influence of the additional data on the asphalt cooling rate predictions?
- Which methods could be implemented to validate the new predictions of cooling rate in ASPARiCool, to then evaluate the final results?

1.3.3. Scope

This project aims to improve the prediction of cooling rate of the ASPARiCool tool by obtaining empirical data. The scope of the study was limited to field measurements inside The Netherlands in the Twente region during the months of May and July. Getting data was carried out on the edge of the road profile using different types of asphalts mixtures and thicknesses. The measurements started from the temperature at which asphalt leaves the paver until 60 °C with a time step of 1 minute. The weather conditions, type of mixture, thickness, and the number of roller passes were also considered.

1.3.4. Research Model

Taking into account the objective of the thesis and the questions proposed, the research model was divided into 4 sections. Each of the first three sections were linked to answer one sub-question and the last section to answer the main question. The research model structure can be seen in Figure 1. The vertical arrows represent that the activities were done in parallel, and the horizontal arrows means that the activities occurred sequentially.

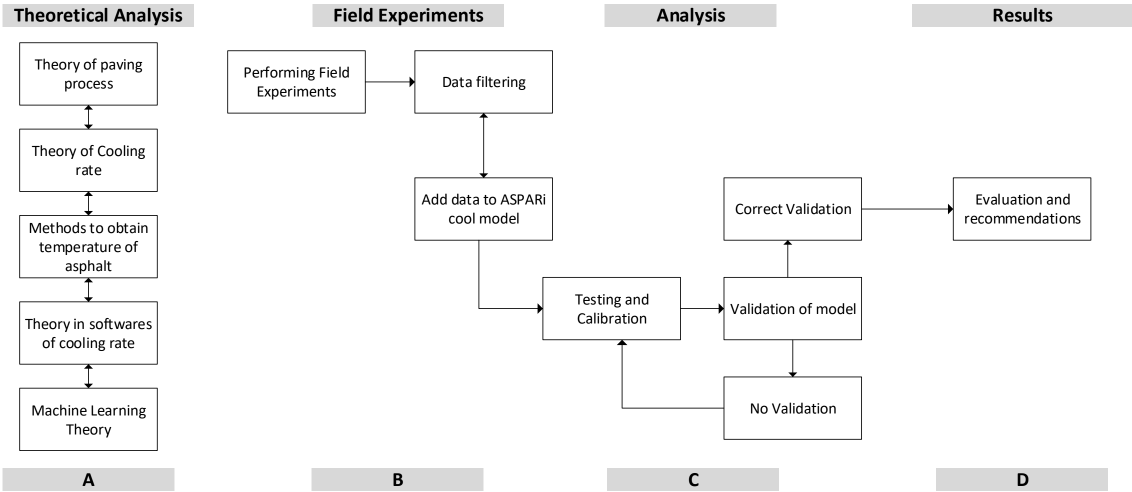

Figure 1: Research Model

In the four sections, each one has a different purpose or activity. In section A, the literature review of topics such as paving process, tools to obtain asphalt temperature on site, cooling rate, and machine learning was done. In section B, the collection of data from field experiments was performed together with the analysis of data collected from field experiments and the addition of this data to ASPARiCool tool. In section C the validation of the model and new results were carried out. Finally, the evaluation and recommendations are discussed.

2. Theoretical Framework

2.1. Asphalt Paving Process

The construction of roads is a linear process. In the Dutch context, the profile of the road pavement comprises of five layers represented in Figure 2. The bottom layer is natural soil (sand). On top of it a more resistant layer is placed made up of recycled concrete and brick. Then the three upper layers are made of asphalt: the base layer, binder layer, and surface layer (EUPAVE, 2020). Road maintenance begins by removing the current surface layer, and then analyzing the binder layer to decide whether the repair of it is necessary. After this process is completed, the paving process can start and, a new layer of asphalt is added. This process is done slowly, depending on the width and length of the section. Finally, the rollers perform the compaction (Mrugacz, 2020).

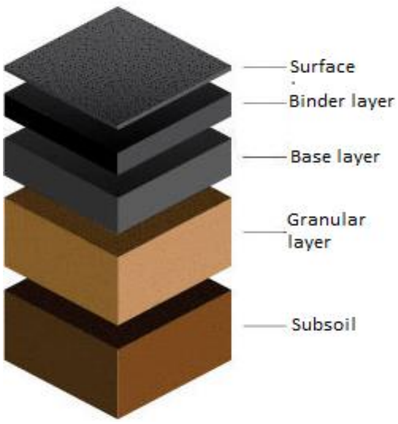

Figure 2: Ground layers

During the asphalt paving process, the compaction step has a great impact on the level of quality of the road (Arbeider, 2017); therefore, it will be explained more in detail. The compaction aims to obtain an optimum density (Chadbourn, et.al., 1996). If the correct level of compaction is not achieved, some negative consequences will emerge: Greater air void content (Qian et al. 2019), reduction of contact and friction among particles, and a possible decreasing in smoothness due to the loading of vehicles (Huerne, 2004). Therefore, by applying appropriate compaction the desired density is achieved. Together with this, the optimization of stiffness and resistance to fatigue, durability to withstand weathering, resistance against deformation and moisture, the bearing capacity to support the traffic loads and more stable result is obtained (Chadbourn, et.al., 1996; Bijleveld, et.al., 2012; Huerne, 2004).

For carrying out an adequate compaction process, several factors need to be considered. According to Arbeider (2017) and Huerne (2009), some of them are speed of pavers, roller capacity, type of mixture, and the Hot Mix Asphalt (HMA) temperature variation which is one with the most significant impact. Chadbourn et al. (1996) explained that when the temperature goes down from 135°C to 63°C, the resistance to compaction is ten times bigger. Moreover, when it goes from 135°C to 57°C, the viscosity increases by 1000. Therefore, if the process is carried out within a specific temperature and time range, the quality and life span of the asphalt improve (Miller et al. 2019). A typical compaction window is shown in Figure 3. A line enclosed by two points represents it. One with the highest temperature and the time where compaction can start, and the other with the lowest temperature and the time where it marks that rollers pass after this moment are not optimal.

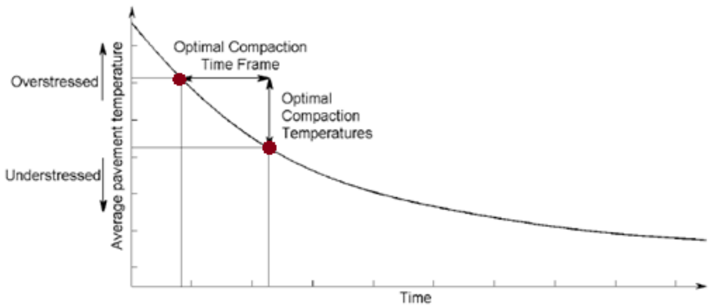

Figure 3: Compaction window of asphalt (Miller et al. 2019)

2.2. Cooling rate of asphalt

The temperature of asphalt is an essential factor since it is one of the factors that determine whether or not the asphalt is compacted outside the ideal range. Two things can occur: on the one hand, if the temperature during compaction is low, the result would be an under-stressed asphalt since the force applied is too low to allow a higher density (Arbeider,2017). On the other hand, if the temperature is very high, overstressed asphalt would be obtained because the rollers will only move the material but not compact it due to the absence of stability, leading to a loss of some mechanical properties (Bijleveld et al. 2012).

The cooling rate is defined as the change in the temperature over time. The cooling rate curve is a graph as shown in Figure 3 in which is displayed the temperature on the y-axis and time on the x-axis (Blasso, 2018). Determining the cooling rate of the asphalt in real time is complex.

According to Miller (2010), as cited by (Bijleveld, 2015), each type of asphalt has its optimum temperature range, so each mix has a different cooling rate and optimal temperature window. At the same time, the temperature decreases depending on the ambient conditions, the thickness of the layer, etc. (Arbeider, 2017; Miller, 2010). Moreover, as Vasenev (2012) explains, the asphalt does not have a homogeneous temperature, it is influenced by the asphalt moving in the paver, giving a range of 110° to 150°C depending on the type of mixture. Besides, several layers may be paved, or even within the same layer of asphalt, the temperature varies. As stated by Ismail (2019), the surface temperature is lower than the temperature inside the core of asphalt layer. In some projects, the ideal temperature range is given as recommendations by the mix designer who has calculated it before. However, this does not have the same impact since the specific characteristics of each project are different (Vasenev, 2012). The compaction process usually takes place when the asphalt temperature is between 160°C to 80°C. If compaction is done after 80°C, then the quality may be reduced (Hashim et. al. 2018). As a consequence, the process of calculating and predicting the cooling rate of asphalt is challenging. The factors that affect the variation of the cooling rate of asphalt are explained below.

2.2.1. Types of mixtures

The mixtures used are different in each part of the world; since the scope of this research is limited to the Netherlands, the mixtures that will be explained are: Asphalt Concrete (AC), Porous Asphalt (PA), and Stone Mastic Asphalt (SMA). The first mixture, AC, is composed mainly of bitumen and aggregates, making it resistant to abrasion. However, it is not the best sustainable option (Ozgan & Serin, 2012). Depending on the intended use, the grain size varies, denoted by a suffix number (AC22, AC16, AC11, AC8).

The second mixture is PA; this mixture is widely used in The Netherlands. The PA mixture has sub-classes depending on the grain size (PA16, PA11, PA8, PA5). Porous Asphalt helps to improve traffic safety, especially under rainy conditions, since the water passes through the voids keeping the surface dry thus avoiding splash, spray, and aquaplaning (Pittet et. al. 2006). Moreover, this type of layer contributes to the reduction of noise. According to Rijswaterstaat (n.d.), more than 85% of the motorways use silent asphalt. However, the disadvantages of this mixture are that the water can remain inside the layer for a long time which strips the binder film. Also, since the layer has more voids they tend to be blocked by dust or dirt. Moreover, in weather conditions with snow or ice, the mixture requires two times more de-icing salt than other mixtures. Therefore, for all these disadvantages the lifespan is shorter (Bondt et. Al. 2016); the average life expectancy of a slow lane is 11 years, while a fast lane is 17 years (Rijswaterstaat, n.d.)

Finally, the SMA is a mixture with an essential percentage of material of 2mm and more prominent, and the spaces are filled with mastic (sand, filler, bitumen). Moreover, this mixture is capable of withstanding heavy loads due to braking and spiral traffic such as roundabouts. Also, the critical point is that it has a long shelf life (Uden, n.d.). The SMA mixture is classified in: SMA-NL, SMA-NL 11B, SMA-NL 8G, and SMA-NL 5. The SMA-NL, as top layer, has a lifespan of up to 20 years (Gemeente Oss, n.d.).

Since each mixture type has different characteristics, the cooling rate will be different, thus affecting the cooling rate prediction. An essential factor in mixtures is the coefficient of thermal conductivity. Thermal conductivity is expressed in watts per meter Kelvin (W/mK) and is the rate of heat loss per unit of area of a material (Donev et.al. 2020). Therefore, the cooling rate is slower if the mixture requires more heat to change temperature (ISAAC, n.d).

2.2.2. Thickness of layer

The thickness of the new layer is an important factor in the cooling rate of the asphalt. Since the change in temperature determines the cooling rate, if the layer thickness is greater, the heat will be held longer, so the slope of the cooling rate curve will be lower. This allows roller operators to make the necessary passes within the optimal range (Scherocman & Walker, 2008). A study conducted by Hainin, et. al. in 2013 using asphalt samples showed that the thinner the layer, the lower the Time Available for Compaction (TAC). The results obtained were that for a 25mm layer the TAC is 13 min; for a 32mm the TAC is 23 min; and for >44mm the TAC is 50min. Therefore, if the layer is thicker it can be compacted easier than thinner layers.

