The problem of overfitting in the prediction of the cooling rate of asphalt mixes within the ASPARiCool tool's MLP algorithm

ASPARi
Paving the way forward

UNIVERSITY
OF TWENTE.

Bachelor Thesis in Civil Engineering

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Preface

Before you lies the bachelor thesis "The problem of overfitting in the prediction of the cooling rates of asphalt mixes", this thesis was conducted to investigate the problems faced in the prediction of the cooling rates of asphalt mixes in the paving of road. This thesis serves as a proof of the completion of the Bachelor of Science degree in Civil Engineering at the University of Twente. This thesis was undertaken at ASPARi but conducted at home because of the COVID-19 pandemic.

First, I would like to thank dr. Seirgei Miller for introducing me to the world of research and providing me with a chance to conduct my thesis at ASPARi. Secondly, I would like to thank ir. Marco Oosterveld from BAM for providing me with the essential data needed to complete this assignment. Thirdly, I would like to thank my supervisor Denis Makarov for putting a lot of his time and effort in helping me to understand and solve the aspects of this research that I found challenging.

Last but not least I would like to thank my parents for their unconditional love and continuous support and my friends and family for their counsel.

Shaffie Juma
29th August, 2020

Key Terminologies

Acronym		Descriptions
ASPARi	Asphalt Paving Research and Innovation	ASPARi is a collaborative research effort between the University of Twente and the largest civil engineering contractors in the Netherlands.
ML	Machine learning	An application of artificial intelligence whereby a machine learns by finding patterns within the data in order to classify or make predictions on new data.
ANN	Artificial neural network	ANN is a multilayer feedforward network which is used to model the relationship between a set of the input data and output data.
MLP	Multilayer perceptron algorithm	An MLP algorithm is an example of an ANN that is used to model the relationship between a set of input and output data. It can be used to distinguish non linear relationships within the input and output data.
AC	Asphalt concrete	Type of asphalt pavement which consists of a combination of fine aggregates, coarse aggregates and asphalt cement(binder).
PA	Porous asphalt	Type of asphalt pavement which has high water drainage capacity.
SMA	Stone mastic asphalt	Stone mastic asphalt mix consists of asphalt cement, binders and fibres. This open grade asphalt mix is porous and designed to ensure that surface water in the asphalt drains.

Abstract

The ASPARiCool tool is an asphalt mix cooling rate prediction tool developed by ASPARi that uses machine learning. The role of the ASPARiCool tool is to guide the compactor operators on the suitable time window required to compact the asphalt mix to ensure the highest quality. At the moment, the ASPARiCool tool is still in its development phase, and one of the main problems is that the tool is not making good predictions of the cooling rates of asphalt mixes. The prediction problem in the tool has been identified as an overfitting problem which is the most common problem that is faced by many machine learning prediction tools.

The ASPARiCool tool uses a Machine Learning algorithm known as Multilayer Perceptron Algorithm (MLP) to determine patterns between asphalt cooling features and the temperatures of asphalt mixes. The asphalt mix cooling features comprise of time, type of asphalt mix, ambient temperature, type of underlayer, the temperature of the underlayer, wind speed and amount of rainfall. These features are significant in making accurate predictions of the cooling rates of asphalt mixes.

In this study, the MLP algorithm, which is used in the ASPARiCool tool, was investigated. The investigation involved the development of a new prediction model that uses a similar algorithm and parameters as the ASPARiCool tool. Next, an analysis was conducted in the new prediction model to identify the effect of the asphalt cooling features in the overfitting problem of the MLP algorithm.

The results of the analysis showed that MLP algorithm parameters which are, the number of neurons, type of activation function and type of solver would result in the MLP algorithm to overfit when predicting the cooling rates of asphalt mixes. Also, this research concluded that the asphalt cooling features which are time, type of asphalt mix, ambient temperature, solar radiation and windspeed resulted in a good fit MLP algorithm that made good predictions of the cooling rates of asphalt mixes.

The results of this thesis will help contribute to the ASPARi research team by advising the most suitable MLP parameters that will help to make good predictions of the cooling rates of different asphalt mixes based on the current amount data available.

Contents

1.0. Introduction

1.1. Motivation

The quality of the asphalt pavement during the compaction phase in the asphalt paving process is influenced by the compaction temperature of the asphalt mixture. The compactor operator needs to estimate the optimal compaction time window during paving operations. Suppose the operator compacts the asphalt mix at high temperatures the fluidity of the binder increases causing the roller loads to displace or shove off the materials simply. Low compaction temperature, on the other hand, reduces the lubrication of the mixture and the bitumen, which results in an open surface that may cause premature failure due to low density (Kari, 1967).

In the past, traditional approaches were used to determine the compacted temperature. One of the approaches used included plotting the graph of log-viscosity versus log temperature. The ideal compaction temperature was then determined in the graph by relating it to a viscosity value of 1.7. This traditional approach is no longer appropriate since it sometimes indicated high temperatures (Vasenev, Hartmann, & Dorée, 2012). Another approach involved calculating the cooling rate of the asphalt layer due to weather and environmental conditions by a formula (Bossemeyer, 1966).

Timm (2001) stated that there is an ideal temperature window to compact the asphalt mix that will result in a high probability of the asphalt pavement to reach the desired mechanical characteristic. In response, researchers have developed windows-based tools to predict cooling rates of asphalt mix. Such tools include PaveCool and Calcool. The problem of these tools is that there are discrepancies between the measured and predicted cooling rate during validation. The researchers state that more scientific studies are needed to create tools that have minimum differences between the measured and predicted cooling rates of asphalt mixes. (Timm et al., 2001 and Chadbourn and Newcomb, 1998).

Recently, software tools have been developed that can predict the cooling rate of asphalt mixes during the compaction phase. These tools help compactor operators to make well-founded decisions on the most suitable compaction time in asphalt pavement construction. One of the tools which are used to predict the cooling rate of asphalt mixes during paving operations is the ASPARiCool tool. The ASPARiCool tool uses Machine Learning (ML) algorithm called Multilayer Perceptron (MLP) to predict the cooling rate of the asphalt mix from asphalt cooling rate features. Such features used in the cooling rate prediction include; the type of asphalt mixes, type of underlayers, surface temperature, core temperature, and weather conditions like rain, wind speed, solar radiation, ambient temperature, and humidity (K.Ong-A-Fat, 2019).

The ASPARiCool tool shows much potential to generate an accurate prediction of the cooling rate of asphalt mixes. However, in the current status of the tool, the ASPARiCool tool has an overfitting problem that leads to inaccurate cooling rate predictions of asphalt mixes (Baars, 2020).

1.2. Research Strategy

1.2.1. Research Problem

In the prediction of the asphalt cooling rate in the ASPARiCool tool, the problem of overfitting arises in the asphalt cooling curves. This problem is seen in the asphalt cooling curve graphs in which the predicted temperatures of the asphalt mixes begin to rise over time. The overfitting problem in the ASPARiCool tool will result in the compactor operator to fail to determine the most optimal compaction time window of the asphalt mix and subsequently affect the future quality of the asphalt pavement. Previously Baars (2020) has attempted to solve the problem of overfitting by increasing the amount of training data into the ASPARiCool tool. This has resulted in a decrease in overfitting, although the author suggests that more training data is required to solve this problem. Addressing the problem of overfitting is significant for the development of the ASPARiCool tool which will be able to predict more accurately the cooling rate of asphalt mixes and help roller compactor operators to determine the most optimal compaction time needed for compaction.

1.2.2. Research Aim

The objective of this research is to investigate the problem of overfitting in the prediction of the cooling rate of different asphalt mixes in the ASPARiCool tools MLP algorithm. This research aims to find out the cause of overfitting and how the problem of overfitting can be solved in the ASPARiCool tool's MLP algorithm.

This research will provide recommendations on how to approach the problem overfitting of ASPARiCool tool by clearly realizing how the current ASPARiCool Machine learning (ML) algorithm works. Next, a new prediction model that uses similar MLP algorithm will be built to compare the predicted cooling rates of asphalt mixes.

1.2.3. Research Question

The main research question is as follows:

"How do the asphalt cooling rate features influence the problem of overfitting in the prediction of the cooling rate of asphalt mixes in the MLP algorithm?"

1.2.4. Research methodology and outline

This section describes the approach that will be taken to answer the main research question followed by a description of the research outline in Table 1.

To address the main research question, first, a literature study will be conducted in order to understand the problem of overfitting and to determine the methods used to address overfitting of the ASPARiCool tool. Secondly, the data that will be used to assess the ASPARiCool tool will be prepared. Thirdly, a preliminary analysis will be conducted to check whether the ASPARiCool tool is overfitting as described in the previous studies. Fourthly, a new similar prediction model will be developed that uses similar algorithm known as MLP to address the overfitting problem in the ASPARiCool tool. Fifth, a preliminary analysis will be conducted in the new MLP prediction model to check whether the similar overfitting problem occurs as in the ASPARiCool tool and to define the overfitting boundaries. Lastly, an analysis will be conducted in the new MLP prediction model to investigate the influence of the asphalt cooling features in the overfitting of the new MLP prediction model and to answer the main research question.

The figure 1 below represents the overall research outline. The explanation of the outline is illustrated in Table 1 below:

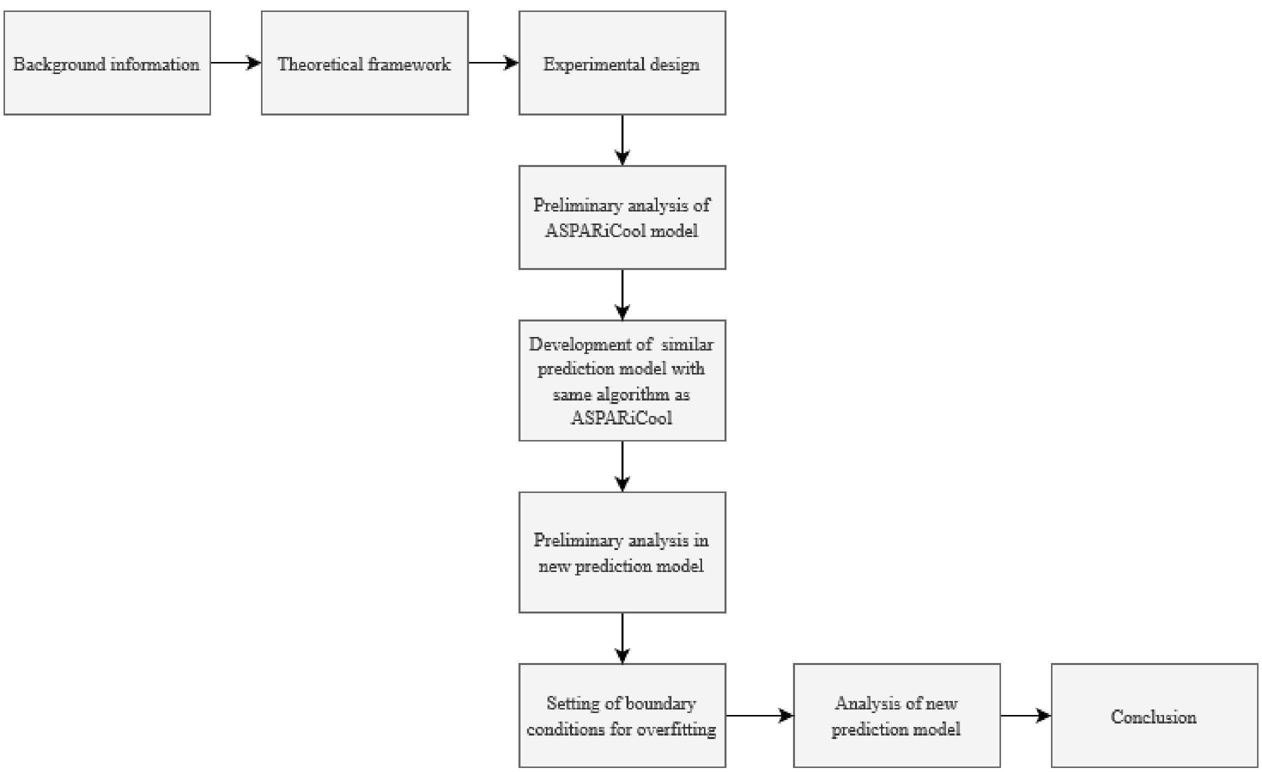

Figure 1: Research methodology

Table 1: Research outline

Title	Section	Description
Background information	Section 2.0	Consists of a literature review relating to the research topic
Theoretical framework	Section 3.0	This section provides a theory of the key concepts that will be used in this research. The theoretical concepts are retrieved from the background information.
Experimental design	Section 4.0	This section provides an elaboration on the data, model evaluation strategy and the modelling tools used in the prediction of the cooling rates of asphalt mixes.
Preliminary analysis of ASPARiCool model	Section 5.0	In this section, a preliminary analysis of the ASPARiCool tool using the specified datasets will be conducted. This analysis aims to check whether the ASPARiCool tool is overfitting
Development and preliminary analysis of new asphalt cooling rate prediction model	Section 6.0	In this section, a new asphalt cooling rate prediction model is developed that uses the same algorithm as the ASPARiCool tool, and a preliminary analysis is conducted using similar settings and data as in ASPARiCool tool in order to address the overfitting problem in the ASPARiCool tool
Boundary conditions for overfitting	Section 7.0	In this section, the boundary conditions regarding overfitting are defined.
Analysis of the new prediction model:	Section 8.0	In the analysis of the new prediction model, the problem of overfitting and underfitting will be addressed based on the research questions.
Conclusion	Section 9.0	This section will consist of answers to the main research question, discussion and recommendations for ASPARi

2.0. Background information

This section consists of the theoretical background which is used to address the problem of overfitting and underfitting. This section enables us to gain knowledge of the basic concepts that are important in order to answer the main research question. The first part of comprises of the cooling process of asphalt mixes, followed by the basic idea behind machine learning which is used in making predictions of the cooling rate of asphalt mixes. Next, the problem of overfitting and underfitting in machine learning models will be reviewed. This section will define overfitting and underfitting in prediction models as well as elaborate on the approach used to overcome overfitting and underfitting in prediction models.

2.1. Asphalt cooling process

To understand the cooling process of asphalt mix during pavement operations, first, the construction process of asphalt pavement is elaborated. Within the asphalt construction process, the laydown phase and compaction phase will be further elaborated because the cooling process of asphalt is significant in these phases. The production phase and transportation of the asphalt mix will not be discussed in this research.

2.2. Asphalt construction process

The asphalt construction process is divided into four phases which are (1) production phase (2) transportation phase and (3) laydown phase and (4) compaction phase.

In the laydown phase, the trucks feed the paver with asphalt mix. The asphalt mix is temporarily stored in a hopper. A conveyor system then transports the asphalt mix to the rear of the paver where the paver spreads a uniform layer of asphalt mix to a specified thickness and shape. The material which is discharged by the paver is pre compacted by the vibrations produced by the paver machine and its weight (Bijleveld, 2015).

After the spreading the asphalt mix, while it is still warm, the rollers are tasked with the compaction phase to achieve the specified density and mechanical properties of the asphalt mix. There are three phases which occur during the compaction phase. These are (1) breakdown rolling, (2) intermediate rolling, and (3) finishing rolling. Each of the three compaction phases depends on specific temperature interval range for compaction hence the knowledge of the compaction time window is vital for roller operators to ensure that the highest quality of asphalt pavement is reached (Arbeider, Miller, Dorée, & Oosterveld, 2017).

2.3. Compaction time interval

The choice of compaction time is traditionally based on personal experience to determine surface temperatures. The process used to determine the temperature of the asphalt itself is not reliable. Often the operators estimate the temperature based on the colour of asphalt surface, but this method has its setbacks when the operations are conducted at night. Uncertainties in estimation of the temperature result in the final poor quality of asphalt pavements. The density of an asphalt mixture plays an essential role in the quality of an asphalt pavement. When an asphalt mix reaches the desired density, the characteristics of the asphalt mix such as stiffness, fatigue characteristics, resistance against deformation and moisture are optimised. The temperature of a compacted asphalt mix has a direct effect on the desired density of an asphalt mix (Bijleveld, Miller, Bondt2, & Dorée, 2012).

Timm et al. 2001 describe an optimal window for compaction (see Figure 2) where the desired mechanical properties of asphalt are achieved with a high degree of probability by a cooling curve of the asphalt mix. Depending on the cooling rate of the asphalt mix, if the asphalt mix is compacted outside the time windows, the asphalt mix will be under stressed or overstressed.

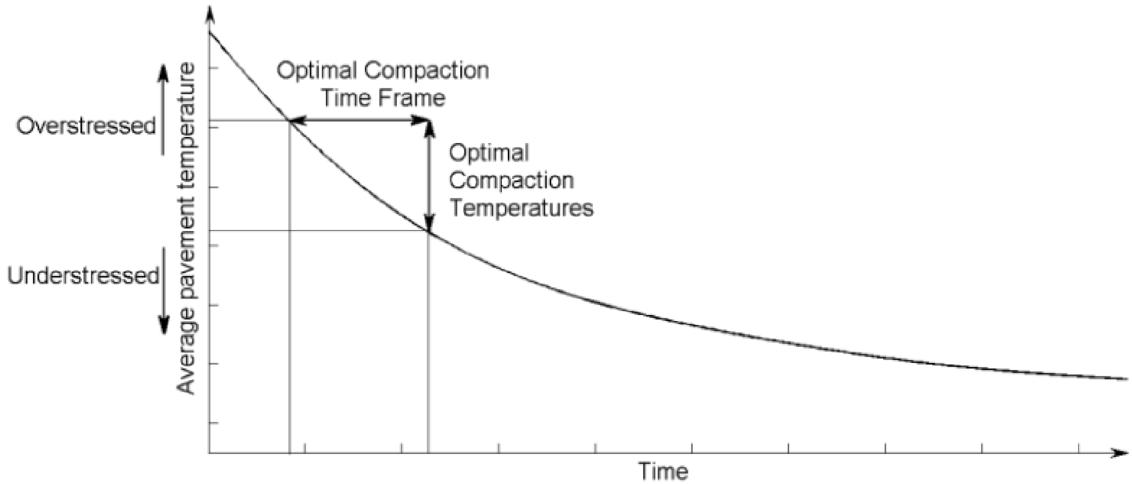

Figure 2: Cooling rate of asphalt and optimal compaction time

2.4. Features that contribute to the cooling rate of asphalt mixes.

The effect of the different features that affect the cooling rate of asphalt was elaborated from a literature review based on different studies which were conducted to determine the cooling rate of asphalt mixes. The effect of the features in the cooling rate of asphalt mixes are elaborated in the table 2 below:

Table 2:Summary effect of features in asphalt cooling rate

Features	Details	References
Type of asphalt mix	AC concrete mix cools faster than SMA under similar conditions	(Chadbourn & Newcomb, 1998)
	PA cools faster compared to AC concrete due to presence of high voids	(Chang, Chang, & Chen, 2009)
Lift thickness	Thick lifts have high heat retention capacity compared to thin lifts, especially in cold regions	(Epps, Gallaway, Harper, William W. Scott, & Seay, 1969)
Type of underlayer	The lower the temperature of the underlayer the faster the cooling rate of the lift	(Baars, 2020)
	Asphalt as an underlayer has a high cooling rate than sand as an underlayer except when the sand is wet or frozen	(Baars, 2020)
Ambient temperature	Hot air temperature decreases the cooling rate; hence it increases the time available for compaction while low air temperature increases the cooling rate	(Miller, 2010)
Wind speed	Increased wind speed increases the cooling rate of the asphalt mix	(Wise & Lorio, 2004)
Rain	Rainfall increases the cooling rate of asphalt mixes. Heavy rainfall causes the asphalt to cool and harden	(Ismail, et al., 2019)
Solar radiation	Increased solar radiation decreases the cooling rate of the asphalt mix	(Bijleveld, Professionalising the asphalt construction process, 2015)
Surface and core temperature	The surface temperature of the asphalt mix has a high cooling effect compared to core temperature, although there is a high correlation between the two.	(Huerne, Dorée, & Miller, 2009)

The next section describes the literature behind Machine Learning (ML).