2.2.3. Underlying layer type

During the road construction, the new asphalt layer is built over another layer that is already established previously. Since this underlying layer has been exposed to weather conditions longer, its temperature is much lower than the temperature at which the asphalt leaves the paver. At the moment that the asphalt makes contact with the underlying layer, the heat transfer starts in both directions. The phenomenon that occurs here is called conduction, which is the heat transfer between two solids (Aletba, et al., 2021). Therefore, the type of underlying layer plays an important role in the cooling rate since, depending on the material, the thermal conductivity varies making the heat transfer faster or slower. As stated by Scherocman (2000), “there is more rapid cooling of the mix downward into the base than upward into the ambient air”. Moreover, the base layer also affects the level of compaction and stiffness achieved. This depends on the conditions of the underlying layer, such as cracked asphalt pavement, new asphalt concrete layer or cold mix asphalt layer (Scherocman & Walker, 2008).

2.2.4. Underlying Layer Temperature

As explained in the section above, the underlying layer is an important factor in predicting the cooling rate. Besides the material, the initial temperature of the underlying layer is also influential. In the new layer of asphalt, the surface transfers heat to the air; but at the bottom, the heat transfer is carried out with the underlying layer. Therefore, the colder the lower layer, the steeper the slope of the cooling rate curve. According to Scherocman (2000), the underlying layer temperature is more important than the air temperature to predict the TAC, especially for thinner layers.

2.2.5. Initial Temperature of Asphalt

When the asphalt leaves the paver, the cooling begins. To predict the cooling rate, it is necessary to know the initial temperature at which the asphalt is released. If the mixture is stored inside trucks and put on hold for a long time, the mixture starts to cool down inside them. Therefore, when the new layer is placed the initial temperature is lower, thus giving a lower TAC.

2.2.6. Wind speed

The wind in The Netherlands is an important factor to consider since the speeds on certain days can be very high. According to Hashim et. al. (2016), the wind tends to disperse the heat of the mixture. This process occurs horizontally on the surface, reducing the asphalt temperature. In addition, the exposure to high wind speeds produces a higher impact on thin layers. Since the wind has direct contact with the surface, the effect of wind is more significant on the surface than in the core temperatures (Hashim 2016). Apart from the cooling effect, since the mixture can cool so quickly, a crust may be formed on the surface. Therefore, the crust formed needs to be broken before the compaction process is carried out (Scherocman J. , 2000). A study conducted by Hashim et. al. (2016), shows the effect of the wind on cooling rate with data and graphs. This study was conducted using four scenarios and the ACW14 mixture. The first without wind, the second with a wind speed of 5km/h, the third with 10km/h, and the last with 15km/h. Figure 4 shows the cooling rate curve in the four scenarios. As can be seen, as the wind speed decreases, the slope decreases; thus, the TAC increases. Table 14 of Appendix A shows the cooling rate of each scenario.

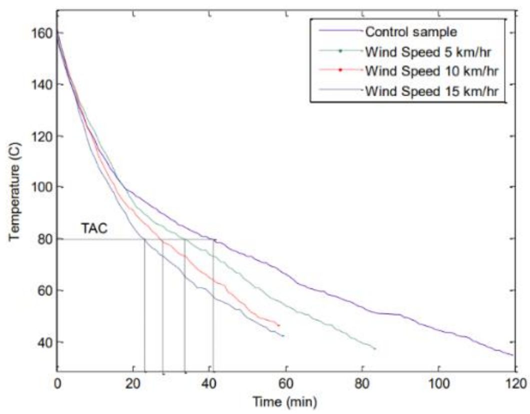

Figure 4: A comparison of cooling rate time at various wind speeds (ACW14) (Hashim et.al. 2016).

2.2.7. Outside Ambient Temperature

The difference between the asphalt temperature and the ambient temperature is proportional to the cooling rate of asphalt (Badruddin, et al., 2021). According to Wang, et.al. (2014) as cited by

Baars (2020), the asphalt temperature decreases faster at lower ambient temperatures. This occurs because, the bigger the difference between the temperature of the asphalt and the environment, the more significant the exchange of heat. This exchange occurs through the movement of heat from the hotter space to the colder until reaching an equivalent temperature (Badruddin, et al., 2021). Therefore, the colder the ambient temperature, the faster the cooling rate of the asphalt.

2.2.8. Weather Conditions

In the case of weather conditions, three general cases are explained: Sunny day, the cloudy weather, a rainy day.

On a sunny day, solar radiation is also an important factor to consider in predicting the cooling rate. According to Aletba, et. al. (2021), the process starts when the surface layer of asphalt absorbs the heat from solar radiation and transfers it to the lower layers. An important feature is that asphalt can absorb and store more heat than other natural layers. For this reason, the temperature of asphalt can reach 70°C when exposed to high solar radiation (Hassam, et al. 2021). In this process, two things happen. Part of the energy is reflected; heat is not absorbed, and the rest of heat is absorbed and transferred to the rest of the layer (Aletba, et al., 2021). In Figure 5 the forms of heat transfer in the asphalt are shown. Temperature variations caused by solar radiation are measured by the amount of short-wave radiation (Solaimanian and Kennedy, 1993).

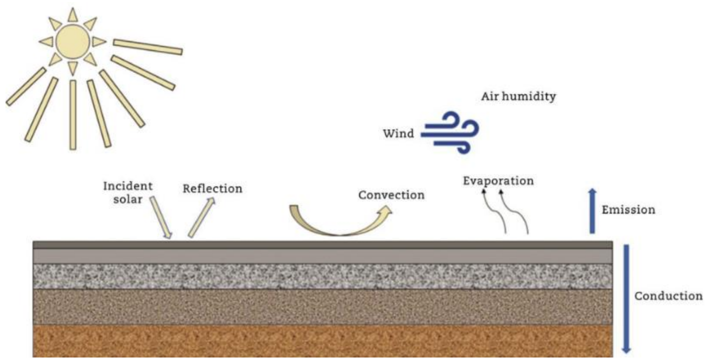

Figure 5: Heat transfer in asphalt (Aletba, et. al. 2021)

The cloud coverage in the sky influences the cooling rate since they have an impact on solar radiation. With a higher percentage of clouds blocking the sun, the solar radiation effect is lower (Li, 2012). Figure 6 shows the level of solar radiation for 10 days. According to the study carried out by Li (2012), from March 13 to 17th, the cloud coverage was higher than on the other days. This higher level of clouds impacted the amount of solar radiation. On the days at which the cloud coverage was lower (03/18/12) the solar radiation was the maximum with a value of 1000W/m^2. However, on the cloudiest day, the radiation dropped to 200 W/m^2.

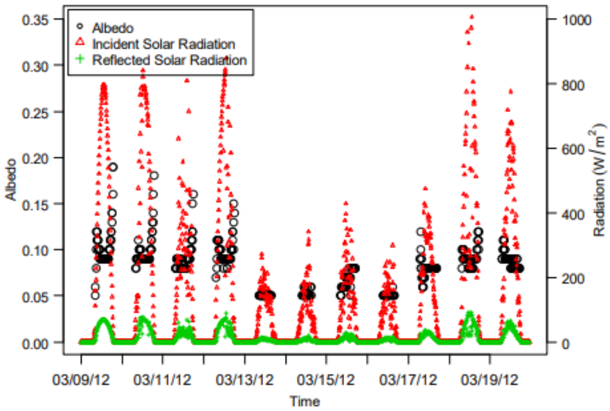

Figure 6: Influence of cloud on solar reflectivity (Li, 2012)

Finally, in the case of a rainy day, many problems may appear on the asphalt structure. This occurs because the rain can infiltrate the asphalt at a colder temperature, and since it is a heat conductor, it takes heat from the mixture (Hashim, Arshad, Shaffie, Noh, & Azhar, 2018). Due to its lower temperature, rain affects the temperature of the asphalt very quickly. As explained by Hashim et.al. (2018), very light rain can absorb the heat 98% faster than a non-rainy day. Since the rain varies in intensities, a more detailed analysis is shown in the next section.

2.2.9. Rain

As explained before, rainfall can influence the cooling rate of asphalt depending on the intensity. In a study done by Ismail, et.al. 2019, the cooling rate comparison of four scenarios is shown. The first is a dry scenario, the second is light rain, the third is moderate rain, and the last one is heavy rain. Table 15 from Appendix A shows the rainfall intensity with which each case is defined.

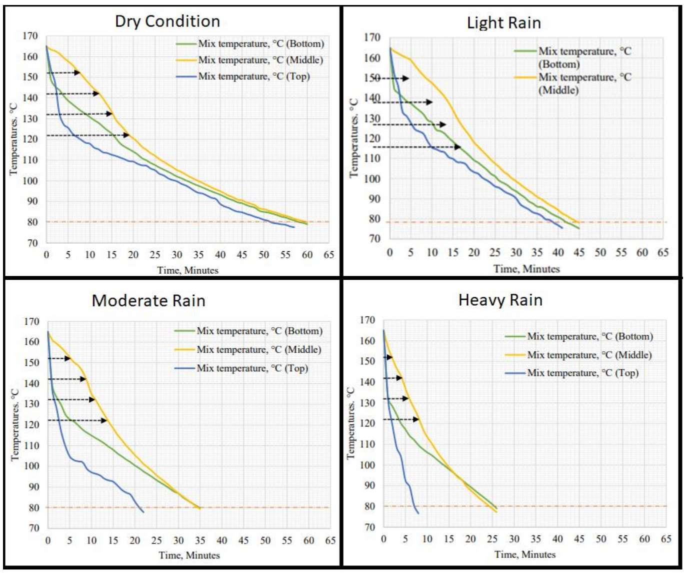

Figure 7: Cooling curves from different rain intensities (Ismail, et.al. 2019)

The study took into account three depths of asphalt layer: The surface, the middle, and the bottom. In Figure 7, it can be seen that the asphalt temperature decreases less rapidly in the dry scenario. On the other hand, as the rain increases, the cooling rate also increases. With this, it can be seen that in the heavy rain scenario, the temperature drops drastically in the first 8 minutes, which does not allow an optimal compaction process. Moreover, in all scenarios, the cooling rate curve of the middle of the layer is the smallest. The reason is that the surface layer is in contact with air temperature, water, etc. Similarly, the bottom layer is in contact with the underlying layer which is cooler.

2.3. Tools to predict the cooling rate of asphalt

Since the cooling rate is complex to obtain, operators of the machines are responsible for determining the time and the way to carry out the compaction. Therefore, this process depends mainly on them and their experience (Bijleveld, 2015; Arbeider, 2017).

To calculate the cooling rate some theoretical models were proposed. A study of log-viscosity versus log temperature was carried out, and theoretical formulas of cooling rate were also applied. However, on several occasions these methods gave higher temperatures as cited by Vasenev et al. 2012. Also, some tools were developed to predict the cooling rate. One of them is Pavecool, which is a software created by the University of Minnesota (Chadbourn et al. 1998). Moreover, there are two variations of PaveCool which are MultiCool and PaveCool Freeze. However, these three tools are not appropriate for Dutch conditions since they are based on theory and lab tests with mixtures mainly used in the USA (Miller et al. 2019). For this reason, in The Netherlands, a software tool based on data from actual projects was developed, named ASPARiCool. However, the software is not implemented yet because precise results cannot be observed due to the limited data (Baars, 2020). Further explanations of the tools are given below.

2.3.1. PaveCool

The PaveCool software was developed at the University of Minnesota with the support of the Minnesota Asphalt Paving Association and the Minnesota Department of Transportation. This tool was developed to help operators and engineering to make better decisions regarding the time at which the compaction has to be carried out (Chadbourn et al. 1998). PaveCool is based on theory and thermodynamic models, for which lab experiments were carried out. To predict the cooling rate curve, the tool requires some input parameters.

2.3.1.1 Input parameters

The PaveCool tool is divided into four sections regarding the input: Date, Mix Specifications, Environmental Conditions and Existing Surface. The software allows to use the SI and English Units, for this research, the SI is used. An overview of the input screen on PaveCool is represented in Figure 32 of Appendix A.

Date and time

In the first section, the date and time when the paving starts have to be included. This input is used to determine the angle of the sun to then calculate the net solar flux.

Mix Specifications

For this section, four parameters are required. For the mixture type case two options are included: Fine/Dense or Coarse/SMA. After choosing one material, the properties for heat flow calculations are set automatically. The thermal properties values for each mixture and their calculation are shown in Table 17 from APPENDIX A. Secondly, the Binder Grade is needed. The next parameter is the layer thickness. This value has to be the desired thickness after the compaction process. The range in PaveCool is from 13mm to 274mm. The last input is the initial temperature of the asphalt mixture. (Minnesota Department of Transportation, n.d.).

Environmental Conditions

In the environmental conditions, four parameters are needed. The first parameter is the air temperature; this is the average outside temperature during the project. It is used to determine the speed of the loss of heat in the air and has a range from -40°C to 49°C. Wind speed is the second parameter. The range goes from no wind 0km/h to 193 km/h. As a third input, the sky conditions are required. For this case, 5 options are available: Clear & Dry, Hazy, Partly Cloudy, Mostly Cloudy, and Overcast. The detailed explanations are shown in Table 18 of Appendix A. Finally, the latitude ranges from -90 to 90, where negative latitudes mean Southern Hemisphere and positive latitudes Northern Hemisphere. The latitude is used together with the date and time to calculate the position of the sun (Minnesota Department of Transportation, n.d.).

Existing Surface

For the last section, the characteristics of the underlying surface are required. The first parameter is the type of material of the underlying layer. There are four options: Asphalt, Portland Cement Concrete (PCC), Granular base, and Subgrade soil. The thermal properties of these layers are used in the heat flow calculations, the characteristics of each type are shown in of Appendix A. According to the Minnesota Department of Transportation (n.d.), the asphalt and PCC do not change their characteristics with temperature and moisture variation. However, the granular base and subgrade soil have an effect on their thermal properties. Therefore, in these options the moisture and condition of the material are required. For the moisture, dry or wet are the options. While, for the condition, frozen or unfrozen can be chosen. The last parameter is the initial surface temperature. Having all the inputs filled the Calculate button can be pressed to get the output.

2.3.1.2 Output

The outputs that the PaveCool tools shows are three. The first one is the recommended time at which compaction should start and end. The second output is the cooling rate curve. An example of the curve obtained from PaveCool is shown in Figure 8. In the graph, it is also shown the time at which rolling has to start and stop. The last output is the report. In the exported file, the input parameters and the temperature of the asphalt in a time step of one minute that was used to display the cooling curve are shown.

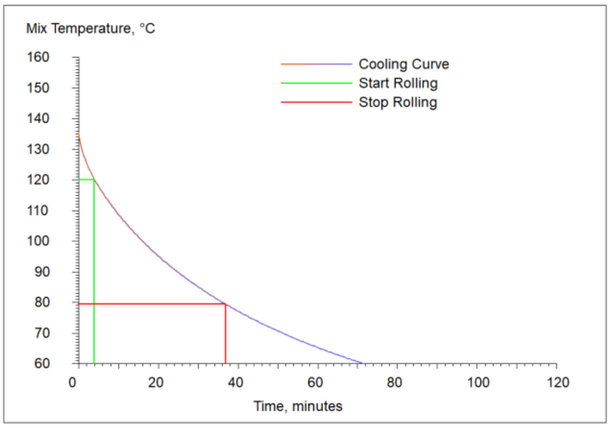

Figure 8: Cooling rate curve prediction from PaveCool tool

2.3.1.2 Limitations

The software is a help/insight for the user to know how the conditions in which the project is carried out will affect the time available for compaction. But it should not be used as a substitute for the judgment of engineers. In addition, the theories and features used are based in the United States, therefore if the program is to be used in another country this must be taken into account. In the case of the material mix, the PaveCool program only allows choosing between two types of materials. However, the number of types of asphalt used are many with different thermal properties. Finally, the PaveCool tool can be used to predict the cooling curve for one layer, if the project has more than one layer; other programs such as MultiCool have to be used.

2.3.2. MultiCool

The MultiCool tool is used to predict the cooling rate of asphalt to then make the calculations in the field regarding TAC easier. MultiCool V2.0 was developed at the Autburn University in association with the National Asphalt Pavement Association. The main additional change made in MultiCool compared to PaveCool is that Multicool allows adding more than one layer for the prediction. Therefore, it lets the user know how quickly each layer of asphalt cools, and what is the best time to add the next layer. Moreover, MultiCool can fill automatically some input requirements such as time, date, location, and weather information. Thus, the user just needs to add the mixture and underlying characteristics (NAPA, 2014).

The inputs required for the cooling rate prediction are the same as PaveCool, the extra data needed is the number of layers to be used. For each layer, the thickness, the temperature of the mixture, and weather conditions can be specified separately. The output from MultiCool gives the same results as PaveCool even though each layer is represented in the cooling rate graph. In Figure 9 is displayed an example of the MultiCool output. From the output the TAC for each layer and total TAC is given in minutes. Moreover, the graph shows the recommended time at which the next layer should be added. However, the difference in the graph compared to PaveCool is that MultiCool does not show the times at which compaction should start.

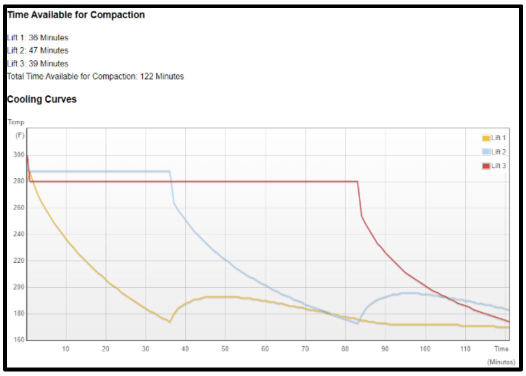

Figure 9: Cooling rate curves prediction from MultiCool tool

2.3.3. PaveCool Freeze

PaveCool Freeze tool is a variation of the 2.4 version of PaveCool software. The program was developed by the Minnesota Department of Transportation together with the University of Minnesota (Chadbourn et al. 1998). The difference between the PaveCool Freeze compared to PaveCool tool is that it allows the prediction of the TAC during adverse weather conditions. The interface of PaveCool Freeze is similar to PaveCool. However, two extra inputs can be added. The first is the rate of change in the air temperature. This value is the degree (°C) variation per hour, the value can be negative or positive. Moreover, since PaveCool predicts the cooling rate from the temperature that asphalt leaves the paver until it reaches 60°C, PaveCool Freeze predicts from 60°C until the temperature that the user desires. This value of the stop temperature is the second input added to the software. From the output, three sections can be obtained. The export data where the asphalt temperature every 1 minute is shown. The second output is the time that the asphalt takes to reach the stop temperature. Finally, the Cooling curve. In Figure 10 is shown the input and output from PaveCool Freeze. The cooling curve graph has three lines: The cooling curve of asphalt, the air temperature variation, and the stop temperature. In the example shown, a rate of -5°C/hour of air temperature is used, with a stop temperature of 20°C. Since the HMA temperature starts at 60°C the time that takes until it reaches 20°C is estimated to be 1 hour with 9 minutes.

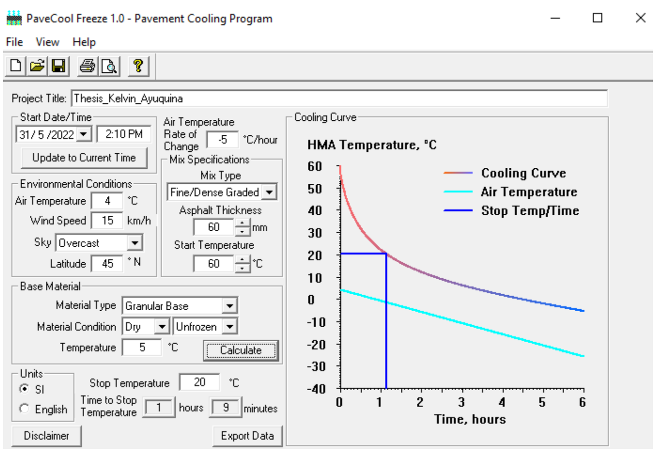

Figure 10: Cooling rate curve from PaveCool Freeze tool

2.3.4. ASPARiCool

The currently existing asphalt cooling rate prediction programs do not have high accuracy in Dutch conditions. A software named ASPARiCool was created by ASPARi to offer more accurate and consistent predictions inside the Netherlands. The tool was developed using historical data from different projects under different climatic conditions (Ong-A-Fat, Miller, & Makarov, 2019). The aim of the project is to predict the cooling rate of asphalt mixtures under different conditions. The interface and management of the ASPARiCool tool is easy, thus allowing operators and site managers to use it before the project starts.

The ASPARiCool tool performs the prediction using Machine Learning with a Multilayer Perceptron algorithm (MLP). According to Ong-A-Fat, et.al. (2019), the use of Machine Learning allows the tool to be more realistic and flexible when the data set is large. This allows a better adaptation to different environments with higher accuracy in predictions. However, since the model needs the collection of data from field projects; errors during the collection can be obtained which will affect the predictions (Ong-A-Fat, Miller, & Makarov, 2019). A further explanation regarding Machine Learning is done in section 2.4.

According to Ong-A-Fat, et.al (2019), ASPARiCool is made up of three layers. The first layer is the input, where a prediction model is needed. Having the data, the prediction layer trains the model. Finally, the output layer is where the user can predict new cooling curves by selecting the parameters. To follow this workflow, a software architecture was implemented.

2.3.4.1. Software architecture

The program interface is controlled by the View class, which is connected to the Controller class. The Controller class is used to connect the View class with the Model class where all the logic is written. The model contains four classes. The ExcelReader class is used to read the data uploaded. Next, the data is extracted by the ArffPrinter, which then stores the data in the Project class. Then, the Classifier class creates the ML which is used for predicting the cooling rate of asphalt (Ong-A-Fat, Miller, & Makarov, 2019). A representation of the architecture is shown in Figure 33.

2.3.4.2. Interface

The program interface is divided into two sections: input, and output. In Figure 11 the start of the tool is shown. The input section is divided into two subsections. The first subsection where the data for training the program is uploaded, and it is where project data can be added to make the prediction. The second subsection is where future project predictions are made. For this, the user must choose the characteristics of the project in each of the dropdown menus. To obtain the cooling rate graph which is the output section, all the inputs have to be filled out.

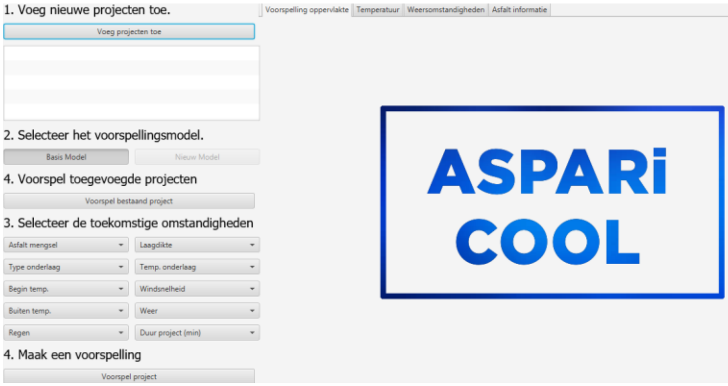

Figure 11: ASPARiCool interface

2.3.4.3. Input parameters

For the first subsection of the input parameters, the data collected from projects to train and validate the model needs to be uploaded. The data from the projects must be in an excel file where data has to be arranged as in Table 1. In the first row from Table 1, the characteristics of the project are established. The characteristics needed are the asphalt mixture, thickness, the type of underlying layer and the underlying temperature before the projects start. The speed of the wind, the air temperature, the solar radiation, and the amount of rain are also required. In the third row, the start time and temperature of asphalt data from field projects are written. After the model is trained, in the same section the prediction of the cooling rate of past projects can be executed.