2.5. Machine learning in predictions

ML is a form of artificial intelligence (AI) that performs tasks such as prediction without the need of being programmed. ML relies on available information from a given task (training data) in order to predict new outcomes. In ML, training is the process whereby the machine learns from the previous example of a task. After learning, the same task is performed from new data (testing data). This process is known as inference. ML employs two strategies, namely, supervised, and unsupervised ML. In supervised Machine Learning (ML), there is prior knowledge of what the output value of the data samples should be. The aim of supervised Machine Learning (ML) is to learn the relationship between the input and the output values of the sample, making it very useful in predicting outcomes. After the machine has learned the relationships, the new input value is fed into the machine, and the machine will predict a new output value from the learned relationship.

In Unsupervised Machine Learning (ML), there is no prior knowledge of the output value in the sample. The aim of unsupervised Machine Learning (ML) is to learn about the structure of the input values. In unsupervised Machine Learning, there are no output labels. The unsupervised Machine Learning (ML) is used for classification problems and dimension reduction (Louridas & Ebert, 2016)

2.5.1. Machine learning algorithms

Many ML algorithms exist that are used for prediction for non-linear relationships, e.g., decision trees, random forest, multilayer perceptron algorithms support vector machines (SVM), support vector regression (SVR) (Mosavi, Ozturk, & Chau, 2018). The Decision trees, random forests algorithms, and Multilayer perceptron are going to be further discussed. These algorithms are discussed because they can make predictions from nonlinear relationships.

Decision trees are the most straightforward ML algorithm approach (Leo, Luhanga, & Michael, 2019). This algorithm uses previous historical data to predict new data. Decision tree classifiers are structured as trees. The nodes represent the features, the edges represent the feature values, and the leaves represent the classes. The biggest problem of decision trees is overfitting (Badillo, et al., 2020). Badillo et. Al (2020) further states that decision trees are not used in their original form, and the reason is that decision trees are prone to overfitting. Decision trees have become a building block for random decision forests.

Random forest algorithm operates by combining decision trees on various subsamples of a dataset. Then, the combined decision trees are averaged in order to improve the accuracy in prediction. Random forest is used in classification and regression problems. Random forests are used to scale the volume of large data sets while retaining statistical efficiency. Another significance is its ability to operate with small data sets with high accuracy predictions. The downside of random forest is that it can feel like a black box approach hence no interpretability. Also, it is complex to build compared to decision trees, in case of regression, it fails to predict data beyond the training data and time-consuming in the prediction process (Biau & Scornet, 2016).

MLP is a known artificial neural network technique. This algorithm is used in the ASPARiCool model. MLP was developed to be able to classify nonlinear separable sets (Kotsiantis S. , 2007). The main advantages of MLP are such that the distribution of training datasets is not dependant on pre assumptions, no decision is set on the significance of the input measurements, and the most input measurements are selected based on their weights in the training process. The MLP consists of input layers, hidden layers, and output layers (Pham, Tien Bui, Prakash, & Dholakia, 2017). The challenges that exist include, model robustness, the choice of the model inputs, model weight optimisation and the validation of the model performance (Shahin, Jaksa, & Maier, 2001).

2.5.2. Overfitting and underfitting in ML algorithms

The biggest problem with these prediction algorithms is overfitting and underfitting. Overfitting occurs when the model performs better on the training data but fails to perform well on testing data; this means that the model has memorised the training data. Overfitting causes the problem of generalisation in the model in which the model fails to predict new outcomes (Kotsiantis S. , 2014). Overfitting in regression models is mainly caused by (1) an excessively high number of features, and (2) complexity of the algorithms. The presence of a high number of features in a regression model causes the model complexity to increase; hence the model fails to generalize. When the complexity of the model is high, the regression line will then fit all the training data points, including the noisy data, as shown in figure 3.

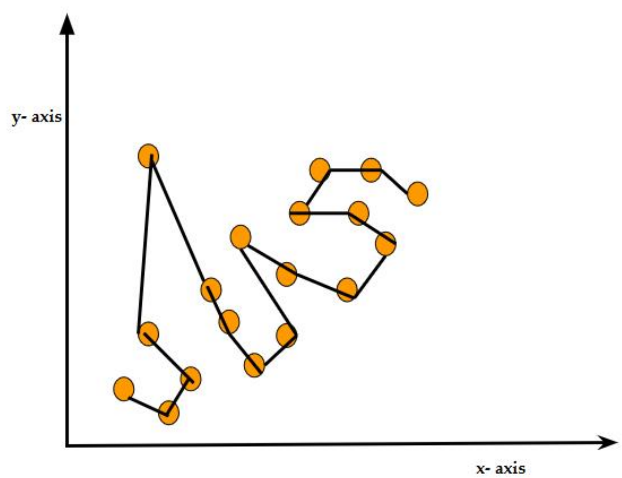

Figure 3: Simple linear regression: Overfit model

Kotsiantis S., (2014) and Liu et al. (2005) state that from a given set of input features, an approach for overfitting is perform feature selection. Feature selection involves filtering irrelevant or redundant features from the dataset. From the literature, there are three currently known feature selection methods. These are filter method, wrapper method and embedded method (Chandrashekar & Sahin, 2014). In this study, the filter method approach is discussed because according to Chandrashekar and Sahin, (2014), it is not computational intensive compared to other selection methods.

The filter method is a feature selection process in which the features in a dataset are evaluated against a predictor. In this method, the features are ranked and removed based on a specific ranking method. After the features are ranked, the less relevant features are removed based on the ranking. The authors identify two types of ranking methods available which are (1) correlation-based method and (2) mutual information gain. The correlation-based method calculates the correlation coefficient between the input and the output to establish rank. This method is most suitable for linear relationships while the mutual information gain is based on the concept of Entropy theory, this technique is essential for different types of relationships including non-linear relationships of the input and output features (Chen, Wilbik, van Loon, Boer, & Kaymak, 2018).

Underfitting in machine learning occurs when the machine learns from some part of the training data. In underfitting, the ML algorithm fails to fit the training data, and therefore the trends in the data are missed. When a model is under fitted, the machine will fail to generalise (Badillo, et al., 2020). A model under fits when it is insufficiently sophisticated such that it fails to capture the relationship between the feature datasets and the target variables. The possible approach for underfitting is to add more feature data. Zhang and Ling (2018) reaffirmed this approach by stating that the addition of more features alleviates underfitting. Besides, there needs to be an optimum number of training data. Another approach mentioned is to change the ML algorithm. Using a different ML algorithm that can process the available training data can solve underfitting. Figure 4 below represents a regression line in an underfitted model.

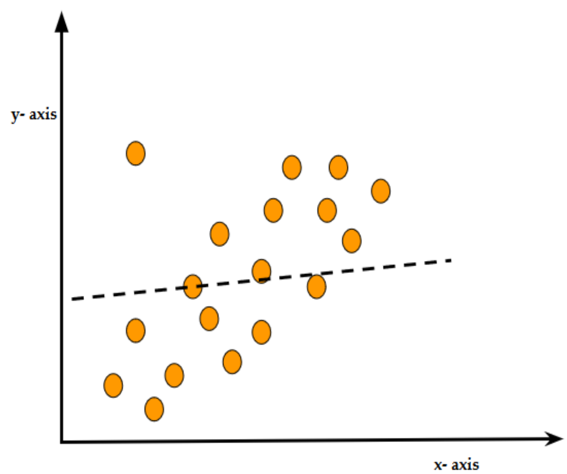

Figure 4: simple linear regression: Underfit model

2.6. Key points background information

The following key points are identified from the background information. These key points will be used in the rest of the research to address the problem of overfitting in the ASPARiCool tool's MLP algorithm.

1. The ASPARiCool tool uses supervised ML to predict the cooling rates of asphalt mixes.
2. The MLP algorithm is used in the ASPARiCool tool. The problem of the MLP algorithm lies in its complexity.
3. MLP algorithms are used to make predictions for nonlinear feature relationships.
4. Overfitting occurs when a prediction model performs well on the training data but performs poorly on the validation data.
5. The number of features used in an ML prediction model influences the overfitting problem.
6. A suitable approach for overfitting is to perform feature selection. The literature identifies the feature selection method called mutual information gain as suitable for non-linear relations.
7. Underfitting occurs when the prediction model fails to fit the training data in the result, the model fails to capture the trends in the data. Underfitting is caused by an overly complicated algorithm or when a small amount of data is used to train the model.

3.0. Theoretical framework

In this section, the key concepts that will be used to answer the research question are elaborated. These concepts have been retrieved from the background information and are essential in addressing the problem of overfitting in the ASPARiCool tool algorithm. In this section, firstly, the ASPARiCool tool is presented. Secondly, the theory about ANN is presented.

3.1. ASPARiCool tool

ASPARiCool tool is one of the new tools which predicts the cooling rate of asphalt. The tool is an Artificial Neural Network (ANN) that makes predictions of the cooling rate of asphalt mixes. This tool was developed to overcome the limitations of Pavecool and Calcool. ASPARi has developed this tool to determine the asphalt cooling rate of different asphalt mixtures used in the Netherlands. The programming language used to build this tool is JAVA (Fat, 2019).

The ASPARiCool tool predicts the cooling rate of asphalt mixes by utilizing Machine Learning (ML). The type of Machine Learning used in the ASPARiCool is supervised machine learning because of the algorithm trains from previously collected asphalt cooling measurements. The ASPARiCool tool predicts the surface temperature in time. Since the predicted asphalt temperature is a numeric value, the supervised machine learning technique used is regression. The regression algorithm is the Multilayer Perceptron algorithm (MLP).

The ASPARiCool tool consists of three main parts. The first part consists of the input. The second part consists of an MLP regression algorithm, and the third part consists of the output. The input is where the attribute data are incorporated while the regression model consists of a Multilayer Perceptron Algorithm (MLP), which is an Artificial Neural Network (ANN). The output of the tool is a cooling curve that represents the cooling rate of asphalt mix over a specified time interval. The general representation of the ASPARiCool tool is elaborated in Figure 5.

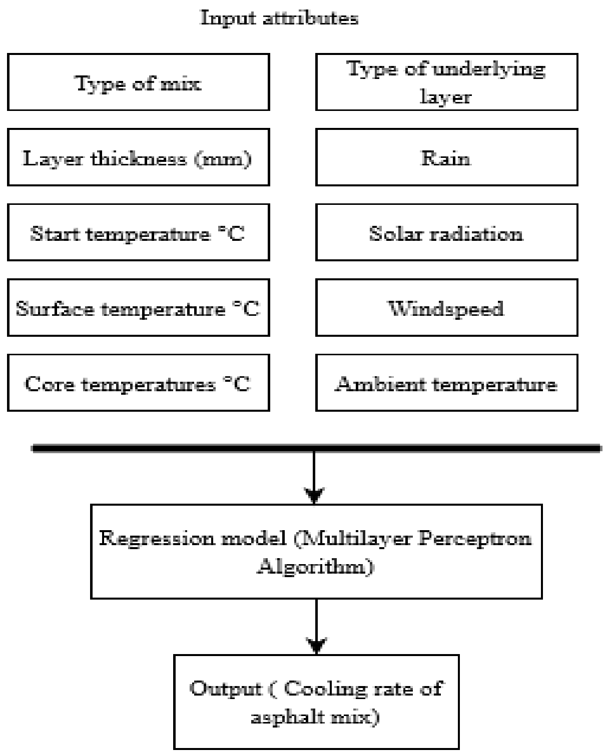

Figure 5:General structure of ASPARiCool prediction model

As previously mentioned, the ASPARiCool tool's main algorithm is an MLP which is an ANN. The MLP algorithm makes numeric predictions of the cooling rate of asphalt mixes; therefore, it is essential to elaborate on the functionality of the ANN.

3.2. Artificial Neural Network

An ANN is a multilayer feedforward network which is used to model the relationship between a set of the input signal and output signal. An ANN uses the same model derived from the understanding of the human brain. The ANN consists of interconnected neurons or perceptrons. Each neuron can make decisions and feed those decisions to other connected neurons which are organized in interconnected layers. The connected neurons comprise of weights (w), which represent the importance of the connection to the output. The ANN consists of three layers which are the input, hidden layers, and the output layer.

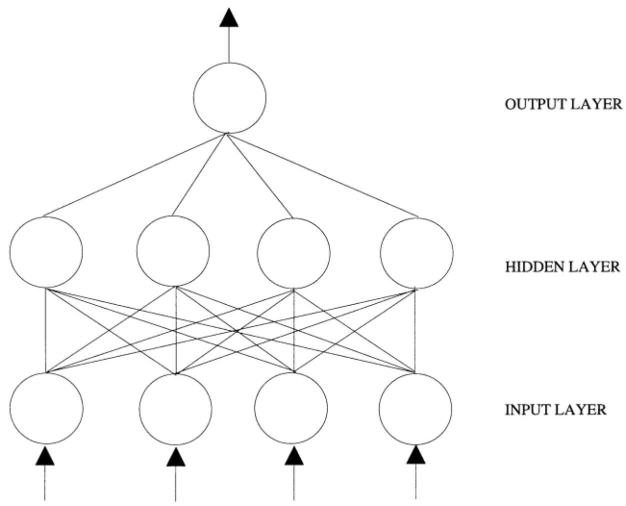

Figure 6: Structure of an ANN (Zhang, Eddy Patuwo, & Y. Hu, 1998)

3.2.1. The training process of the ANN

The training inputs are first entered into the input neurons. The weights are assigned to the activation values of the input neurons and summed up in the first hidden layer. An activation function then transforms the sum of the weighted values to the neurons in the next layer. In this case, the activation value becomes the new input in the next layer. The process is repeated until the output is determined (Zhang, Eddy Patuwo, & Y. Hu, 1998).

The mathematical approach of the training process is presented below whereby each of the input is multiplied to weights w, and the final products are summed and then passed by an activation function f to produce and output $y(x)$ (Lantz, 2013).

$$y(x) = f(\sum_{i=1}^{n} w_i x_i) \qquad (1)$$

3.2.2. Activation function

The task of an activation function is to transform the neuron net input into a single output signal. Activation functions are useful because they introduce nonlinear relationships in ANN's (Zhang, Eddy Patuwo, & Y. Hu, 1998). According to the authors, the use of activation functions depends on the type of problem that is to be addressed. The most common activation functions are logistic and rectified linear unit (relu). For example, the logistic (sigmoid activation function) is used in models that predict an output value between 0 and 1 while the relu activation function is used to predict output values from 0 to infinity (Sharma, 2017). The formulas for these activation functions are represented below:

Sigmoid (logistic activation function)

$$f(x) = \frac{1}{1+e^{-x}} \tag{1}$$

Relu (Rectified linear unit)

$$f(x) = \begin{cases} 0 \; for \; x < 0 \\ x \; for \; x \geq 0 \end{cases} \tag{2}$$

3.2.3. Loss function

This function calculates the error between the actual value and the predicted value.

3.2.4. Backpropagation

The back-propagation process ensures that the network is learning by minimizing the loss function by updating the weights in the neurons to ensure that a minimum square error is reached.

In this process, the output signal moves back from the predicted network to the neurons that generated the prediction. The error from the forward process is propagated back to the neurons to modify the connection weights. This process ensures that the total error of the network is reduced. The gradient descent technique is used to determine how much the connection weights should be changed in the backpropagation. The gradient descent is a mathematical process that uses the derivative of the activation function in each neuron to identify the gradient of the direction of the incoming weight (Lantz, 2013). The gradient specifies how steeply the error is going to be minimized or increased when the weight changes. In minimizing the error in ANN, the solver is an algorithm which is used to specify the weight optimization across the neurons by an amount known as the learning rate. The two most common types of solvers are Adaptive Gradient Algorithm (adam) and the stochastic gradient descent (sgd). The adam solver employs adaptive learning technique to find individual learning rate of in the neurons. On the other hand, the 'sgd' solver maintains a single learning rate for all updated weight while maintaining the learning rate.

4.0. Experimental design

In this section, a detailed description of the preliminary steps taken to predict the cooling rates of asphalt mixes is presented. This section consists of a data collection procedure, followed by data preparation and pre-processing. Next, the theory behind the evaluation metrics used to check the performance of the prediction models is presented. Lastly, the prediction model implementation tools are elaborated.

4.1. Data collection

In order to predict the cooling rate of asphalt mixes in machine learning models, asphalt cooling mix data during the road paving process needs to be acquired. The data needs to be collected from various asphalt paving projects. The data that affects the asphalt cooling mix is linked to surface and core temperatures of asphalt mix in order for a supervised machine learning model to be trained.

The data used to train the model and predict the cooling rate of asphalt mixes was acquired from the ASPARi historical database and previous BAM projects. It consists of feature measurements that have been conducted on various road construction projects in the Netherlands. Table 3 below shows the description of the input data features that were measured in the various road construction projects. These features were chosen because they affected the cooling rate of asphalt mixes.

Table 3: Description of features used in the asphalt cooling rate prediction model

Features	Description
Time	Is the time recorded at a specific temperature of asphalt mix during paving. (minutes)
Type of asphalt mix	Consists of seven mixes which are AC 22, AC 16, PA 16, SMA-NL 11B,SMA-NL 11B AC 8, and AC 11.
Underlayer temperature	The temperature of the asphalt underlayer in °C
Underlayer type	Consists of 3 types of underlayers which are sand, stone and asphalt.
Thickness	Consists of the thickness of the asphalt mix (mm)
Windspeed	Windspeed recorded during asphalt paving in km/h.
Outside temperature	The ambient temperature during asphalt pavement (°C.)
Solar radiation	Radiant energy emitted by the sun during asphalt pavement. (W/m2)
Rain	Amount of rainfall recorded during the pavement process (mm).
Measured surface and core temperatures	The temperature of the asphalt pavement after the asphalt mix has been spread out before compaction of the asphalt mix (°C).

In this research, two datasets were prepared in the prediction model. The dataset consists of surface temperatures and core temperatures combined with features that affect the cooling rate of asphalt mixes.

Some of the measurements in the dataset had missing values for the features. The missing measurements consisted of weather conditions, type of underlayer and underlayer temperature. The following assumptions were made to counter this problem:

1. The weather data was retrieved from the KNMI website by looking at the location of the asphalt construction site and retrieving weather information from the weather station, which is the closest to the construction site.
2. If the thickness of the asphalt mix layer was greater than 50 mm, the type of underlayer selected was sand.
3. If the thickness of the asphalt mix layer was less than 50 mm, the type of underlayer selected was asphalt.
4. The type of underlayer for all porous asphalt mixes was stone.

Table 4 and Table 5 below presents a brief overview of the input features which were used to predict the cooling curves in the ASPARiCool tool. From Table 4; Dataset 1, the type of asphalt mix with the highest amount of measured data was AC 22 with 42 measurements while AC 8 has the lowest number of measurements collected. Besides, many measurements were taken during cold temperatures because the mean outside temperature is 14.6 °C. Lastly, the type of underlayers used comprised of stone, sand and asphalt.

Table 4:Dataset 1: Statistics of features that affect the cooling rate of asphalt mixes (surface temperatures)

Input features	Thickness (mm)	Underlayer temperature (°C)	Type of underlayer	Wind speed (Km/h)	Outside temperature (°C)	Solar radiation (W/m2)	Rain (mm)	Measured Surface temperature (°C)
Min	30 mm	-0.2 °C	Sand	0 km/h	-0.4 °C	0 W/m2	0 mm	15.9 °C
Max	80 mm	36 °C	Stone	32 km/h	26.2 °C	668 W/m2	2 mm	170 °C
Mean	54.18 mm	12.07 °C	Asphalt	9.45 km/h	14.6 °C	79.12 W/m2	0.07 mm	82.38 °C

From Table 5 below, the core temperature the type of asphalt mix with the highest amount of measured data was AC 22 with 25 measurements while AC 11 has the lowest number of measurements collected at three measurements. Besides, many measurements were taken during cold temperatures because the mean outside temperature is 12.3 °C. Also, the type of underlayers is stone, sand and asphalt.

Table 5:Dataset 2: Statistics of features that affect the cooling rate of the asphalt mix (Core temperatures)

Input features	**Thickness (mm)**	**Underlayer temperature (°C)**	**Type of underlayer**	**Wind speed (Km/h)**	**Outside temperature (°C)**	**Solar radiation (W/m2)**	**Rain (mm)**	**Measured core temperature (°C)**
Min	30 mm	0.1 °C	Sand	3.6 km/h	4.1 °C	0 W/m2	0 mm	23.33 °C
Max	80 mm	34 °C	Stone	32.4 km/h	26.2 °C	241 W/m2	1.1 mm	177 °C
Mean	47.5 mm	12.3 °C	Asphalt	15.11 km/h	14.13 °C	66.08 W/m2	0.11 mm	90.63 °C

4.2. Data preparation ASPARiCool tool preliminary analysis

The preliminary analysis was conducted using two sets of data. The first dataset(Table 4) consisted of surface temperatures of asphalt mix and other features that affect the cooling rate of asphalt mixes. In contrast, the second set of data Table 5 consisted of the core temperature of asphalt mixes and other features that affect the cooling rate of asphalt mixes—both datasets comprised of individual feature measurements that were collected at different construction sites. The measurements were stored in an xlsx excel format before being uploaded into the ASPARiCool tool. Table 6 below presented the amount of data used in the ASPARiCool tool.

Table 6: Amount of training data used in the ASPARiCool tool

Type of asphalt mix	**Dataset 1: surface temperature data**	**Dataset 2: core temperature data**
AC 22	42	25
AC 16	17	3
AC 11	1	11
AC 8	3	5
PA 16	10	NA
SMA NL 8G+	18	17
SMA NL 11B	13	18
The total amount of data	104	79

Before inserting the datasets into the ASPARiCool tool, the datasets were separated into training and validation data. The training data was used to train the ASPARiCool tool while the validation data which comprised of different types of asphalt mixes was used to check the prediction performance of the ASPARiCool tool by comparing the measured temperatures and the predicted temperature of the asphalt mixes. The validation data comprised five asphalt mixes. The asphalt mixes PA 16, and AC 11 was not used to check the performance ASPARiCool tool because the amount of AC 11 measurements for the surface temperature dataset was one. Also, there were no recorded PA 16 measurements in dataset two; hence it was not possible to compare the surface temperature and core temperatures of these types of asphalt mixes in the ASPARiCool tool.

Table 7 presents an overview of the validation data measurements for both the surface and core temperatures which were used to check the performance of the ASPARiCool tool in the prediction of surface and core temperatures:

Table 7: Validation data for the different types of asphalt mixes used to check the performance of ASPARiCool tool

Type of mix	Thickness (mm)	Type of underl ayer	Temperature of underlayer	Windspeed (km/h)	Outside temperature	Solar radiation (W/m2)	Rain (mm)
AC 8	30	Asphalt	10	23	10	0	0
AC 16	40	Asphalt	7	21	6	0	0
SMA-NL 11B	35	Asphalt	7	8	7	0	1.1
SMA-NL 8G	35	Asphalt	17.8	10.8	21.8	206	0
AC 22	60	Sand	8.85	18	12.85	36	0

4.3. Data preparation new prediction model

The initial step in the data preparation phase was to extract validation data from the datasets. The validation data consisted of five types of asphalt mixes. The validation data was used to check the cooling curves of the predicted cooling rates of asphalt mixes. The data that was used for the new prediction model was similar to the one used in the ASPARiCool tool preliminary analysis(Table 6). The only difference was in the way the data was inputted into the new prediction model. The data input strategy for ASPARiCool tool was to insert individual measurements comprising of xlsx excel format into the ASPARiCool tool while for the new prediction model; the data input strategy was to combine all the measurements from Table 6 into a single csv excel format then insert the single csv file into the new prediction model. This was done separately for surface temperature measurements and core temperatures measurements of asphalt mixes. The datasets for the new prediction model are illustrated in Table 8 below.

Table 8: Dataset 1 and Dataset 2 file names for the new prediction model

Dataset 1 file name: Surface temperatures		**Dataset 2 file name: Core temperatures**	
Model data	Validation data	Model data	Validation data
Surface_Dataset_1.csv	AC_8_Surface_Valid.csv	Core_Dataset_2.csv	AC_8_Core_Valid.csv
	AC_16_Surface_Valid.csv		AC_16_Core_Valid.csv
	AC_22_Surface_Valid.csv		AC_22_Core_Valid.csv
	SMA-NL_8G_Surface_Valid.csv		SMA-NL_8G_Core_Valid.csv
	SMA-NL_11B_Surface_Valid.csv		SMA-NL_11B_Core_Valid.csv

4.4. Data pre-processing for new prediction models

In this phase, all the asphalt cooling measurements with missing values in both the datasets were removed. Secondly, the features, which are the type of asphalt mix and type of underlayer, which consisted of qualitative categorical features, were converted into numeric labels through the use of dummy variables. This was done because the prediction model can only predict numbers and not texts. The dummy variable can only take two quantitative values, which are zero and one. The value one represents the presence of the qualitative categorical feature, while zero represents the absence. The dummy variable is used when the data contained in the attribute are not conventionally measured on a numeric scale. In this case, the attributes 'type of asphalt mix' and 'type of underlayer' was not to be measured on a numeric scale because the model would have assigned numeric weights to the qualitative categorical features and affect the prediction performance of the cooling rate of asphalt mixes. After the dummy variables were applied to the categorical features, the categorical labels are converted into features; hence the total amount of features increased to eighteen features in dataset one and sixteen features in dataset two. The feature set excel format of datasets one and datasets two are illustrated in

Appendix B.

Another step taken in the pre-processing phase was to separate the independent x variables (the type of asphalt mix, type of underlayer, underlayer temperature, solar radiation, wind speed, rain, and ambient temperature) and the dependant variable (Core and Surface temperature of asphalt mix).

Lastly, the train and test split function was used to separate the datasets into training and testing data. This train and test split function was used to evaluate the performance of the model and check whether the model overfits. The x and y variables were split into 60 % training and 40 % testing data.

4.5. Model evaluation metrics

4.5.1. Root mean square error

The RMSE was used as the model performance evaluators for the asphalt cooling rate prediction. The RMSE was chosen because it measures how far the deviation is between the measured value and the predicted value. Besides, the RMSE is useful because it assigns high weights to large errors; hence for this research, it was useful for large undesirable errors relating to temperatures (Chai & Draxler, 2014).

The RMSE is a measure of the standard deviation between the observed values and the predicted values (Barnston, 1992). In this research, the RMSE measures the standard deviation between the predicted temperature and the measured temperature of asphalt mixes. The RMSE is a negatively oriented score. This means that a lower RMSE value indicates a more accurate and consistent asphalt cooling rate prediction model. The formula which is used to calculate the RMSE is presented:

$$RMSE = \sqrt{\frac{\sum(y_i - x_i)^2}{n}} \qquad \textbf{(1)}$$

Where
y_i is the predicted temperature of the asphalt mix
x_i is the measured temperature of the asphalt mix
n is the number of samples used in the measurements

4.6. Implementation tools

This section describes the implementation tools and the libraries that were used to perform essential functions in the prediction of the cooling rates of asphalt mixes. A detailed function python code can be found in Appendix A.

Programming language: Python 3. Python 3 was chosen because it is a relatively simpler language to use compared to JAVA (Anaconda, 2020).

Programming platform: Jupyter lab. This is an open-source programming platform. (Jupyter, 2020).

Supporting libraries: Python 3 supports different scientific libraries. The following libraries were used in the new asphalt cooling rate prediction model:

1. Pandas pd – comprises of a data analysis toolkit (pandas, 2020).
2. Numpy np – performs mathematical and logical operations in multidimensional arrays and matrices. (NumPy, 2020)
3. Scikit learn – imports libraries used in developing the model (Scikitlearn, 2019)
   - MLPRegressor: Multilayer perceptron regression algorithm
   - Mutual information regressor – Feature selection algorithm
   - Train-test splits: Splits the data into training and testing data.
   - Metrics for scoring: provides scorings for the model predictions.

- square root(sqr), mean square error (mse)

4. Matplotlib – used for 2-dimensional plotting and data visualization. (Matplotlib, 2020).

5.0. Preliminary analysis ASPARiCool tool

This section describes the performance of the predicted asphalt mix cooling curves in the ASPARiCool tool. The validation data in Table 7 was used to check the performance of the ASPARiCool tool by comparing the curves of the predicted temperatures and the measured temperatures of the asphalt mixes. The results of the preliminary analysis of the ASPARiCool tool are divided into two parts, surface temperature predictions and core temperature predictions of asphalt mixes.

In evaluating the performance of the ASPARiCool tool, the RMSE between the measured temperature of the asphalt mix and predicted temperature of the asphalt mixes was calculated for the three compaction phases. The compaction phases comprised of breakdown phase intermediate rolling phase and finishing rolling phase as elaborated in section 2.2

Two types of asphalt mixes were considered for this analysis, the SMA and AC mix. Each of these mixes has its own compaction temperature, as illustrated in Table 9 below:

Table 9: Compaction time windows for asphalt mixes (retrieved from ASPARi research)

Type of mix	**Breakdown phase temperature °C**	**Intermediate rolling phase temperature °C**	**Finishing rolling phase Temperature °C**
SMA	140 - 120	120 -100	100 -80
AC	150 120	120 -100	100 -80

As previously mentioned in section 4.5, the RMSE value for this analysis represented the standard deviation between the measured asphalt mix temperature and the predicted asphalt mix temperature. Furthermore, the lower the RMSE value represented a better model performance in predicting the cooling temperature of the asphalt mix because it closely related the measured temperature of the asphalt mix. Before looking at the results of the predicted temperatures, the parameters used in the ASPARiCool tool MLP classifier were identified:

5.1. Parameter identification ASPARiCool tool

To identify the model parameters, the MLP classifier file, located inside the ASPARiCool java program, was decompiled. The next step followed was to retrieve the parameter values for the MLP classifier. The ASPARiCool tool parameters and their descriptions are elaborated in Table 10. From the table below, the type activation function and the type of solver could not be determined from the MLP classifier code:

Table 10: Parameters used in the ASPARiCool tool. Description of parameters retrieved from (Scikitlearn, 2019) and (Lantz, 2013)

Parameters	Value	Explanation
Number of hidden layers	3	Processes signals from the input node to the output node. Adding more layers will increase the complexity and increase the signal processing ability
Number of neurons in the hidden layers	Not known	Determines the complexity of the task learned in the network.
Activation function	Not known	Transforms neuron net input into an output function within the network layers
Maximum iterations	2000	Determines how many times the data is trained in the model.
Learning rate	0.1	Determines the schedule for updating the input weights.
Type of solver ▪ **Adaptive moment estimation(adam)** ▪ **Stochastic gradient descent (sgd)**	Not known	Updates network weights iteratively based on training data to minimize the error in the predictor
Momentum	0.2	Used to increase the speed of learning effect of the MLP

The next section elaborates on the prediction results for dataset one and dataset two.

5.2. Dataset 1: Surface temperature predictions

Table 11 present the RMSE values of the surface temperature dataset for the five types of asphalt mixes that were trained in the model. The AC 16 mix predictions were poor at the breakdown compaction phase compared to the intermediate and finishing rolling phase. The predictions for AC 8 and AC 22 were poor because of the RMSE value in the intermediate and finishing rolling phase were high. The SMA mixes performed better than the AC mixes because of the lower RMSE values in the breakdown and intermediate phase, although the RMSE values were higher in the finishing rolling phase.

Table 11:Performance scores for different types of asphalt mixes in ASPARiCool tool- Surface temperatures

Type of mix	**The total amount of data**	**Root mean square error between measured surface and predicted surface temperature (RMSE)**		
AC		Breakdown phase (150°C-120°C)	Intermediate rolling phase (120°C -100°C)	Finishing rolling phase (100°C – 80°C)
AC 16	17	10.26	4.23	7.62
AC 8	3	6.27	13.88	17.63
AC 22	42	21.95	24.61	24.91
SMA		Breakdown phase (140°C - 120°C)	Intermediate rolling phase (120°C - 100°C)	Finishing rolling phase (100°C – 80°C)
SMA-NL 8G	18	2.70	8.01	10.65
SMA-NL 11B	13	2.02	6.49	18.17

The cooling curves are presented below. The cooling curves of the asphalt mixes show more significant deviations between measured temperatures and predicted temperatures of the asphalt mixes and a rising effect is observed at the end of the cooling curves. This indicates that the MLP algorithm used in the tool was overfitting in the prediction of these mixes.

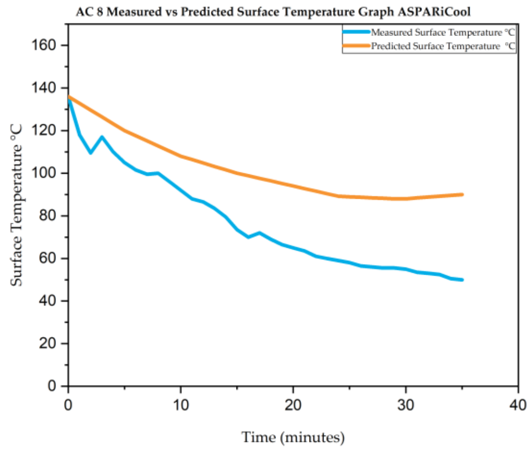

Figure 7:Dataset 1, AC 8 cooling curves ASPARiCool

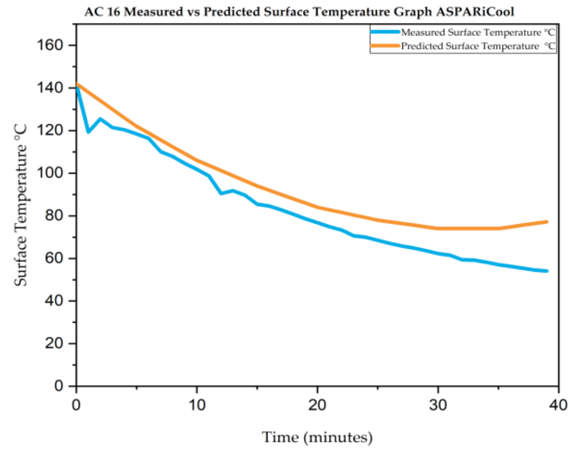

Figure 8:Dataset 1, AC 16 cooling curve ASPARiCool

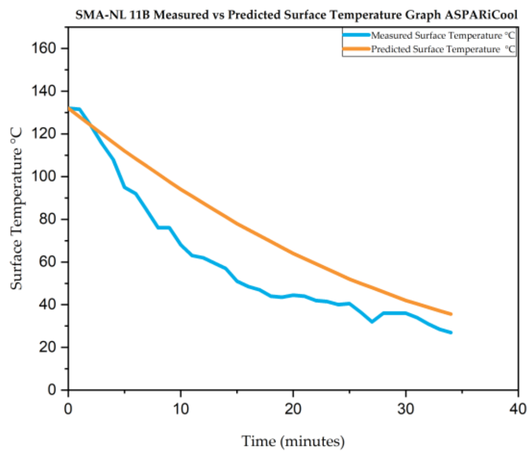

Figure 9:Dataset 1, SMA-NL 11B cooling curve ASPARiCool

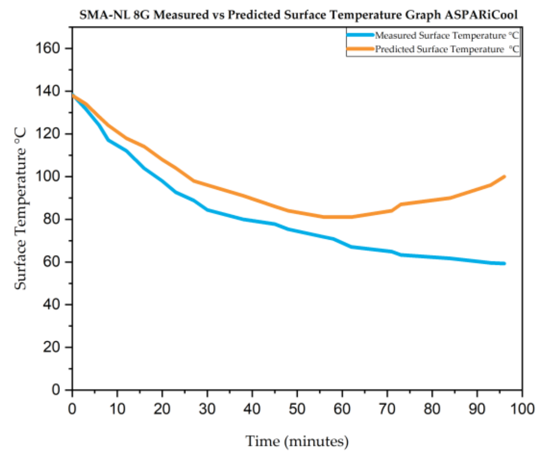

Figure 10: Dataset 1, SMA-NL 8G cooling curve ASPARiCool

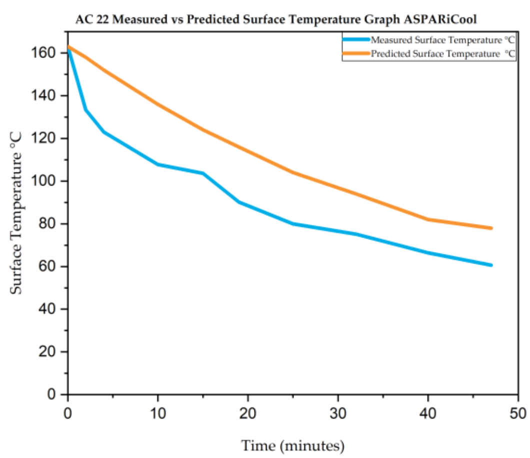

Figure 11:Dataset 1, AC 22 cooling curve ASPARiCool

5.3. Dataset 2: Core temperature predictions

Table 12 present the RMSE values for the five types of asphalt mixes. Starting with the AC mixes, the worse performing mix is AC 22, which has high RMSE values in all compaction phases. AC 8 mix recorded a lower RMSE value of 6.21 in the breakdown phase, but the intermediate rolling phase and finishing rolling phase RMSE values, which were greater than 8. The tool showed a better performance in predicting the cooling rate of the AC 16 mix because of the lower RMSE values in all the rolling phases. The SMA-NL 8G mix performed poorly in the finishing rolling phase compared to the other compaction phases. Lastly, the SMA-NL 11B performed poorly in the breakdown compaction phase and finishing rolling phase.