Table 1:Input Format for data projects in ASPARiCool

Asphalt mixture	Layer Thickness (mm)	Sublayer Type	Temp. Sublayer (°C)	Wind speed (km/h)	Outside temperature (°C)	Solar radiation (w/m2)	Rain (mm)
Time	Surface temperature						

The second subsection is used for cooling rate predictions using the dropdown menu. In this case, the program has 10 input parameters. The effect of each parameters on the cooling rate predictions is explained in section 2.2. For each parameter, the options are already set by the program.

The first parameter is mixture type. Within this parameter, the types of asphalt used are: AC22, AC16, AC11, AC8, PA16, PA11, PA8, PA5, SMA-NL, SMA-NL 11B, SMA-NL 8G, SMA-NL 5. The second parameter is the desired thickness of the asphalt. The units used are millimetres; the values between each have a difference of 10mm. The smallest value that can be selected is 10mm up to a maximum value of 100mm. The third input regarding the asphalt is the temperature at which it will be delivered. This value can be chosen in the range from 100°C to 200°C, with intermediate values increasing by 5.

Apart from the asphalt to be used, the characteristics of the underlying layer are required. The type of underlying layer can be chosen from three options which are: sand, asphalt, and rock. In addition, the temperature of the sublayer is also required. The range of this parameter is from 10°C to 100°C with a difference of 10 degrees between each value.

In climatic conditions, three factors are used for prediction. The wind speed where the user can choose from no wind (0km/h) to wind speed of 12km/h. The next parameter is the air temperature, the values have a difference of 2 degrees between each one, and it has a range from -10°C to 40°C. The amount of rain is also necessary. This value is expressed in mm, and it ranges from a dry condition (0mm) to rain of 5.5mm. Then the type of weather in the project is required. Three types of weather are displayed in the dropdown menu: cloudy, sunny, and rainy.

The last input required is the duration of the project. This value is used to make the predictions until the indicated time. The user must indicate the time in minutes; in this parameter, the time step is 5 minutes with a minimum value of 5 minutes and a maximum value of 100 minutes.

According to Ong-A-Fat, et.al. (2019), it is possible to add more parameters that affect the cooling rate such as humidity, solar radiation, etc. in order to improve the accuracy of the prediction. However, by adding these parameters, the use of the application becomes more complex; since obtaining these values before the start of the project are more difficult for the operator.

2.3.4.4. Output

The ASPARiCool tool predicts the cooling rate of asphalt. The output from the software is a graph where the prediction of the cooling curve of the asphalt and the data from field projects are plotted. An example of the output from the tool is shown in Figure 12.

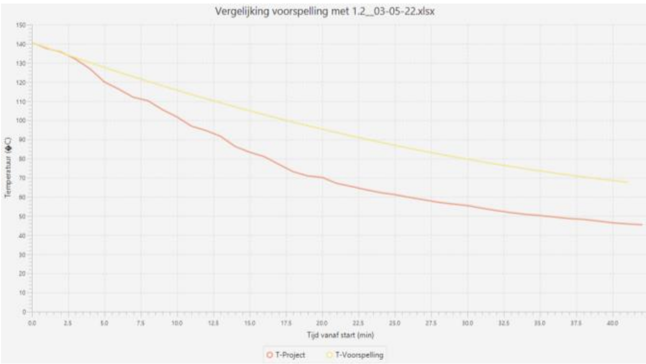

Figure 12:Example of output from ASPARiCool tool

2.3.4.5. Limitations

ASPARiCool tool is based on Machine Learning, therefore to make accurate predictions, real data from field projects are needed. Thus, the main limitation of the tool is that if there are not enough data from similar projects, the cooling rate prediction will be inaccurate. Moreover, since data is obtained from the field, errors in the data collection can lead to errors in the prediction.

2.4. Machine learning

Artificial Intelligence (AI) is the basis of algorithms created that simulate human actions. AI began its development in the 1950s by doing predictions similar to statisticians using a calculator;

making statistics a basis of AI. Some of the statistical methods used in the past that are still used are: regression, clustering, probability theories, and decision trees (TutorialsPoint, 2019). With the growth of technology, new branches like Machine Learning (MI) were started.

Machine Learning was developed to make programs or algorithms that can learn from data. To develop a Machine Learning system a model is necessary. Inside the model the information learned has to be stored in a structure called hypothesis (Lawrynowicz & Tresp, 2014). Within these systems the use of programming languages is necessary. Machine Learning supports languages like: Python, Java, Julia, R, Matlab, and C++. Moreover, Machine Learning can be classified into five types which are: Supervised Learning, Unsupervised Learning, Reinforcement Learning, Deep Learning, and Deep Reinforcement Learning

2.4.1. Artificial Neural Networks

Artificial Neural Networks (ANN) are a subset of ML and are the main basis for Deep Learning algorithms. According to Carioni (2022), ANN is "a way to create a suitable hypothesis class H that is also easy to optimize". ANN were created to develop algorithms that are capable of imitating human brain behaviour. However, since ANN are models, one of the most frequent problems that exist is overfitting during the training, it is explained in section 2.4.2. (Carioni, 2022). Some types of architectures developed are: Multi-Layer perceptron (MLP), Auto Encoder, Variational AE, etc (TutorialsPoint, 2019). In this research, the MLP is explained below.

Multi-Layer Perceptron Algorithm

To define the MLP, it is first necessary to define the Perceptron. A Perceptron is a basic classifier simulating a model of a biological neuron (Carioni, 2022). A representation of a Perceptron model is shown in Figure 13, and; the definition in mathematics is given by:

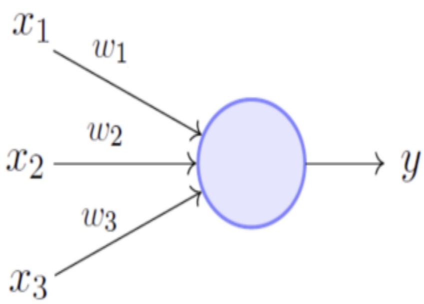

Figure 13: Perceptron Model (Carioni, 2022)

$$F_{w,b}(x) = f(w^T x)$$

Where f is defined as:

$$f(x) = \begin{cases} 1 & if\ x > 0 \\ 0 & otherwise \end{cases}$$

A Multi-Layer Perceptron (MLP) algorithm or Feed-forward neural network is the union of several perceptrons connected and ordered one next to another inspired by the connections of the brain (Carioni, 2022). An example of an MLP algorithm is shown in Figure 14. Inside the model, some characteristics can be defined. The circles are called neurons, the columns of neurons are layers, the first layer is named the input layer, the last layer is the output layer, and the layer in between are the hidden layers.

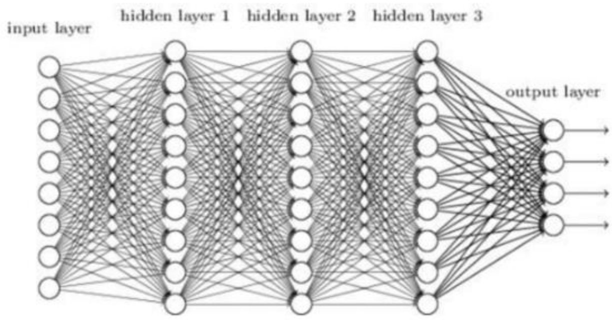

Figure 14: MLP Algorithm (Carioni, 2022)

2.4.2. Overfitting and underfitting

Underfitting is a type of problem that occurs in prediction models when the machine does not learn from all the data. Therefore, at the moment, predicting the model will not be accurate since data will be missing (Juma, 2020). On the other hand, as explained by Kotsiantis (2014), overfitting occurs when the model memorized all the data; making accurate predictions with training data, but not accurate for testing. Overfitting can be caused due to the complexity of the model, or the excessive number of features (Juma, 2020). Two solutions proposed by Carioni (2022) to solve the overfitting problem are: reduce the number of epochs (a complete pass through the data in the algorithm) in the training model by making an early stopping. A second solution is to add more data for training the model.

Figure 15 shows the graphs where the underfitting and overfitting problem occurs.In the left image, the underfitting problem is displayed. This is the case where the model misses important data. In the right image, the overfitting problem occurs due to the model memorizing all the data. In this prediction the degree of the curve is 15, making it to complex, giving inaccurate prediction. However, in the image in the middle, the best prediction is shown.

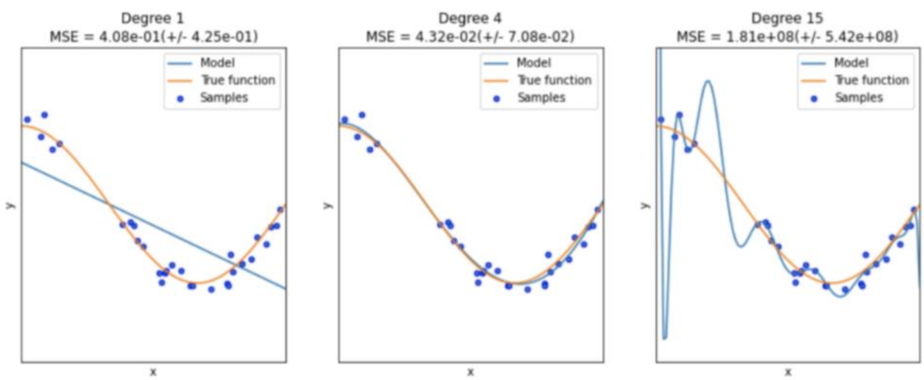

Figure 15: Overfitting and Underfitting problem (Carioni, 2022)

2.4.3. Machine Learning in ASPARiCool

ASPARiCool tool was developed using the platform Eclipse with the Java language. The ASPARiCool software is based on an ANN, in which the MLP algorithm was used. In Table 2 the parameters that were used to define the MLP inside Eclipse are explained.

Table 2: Multi-Layer Perceptron parameters for ASPARiCool tool

Parameters	**Value/Name**	**Description**
Learning Rate	0.1	The amount that the parameters weights are updated during training, the value is a small positive value in the range from 0.0 to 1.0 (Brownlee, 2019).
Momentum	0.2	It is an extension to the gradient descent optimization algorithm that allows the search to build inertia in a direction in the search space (Brownlee, 2019).
Training Times	2000	Number of times that data will be trained inside the model (Murphy, 2019).
Hidden Layers	3	Layers of nodes between the input and output layers. With a higher number of hidden layers the complexity is higher (Brownlee, 2018).
Classifier	train	Process to take the data known and create a classifier on the basis of that known data (MarkLogic, n.d.).

3. Field Measurements

Field measurements on construction projects are of great importance since this is where the data is obtained. For this, joint work was carried out with ASPARi personnel as well as with its technology. The methodology used here was the Process Quality improvement method (PQi).

3.1. Process Quality improvement method (PQi)

This method is based on monitoring the asphalting process using GPS, infrared and other sensors. All the information obtained is shared among all ASPARi members for future analysis, and proposal of new alternatives. The approach of this method is to improve the operation quality of the asphalting process. Moreover, during the PQi; different types of elements are combined such as theory, quality control, element of process quality, and feedback systems (Bijleveld et. al., 2012). The equipment used to undertake cooling rate measurements is explained in section 3.2.

3.2. Equipment

The main equipment that are needed are the thermocouples, the data-loggers, the infrared camera, 3D stands and the weather station.

Thermocouples

The thermocouples are temperature sensors. They consist of a positive non-magnetic leg and a negative magnetic leg. The type of thermocouples used is K-Type. The range of temperature that can be read is from -50°C to 204°C. It has a tolerance class of ± 1.5K (Tempsens, n.d.). The K-Type thermocouple is shown in Figure 16.

Figure 16: K-Type thermocouple

Data-logger

The data-loggers are used to connect the thermocouples for logging temperature information. In addition, data can be automatically saved to an SD card. Four thermocouples can be connected to the data-loggers used during this research. This allows the core temperature to be taken at different depths at the same point. An example of the data-logger used is shown in Figure 17

Figure 17: Data-logger

3D stands

Figure 18: 3D stands

The 3D stands are supports that were designed to be able to keep the thermocouples inside the asphalt layer at specific depths. The height of the 3D stand has to be at least 1cm lower than the thickness of the asphalt layer to prevent damage to the surface. In Figure 18 the 3cm support is represented. The heights at which the thermocouples are placed with respect to the bottom of the layer in each stand are detailed below.

- 6cm stand: Four core temperatures (1.2cm, 2.2cm, 4.2cm and 5.2cm)
- 5cm stand: Four core temperatures (1.2cm, 2.2cm, 3.2cm and 4.2cm)
- 4cm stand: Three core temperatures (1.2cm, 2.2cm, and 3.2 cm)
- 3cm stand: Three core temperatures (0.9cm, 1.5cm, and 2.2 cm)
- 2cm stand: Two core temperatures (0.9cm, and 1.5cm)

Infrared camera

Figure 19: Infrared camera

The infrared camera represented in Figure 19 measures the energy of objects, to then convert the infrared data into the surface temperature of a specific point. The infrared camera is used to obtain the surface temperature of the new asphalt layer during the construction process. The location where the temperature is measured is above the 3D stand.

Weather station

Figure 20: Weather station

The weather station measures different characteristics of the weather during the construction. The data extracted from the weather station are the air temperature, wind speed, amount of rain, and solar radiation. For the current research, the Vantage Vue Weather Station from Davis is used, it is displayed in Figure 20.

3.3. Set-up on construction site

Figure 21: Set-up to collect temperature data

To start data collection, it is necessary to install the equipment mentioned above. First of all, the weather station has to be placed in an open space. The weather station can stay in the same place throughout the process on the same project. Then, the 3D stands have to be fixed to the ground and the infra-red camera pointing at the same location. The thermocouples must be connected to the data-logger. At the time the paver passes through the collection point, the data record has to start. The data recorded are the surface and the core temperatures with a time step of one minute. This process is carried out until the surface temperature of the asphalt drops to approximately 60°C. In Figure 21 the set-up during the construction process is represented.

4. ASPARiCool evaluation using historical data

To determine the current prediction accuracy of the cooling rate using ASPARiCool tool, an analysis was performed only with the data that was used when the program was developed. However, not all historical data was taken with a time step of 1 minute. Therefore, this can be a factor affecting the prediction of the cooling rate. In total, the data used was from 31 projects. The number of projects taking into account and their corresponding asphalt type is shown in Table 3. Of the 31 projects; 24 data projects were used to train the model. The rest of the data was used to validate the model, the projects used were 2 from AC22, 2 from PA16, and 2 from AC16.

Table 3: Numbers of projects from historical data

Mixture Type	Amount of projects
AC16	4
AC22	20
PA16	7
Total	**31**

To determine the current accuracy of the model, the difference between the temperature obtained in the field measurements and the predicted data was taken into account. During the training of the 24 models, an average temperature difference of 6.5°C was obtained, while the average temperature difference in the last point of the 24 projects was 17°C. With these values, it can be concluded that due to the fact that the amount of data is limited and an equal time step is not used, the training of the model was not precise. In addition, in Table 19 of Appendix B, the average difference and final difference per project are detailed.

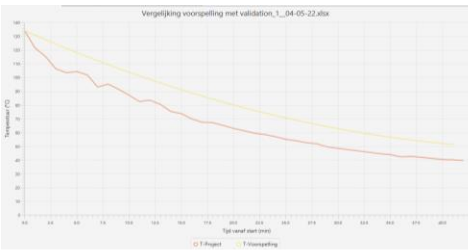

Figure 22: Cooling rate prediction historical data surface:PA16_1_Validation_S

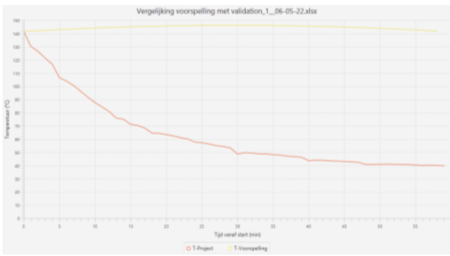

Figure 23: Cooling rate prediction historical data surface:PA16_2_Validation_S

Regarding the prediction of the cooling rate of the 6 validation models, an average temperature difference of 40.6°C was obtained. Moreover, the average temperature difference in the last point of the 6 projects was 71.6°C and an average RMSE of 51.9. Figure 22 and Figure 23 display the most and least accurate predictions. Since the temperature difference is too large, the program cannot be used to predict the cooling rate just using the historical data. The cooling curves and RSME values for each project are shown in Appendix B. Therefore, the collection of extra data was carried out. In the next section, the data obtained during May and June are explained.

5. Data obtained from field measurements

In this section, an analysis of the data obtained during the field measurements is performed. The projects were carried out in the Twente region, in which different types of asphalt were used. In the projects, the surface temperature and the core temperature at different depths taking into account the thickness of the asphalt that was built were recorded. Therefore, first the analysis of the difference among the temperature in surface and core was carried out.

5.1. Asphalt temperature at different heights

Asphalt temperature at different depths may be different due to the factors explained in section 2.2. Each factor can affect it to a greater or lesser extent, an example is the temperature of the underlying layer. To represent the effect of cooling rate at different depths, the data of the temperatures at one location is plotted in Figure 24. The asphalt used was SMA-NL 8G with a thickness of 40mm, the underlying layer was asphalt with an initial temperature of 11°C, the air temperature was 7.5°C, wind speed of 0.9km/h, and no rain. In the graph; the curve represented with T1 is at 2.2cm, T2 is at 1.5cm, T3 is at 0.9cm from the bottom. As can be seen from the graph, the temperature of the curve T3 which is the closest to the underlying layer has a steeper cooling rate at the beginning of the graph. This steeper slope is due to the direct contact with a solid with a lower temperature producing the transfer of heat in a faster way. Moreover, the Surface temperature has a similar rate as T1, and T2 at the beginning but as time passes the impact of air temperature becomes higher making a smaller difference. This pattern does not occur in all cases since other factors also play a role such as type of mixture, rain, and thickness.

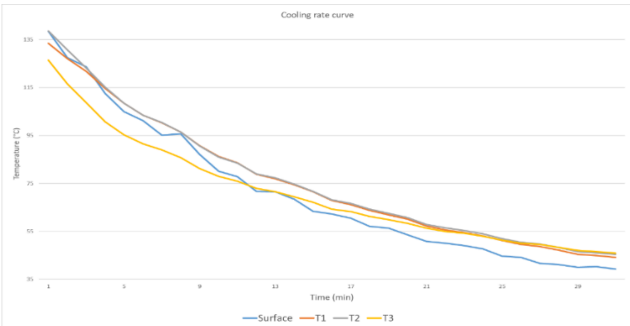

Figure 24:Representation of the difference of Cooling rate at different heights

5.2. Cooling rate curves analysis with rainy conditions

During the collection of data, the rainy conditions were not usual. In this section, a comparison of the cooling rate during rainy and dry conditions is carried out. In Figure 25 the two curves are represented. The temperature data was obtained during the same day, for this reason, the mixture type, thickness, and underlying layer are the same. Yet, the air temperature and wind speed changed. As can be seen from Figure 25, the arrow points the cooling curve with an average rain of 0.08mm, while the other line is the curve during dry conditions. As explained in section 2.2.9, a light rain can drastically affect the temperature of the asphalt. The time it takes for the asphalt to reach 60°C was 84 minutes for dry conditions and 37 in rainy conditions. Additionally, the air temperature (18°C) during dry conditions was lower, and in rainy conditions was 22.7°C. Meaning that, even if there is a lower temperature on a non-rain day, the impact of the outside temperature is not that big compared to the rain.

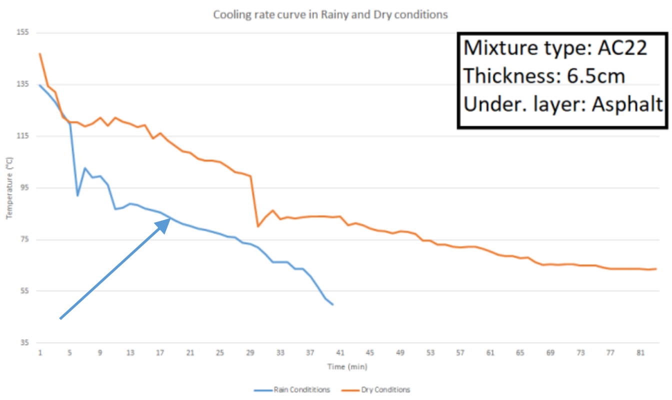

Figure 25: Cooling curves in a rainy and dry conditions

5.3. Effect of thickness in field measurements

Depending on the type of layer being built, the thickness can vary. For example, a sub-layer can have a higher thickness compared to a surface layer. In this chapter, two cooling rates are compared in layers of different heights. A project in which the AC16 mixture was used, with a thickness of 25mm, is compared to a project with a layer thickness of 60mm and mixture type AC16. The weather conditions and underlying layer were similar and the detailed characteristics are shown in Table 16 of Appendix A. For this analysis, the surface temperature and the core temperature at 1cm from the bottom were used. The cooling curves are represented in Figure 26.

From the data obtained, it can be seen that both the surface and the core temperature have a faster cooling rate when the thickness is smaller. In the case of the 25mm thickness, the temperature of asphalt takes approximately 25 minutes to cool until 60°C. Meanwhile, the thicker 60mm layer took approximately 85 minutes to cool to 60°C.

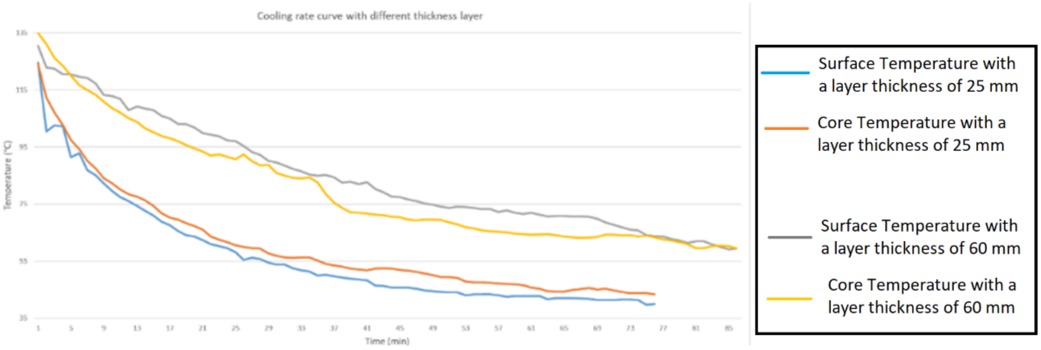

Figure 26: Cooling rate curves using different thickness layers

5.4. Format and characteristics of cooling rate data obtained

In the two months of data collection, there were several project days, each with different characteristics and locations. In this section, an example of the collected data is explained. The rest of the details of each project can be found in Appendix C. The features that were extracted are based on the data needed as input in the ASPARiCool tool and are explained in section 2.3.4.

5.5.1 Location 1 on day 03/05

The first information recorded for each cooling rate curve is more general information such as the contractor, date, and location. Next, information concerns to the materials used; in this section are the Data-Logger number, and the size of the 3D stands with the depths of core temperatures. Then, the type of mixture, thickness, and type of underlying layer with its initial temperature was record. Finally, the weather condition data was registered (Wind Speed, Outside temperature, Solar radiation, Rain). This information was recorded in tables as shown in Table 4. In this report, these data are represented by a graph showing the cooling curve, as shown in Figure 27.