Table 12:Performance scores for different types of asphalt mixes in ASPARiCool tool- Core temperature dataset

Type of mix	**The total amount of data**	**Root mean square error between measured core temperature and predicted core temperature(RMSE)**		
AC		Breakdown phase (150°C-120°C)	Intermediate rolling phase (120°C -100°C)	Finishing rolling phase (100°C – 80°C)
AC 16	3	0.71	1.92	8.09
AC 8	5	6.21	17.31	23.73
AC 22	25	22.84	32.35	39.95
SMA		Breakdown phase (140°C - 120°C)	Intermediate rolling phase (120°C - 100°C)	Finishing rolling phase (100°C – 80°C)
SMA-NL 8G	17	3.53	3.88	9.29
SMA-NL 11B	18	8.77	2.22	8.58

The cooling curves for the core temperature dataset show that the predicted core temperatures are increasing indicating that the MLP algorithm used in the tool was overfitting in the prediction of these mixes.

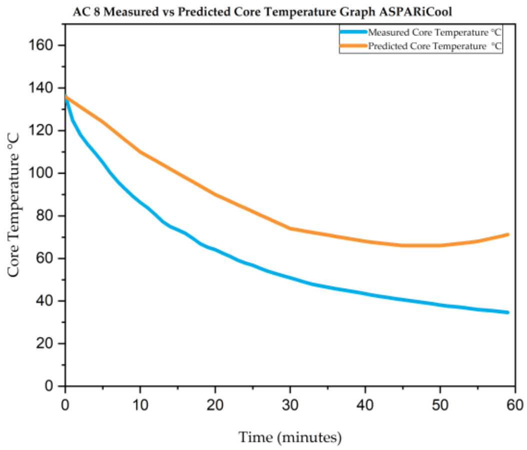

Figure 12: Dataset 2, AC 16 cooling curve ASPARiCool

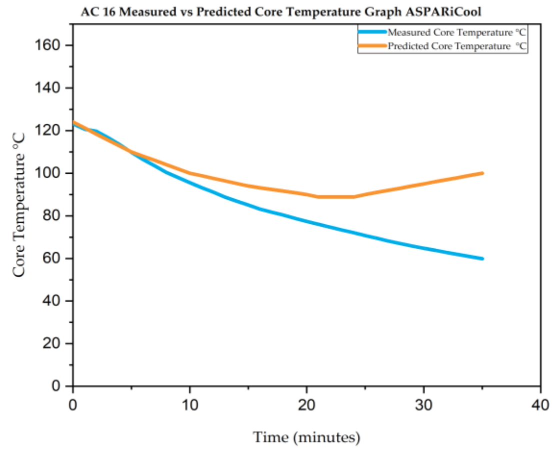

Figure 13: Dataset 2, AC 16 cooling curve ASPARiCool

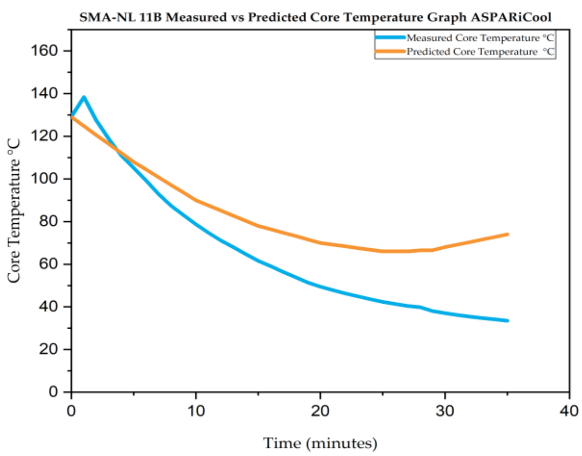

Figure 14: Dataset 2, SMA-NL 11B cooling curve ASPARiCool

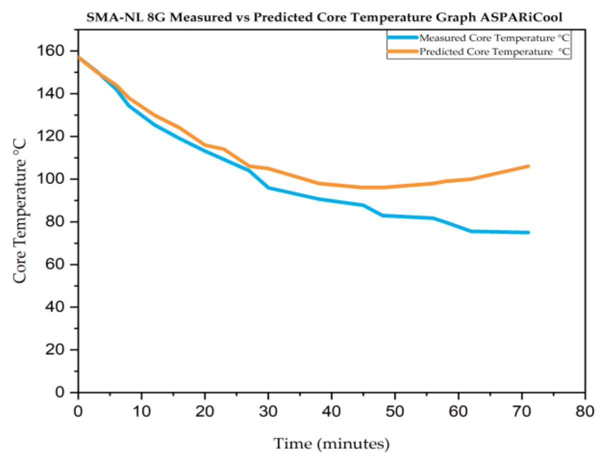

Figure 15:Dataset 2, SMA-NL 8G cooling curve ASPARiCool

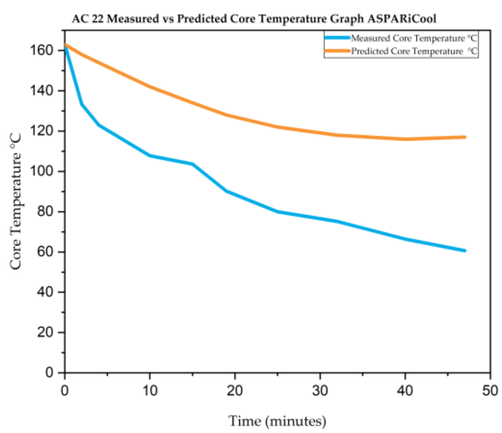

Figure 16: Dataset 2, AC 22 cooling curve ASPARiCool

5.4. Discussion preliminary analysis ASPARiCool tool

The cooling curves show that the predicted temperatures of the surface and core dataset are rising with time, especially at the intermediate (120°C -100°C) and finishing rolling phase(100°C-80°C). The rising effect is indicated by the higher RMSE values between the predicted temperatures and the measured temperatures. For example, the cooling curve of SMA-NL 8G mix for dataset 1 (Figure 10) shows that the predicted temperature of the asphalt mix begins to rise at the intermediate rolling phase whereby the RMSE value is 8.01 as represented in Table 11. Another example can be seen in the cooling curve of AC 16 mix for dataset 2 (Figure 13) whereby the cooling curve shows a rise in the predicted core temperature of the mix at the finishing rolling phase in which the RMSE value is 8.08 as represented in Table 12.

According to previous research by Baars, 2020, the problem of the rise in the cooling curves is overfitting of the ASPARiCool prediction tool, although this problem was not correctly defined because the tool was considered a black box since the model could only be viewed in terms of the input and output because it is still in the development phase.

Another problem was some parameters of the MLP algorithm, which comprise of the number of neurons, activation function, and solver type could not be known hence the prediction performance of the tool might have been affected. Furthermore, the tool only showed asphalt mix cooling curves, but there was no option to download the cooling curve values; hence the RMSE values between the measured and predicted temperatures of the asphalt mix that were calculated in the preliminary analysis were not significantly accurate.

6.0. Development of an asphalt cooling rate prediction model

To address the problem of overfitting in the ASPARiCool tool's MLP algorithm, a similar model which predicts the cooling rate of asphalt mixes was built. A similar prediction model was built to address the problem of overfitting in the ASPARiCool tool because there was limited time to learn JAVA programming language, which was used in the ASPARiCool tool.

6.1. New asphalt cooling rate prediction model

The algorithm used in the new prediction model was the MLPRegressor. The MLPRegressor is a multilayer perceptron algorithm that utilizes feed-forward network propagation to conduct supervised machine learning regression. The MLPRegressor trains iteratively based on the chosen MLP model parameters and record a score depending on the specified maximum iterations (Scikitlearn, 2019). The MLPRegressor consisted of the following parameters:

1. Number of hidden layers
2. Number of neurons in each of the hidden layers
3. Activation function for hidden layers
   - Rectified linear unit function (relu)
4. Type of solver
   - Adam
5. Momentum

6. Learning rate

The model development steps have been summarised in Figure 17 below:

Figure 17: Development steps of new asphalt mix cooling rate prediction model

The detailed steps taken to develop the new prediction model were elaborated below. The detailed python code and descriptions are presented in Appendix A for each of the steps taken:

Step 1: Importation of scientific libraries into the python 3 web interface.

Step 2: Importation of the dataset one (**Surface_Dataset_1.csv**) and dataset two (**Core_Dataset_2.csv**) to make asphalt cooling rate predictions(Table 8).

Step 3: Data pre-processing. The process comprised of the following:

A. Removal of rows in the data with missing values.
B. Application of dummy variables to features with qualitative categorical attributes (Suits, 1957).Appendix B
C. Separation of the variables into independent and dependant variables.
D. Split the data into training and testing data

Step 4: Application of MLPRegressor algorithm.

A. Application of independent and dependent variables into the MLPRegressor
B. Tuning of parameters of the MLP Regressor algorithm.

Step 5: Importation of validation data which comprises of different types of asphalt mixes

Step 6: Test the model performance on validation data

A. Calculate RMSE values between the measured and predicted surface temperatures of asphalt mixes
B. Return the cooling curves of the measured surface temperature and the predicted surface temperature of the asphalt mixes.

6.2. Preliminary analysis of new asphalt cooling rate prediction model

The preliminary analysis was conducted using similar parameters and datasets that were used in the ASPARiCool tool. The goal of conducting a preliminary analysis was to investigate whether the new prediction model overfitted like the ASPARiCool tool.

The following steps were taken in the preliminary analysis:

1. The new prediction model used similar datasets as the ASPARiCool tool.

Two datasets that consist of core and surface temperatures of asphalt mixes, including other features that affect the cooling rate of asphalt mixes were used in the preliminary analysis of the new prediction model. Table 13 below provides an overview of the amount of data used.

Table 13: Amount of training data for a new prediction model

Type of asphalt mix	**Amount of surface temperature data**	**Amount of training core temperature data**
AC 22	42	25
AC 16	17	3
AC 11	NA	11
AC 8	3	5
PA 16	10	NA
SMA NL 8G+	18	17
SMA NL 11B	13	18
Total amount of data	104	79

2. One set of measurements was separated in each type of mix to be used as validation data.

3. The parameters which include, activation function, solver and the number of neurons in each of the hidden layers were not known in the MLPclassifier algorithm in the ASPARiCool tool; therefore, the activation function and solver was set to relu (rectified linear unit) and adam, respectively. These parameters are also the default function for the MLPRegressor algorithm, which was used in the new prediction model (Scikitlearn, 2019).

4. The standard number of neurons in each of the hidden layers was calculated by taking 2/3rd of the total amount of features (18 features) plus one. This rule is considered a standard rule of thumb because there is no specific formula to calculate the number of neurons in each of the hidden layers (Panchal et al. 2011).

Table 14 below illustrated the overview of the data and the parameters used for the algorithm of the new prediction model.

Table 14: MLPRegressor input data and parameters

MLPRegressor input data	**Value**
Dataset 1: Total amount of surface data measurements	104
Dataset 2: Total amount of core data measurements	79

MLP Regressor Parameter	
Learning rate	0.1
momentum	0.2
Activation function	relu
solver	adam
Max iterations	2000
Hidden layer sizes	3
Number of neurons in the hidden layer	(13,13,13)

5. The performance of the new prediction model was determined by comparing the RMSE between the predicted and measured temperatures of the asphalt mixes and by checking the cooling curves of the asphalt mixes.

6.3. Results of the preliminary analysis in the new prediction model

In evaluating the performance of the new prediction model, the RMSE between the measured temperature of the asphalt mix and predicted temperature of the asphalt mixes was calculated for the three compaction phases. The compaction phases comprised of breakdown phase intermediate rolling phase and finishing rolling phase.

6.3.1. Dataset 1: Surface temperature predictions

Table 15 present the RMSE values of the surface temperature dataset for the five types of asphalt mixes that were trained in the model. The RMSE values indicate the temperature deviations between the measured temperature and predicted temperatures of the asphalt mixes. From the table below, the AC 16, AC 8, and SMA-NL 11B mixes indicated very high-temperature deviations between the measured and predicted surface temperatures. The new prediction model performed better for SMA-NL 8G mixes because the RMSE in the breakdown, intermediate rolling and finishing rolling phase were 1.4, 5.5 and 5.6 respectively hence this indicates the MLP algorithm used in the new prediction model was not overfitting when predicting SMA-NL 8G asphalt mix.

Table 15:Performance scores for different types of asphalt mixes in new prediction model- Surface temperature dataset

Type of mix	The total amount of data	Root mean squared error between predicted temperature and measured temperature of asphalt mixes (RMSE)		
		Breakdown phase	Intermediate rolling phase	Finishing rolling phase

		(150°C-120°C)	(120°C -100°C)	(100°C – 80°C)
AC 16	17	24.56	17.16	6.33
AC 8	3	22.08	12.94	10.07
AC 22	42	5.77	9.79	9.04
SMA		Breakdown phase (140°C - 120°C)	Intermediate rolling phase (120°C - 100°C)	Finishing rolling phase (100°C – 80°C)
SMA-NL 8G	18	1.4	5.5	5.6
SMA-NL 11B	13	35.93	26.10	12.36

The cooling curves are presented in the figures below. As can be seen, the SMA-NL 8G mix cooling curve, which consisted of 17 measurements performed better compared to the other cooling curves. The problem seen for the rest of the cooling curves is that the predicted surface temperature at the beginning of the curves was considerably lower compared to their respective measured surface temperature indicating that the new MLP algorithm was overfitting when predicting the AC 8, AC 16, and SMA-NL 11B mixes.

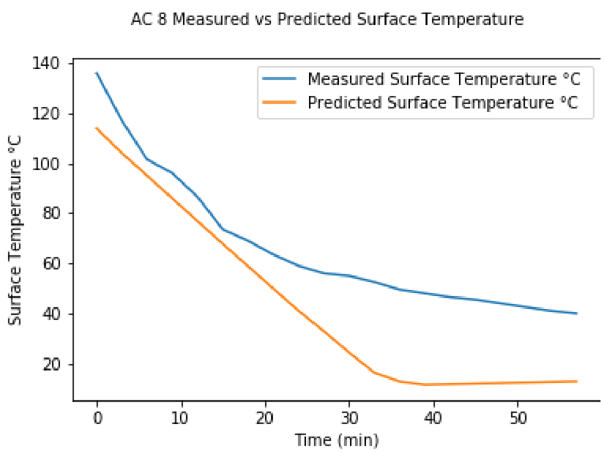

Figure 18: Dataset 1, AC 8 cooling curves New prediction model preliminary analysis

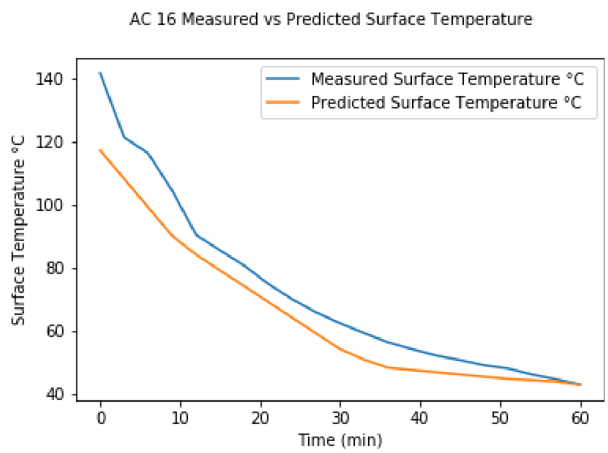

Figure 19: Dataset 1, AC 16 cooling curves New prediction model preliminary analysis

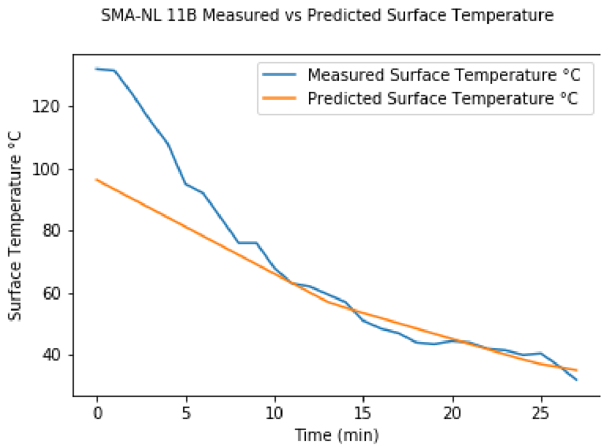

Figure 20:Dataset 1, SMA-NL 11B cooling curves New prediction model preliminary analysis

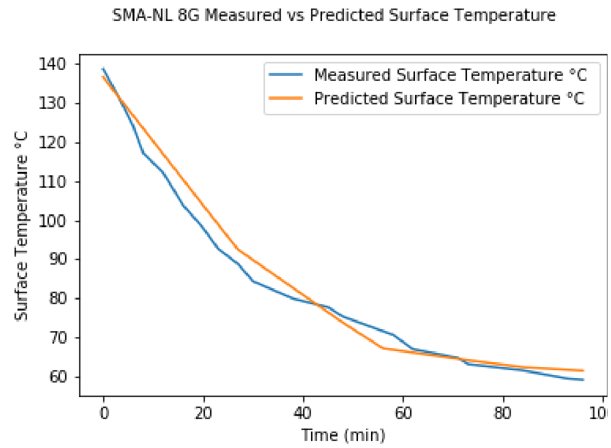

Figure 21: Dataset 1, SMA-NL 8G cooling curves New prediction model preliminary analysis

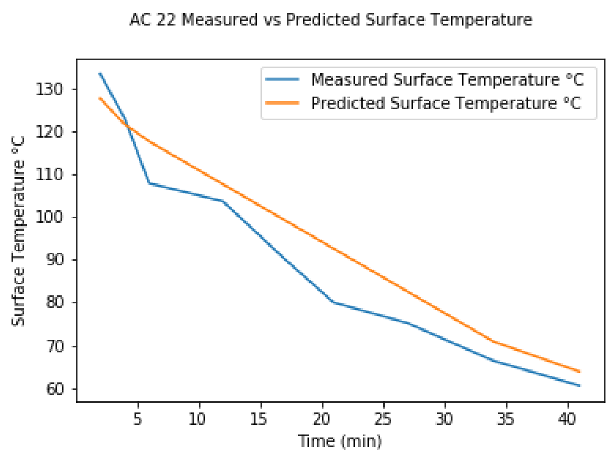

Figure 22: Dataset 1, AC 22 cooling curves New prediction model preliminary analysis

6.3.2. Dataset 2: Core temperature predictions

Table 16 below presents the RMSE values for the five types of asphalt mixes. The RMSE values indicate the temperature deviations between the measured temperature and predicted temperatures of the asphalt mixes. Starting with AC 16 mix, the RMSE value was high for the intermediate and finishing rolling phase while the AC 8 and AC 22 mix recorded slightly high RMSE values in the breakdown phase compared to the intermediate and finishing rolling phases. Furthermore, the prediction model performed was overfitting when predicting the SMA-NL 11B mixes because all the compaction phases showed high-temperature deviations. The new prediction model performed well in the prediction of SMA-NL 8G mix because the temperature differences in the breakdown, intermediate and finishing rolling phases was low.