Table 4: Project characteristics location 1 on 03/05/2022

<table>
<tr><td>Contractor:</td><td colspan="2">BAM</td><td>Date:</td><td colspan="2">03/05/2022</td></tr>
<tr><td>Location:</td><td colspan="2">N35 at 73.5</td><td>Data-Logger:</td><td colspan="2">BAM 6</td></tr>
<tr><td>3D height:</td><td colspan="2">3cm</td><td># Core temperatures:</td><td colspan="2">3</td></tr>
<tr><td>Height T1:</td><td>2.2cm</td><td>Height T2:</td><td>1.5cm</td><td>Height T3:</td><td>0.9cm</td></tr>
<tr><td>Mixture type:</td><td colspan="2">SMA-NL 8G</td><td>Thickness:</td><td colspan="2">40mm</td></tr>
<tr><td>Underlying layer:</td><td colspan="2">Asphalt</td><td>Tem. Under. Layer:</td><td colspan="2">13.8</td></tr>
<tr><td>Wind Speed (km/h):</td><td colspan="2">0 km/h</td><td>Outside temperature:</td><td colspan="2">10.6°C</td></tr>
<tr><td>Solar radiation:</td><td colspan="2">0 W/m²</td><td>Rain</td><td colspan="2">0mm</td></tr>
</table>

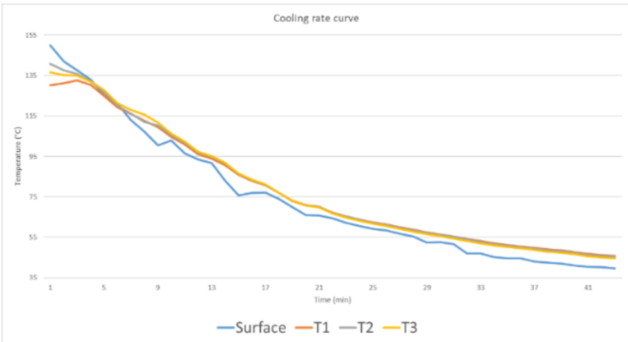

Figure 27: Cooling rate curves location 1 on 03/05/22

5.5. Overview of data obtained during research

In the following table the data obtained during the months of May and July is classified taking into account the mixture type.

Table 5: Data obtained during research

Mixture Type	# of surface temperatures	# of core temperatures
AC 16	24	61

AC 22	12	40
PA 16	15	27
SMA NL 8G	19	39
TOTAL	**64**	**153**

6. Analysis of the ASPARiCool tool accuracy

To determine the best performance of the ASPARiCool tool, the analysis was performed in three different scenarios. First, all the data obtained (historical data, and data during this research) was used to train the program. A second analysis was performed taking the data only from the same family of mixtures. In other words, three training sessions of the program were carried out; one for the AC family, one for PA, and one for SMA-NL. And finally, the last analysis was performed using the data of each mixture available. Table 6 shows the number of projects per mixture type. This analysis was carried out separately for surface and core temperatures.

Table 6: Data description per mixture type

Family	Mixture type	# surface temp. measurements per mixture type	Percentage surface temp. measurements	# surface temp. measurements per family	# core temp. measurements per mixture type	Percentage core temp. measurements	# core temp. measurements per family
AC	AC 8	4	3%	86	6	3%	129
	AC 11	1	1%		0	0%	
	AC 16	33	25%		62	32%	
	AC 22	48	36%		61	31%	
PA	PA 5	0	0%	22	0	0%	26
	PA 8	0	0%		0	0%	
	PA 11	0	0%		0	0%	
	PA 16	22	17%		26	13%	
SMA	SMA-NL	0	0%	23	0	0%	41
	SMA-NL 5	0	0%		0	0%	
	SMA-NL 8G	19	15%		38	19%	
	SMA-NL 11B	4	3%		3	2%	
TOTAL		**131**	100%	131	**196**	100%	196

Ten projects were used in each scenario to validate the ASPARiCool tool. The number of projects used for validation are: one AC8 project, two AC16 projects, two AC22 projects, two PA16 projects, two SMA-NL 8G projects and one SMA-NL 11B. For the analysis of the accuracy of the ASPARiCool tool, three factors were used in each validation project. The average difference temperature which is the difference between the predicted value and the real value every minute and then the average of all these values. The second factor is the temperature difference at the final minute. And finally, the Root Mean Square Error (RMSE). RMSE is the standard deviation of the prediction errors (residuals). In the case of the RMSE, when the value is closer to zero, it means that the difference between the observed and predicted values is minimal, therefore the model is accurate. However, if the RMSE value increases, the accuracy decreases (Moody, 2019). For the calculation of the RMSE the following formula was used:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\widehat{y_i} - y_i)^2}{n}}$$

Where:

- $n =$ Number of observations (each observation is one minute)
- $\widehat{y_i} =$ Predicted values
- $y_i =$ Observed values

The results per scenario for surface and core temperatures are explained in the following sections.

6.1. First scenario surface temperature: All data is used for training the model

In this scenario, the ASPARiCool tool was trained using all the surface temperature data except for the ten projects for the validation. Inside the ASPARiCool tool, an option was added in which the predicted data can be obtained at 1-minute interval. Then the average difference, end difference, and RSME value were calculated. In Table 7 are shown the values in °C obtained for this case. Moreover, the cooling curves prediction graphs per project are shown in Appendix D.

Table 7: Results from surface temperature prediction in scenario one

Name	Average Difference	End Difference	RMSE
AC8_1_Validation_S	-15.5	-15.9	20.0
AC16_1_Validation_S	7.4	8.2	7.5
AC16_2_Validation_S	7.6	10.9	8.0
AC22_1_Validation_S	4.1	16.9	5.7
AC22_2_Validation_S	10.5	21.0	11.8
PA16_1_Validation_S	33.2	38.7	34.5
PA16_2_Validation_S	37.4	36.6	38.5
SMA-NL_8G_1_Validation_S	42.9	54.0	45.6
SMA-NL_8G_2_Validation_S	20.9	22.8	22.1
SMA-NL_11B_1_Validation_S	44.3	39.5	46.3
Average	19.3	23.3	24.0

6.2. Second scenario surface temperature: Data per family is used for training the model

In this scenario, the ASPARiCool tool was trained 3 times, namely for the AC, PA, and SMA families. The results of this scenario are an average temperature difference of 10.6 °C, average end difference of 25.9°C and an average RMSE of 21.4°C. The cooling curves prediction and results for each project are displayed in Appendix D.

6.3. Third scenario surface temperature: Data per mixture type is used for training the model

In the last scenario, the process was carried out 6 times. Each training and validation process was done using a different mixture type. The mixture types used were: AC8, AC16, AC22, PA16, SMA-NL 8G, and SMA-NL 11B. The other mixtures available inside the ASPARiCool tool were not used since data from field measurements was not obtained. The average results of this scenario are an average temperature difference of 6.3 °C, average end difference of 5.3°C and an average

RMSE of 11.2°C. In Figure 28 and Figure 29 are displayed the worst and best performance,. The cooling curves prediction and results per project are shown in Appendix D.

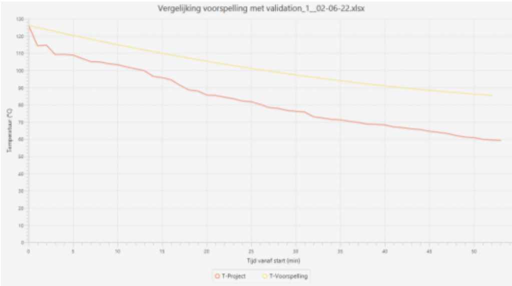

Figure 28: Cooling rate prediction third scenario surface:AC16_1_Validation_S

Figure 29: Cooling rate prediction third scenario surface:PA16_1_Validation_S

6.4 First scenario core temperature: All core data is used for training the model

In this scenario, the ASPARiCool tool was trained using all the core temperature data except the ten data projects for the validation. The average results of this scenario are an average temperature difference of 1.6 °C, average end difference of -5.2°C and an average RMSE of 13.1°C. The cooling curves prediction and results for each project are displayed in Appendix D.

6.5. Second scenario core temperature: Data per family is used for training the model

For the second scenario, the ASPARiCool tool was trained 3 times, each time for a different family type (AC, PA, and SMA-NL). The average results of this scenario are an average temperature difference of 5.3°C, average end difference of 5.6°C and an average RMSE of 10.3°C. The cooling curves prediction and results for each project are displayed in Appendix D

6.6 Third scenario core temperature: Data per mixture type is used for training the model

The last scenario with core temperature data was carried out 6 times. Each training and validation was done using a different mixture type (AC8, AC16, AC22, PA16, SMA-NL 8G, and SMA-NL 11B). The average results of this scenario are an average temperature difference of 7.1 °C, average end difference of 12.3°C and an average RMSE of 10.2°C. The cooling curves prediction and results for each project are displayed in Appendix D.

Initial conclusion - From this first analysis, the best performance for both the surface and core temperature was in the third scenario. In this scenario, the model was training using just the data of the specific mixture type. For the surface data, the average difference was 13.8, the average end difference was 9.8, and the average RSME of 14.7. On the other hand, the least accurate predictions were obtained in scenario one, where all the data was used for training the model. For this case, the average difference was 19.3, the average end difference of 23.3, and the average RMSE of 24.

7. Sensitivity analysis

As can be seen in section 6, the accuracy of the ASPARiCool tool can be improved. For this, a sensitivity analysis of the parameters used in Machine Learning was developed in order to determine the parameter with the most influence in the prediction of the cooling rate. There are four parameters that control the operation of the MLP. The first is the learning rate with a current value of 0.1, the second is the momentum with a value of 0.2, the third is the training times of 2000, and finally the number of hidden layers with 3. Each of these values was altered four times. For learning rate, momentum, and training times a change of ±10% and ±20% of its current value was done. While for hidden layers (layers of nodes between the input and output layers) an integer is required, a change of ±1 unit and ±2 units was used. The values are shown in Table 8.

Table 8:Parameters value for sensitivity analysis

Parameter	-20% value	-10% value	Current value	+10% value	+20% value
Learning Rate	0.08	0.09	0.1	0.11	0.12
Momentum	0.16	0.18	0.2	0.22	0.24
Training times	1600	1800	2000	2200	2400
Hidden Layers	1	2	3	4	5

To carry out the sensitivity analysis, the data of the PA16 family were used as training data and the two previously selected projects were maintained as validation data. Also, the factor taken into account to determine the sensitivity for each parameter was the RSME. Table 9 shows the results of the RMSE for each variation of the four parameters. The lowest RMSE values are circled. For the learning rate, momentum, and training times a decrease of 20% in the value, results in the best performance for both validation projects. However, for the Hidden layers, the increase to 5 layers gave the best result for project one, but the worst result in project two. Taking into account both projects, 1 hidden layer was the best option. With this results, a combination of change in more than one parameter was carried out.

Table 9: Sensitivity analysis result

Project Name	PA16_1_Validation_S					PA16_2_Validation_S				
Change	(-20%)	(-10%)	(0%)	(+10%)	(+20%)	(-20%)	(-10%)	(0%)	(+10%)	(+20%)
Parameter	RSME	RSME	RSME	RSME	RSME	RSME	RSME	RSME	RSME	RSME
Learning Rate	5.24	5.28	5.32	5.34	5.34	10.19	10.80	11.67	12.80	14.14
Momentum	5.30	5.31	5.32	5.32	5.33	11.19	11.42	11.67	11.96	12.28

Training times	5.26	5.29	5.32	5.33	5.35	10.36	10.94	11.67	12.56	13.55
Hidden Layers	4.56	4.92	5.32	4.70	4.51	11.53	20.38	11.67	17.44	19.92

8. Calibration of ASPARiCool tool

From the sensitivity analysis, it is clear that the MLP has factors that influence the prediction of the cooling rate. To obtain a better performance of ASPARiCool, the calibration of the parameters was carried out. For this process, five combinations were made with different values of the parameters. **¡Error! No se encuentra el origen de la referencia.** from **¡Error! No se encuentra el origen de la referencia.** shows the values for each case. During the sensitivity analysis, the data used was PA16. Therefore, to make the calibration more independent, the AC22 mixture surface data was used to train the model and the two AC22 projects to validate the results.

To determine the new performance of the ASPARiCool tool using the new parameters values, the average difference, end difference and RMSE were calculated for each combination. Then a comparison was made between all the combinations to see the one with the best prediction. Table 10 shows the average results of the five combination in the two validation projects. The detailed results per combination are shown in Appendix E.

Table 10: Result cooling rate prediction of the five combinations

Combination	Average Difference	End Difference	RMSE
Combination 1	1.7	4.6	4.6
Combination 2	8.0	14.0	11.9
Combination 3	6.7	11.4	11.9
Combination 4	3.4	9.2	5.3
Combination 5	12.1	17.8	13.2

Of the five combinations of different parameter values, the best option was combination 1 in which the learning rate was 0.08, the momentum of 0.16, 1600 training times, and 1 hidden layer. The values are similar to the sensitivity analysis of PA16. In both cases, the better performance was using the values of combination 1. The calibration was done just using the AC22 mixture. In the following section, a complete analysis using all the data was carried out.

9. Analysis of ASPARiCool tool using new parameter values

To compare the performance of the ASPARiCool tool with the initial parameter values (section 6), another analysis using the parameter values of combination 1 obtained in the calibration was done. The study was carried out for three scenarios of surface temperature and three for core temperature. The scenarios are the same as those used in section 6.

9.1. First scenario surface temperature: All data is used for training the model (New parameters values)

The results of this scenario gave an average temperature difference of 11.9 °C, average end difference of 14°C and an average RMSE of 13.7°C. The cooling curves prediction and results for each project are displayed in Appendix F.

9.2. Second scenario surface temperature: Data per family is used for training the model (New parameters values)

The results of this scenario gave an average temperature difference of 7.1 °C, average end difference of 16.4°C and an average RMSE of 10°C. The cooling curves prediction and results for each project are displayed in Appendix F.

9.3. Third scenario surface temperature: Data per mixture type is used for training the model (New parameters values)

The results of this scenario gave an average temperature difference of 4.7 °C, average end difference of 9.8°C and an average RMSE of 7.8°C. The cooling curves prediction and results for each project are displayed in Appendix F. This scenario gave the best performance for predicting the cooling rate for surface temperature. Figure 30 and Figure 31 represent the least and most accurate cooling curves respectively.

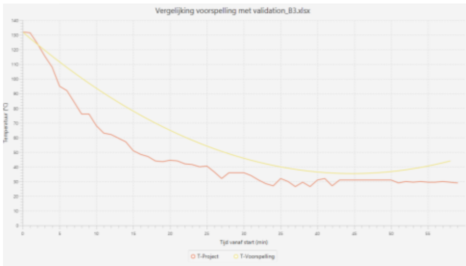

Figure 30: Cooling rate prediction new parameter values third scenario surface:SMA-NL_11B_1_Validation_S

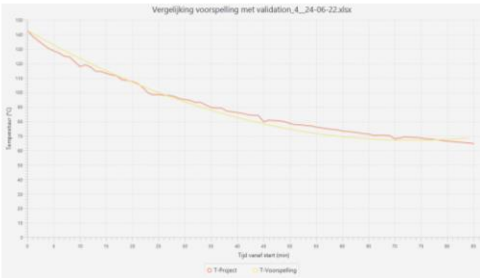

Figure 31: Cooling rate prediction new parameter values third scenario surface:AC22_1_Validation_S

9.4. First scenario Core temperature: All data is used for training the model (New parameters values)

The results of this scenario gave an average temperature difference of 7.5 °C, average end difference of 10.4°C, and an average RMSE of 11.1°C. The cooling curves prediction and results for each project are displayed in Appendix F.

9.5. Second scenario Core temperature: Data per family is used for training the model (New parameters values)

The results of this scenario gave an average temperature difference of 5.8 °C, average end difference of 8.6°C, and an average RMSE of 9.3°C. The cooling curves prediction and results for each project are displayed in Appendix F.

9.6. Third scenario Core temperature: Data per mixture type is used for training the model (New parameters values)

The results of this scenario gave an average temperature difference of 7.3 °C, average end difference of 9.8°C, and an average RMSE of 10°C. The cooling curves prediction and results for each project are displayed in Appendix F.

From the analysis using the new parameters for the MLP, the best performance for the surface temperature was in the third scenario. In this scenario, the model was trained only using the data of the specific mixture type. For the surface data, the average difference was 4.7, the average end difference was 9.8, and the average RSME of 7.8. The most accurate prediction of the core temperatures was in scenario two, with an average difference in temperature of 5.8, an average difference of 8.6, and an average RSME of 9.3.

10. Reflection on results

During this bachelor project, the cooling rate of asphalt and the ASPARiCool tool were studied.

The cooling rate of the asphalt has a direct effect on the construction and the final quality of the asphalt. This is because it is a crucial factor in determining whether the compaction process is carried out at the right time. If this is not the case, the density of the final layer will not be the most optimal, and with it, a greater air void content, a reduction in particle friction, and a lower smoothness due to the loading vehicles are obtained. Thus, the cooling rate of asphalt needs to be predicted correctly taking into account the factors that affect it. The compaction process must be performed in the ideal temperature window to obtain the desired density. With this, durability to withstand weathering, the bearing capacity to support the traffic loads, optimization of stiffness, resistance against deformation, and a longer life span are obtained (Huerne, 2004).

To determine the influence of additional data in ASPARiCool on the prediction of the cooling rate, two analyzes were performed. First, the program was trained using only the Historical Data (31 projects). Secondly, the training was carried out using the data obtained during this research, plus the data obtained previously (131 data projects). For the validation of the program, 6 projects were used in both cases. The results obtained using only the historical data was an average temperature difference of 40.6°C while with all the data was 16.7°C. In the difference in the final temperature, the average of the 6 projects for the historical data was 71.6°C, and with all the data 22°C. Finally, the average RSME for the case of historical data was 51.9, and in the second case it was 17.7. The detailed results by case and project are shown in Table 11. From this first analysis, it can be determined that an increase in data produces a better training of the program and therefore a higher accuracy in the predictions.

Table 11: Comparison of prediction in cooling rates by adding new data

Project Name	Average Temperature Difference (°C)	Final Temperature Difference (°C)	RMSE (°C)
Just historical data			
AC16_1_Validation_S	37	10.2	42.8
AC16_2_Validation_S	56.6	37.9	61.3
AC22_1_Validation_S	38.7	159.9	65.2
AC22_2_Validation_S	15.5	109	41.7
PA16_1_Validation_S	14.6	11.1	15
PA16_2_Validation_S	81.3	101.7	85.7
Average	**40.6**	**71.6**	**51.9**
All the data			
AC16_1_Validation_S	7.4	8.2	7.5
AC16_2_Validation_S	7.6	10.9	8.0
AC22_1_Validation_S	4.1	16.9	5.7
AC22_2_Validation_S	10.5	21.0	11.8
PA16_1_Validation_S	33.2	38.7	34.5
PA16_2_Validation_S	37.4	36.6	38.5
Average	**16.7**	**22.0**	**17.7**

Moreover, since the cooling rate is affected by factors such as the type of mixture, thickness, weather conditions, among others. An analysis was carried out in three scenarios in which a classification of the data was made taking into account the mixture type. In the first scenario, the model was trained using all the data. In the second scenario, only the data from each family (AC, PA, SMA-NL). And in the third scenario, the model was trained and validated using only the data from the specific mixture type (eg. AC22). Table 12 shows the average results of the ten projects used for surface and core temperature. With this analysis, it was concluded that the model performs a better prediction when the data used was only from the specific mixture (Scenario 3). However, the first scenario gave the worst accuracy. In addition, from this analysis, it can be seen that among the ten projects used, the poorest prediction was for the SMA-NL 11B, because the amount of data for this type of mixture was minimum. Moreover, in all the three scenarios the prediction of the cooling rate was more accurate when using the core temperature. This occurred due to the number of measurements of core temperature where higher than the surface temperature.

Table 12: Results of cooling rate predictions in the three scenarios

Scenario	Average Temperature Difference (°C)	Average Final Temperature Difference (°C)	Average RMSE (°C)
First Scenario Surface	19.3	23.3	24.0
Second Scenario Surface	10.6	25.9	21.4
Third Scenario Surface	6.3	5.3	11.2
First Scenario Core	1.6	5.2	13.1
Second Scenario Core	5.3	5.6	10.3
Third Scenario Core	7.1	12.3	10.2

However, the results obtained did not give enough accuracy to use in the field. For this reason, a sensitivity analysis of the parameters that control the MLP was performed. In this way, it was determined that the learning rate and the number of hidden layers are the parameters that have the most influence on the prediction of the cooling rate. The ones that have a smaller effect are momentum and training times. Then, a calibration of the model was carried out as explained in section 8 to obtain better results. The results obtained for each scenario are shown in Table 13. Compared with the results obtained before, the error using the new parameters was lower in all scenarios. The best performance was in the scenario three with a RSME of 7.8. While the first scenario was the worst with a RSME of 13.7.

Table 13: Results of cooling rate predictions in the three scenarios using new parameters

Scenario	Average Temperature Difference (°C)	Average Final Temperature Difference (°C)	Average RMSE (°C)
First Scenario Surface	11.9	14.0	13.7
Second Scenario Surface	7.1	16.4	10.0
Third Scenario Surface	4.7	9.8	7.8
First Scenario Core	7.5	10.4	11.1
Second Scenario Core	5.8	8.6	9.3
Third Scenario Core	7.3	9.8	10

11. Discussion and Recommendation

Throughout this project, some limitations were found that can be improved or investigated in future research. During the data collection, the precision of the equipment was omitted, assuming that the data obtained was accurate enough to train the program. The mixture types used were AC8, AC16, AC22, PA16, SMA-NL 8G and SMA-NL 11B. However, the number of projects were different in each mixture, this produced a variation in the results of the prediction of the cooling rate in each mixture. Therefore, continuing to obtain data is essential. Moreover, since the cooling rate change with several factors, it is important to obtain data that have variations of these. For example, during the two months of research there were only two days of rain, making the forecast for a rainy day less accurate.

During the data collection it was noticed that the surface temperature changed after a roller passed due to the water used during compaction. On certain occasions the temperature dropped drastically, however it increased again. Since the temperature was taken every minute, when plotting the data, the temperature went down and up again so the cooling curve was not smooth. Therefore, a recommendation would be that after a roller pass, wait at least one minute to register the value. This avoids these peaks that can affect the prediction.

Within the ASPARiCool tool the focus was only on the MLP and its parameters due to limited time and knowledge in Java. Consequently, important parts that are used for cooling rate prediction could be omitted. Also, in the cooling rate prediction the higher temperature difference was in the final minutes. This problem occurs because the temperature prediction starts to increase again at the end. This was reduced when the MLP parameters were changed, however, the problem persisted for certain projects. To avoid the increase in temperature two options are recommended. First, modify the model by adding a boundary in which the temperature of the next minute is not higher than the previously predicted temperature. Secondly, analyze new combinations for the MLP parameters, or develop a code in which new values of the parameters can be obtained that produces the most accurate predictions.

Additionally, using Machine Learning in the prediction of the cooling rate, factors such as the type of mixture, layer thickness, and weather conditions have the same weights. Carrying out a study to determine the weight of each factors on the cooling rate, to then add the values in ASPARiCool could improve the accuracy. Besides, by classifying the data taking into account the mixture type the accuracy increased. Thus, in future analysis the project data can be divided taking into account other factors such as thickness. Finally, I recommend making the program more helpful during the projects for operators and site managers. Allowing to export data and recommending the time at which compaction should start and end would be important.

12. Conclusion

The objective of this research was to improve the prediction accuracy of the ASPARiCool tool with additional field measurements and to calibrate and validate the model. To achieve this objective, a main question was proposed: **How can the predictions of the cooling rate calculated by the ASPARiCool tool be improved, so that it can be implemented on construction sites?**

The ASPARiCool tool works using the MLP of Machine Learning. Therefore, to train the model data is necessary. Based on a quantitative analysis performed during this bachelor thesis, it was concluded that as more data is used to train the model, the accuracy in predicting the cooling rate improves. Since the cooling rate is affected by factors such as mixture type, thickness, underlying layer and weather conditions, the data was classified by groups taking into account their mixture type. Using the new data sets, it was concluded that the accuracy in the ASPARiCool tool improves. Thus, a study with more specific data groups can bring new positive results. Finally, the MLP works with four parameters. The values were modified by performing a sensitivity analysis and a calibration. The results given for these two processes were 0.8 for the Learning rate, 0.16 for momentum, 1600 training times, and 1 hidden layer. Using the new values for the MLP the performance of the tool was the best with a RMSE of 7.8. Therefore, by adding more data, using the specific mixture type data projects as training data, and using the new values for the parameters in the MLP, the cooling rate prediction is improved.