Table 16:Performance scores for different types of asphalt mixes in new prediction model- core temperature dataset

Type of mix	Total amount of data	Root mean squared error between predicted temperature and the measured temperature of asphalt mixes (RMSE)		
AC		Breakdown phase (150°C-120°C)	Intermediate rolling phase (120°C -100°C)	Finishing rolling phase (100°C – 80°C)
AC 16	3	5.21	11.06	18.94
AC 8	5	24.62	6.19	8.47
AC 22	25	9.52	1.63	0.63
SMA		Breakdown phase (140°C - 120°C)	Intermediate rolling phase (120°C - 100°C)	Finishing rolling phase (100°C – 80°C)
SMA-NL 8G	17	4.08	0.19	4.09
SMA-NL 11B	18	36.04	27.93	18.46

The cooling curves produced by the new prediction model are presented below. From the cooling curves, there are high deviations between the predicted temperature and measured temperatures of the asphalt mixes except for AC 22 and SMA-NL 8G. Also, the predicted core temperatures of the AC 8, SMA-NL 11B, AC 22 are relatively lower at the beginning of the curves indicating that the new MLP prediction model was overfitting when predicting these mixes.

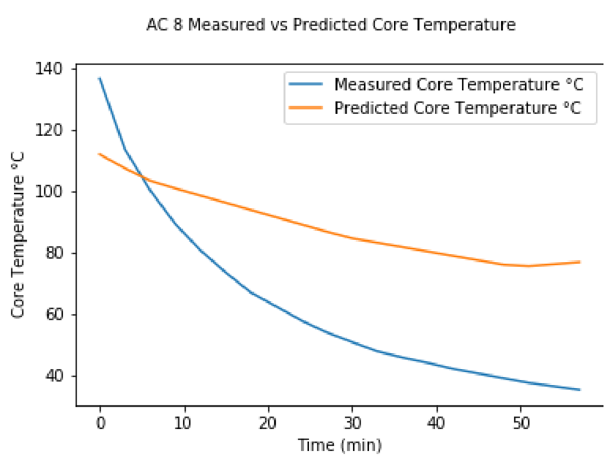

Figure 23: Dataset 2, AC 8 cooling curves New prediction model

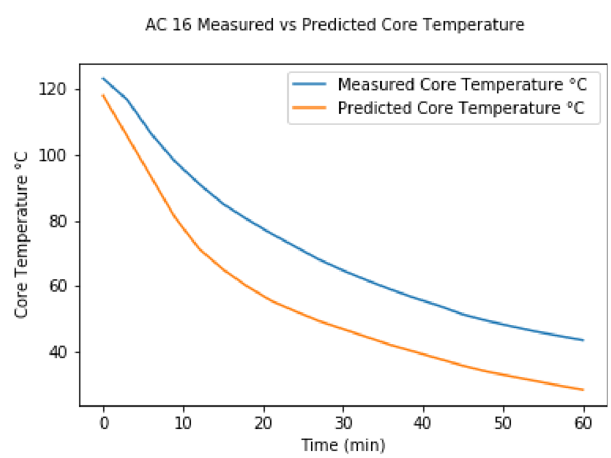

Figure 24:Dataset 2, AC 16 cooling curves New prediction model

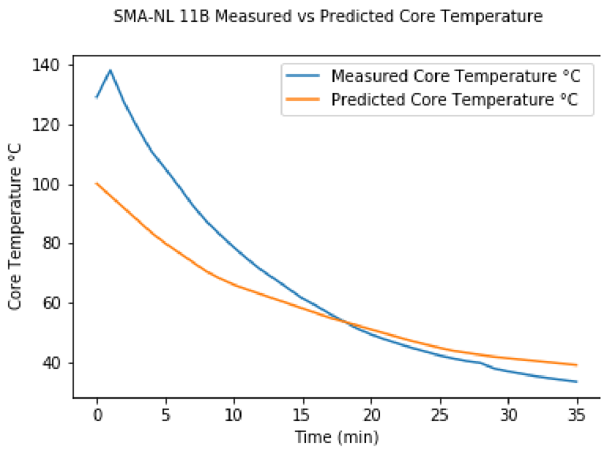

Figure 25: Dataset 2, SMA-NL 11B cooling curves New prediction model

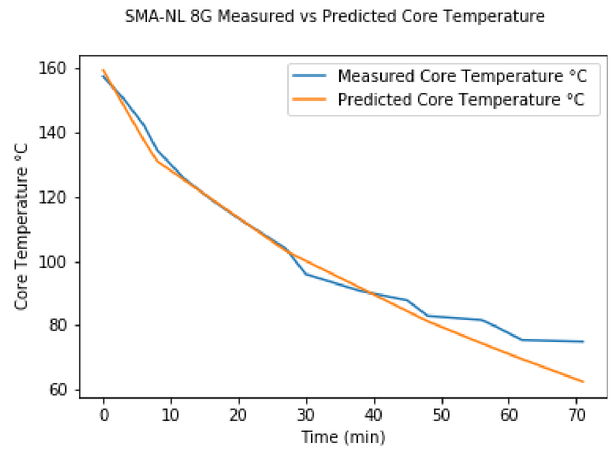

Figure 26:Dataset 2, SMA-NL 8G cooling curves New prediction model

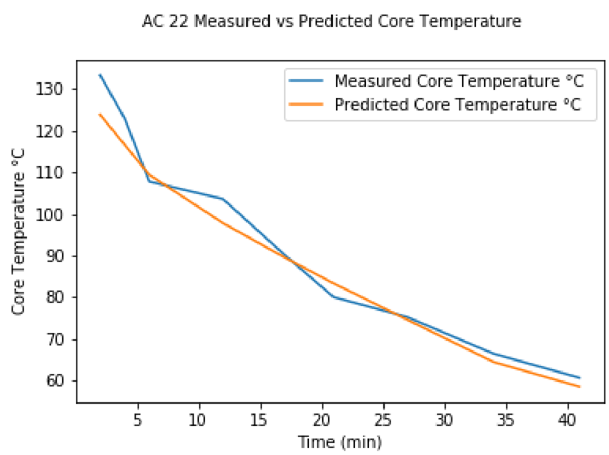

Figure 27: Dataset 2, AC 22 cooling curves New prediction model

6.3.3. Discussion preliminary analysis new prediction model

The preliminary analysis shows that the new MLP prediction model made a poor prediction for AC 8, AC 16, SMA-NL 11B and AC 22 because the RMSE values between the measured temperatures and predicted temperatures were high. Also, the predicted cooling curves were much lower at the beginning compared to the measured temperatures of the asphalt mixes. In contrast, the SMA-NL 8G mix performed better with lower RMSE value between the measured and the predicted cooling curves in both the core and surface temperature datasets. The poor performance of the AC 8, AC 16, SMA-NL 11B and AC 22 cooling curves indicated that the new prediction model was overfitting in the prediction of these mixes. The same problem was noticed in the ASPARiCool preliminary analysis in which the RMSE between the measured and the predicted temperatures in some specific asphalt mixes were higher in the asphalt compaction windows.

7.0. Conditions to detect an overfitting asphalt cooling rate prediction model within the MLP algorithm

Based on the results of the preliminary analysis of the ASPARiCool tool and the new prediction model, the conditions that will be used to define an overfit MLP asphalt cooling rate prediction model in the analysis of the new prediction model are stated.

The first method that will be used to define overfitting is by comparing the RMSE values between the measured and the predicted temperatures of the asphalt mixes in the breakdown phase, intermediate rolling phase and finishing rolling phase.

The MLP algorithm will overfit when predicting the cooling rate of asphalt mixes if the RMSE value between the measured and predicted temperature is greater than 8 in the breakdown phase, intermediate rolling phase and finishing rolling phase. The value of 8 is chosen based on the preliminary analysis conducted in the ASPARiCool tool. As it can be observed in the AC 16 cooling curve in Figure 13 , the predicted temperature of the mix was increasing at the finishing rolling phase (100°C -80 °C). The recorded RMSE value between the predicted temperature and the measured temperature of the asphalt mix in the finishing rolling phase was 8.09 which meant that a RMSE value of 8 indicated that the ASPARiCool tool was overfitting.

The second method to detect overfitting is to look at the measured and predicted temperatures in the cooling curves of the asphalt mixes. Generally, an MLP prediction model will overfit if the predicted temperatures of the asphalt mix fails to capture a similar pattern as the measured temperature of the asphalt mix.

From the cooling curves, if the predicted temperatures at the beginning of the cooling curves is either lower or higher compared to the measured temperature of the asphalt mix then the MLP prediction algorithm is overfitting. This effect was observed in the preliminary analysis of the new MLP prediction model whereby the cooling curves of AC 8 , SMA-NL 11B, and AC 22 mixes showed that the predicted temperatures at the start of the cooling curves were lower compared to the measured temperatures (see section 6.3.1 and section 6.3.2).

Also, if the predicted temperatures of the asphalt mixes are increasing with time compared to the measured temperatures of the asphalt mixes, then the MLP prediction algorithm is overfitting. The increasing effect was observed in the preliminary analysis of the ASPARiCool tool whereby the predicted temperatures of AC 8, AC 16, AC 22, SMA-NL 11B and SMA-NL 8G mixes were increasing with time as presented in section 5.2 and section 5.3.

8.0. Analysis of new MLP asphalt cooling rate prediction model

In this section, the problem of overfitting of the MLP algorithm was addressed. According to the background section 2.5.2 , the amount of features can have an influence in overfitting of a ML prediction model, therefore, in this research, the overfitting problem in the MLP algorithm was addressed by conducting feature selection to determine which set of asphalt cooling features influence a good asphalt cooling rate prediction performance. Two approaches were conducted in order to investigate the problem of overfitting. The first approach is to select the best combination of asphalt cooling features that influence the prediction performance of the MLP algorithm and the second approach was to test these features in the MLP algorithm in order to assess the overfitting problem and to check the asphalt cooling rate prediction performance.

8.1. First approach: Feature selection by mutual information gain method

The first approach is to determine the importance of each asphalt cooling mix feature to the temperature of the asphalt mix by using the mutual information gain method described in section 2.5.2. The mutual information gain works by determining a score of how much each asphalt cooling feature is dependent on the surface temperature of the asphalt mix. After the dependency between each asphalt cooling feature and the surface temperature of the asphalt mix is determined, the next step is to successively remove the least dependent asphalt cooling feature successively and grouping the remaining features. This feature selection method was chosen because it is suitable for non-linear features, also because it would have been time-consuming to investigate the effect of overfitting in the MLP asphalt cooling rate prediction model by testing every possible combination of asphalt cooling feature.

The score that determines the dependency is known as IG score. A higher IG score means that the asphalt cooling mix feature is more mutual dependant to the temperature of the asphalt mix (Chen, Wilbik, van Loon, Boer, & Kaymak, 2018).

The mutual information model was developed in Python 3 using the mutual_information_regressor library, which was imported from sklearn. The detailed steps taken to develop the new asphalt cooling rate prediction model were elaborated below. The detailed python code with description can be found in Appendix A for each of the steps taken:

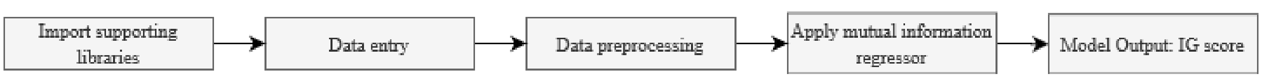

Figure 28: Detailed mutual information gain model development

Step 1: Importation of mutual info regression tool and other libraries from sklearn (see section 4.6)

Step 2: Importation of dataset 1 **Surface_Dataset_1.csv** (Table 8).

Step 3: Data pre-processing. The process comprised of the following:

A. Removal of rows in the data with missing values.
B. Application of dummy variables to features with qualitative categorical attributes (Suits, 1957). Appendix B
C. Separation of the variables into independent and target variable.
D. Splitting of the datasets into 60% training, and 40% testing data.

Step 4: Application of mutual_info_regression algorithm.

E. Application of independent (x) and target variably (y) into the mutual_info_regression.

Step 5: Prediction model output. The model output comprised of IG scores.

8.1.1. Feature selection results

The Table 17 presents the results of the asphalt cooling features that were used to check how dependent each asphalt cooling feature is to the surface temperature of the asphalt mix. A significant point to note is that the time and type of asphalt mix feature were not used in the feature selection analysis because these features were considered as important features that provide much information about the surface temperature of the asphalt mix.

From the Table 17, it can be seen that rain feature recorded the lowest IG score which meant that it provided the least information about the temperature of the asphalt mix. Besides, solar radiation had the highest IG score which meant that it provided much more information about the surface temperature of the asphalt mix compared to the rest of the features.

Table 17: Asphalt cooling features importance scores

Feature	IG score
Time(min)	-
Type of asphalt mix	-
Solar (W/m2)	0.113
Ambient temperature	0.086
Windspeed	0.083
Thickness	0.075
Type of underlayer	0.055
Underlayer temperature	0.051
Rain(mm)	0.036

After the IG scores of the asphalt cooling features were determined, the second approach was to group each of these features listed in Table 17 into different combination of features. These combinations are selected by successively removing the least important feature that provides the least information about the temperature of the asphalt mix. For example, feature set 1 in Table 18 consists of all asphalt cooling features except for rain, which was removed because it had the lowest IG score. Also, the feature set 2 consists of all asphalt cooling features except for rain and underlayer temperature which were removed based on their low IG scores.

Table 18: Combination of features used to check the MLP asphalt cooling rate prediction performance

Feature set 1	Time	Type asphalt mix	Solar radiation	Ambient temperature	Windspeed	Thickness	Type of underlayer	Temperature of underlayer
Feature set 2	Time	Type asphalt mix	Solar radiation	Ambient temperature	Windspeed	Thickness	Type of underlayer	
Feature set 3	Time	Type asphalt mix	Solar radiation	Ambient temperature	Windspeed	Thickness		
Feature set 4	Time	Type asphalt mix	Solar radiation	Ambient temperature	Windspeed			
Feature set 5	Time	Type asphalt mix	Solar radiation	Ambient temperature				
Feature set 6	Time	Type asphalt mix	Solar radiation					

Second approach: Prediction of asphalt cooling feature combinations in the MLP algorithm to investigate overfitting

The second approach was to predict the cooling rates of asphalt mixes using different combinations of asphalt cooling features. The aim of this analysis was to investigate which asphalt cooling features resulted in overfitting problem of the MLP algorithm

The analysis of the new prediction model was conducted using the dataset one (Table 13). Dataset one which comprised of 104 measurements, was chosen because it had a relatively large number of datasets compared to the core temperature dataset two; therefore, it was less prone to overfitting as described section 2.5.2. Also, the same MLP algorithm parameters described in Table 14 were used in the new prediction model.

The effect of overfitting was determined by comparing RMSE between the measured and the predicted surface temperature in the three asphalt compaction windows which are breakdown phase, intermediate rolling phase and finishing rolling phase.

In this analysis, the MLP asphalt cooling rate prediction model will overfit if the RMSE between the measured and predicted surface temperature is higher than 8 in the asphalt compaction windows. Also, the MLP algorithm is considered to be overfitting if predicted temperature of the asphalt mixes does not follow similar trends as the measured temperatures of the asphalt mixes as described in section 7.0

Feature set 1: asphalt cooling rate prediction results

Feature set 1 comprised of time, type of asphalt mix, solar radiation, ambient temperature, windspeed, thickness, type of underlayer and temperature of underlayer.

From Table 19 below, the RMSE values between the predicted and measured temperatures for SMA-NL 8G mix were lower than 8 in all compaction phases compared to the rest of the mixes indicating that for the feature set 1; the MLP algorithm was not overfitting when predicting the cooling rate of SMA-NL 8G mix. In contrast, the MLP new prediction model was overfitting when predicting the cooling rates of AC 16, AC 8, AC 22, and SMA-NL 11B mixes.

Table 19: Feature set 1, RMSE values for asphalt compaction windows

Type of mix	**The total amount of data**	**Root mean square error between measured and predicted surface temperature (RMSE)**		
AC		Breakdown phase (150°C-120°C)	Intermediate rolling phase (120°C -100°C)	Finishing rolling phase (100°C – 80°C)
AC 16	17	21.12	21.13	16.41
AC 8	3	14.28	6.75	7.95
AC 22	42	6.50	10.99	6.56
SMA		Breakdown phase (140°C - 120°C)	Intermediate rolling phase (120°C - 100°C)	Finishing rolling phase (100°C – 80°C)
SMA-NL 8G	18	2.58	1.29	5.28
SMA-NL 11B	13	16.68	10.32	4.15

The cooling curves for feature set 1 show that predicted temperatures at the breakdown phase for AC 8, AC 16, SMA-NL 11B and AC 22 mixes were lower compared to measured temperatures of the asphalt mixes. In addition, the temperature differences between the measured and predicted surface temperatures were high in all the compaction phases. Lastly, the cooling curve for SMA-NL 8G mix showed a good fit compared to the other asphalt mixes.

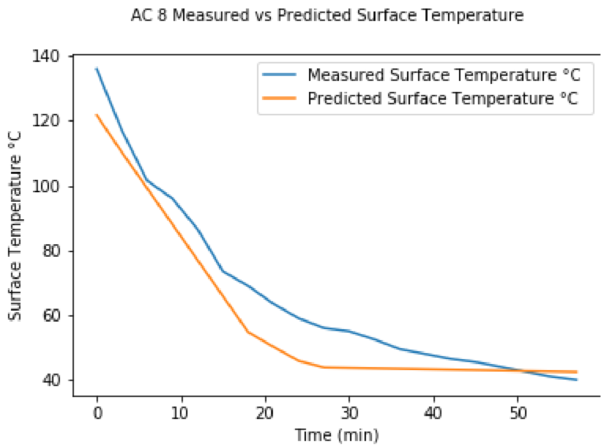

Figure 29: Feature set 1, AC 8 predicted cooling curve

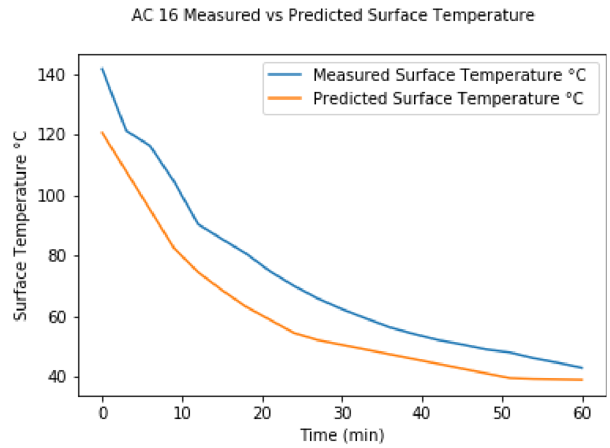

Figure 30: Feature set 2, AC 16 predicted cooling curve

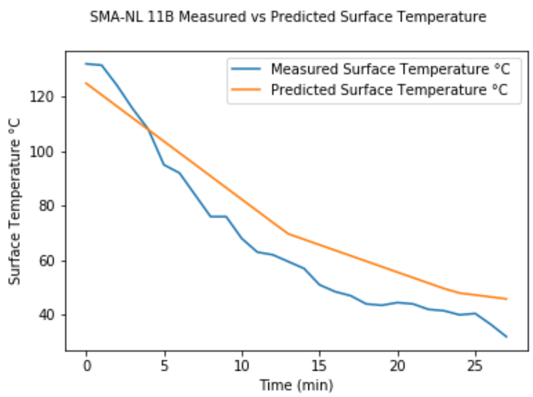

Figure 31: Feature set 1, SMA-NL 11B cooling curve

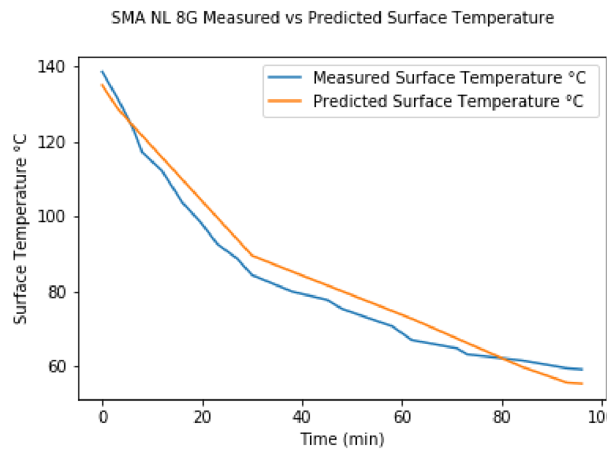

Figure 32: Feature set 1, SMA-NL 8G predicted cooling curve

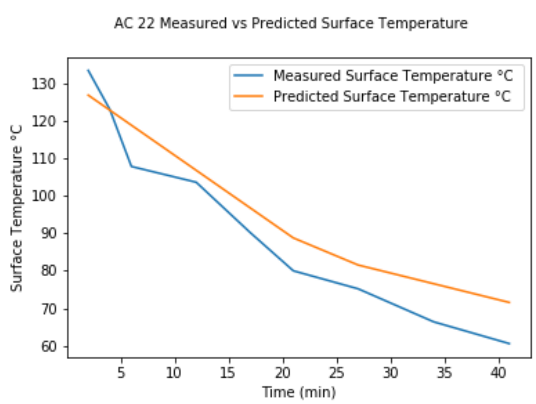

Figure 33: Feature set 1, AC 22 predicted cooling curve

Feature set 2: asphalt cooling rate prediction results

Feature set 2 comprised of time, type of asphalt mix, solar radiation, ambient temperature, windspeed, thickness, and type of underlayer.

From Table 20, The RMSE value between the predicted and measured surface temperature of AC 8, AC 22, and SMA-NL 8G mix were lower than 8°C in all compaction phases hence the MLP algorithm was not overfitting when predicting the cooling rates of these mixes. On the other hand, the MLP algorithm was overfitting when predicting the cooling rate of AC 16 and SMA-NL 11B mix because the RMSE values were greater than 8°C.

Table 20: Feature set 2, RMSE values for asphalt compaction windows

Type of mix	The total amount of data	Root mean square error between measured and predicted surface temperature (RMSE)		
AC		Breakdown phase (150°C-120°C)	Intermediate rolling phase (120°C -100°C)	Finishing rolling phase (100°C – 80°C)
AC 16	17	12.56	14.00	10.52
AC 8	3	2.13	7.66	1.7
AC 22	42	8.04	5.60	12.03
SMA		Breakdown phase (140°C - 120°C)	Intermediate rolling phase (120°C - 100°C)	Finishing rolling phase (100°C – 80°C)
SMA-NL 8G	18	2.58	1.29	5.28
SMA-NL 11B	13	16.68	10.32	4.15

The cooling curves for feature set two are presented below. First, the AC 8, and SMA-NL 8G cooling curves showed small differences between the measured and predicted temperatures of the asphalt mixes in the three compaction phases indicating that the MLP algorithm did was not overfitting when predicting these mixes. The rest of the cooling curves that comprise of SMA-NL 11B, AC 16 and AC 22 had lower predicted temperatures compared to measured temperatures at the breakdown compaction phase indicating that the MLP algorithm was overfitting in the prediction of these mixes.

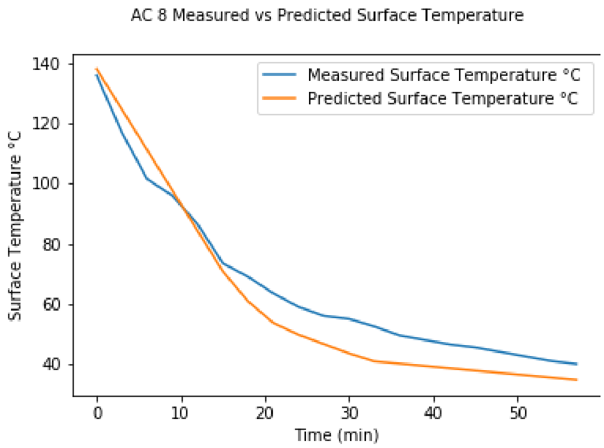

Figure 34: Feature set 2, AC 8 predicted cooling curve

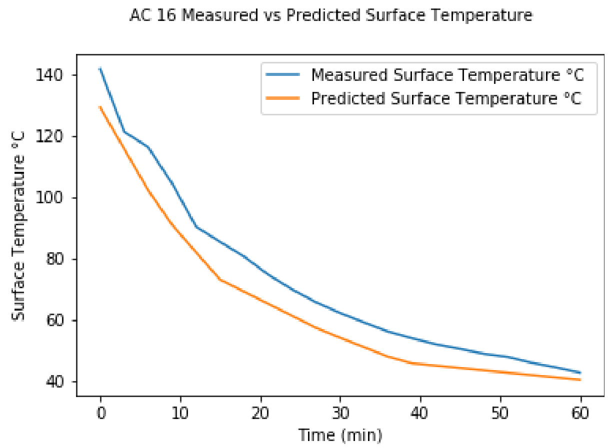

Figure 35: Feature set 2, AC 16 predicted cooling curve

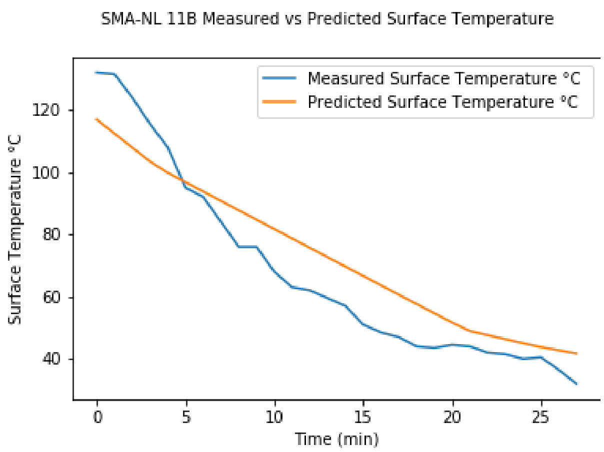

Figure 36: Feature set 2, SMA-NL 11B predicted cooling curve

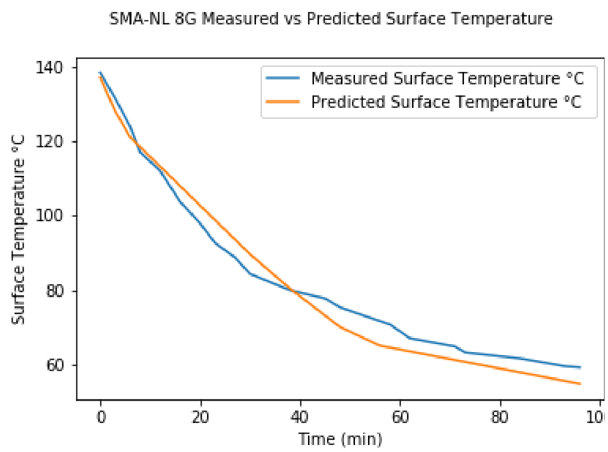

Figure 37: Feature set 2, SMA-NL 8G predicted cooling curve

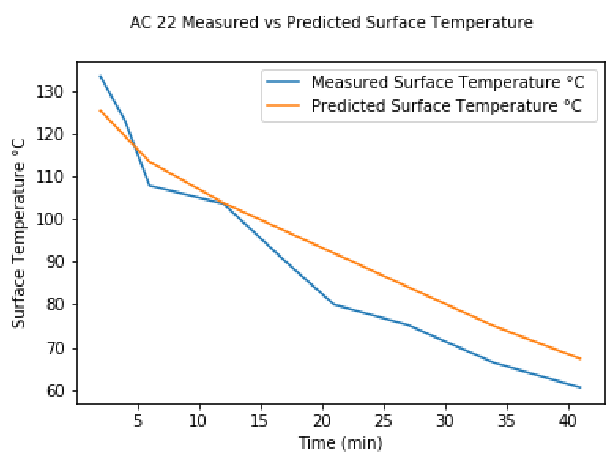

Figure 38: Feature set 2, AC 22 predicted cooling curve

Feature set 3: asphalt cooling rate prediction results

Feature set 3 comprised of time, type of asphalt mix, solar radiation, ambient temperature, windspeed, and thickness.

From Table 21, the prediction model performed better in predicting the AC 22, and SMA-NL 8G mixes because the RMSE between the measured and predicted temperatures did not exceed 8°C. On the other hand, the AC 16, AC 8 and SMA-NL 11B recorded RMSE which were higher than 8°C in all the compaction phases indicating that the MLP algorithm was overfitting in predicting these mixes.

Table 21: Feature set 3, RMSE values for asphalt compaction windows

Type of mix	**The total amount of data**	**Root mean square error between measured and predicted surface temperature (RMSE)**		
AC		Breakdown phase (150°C-120°C)	Intermediate rolling phase (120°C -100°C)	Finishing rolling phase (100°C – 80°C)
AC 16	17	26.23	21.42	11.90
AC 8	3	19.80	10.72	9.57
AC 22	42	5.89	2.02	0.76
SMA		Breakdown phase (140°C - 120°C)	Intermediate rolling phase (120°C - 100°C)	Finishing rolling phase (100°C – 80°C)
SMA-NL 8G	18	8.04	2.24	2.68
SMA-NL 11B	13	37.04	28.71	16.05

The cooling curves for feature set three are presented below. The cooling curves show that the temperature difference between the measured and predicted surface temperatures in the breakdown compaction phases are high for AC 16, AC 8 and SMA-NL 11B. This indicates that the prediction model was overfitting in predicting these particular mixes. The MLP prediction algorithm prediction performance for AC 22 and SMA-NL 8G mixes was good because of the low-temperature differences observed in the cooling curves in the breakdown, intermediate and finishing rolling compaction phases.

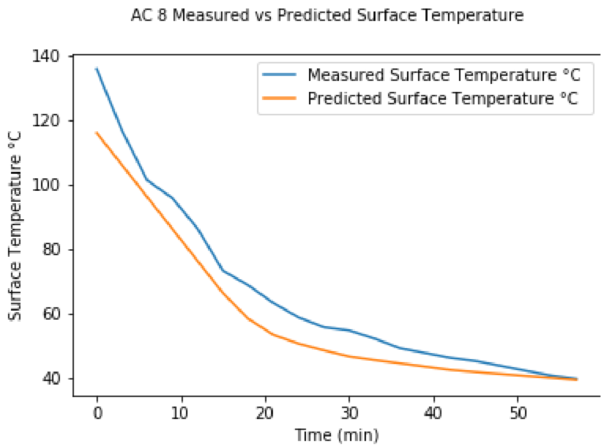

Figure 39: Feature set 3, AC 8 predicted cooling curve

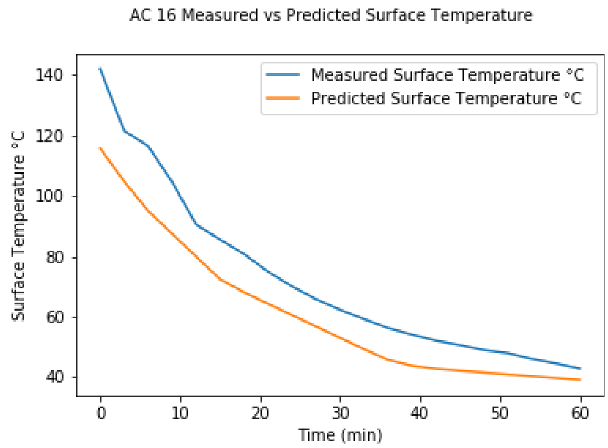

Figure 40: Feature set 3,AC 16 predicted cooling curve

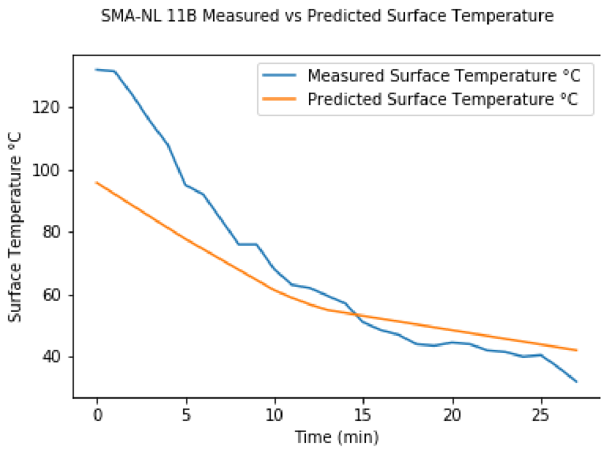

Figure 41:Feature set 3, SMA-NL 11B predicted cooling curve

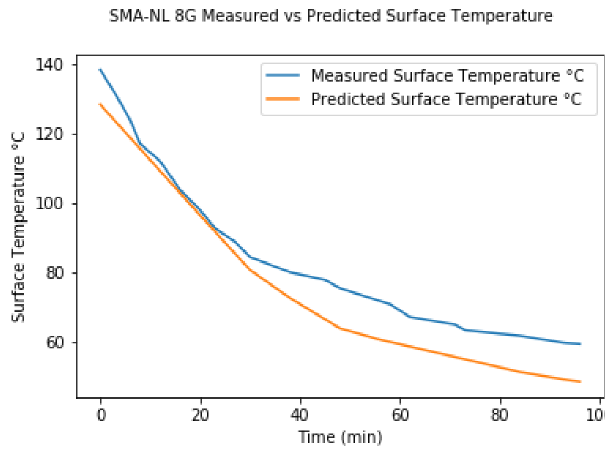

Figure 42: Feature set 3, SMA-NL 11B predicted cooling curve

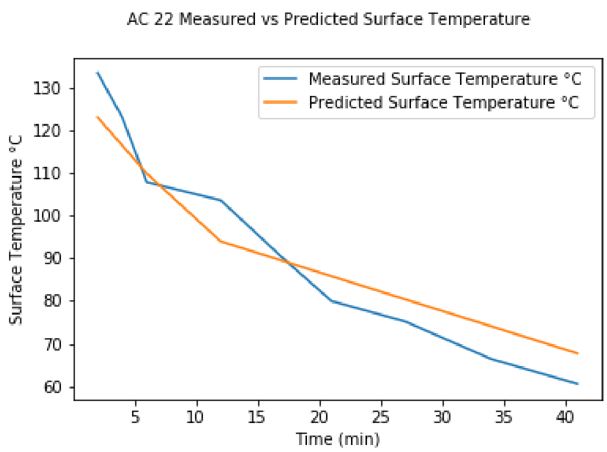

Figure 43:Feature set 3, AC 22 predicted cooling curve

Feature set 4: asphalt cooling rate prediction results

Feature set 4 comprised of time, type of asphalt mix, solar radiation, ambient temperature, and windspeed.

From Table 22, Starting with the AC mixes, the MLP prediction algorithm did not overfit when predicting the AC 16 and AC 22 within the three compaction windows but the MLP algorithm was overfitting when predicting the AC 8 mixes because the RMSE between the measured and predicted surface temperature of the finishing rolling phase was higher than 8°C. For the SMA mixes, the prediction model was overfitting for SMA-NL 11B mix because the RMSE at the breakdown and intermediate rolling phase was higher than the RMSE value of 8°C.

Table 22:Feature set 4, RMSE values for asphalt compaction windows

Type of mix	**The total amount of data**	**Root mean square error between measured and predicted surface temperature (RMSE)**		
AC		Breakdown phase (150°C-120°C)	Intermediate rolling phase (120°C -100°C)	Finishing rolling phase (100°C – 80°C)
AC 16	17	3.2	3.89	6.76
AC 8	3	8.16	5.55	11.86
AC 22	42	2.98	6.78	6.6
SMA		Breakdown phase (140°C - 120°C)	Intermediate rolling phase (120°C - 100°C)	Finishing rolling phase (100°C – 80°C)
SMA-NL 8G	18	6.95	2.07	2.17
SMA-NL 11B	13	22.59	18.04	6.81

The cooling curves for feature set four in **Error! Reference source not found.** are presented. The A C 8, AC 16, and SMA-NL 8G cooling curves indicate that the model was not overfitting. In the contrary, the predicted temperature of SMA-NL 11B mix shows a high deviation between surface and measured temperature at the breakdown and intermediate compaction phase, but the predicted surface temperature captures a similar trend after the finishing rolling phase.