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Appendix A

Table 14:Cooling rate at 10-minute intervals over 30 minutes for ACW14 (Hashim et.al. 2016)

Time	10min	20min	30min
Wind Velocity	**Cooling rate (°C/min)**		
0km/h	3.9	2	1.3
5km/h	4.1	2.2	1.4
10km/h	4.9	2.4	1.5
15km/h	5.3	2.8	1.7

Table 15: Rainfall criteria (Ismail, et.al. 2019)

Type of rain	**Criteria**
No rain	Rainfall rate = 0 mm per hour
Light rain	0 < Rainfall rate < 0.5 mm per hour
Moderate rain	0.5 ≤ Rainfall rate < 4.0 mm per hour
Heavy rain	Rainfall rate ≥ 4.0 mm per hour

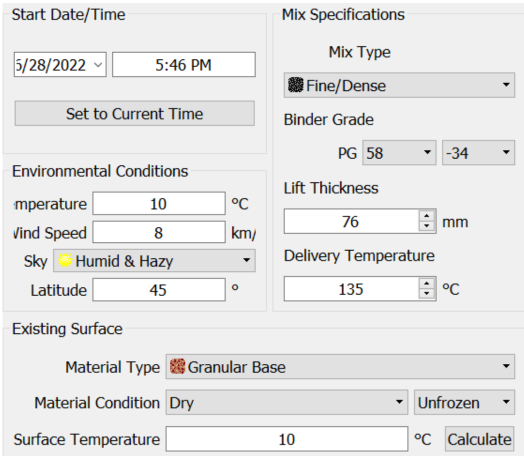

Figure 32:Input parameters in PaveCool

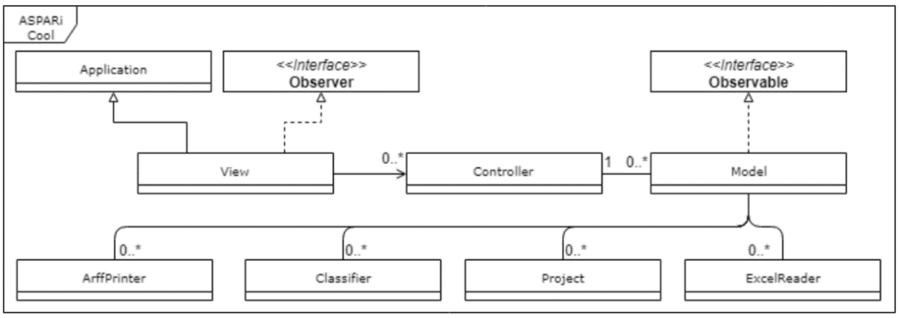

Figure 33:ASPARiCool architecture (Ong-A-Fat, et.al., 2019)

Table 16: Projects characteristics for thickness comparison

Date	**Asphalt mixture**	**Thickness (mm)**	**Underlying layer type**	**Tem. Underlying layer**	**Wind Speed (km/h)**	**Outside temperature (°C)**	**Rain (mm)**
06/05/2022	PA16	25	Asphalt	19.1	4	17.3	0
02/06/2022	AC16	60	Asphalt	19.2	2.6	17.3	0

Table 17:Thermal Properties of Materials (Minnesota Department of Transportation, n.d.)

	Material	Density kg/m^3	Thermal Conductivity W/(m*K)	Specific Heat J/(kg*K)
	Fine (Dense) Asphalt	2000	2.0	1000
	Coarse (SMA) Asphalt	2010	1.5	1010
	Existing Asphalt	2000	1.51	1025
	PCC (Concrete)	2000	0.92	1090
	Granular Base (dry unfrozen)	2000	1.16	963
	Granular Base (wet unfrozen)	2000	1.22	1172
	Granular Base (dry frozen)	2000	2.00	858
	Granular Base (wet frozen)	2000	3.55	963
	Soil (dry unfrozen)	1800	1.35	1172
	Soil (wet unfrozen)	1800	1.87	1591
	Soil (dry frozen)	1800	1.40	963
	Soil (wet frozen)	1800	2.38	1172

Regarding the thermal properties, three characteristics were calculated for each material.

Thermal Conductivity

According to the Minnesota Department of Transportation (n.d.), the thermal conductivity is used in the heat conduction equation described by Fourier's law as a constant of proportionality. Fourier's law establishes that the flow of heat and temperature in the same direction are proportional, this heat conduction is defined by the following differential equation:

$$q_z = -k\left(\frac{dT}{dz}\right)$$

Equation 1: Heat conduction equation

Where:

- $q_z = heat\ flux\ in\ direction\ z$
- $k = thermal\ conductivity$
- $\frac{dT}{dz} = change\ in\ temperature\ with\ depth$

Moreover, to calculate the thermal conductivity (k) for aggregate base and soil the following equations were used:

Unfrozen Base: $k = (0.07 \log_{10} w + 0.4) * 10^{0.01y}$ w≥1

Frozen Base: $k = 0.076 * 10^{0.013y} + 0.032 * 10^{0.0146y}$ w≥1

Unfrozen Soil: $k = (0.9 \log_{10} w - 0.2) * 10^{0.01y}$ w≥7

Frozen Soil: $k = 0.01 * 10^{0.022y} + 0.085 * 10^{0.008y}$ w≥7

Where:

- $k = thermal\ conductivity$
- $w = gravimetric\ moisture\ content$
- $y = dry\ unit\ weight$

Specific Heat

The specific heat is the amount of energy required to raise 1kg of substance by 1°C (Minnesota Department of Transportation, n.d.). In the PaveCool tool, the following equations were used for aggregate base and soil:

$$C_U = \left(0.18 + 1 * \frac{w}{100}\right) * C_w$$

$$C_F = \left(0.18 + 0.5 * \frac{w}{100}\right) * C_w$$

Where:

- $C_U = Unfrozen\ specific\ heat$
- $C_F = Frozen\ specific\ heat$
- $C_W = Specific\ heat\ of\ water = 4187 \frac{J}{kg*K}$

Thermal Diffusivity

To calculate the thermal diffusivity, the specific heat and thermal conductivity calculated before are used. Thermal diffusivity is defined as the measure to know the speed of heat propagation and it is calculated by the following equation (Minnesota Department of Transportation, n.d.):

$$\alpha = \frac{k}{\rho * C_p}$$

Where:

- $\alpha = thermal\ diffusivity\ \left(\frac{m^2}{s}\right)$
- $k = thermal\ conductiviy\ \left(\frac{W}{m} * K\right)$
- $\rho = density\ \left(\frac{kg}{m^3}\right)$
- $C_p = Specific\ heat\ (\frac{J}{kg*K})$

Table 18: Sky conditions for PaveCool tool (Minnesota Department of Transportation, n.d.)

Icon	Condition	Description
	Clear & Dry	Use only for low humidity and/or high altitudes.
	Hazy	Typical sunny day during the summer months.
	Partly Cloudy	Clouds block the sun/sky 50% the time.
	Mostly Cloudy	Clouds block the sun/sky 75% of the time.
	Overcast	Clouds completely block the sun/sky.

Appendix B

Table 19: Difference in temperature during train of historical data

Project Name	**Average Difference of Temperature**	**Final Difference of temperature**
AC16_1	7.94	28.32
AC16_2	1.94	7.12
AC22_1	4.58	11.72
AC22_2	2.49	9.84
AC22_3	14.8	9.24
AC22_4	17.36	25.56
AC22_5	3.39	6.18
AC22_6	2.83	3.13
AC22_7	3.66	5.75
AC22_8	0.83	1.93
AC22_9	9.22	32.82
AC22_10	2.87	11.34
AC22_11	5.02	8.54
AC22_12	2	7.43
AC22_13	2.14	7.62
AC22_14	17.74	51.02
AC22_15	8.19	26.74
AC22_16	17.99	55.13
AC22_17	3.2	7.54
AC22_18	3.69	14.55
PA16_1	18.02	58.41
PA16_2	6.43	15.4
PA16_3	4.79	11.45
PA16_4	1.72	5.66
PA16_5	0.93	3.53
Average	**6.55**	**17.03**

Table 20: Difference in temperature for validation data using historical data

Project Name	Average Difference of Temperature	Final Difference of temperature	RMSE
AC16_1_Validation_S	37	10.2	42.8
AC16_2_Validation_S	56.6	37.9	61.3
AC22_1_Validation_S	38.7	159.9	65.2
AC22_2_Validation_S	15.5	109	41.7
PA16_1_Validation_S	14.6	11.1	15
PA16_2_Validation_S	81.3	101.7	85.7
Average	**40.6**	**22.4**	**51.9**

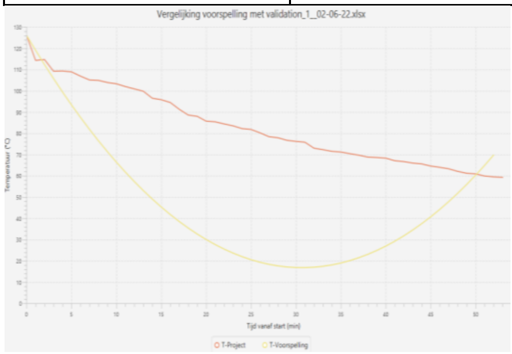

Figure 34: Cooling rate prediction historical data surface:AC16_1_Validation_S

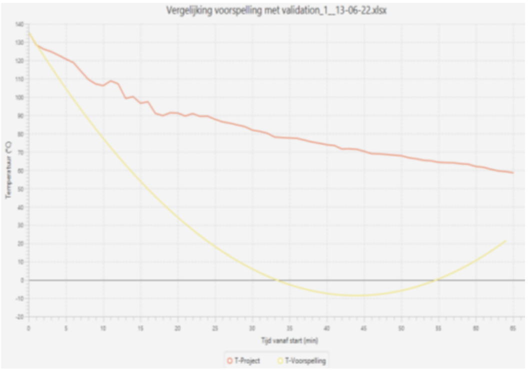

Figure 35: Cooling rate prediction historical data surface:AC16_2_Validation_S

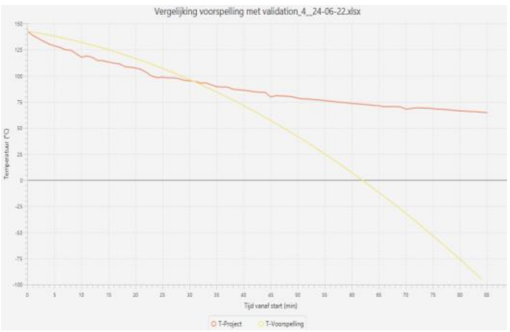

Figure 36: Cooling rate prediction historical data surface:AC22_1_Validation_S

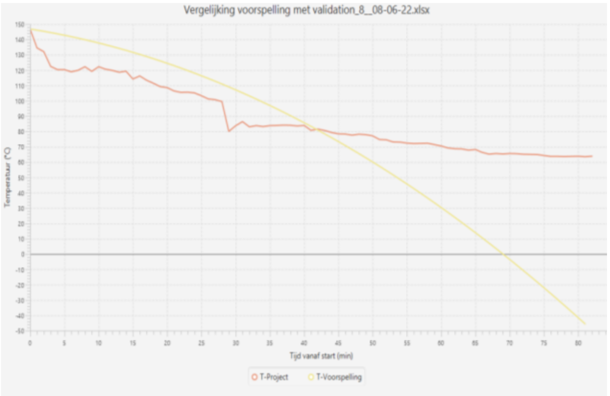

Figure 37: Cooling rate prediction historical data surface:AC22_2_Validation_S