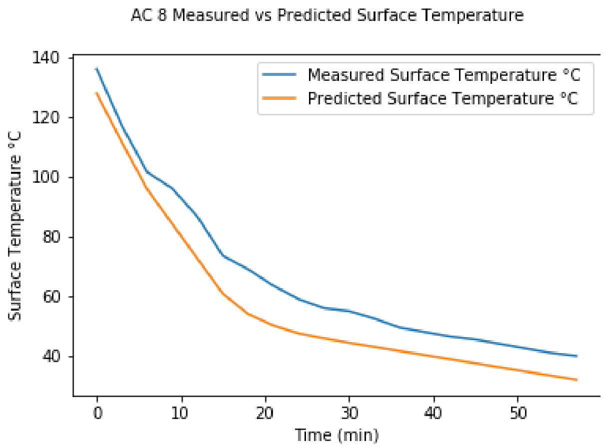

Figure 44: Feature set 4, AC 8 predicted cooling curve

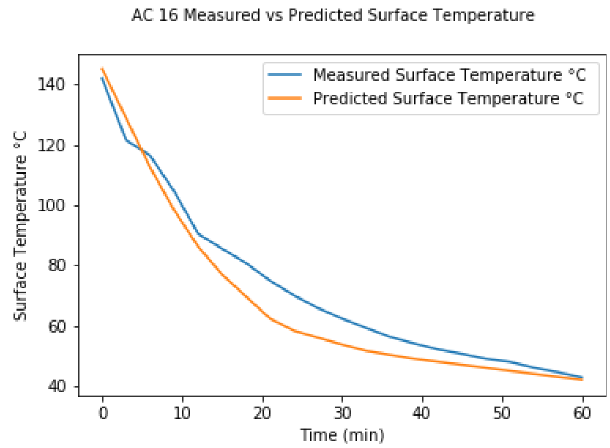

Figure 45: Feature set 4, AC 16 predicted cooling curve

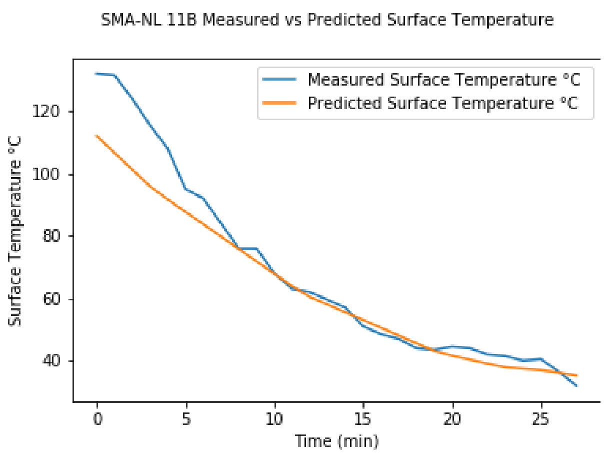

Figure 46: Feature set 4, SMA-NL 11B predicted cooling curve

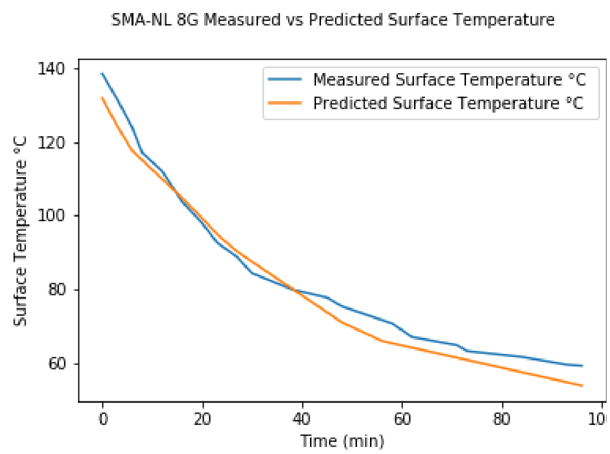

Figure 47: Feature set 4, SMA-NL 8G predicted cooling curve

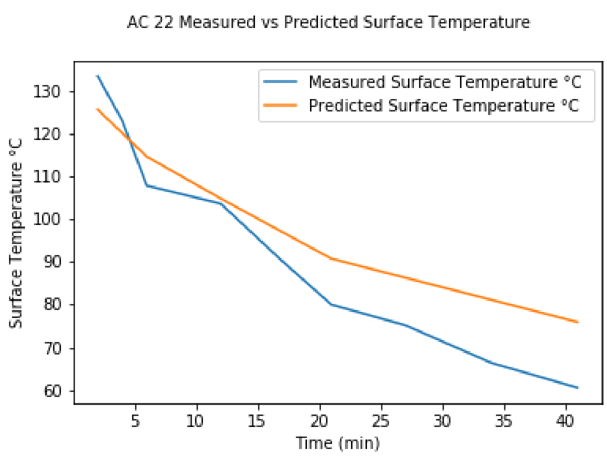

Figure 48: Feature set 4, AC 22 predicted cooling curve

Feature set 5: asphalt cooling rate prediction results

Feature set 5 comprised of time, type of asphalt mix, type of asphalt mix, solar radiation, and ambient temperature.

From Table 23, The RMSE between the predicted surface temperature and measured surface temperature are presented. Generally, all the cooling curves recorded high RMSE values of more than 8 °C except for the AC 8 mix, which had a lower RMSE in all the compaction phases. Hence the MLP algorithm was not overfitting when predicting the cooling rate of the AC 8 mix.

Table 23: Feature set 5, RMSE values for asphalt compaction windows

Type of mix	The total amount of data	Root mean square error between measured and predicted surface temperature (RMSE)		
AC		Breakdown phase (150°C-120°C)	Intermediate rolling phase (120°C -100°C)	Finishing rolling phase (100°C – 80°C)
AC 16	17	17.82	16.48	8.32
AC 8	3	5.15	0.04	6.29
AC 22	42	2.98	9.11	9.51
SMA		Breakdown phase (140°C - 120°C)	Intermediate rolling phase (120°C - 100°C)	Finishing rolling phase (100°C – 80°C)
SMA-NL 8G	18	15.27	13.85	9.75
SMA-NL 11B	13	14.12	8.45	2.74

The cooling curves for the feature set five are shown in the figures below. The cooling curves show that the difference between the measured and predicted surface temperatures of AC 16, SMA-NL 11B, SMA-NL 8G and AC 22 mixes are high. Lastly, the temperature difference in the AC 8 mix indicates that the model performed well in predicting this particular type of mix compared to the rest of the mixes because of the low-temperature deviation between the mesured and predicted surface temperature.

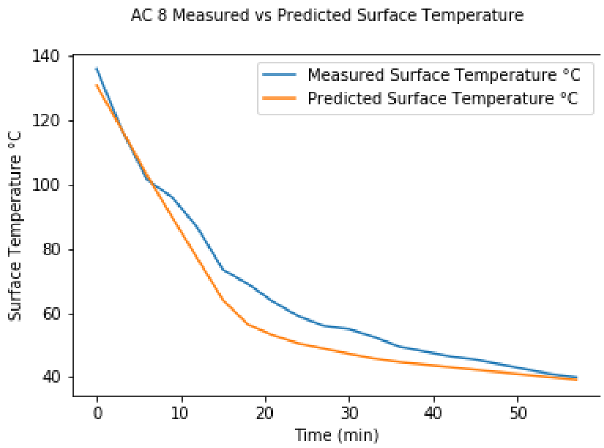

Figure 49: Feature set 5, AC 8 predicted cooling curve

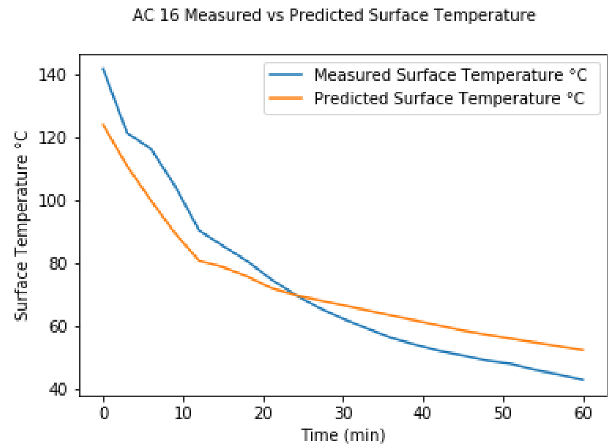

Figure 50: Feature set 5, AC 16 predicted cooling curve

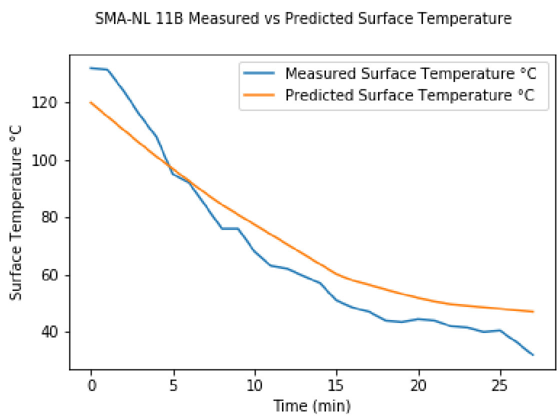

Figure 51: Feature set 5, SMA-NL 11B predicted cooling curve

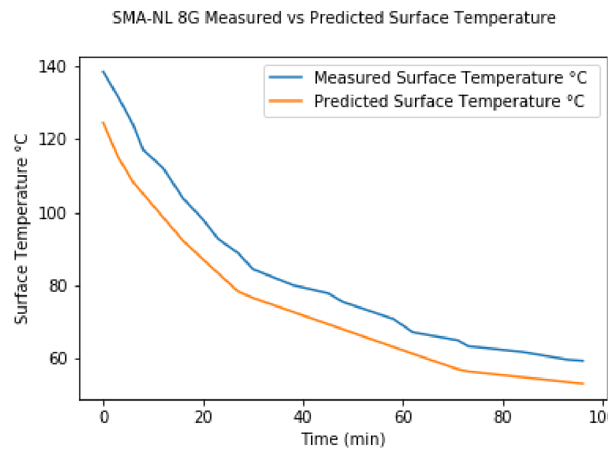

Figure 52: Feature set 5, AC 22 predicted cooling curve

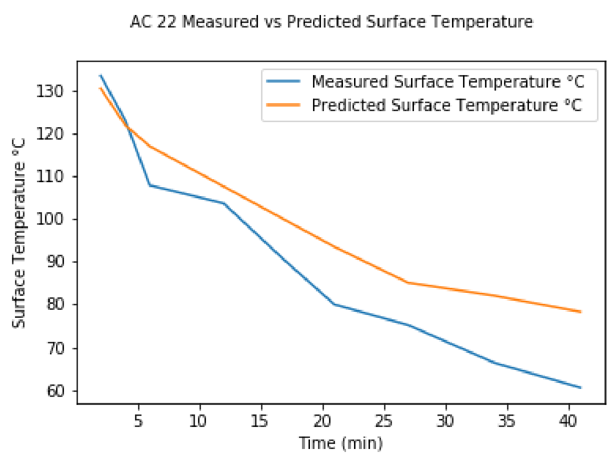

Figure 53: Feature set 5, cooling curve feature

Feature set 6: asphalt cooling rate prediction results

Feature set 6 comprised of time, type of asphalt mix, solar radiation, and ambient temperature.

From Table 23, the RMSE between the measured and predicted temperatures for the AC mix were lower than 8°C in all the compaction phases; hence the MLP prediction model did not overfit for the AC mixes. The SMA-NL and SMA-NL 11B mixes recorded RMSE values which were higher than 8°C for the breakdown and intermediate rolling phase hence the prediction model was overfitting during the prediction of SMA mixes

Table 24: Feature set 6, RMSE values for asphalt compaction windows

Type of mix	The total amount of data	Root mean square error between measured and predicted surface temperature (RMSE)		
AC		Breakdown phase (150°C-120°C)	Intermediate rolling phase (120°C -100°C)	Finishing rolling phase (100°C – 80°C)
AC 16	17	2.48	4.86	5.23
AC 8	3	0.92	2.61	6.37
AC 22	42	6.81	1.34	0.54
SMA		Breakdown phase (140°C - 120°C)	Intermediate rolling phase (120°C - 100°C)	Finishing rolling phase (100°C – 80°C)
SMA-NL 8G	18	15.65	15.36	4.67
SMA-NL 11B	13	17.90	1.34	0.54

From the cooling curves below, the predicted surface temperature in AC 16 mix was increasing in time, especially after the finishing rolling phase indicating that the MLP algorithm was overfitting. For both the SMA-NL 11B mix and SMA-NL 8G mixes, the predicted temperature at the breakdown phase was higher compared to the measured temperature of the mix. Also, the cooling curve of the SMA-NL 8G was linear compared to the measured cooling curve. This meant that the MLP algorithm was overfitting in predicting the SMA-NL 8G and SMA-NL 11B mixes. For the AC 8 and AC 22, the model performed better because the temperature differences between the predicted and measured surface temperatures were low.

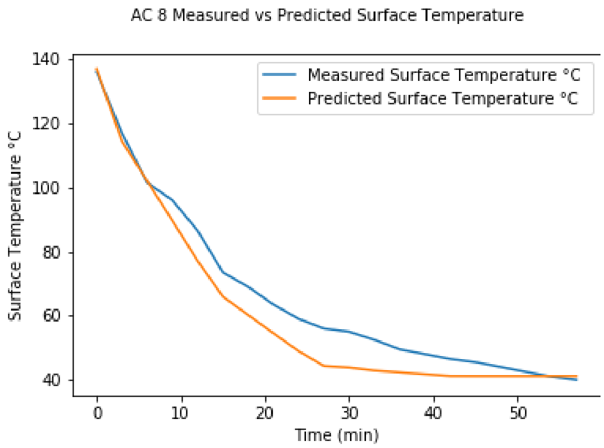

Figure 54: Feature set 6, AC 8 predicted cooling curve

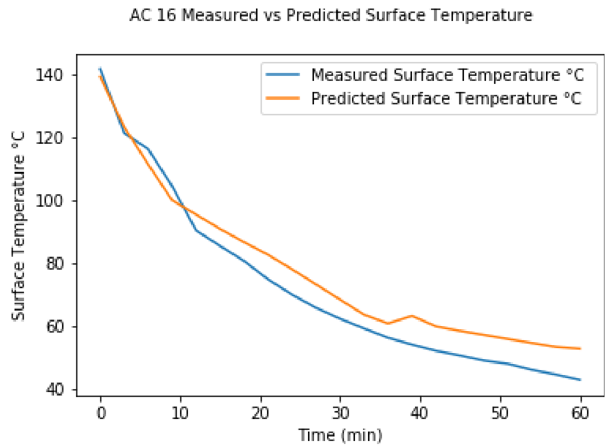

Figure 55: Feature set 6, AC 16 predicted cooling curve

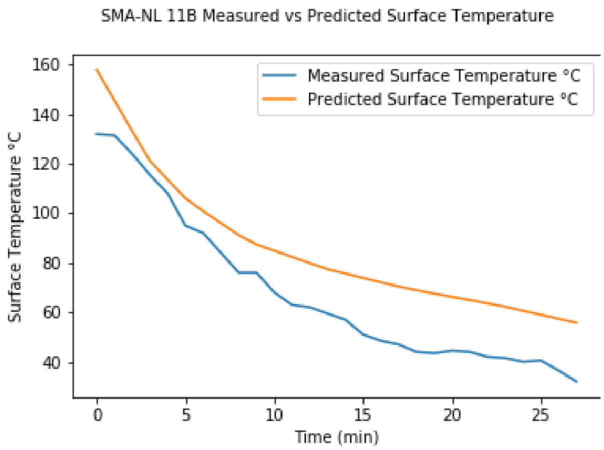

Figure 56:Feature set 6, SMA-NL 11B predicted cooling curve

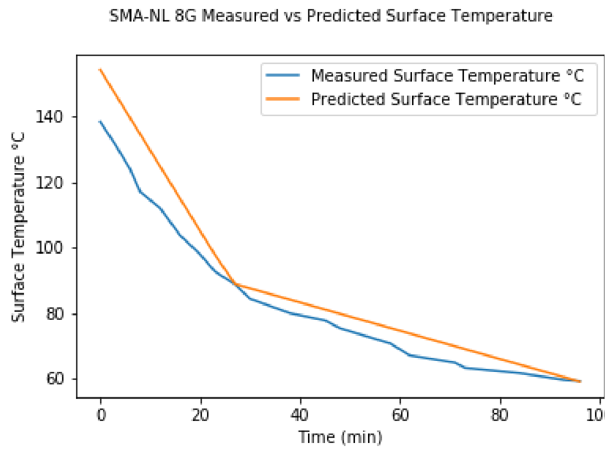

Figure 57: Feature set 6, SMA-NL 8G predicted cooling curve

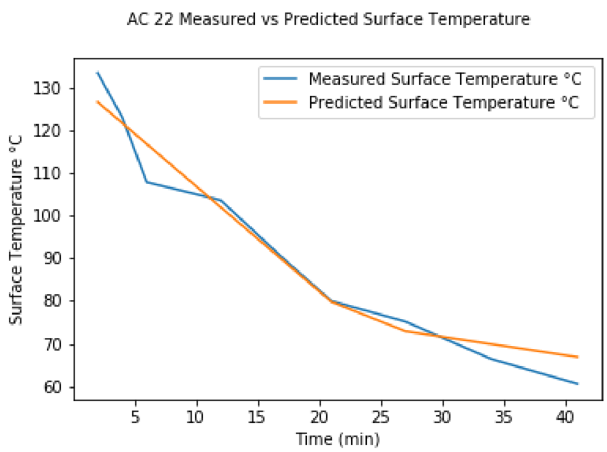

Figure 58: Feature set 6, AC 22 predicted cooling curve

9.0. Conclusion

This section comprises of the conclusion, discussion, and recommendations for ASPARi. The conclusion section provides an answer to the main research question. Next, the discussions are presented, and lastly, the recommendations for ASPARi is provided.

This research aimed to investigate the problem of overfitting in the prediction of the cooling rates of the asphalt mixes in the ASPARiCool tool's algorithm known as MLP. The problem of overfitting occurs when the MLP algorithm fails to predict the cooling rate of asphalt mixes. The overfitting problem is determined by comparing the predicted temperatures of the asphalt mixes with the measured temperatures of the asphalt mixes. If the predicted temperatures of the asphalt mixes fail to capture a similar trend as the measured temperature of the asphalt mix, then the MLP prediction model is considered to be overfitting.

This research comprised of the prediction of the cooling rate of AC 8, AC 16, AC 22, SMA-NL 8G and SMA-NL 11B asphalt mixes based on their respective surface and core temperature dataset. The effect of overfitting was determined by evaluating the performance of the cooling curves within the three compaction windows, which are breakdown phase, intermediate rolling phase and finishing rolling phase. It is important to note that the AC and SMA mixes comprise of their compaction temperature windows elaborated in Table 25 below:

Table 25: Compaction temperature windows for AC and SMA mixes (retrieved from ASPARi Research team)

Type of mix	Breakdown phase temperature °C	Intermediate rolling phase °C	Finishing rolling phase °C
SMA	140 - 120	120 -100	100 -80
AC	150 120	120 -100	100 -80

In order to define overfitting in the prediction of the cooling rate of asphalt mixes, first, the RMSE values between the predicted temperature and the measured temperature of the asphalt mix were determined. The RMSE value determines the temperature deviation about the mean of the predicted and the measured temperatures of the asphalt mixes. The RMSE values are negatively oriented scores which mean that a higher RMSE value in the asphalt compaction phases indicated a poor performing prediction model while a lower RMSE value indicated a good performing prediction model.

From the preliminary analysis of the MLP algorithm conducted in section 5.0 and section 6.2, the boundaries resulting in an MLP prediction algorithm to overfit were defined. Two approaches were used to detect overfitting in the prediction of the cooling rates of asphalt mixes as follows:

1. If the RMSE between the predicted and measured surface temperature is higher than 8 °C, then the MLP algorithm was overfitting. The value of 8 was chosen by checking the cooling curves in the ASPARiCool tool and new prediction model analysis.

2. The MLP prediction model would be overfitting if the predicted temperatures of the asphalt mixes were increasing with time compared to the measured temperature of the

asphalt mixes secondly, if the predicted temperatures at the breakdown compaction phase(150°C - 120°C) were either lower or higher than the measured temperatures of the asphalt mixes.

As previously mentioned, this research is related to the overfitting problem of ASPARiCool prediction tool. The overfitting problem was addressed by constructing and analysing a similar asphalt cooling rate prediction tool. The similarity of the tool lies in the machine learning (ML) algorithm used, which is known as multilayer perceptron algorithm (MLP). The overfitting problem was investigated by considering the surface and core temperature dataset. Table 26 below outlines the input data, and MLP parameters that were used in the MLP algorithm.

Table 26: new MLP algorithm dataset and parameters used in the prediction of the cooling rate of asphalt mixes

MLPRegressor input data	**Value**
Dataset 1: Total amount of surface data measurements	104
Dataset 2: Total amount of core data measurements	79
Initial amount of asphalt cooling features	9
MLP Regressor Parameters	
Learning rate	0.1
momentum	0.2
Activation function	relu
solver	adam
Max iterations	2000
Hidden layer sizes	3
Number of neurons in the hidden layer	(13,13,13)
Types of asphalt mixes used	
AC 8, AC 16, AC 22, SMA-NL 11B and SMA-NL 8G	5
Asphalt cooling features	
Time, type of asphalt mix, solar radiation, ambient temperature, windspeed, thickness, type of underlayer, temperature of underlayer, rain	9

This research focused on answering the main research question which states,

"How do the asphalt cooling rate features influence the problem of overfitting in the prediction of the cooling rate of asphalt mixes in the MLP algorithm?"

Depending on the parameters of the MLP algorithm used, increasing the amount of asphalt cooling features will result in the overfitting of the MLP algorithm when predicting particular types of asphalt mixes.

From this research, given the MLP input data and parameters used in Table 26, when the total number of asphalt cooling features was reduced from nine to four features which comprised of time, type of underlayer, solar radiation and windspeed, the MLP algorithm did not overfit when predicting the cooling rate of AC 16, AC 22, SMA-NL 8G mixes.

In substantiating this answer, different combinations of asphalt cooling features in Table 27 were used to determine whether the MLP algorithm was overfitting during the prediction of the cooling rates of asphalt mixes. These combinations of asphalt cooling features were chosen by successively removing the least important features that will have a minimal contribution in predicting the temperatures of the asphalt mix. The feature importance was determined using the filter selection method known as mutual information gain as elaborated in section 8.1

Table 27: Feature sets applied to the MLP algorithm to investigate the overfitting problem in the prediction of asphalt cooling rate

Original features set	Time	Type asphalt mix	Solar radiation	Ambient temperature	Windspeed	Thickness	Type of underlayer	Temperature of underlayer	Rain
Feature set 1	Time	Type asphalt mix	Solar radiation	Ambient temperature	Windspeed	Thickness	Type of underlayer	Temperature of underlayer	
Feature set 2	Time	Type asphalt mix	Solar radiation	Ambient temperature	Windspeed	Thickness	Type of underlayer		
Feature set 3	Time	Type asphalt mix	Solar radiation	Ambient temperature	Windspeed	Thickness			
Feature set 4	Time	Type asphalt mix	Solar radiation	Ambient temperature	Windspeed				
Feature set 5	Time	Type asphalt mix	Solar radiation	Ambient temperature					
Feature set 6	Time	Type asphalt mix	Solar radiation						

As previously mentioned, an asphalt cooling rate prediction model overfits when the RMSE between measured and predicated temperature of the asphalt mix is higher than 8 in the three asphalt compaction phases, which are breakdown rolling, intermediate rolling and finishing rolling phase.

Table 28 below presents the asphalt mix cooling features that resulted in the MLP algorithm to overfit when predicting the cooling rate of specified asphalt mixes. From the table, it can be observed that for all the asphalt feature sets, the MLP algorithm was overfitting when predicting the cooling rate of SMA-NL 11B mix.

Another significant point noted was that feature set four which comprised of time, type of asphalt mix, solar radiation, ambient temperature and wind speed had an overall better performance compared to the rest of the feature sets because the MLP algorithm was only overfitting in the prediction of SMA-NL 11B mix and AC 8 mixes. However, the rest of the asphalt mixes which comprised of AC 16, AC 22 , and SMA-NL 8G+ mixes showed good performance because their RMSE between the predicted surface temperature and the measured surface temperature was lower than 8 in all the compaction phases. Also, by looking at the cooling curves produced, the predicted surface temperatures followed the same trend as the measured surface temperatures of the asphalt mixes.

Table 28:Poorly predicted cooling curves of asphalt mixes based on the asphalt cooling features sets

Feature sets	Number of features	Type of asphalt mix that performed poorly in predicting the cooling rates of asphalt mixes				
Original feature set	9	SMA-NL 11B		AC 16	AC 8	
Feature set 1	8	SMA-NL 11B		AC 16	AC 8	
Feature set 2	7	SMA-NL 11B		AC 16		AC 22
Feature set 3	6	SMA-NL 11B	SMA-NL 8G	AC 16	AC 8	
Feature set 4	5	SMA-NL 11B			AC 8	
Feature set 5	4	SMA-NL 11B	SMA-NL 8G	AC 16		
Feature set 6	3	SMA-NL 11B	SMA-NL 8G	AC 16		

10. Discussion

10.1. MLP algorithm parameters

This research was related to the investigation of the overfitting problem in the prediction of the cooling rates of asphalt mixes within the ASPARiCool tool. The ASPARiCool tool could not be used to investigate overfitting because there was limited time to learn JAVA language. Therefore, a similar prediction model that uses similar algorithm was built using python in order to solve the problem of overfitting.

The new prediction model was similar because it used the similar MLP algorithm like the ASPARiCool tool, but some of the parameters that were used in the ASPARiCool tool algorithm were either missing or could not be identified. The unknown parameters included the **type of activation function, the type of solver and the number of neurons in the hidden layers**. These parameters are significant in the training process of the MLP algorithm and influenced the prediction performance of the MLP algorithm.

To overcome the overfitting problem, the activation function was set to relu (rectified linear unit) because this activation function is used in predicting numeric output values which are greater than 0. Furthermore, the solver was set to adam (adaptive moment estimation) because the adam solver updates the learning rate of the ANN after every iteration in order to reduce the errors in predictions. Also, the number of neurons in the hidden layer was set to 13 as elaborated in section 6.2. Therefore, the choice of the MLP parameters have a significant influence on the overfitting problem of the MLP algorithm

10.2. Asphalt cooling data

This research was conducted using five types of asphalt mix datasets which are AC 8, AC 16, AC 22, SMA-NL 8G and SMA-NL 11B, which comprised of surface and core temperatures. The PA 16 dataset was not used in this research because the dataset did not have core temperatures; hence it would have been difficult to compare surface temperature and core temperature predictions for this specific type of mix.

Some of the asphalt cooling data was missing. For example, the weather data was missing; therefore, to overcome this problem, the weather data was retrieved from the KNMI website by looking at the weather stations that were close to the construction project this is not a way of collecting weather information from a construction site. Furthermore, the underlayer type was missing for some of the measurements; therefore, it is assumed that if the thickness of the asphalt mix layer was greater than 50 mm, the type of underlayer which was selected was sand. Also, if the thickness of the asphalt mix layer was less than 50 mm, the type of underlayer selected was asphalt.

11. Recommendations for ASPARi

The recommendations are based on the current limitations observed in this research. The following recommendations are proposed:

The following MLP algorithm parameters should be used in predicting the cooling rate of asphalt mixes for the 104 surface datasets and 79 core temperature datasets:

- Activation function should be relu (rectified linear unit)
- The type of solver used should be adam (adaptive gradient algorithm)
- The number of hidden layers should be 3
- The size of the layers should be obtained depending on the number of features present. One approach to determine the number of neurons is to take 2/3rd of the number of features used in the asphalt cooling rate prediction model.

The current research investigated the effect of the asphalt cooling features in the prediction of the cooling rate of asphalt mixes within the MLP algorithm using the parameters mentioned in Table 14. Based on specified parameters the MLP algorithm did not overfit when predicting the cooling rates of AC 22, AC 16, and SMA-NL 8G mixes which consisted of 42, 17 and 18 training data respectively. In contrast, the AC 8 and SMA-NL 8G mixes resulted in the model to overfit because the RMSE values were high in the breakdown and intermediate rolling phases. The amount data that was used for AC 8 and SMA-NL 11B was 3 and 13 respectively which was considerably lower compared to the other mixes. The small number of training data may have resulted in the MLP algorithm to overfit when predicting these mixes. Hence it is recommended to increase the amount of training data of AC 8 and SMA-NL 11B to the same number of training data which was used of AC 22, AC 16 and SMA-NL 8G mixes and check whether the MLP algorithm will overfit.

Lastly, it is recommended to conduct further research by considering all the possible combination of MLP parameters and asphalt cooling features to check whether the MLP algorithm will be overfitting when predicting the cooling rates of asphalt mixes.

12. Specific recommendations to the contractor

Firstly. the current nine asphalt cooling features used to predict the cooling rates of asphalt mixes are suitable in predicting the cooling rates of asphalt mix, but some mixes have very small amount of training data. Hence it is recommended to make sure that the amount of training data is increased to at least 18 measurements for each type of mix to ensure that the MLP algorithm does not overfit during predictions.

Secondly, all the nine asphalt cooling data which comprises of time, type of asphalt mix, solar radiation, ambient temperature, windspeed, thickness, type of underlayer, temperature of underlayer, and rain is required to be collected. There should not be any missing data and there needs to be a proper logbook of how this data was collected to ensure that the data collected is of the highest quality.

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Appendix A

MLP algorithm; New asphalt cooling rate prediction model python code

Step 1: Importation of libraries.

```
In [16]: #Step 1: Importation of scientific libraries

         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import time
         from sklearn import metrics
         from sklearn.neural_network import MLPRegressor
         from sklearn.model_selection import train_test_split
         from sklearn.metrics import mean_squared_error
         from math import sqrt
         %matplotlib inline
```

Step 2: Importation of datasets

```
In [ ]: #import dataset for prediction
        dataset = pd.read_csv(r'C:\Users\Shaffie Juma\Desktop\p\Final Datasets\Surface_Python_data\csv_surface\Surface_Dataset_1
        dataset
```

Step 3: Data pre-processing

```
In [ ]: """ Data pre processing """
        #Data cleaning
        #  Drop rows with missing values
        dataset = dataset.dropna(how='any')
        dataset
        # Convert Categorical qualitative attributes into numerical format by creating dummy variables
        dummies = pd.get_dummies(dataset.Asphalt_type)
        dummies1 = pd.get_dummies(dataset.Underlayer_type)
        dummies
        dummies1
        # Combine the dummies with the original dataset
        merged =pd.concat([dataset,dummies,dummies1],axis='columns')
        merged
        # Drop the Asphalt_type and underlayer type
        dataset_finaln = merged.drop(['Asphalt_type','Underlayer_type','Rain (mm)','Underlayer_temp','Sand','Stone','Asphalt','T
        dataset_finaln


        #seperate into x and y variables from the dataframe
        X = dataset_finaln.drop('Surface_temp', axis='columns')
        X
        y = dataset_finaln.Surface_temp
        y

        #Splitting of the datasets into training and testing data
        xTrain, xTest, yTrain, yTest=train_test_split(X,y, train_size = 0.6, random_state = 34)
```

Step 4: Application of MLP Regressor

```
In [ ]: # Apply MLP regressor algorithm to the training data
        nn = MLPRegressor(hidden_layer_sizes=(13,13,13,),
            activation='relu',
                solver= 'adam',
            learning_rate='constant',
            learning_rate_init=0.1,
            max_iter=2000,
             momentum=0.2,
            random_state=34)
        nn.fit(xTrain,yTrain)
```

Step 5: Importation of validation data

```
In [ ]: #Import previously unknown validation data
        dataset_test_f = pd.read_csv(r'C:\Users\Shaffie Juma\Desktop\p\Final Datasets\Surface_Python_data\csv_surface\
```

Step 5: Prediction model output: Evaluation of model performance by comparing the RMSE values of the measured surface temperature and the predicted surface temperatures.

```
In [ ]: # Testing model performance on validation data

        # Seperate x and y variables
        Y2 = dataset_test_f['Surface_temp']
        Y2
        X1 = dataset_test_f.drop('Surface_temp', axis='columns')
        X1
        X2 = dataset_test_f['Time (min)']
        X2

        # Predict the temperature of asphalt mix based on the validation data
        y_pred=nn.predict(X1)
        y_pred

        #Returns the predicted temperatures of the asphalt mix and the actual temperatures of the asphalt in the validation data
        df=pd.DataFrame({'Time (min)':X2, 'Actual_Surface_Temperature':Y2, 'Predicted_Surface_Temperature':y_pred})
        df
```

```
In [ ]: """RMSE calculation between actual and predicted temperature of asphalt mixes for the different
        compaction windows 140 - 120 , 120 - 100 and 100- 80  degrees"""
        df_f=df.iloc[3:5]
        realVals = df_f.Actual_Surface_Temperature
        predictedVals = df_f.Predicted_Surface_Temperature
        mse = mean_squared_error(realVals, predictedVals)
        rmse = sqrt(mse)
        print(rmse)
```

```
In [ ]: # Plot curves of the actual temperature vs predicted temperature of the asphalt mixes
        import matplotlib.pyplot as plt
        fig = plt.figure()
        fig.suptitle('SMA-NL 11B Measured vs Predicted Surface Temperature', fontsize=10)
        plt.plot(X2, Y2)
        plt.plot(X2, y_pred)
        plt.ylabel('Surface Temperature °C')
        plt.xlabel('Time (min)')
        plt.legend(["Measured Surface Temperature °C ", "Predicted Surface Temperature °C "])
        #plt.savefig('11B rain_und_type_thick_wind_temp.png')
```

Mutual information gain regressor

Step 1: Importation of libraries.

```
In [1]: #Step 1: Importation of scientific libraries
        import pandas as pd
        import numpy as np
        from sklearn import metrics
        from sklearn.model_selection import train_test_split
        from sklearn.feature_selection import mutual_info_regression
```

Step 2: Importation of data

```
In [2]: 
        #import dataset for prediction
        dataset = pd.read_csv(r'C:\Users\Shaffie Juma\Desktop\p\Final Datasets\Surface_Python_data\csv_surface\Surface_Dataset_1
        dataset
```

Step 3: Data pre-processing

```
In [3]: #Data cleaning
        #  Drop rows with missing values
        dataset = dataset.dropna(how='any')
        dataset
        # Convert Categorical qualitative attributes into numerical format by creating dummy variables
        dummies = pd.get_dummies(dataset.Asphalt_type)
        dummies1 = pd.get_dummies(dataset.Underlayer_type)
        dummies
        dummies1
        # Combine the dummies with the original dataset
        merged =pd.concat([dataset,dummies,dummies1],axis='columns')
        merged
        # Drop the Asphalt_type and underlayer type
        dataset_final = merged.drop(['Asphalt_type','Underlayer_type'],axis ='columns')
        dataset_final
```

In [4]:
```
# Data pre-processing
# Convert Categorical qualitative attributes into numerical format by creating dummy variables
dummies = pd.get_dummies(dataset.Asphalt_type)
dummies1 = pd.get_dummies(dataset.Underlayer_type)
dummies
dummies1
# Combine the dummies with the original dataset
merged =pd.concat([dataset,dummies,dummies1],axis='columns')
merged
# Drop the Asphalt_type and underlayer type
dataset_final = merged.drop(['Asphalt_type','Underlayer_type'],axis ='columns')
dataset_final

#seperate into x and y variables from the dataframe
X = dataset_final.drop('Surface_temp', axis='columns')
X
y = dataset_final.Surface_temp
y

#Splitting of the datasets into training and testing data
xTrain, xTest, yTrain, yTest=train_test_split(X,y, test_size = 0.6, random_state = 34)
```

Step 4: Application of mutual_information_regressor

In [5]:
```
# Mutual information
mi = mutual_info_regression(xTrain,yTrain)
mi=pd.Series(mi)
mi.index=xTrain.columns
mi.sort_values(ascending=False,inplace = True)
mi
```

Step 5: Output results: IG scores

Out[5]:
```
Time (min)           0.656658
Solar (W/m2)         0.113672
Temperature          0.086453
Wind_speed (km/h)    0.083157
Thickness (mm)       0.075131
Stone                0.055199
Underlayer_temp      0.051471
SMA-NL 8G            0.043098
Rain (mm)            0.036837
PA 16                0.030059
SMA-NL 11B           0.019175
AC 8                 0.019086
Asphalt              0.017353
AC 22                0.012625
Sand                 0.011736
AC 11                0.000000
AC 16                0.000000
```

Appendix B

The following tables present the feature set in the new prediction model after label encoding the categorical qualitative features.

Asphalt cooling features applied to the MLP algorithm (Dataset 1)

	Time (min)	Thickness (mm)	Underlayer_temp	Wind_speed (km/h)	Temperature	Solar (W/m2)	Rain (mm)	Surface_temp	AC 11	AC 16	AC 22	AC 8	PA 16	SMA-NL 11B	SMA-NL 8G	Asphalt	Sand	Stone
0	0.0	60	6.8	19.8	10.8	108.0	0.0	121.000000	0	0	1	0	0	0	0	0	1	0
1	3.0	60	6.8	19.8	10.8	108.0	0.0	114.000000	0	0	1	0	0	0	0	0	1	0

Asphalt cooling features applied to the MLP algorithm (Dataset 2)

	Time (min)	Thickness (mm)	Underlayer_temp	Wind_speed (km/h)	Temperature	Solar (W/m2)	Rain (mm)	Core_temp	AC 11	AC 16	AC 22	AC 8	SMA-NL 11B	SMA-NL 8G	Asphalt	Sand
0	0.0	60	6.8	19.8	10.8	108.0	0.0	144.000000	0	0	1	0	0	0	0	1
1	3.0	60	6.8	19.8	10.8	108.0	0.0	144.000000	0	0	1	0	0	0	0	1