## QATAR UNIVERSITY

## **COLLEGE OF ENGINEERING**

## EVALUATION AND CALIBRATION OF DYNAMIC MODULUS PREDICTION

## MODELS OF ASPHALT MIXTURES FOR HOT CLIMATES

BY

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A Thesis Submitted to

the College of Engineering

in Partial Fulfillment of the Requirements for the Degree of

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#### ABSTRACT

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Title: Evaluation and Calibration of Dynamic Modulus Prediction Models of

**Asphalt Mixtures for Hot Climates** 

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The dynamic modulus  $(E^*)$  of asphalt mixtures is considered a primary entry in Mechanistic-Empirical (ME) pavement design and analysis. Various models have been

published and aimed to estimate the modulus on the basis of the mixture volumetrics

and material features. This study aims to review four commonly incorporated dynamic

modulus prediction models of Hirsch, Alkhateeb, Witzack 1-37A, Witzack 1-40D and

validate and calibrate Hirsch and Alkhateeb models for use in Qatar. Based on the study

outcomes, the Hirsch model showed a high prediction accuracy of asphalt mixture

moduli before calibration with a coefficient of determination (R<sup>2</sup>) of 87.2% between

predicted and measured values. This R<sup>2</sup> value is improved after calibration to 89.2%.

Alkhateeb model, on the other hand, had a R<sup>2</sup> of 70.8% before calibration, which also

improved to 89.2% after calibration. Based on the study results, it is recommended to

use the calibrated Hirsch or Alkhateeb model in Qatar instead of the uncalibrated

version of the models. The moduli predicted by the Hirsch model before and after

calibration were employed in this study to perform a mechanistic-empirical analysis of

typical pavement structures in Qatar. According to the findings, the percent change in

the predicted fatigue due to the use of the calibrated Hirsch model reached more than

50% with an average value of 17.33%, while the percent change in rutting reached 14%

with an average value of 3.65%. These results highlight the importance of using locally

calibrated models to improve dynamic modulus predictions performance.

## **DEDICATION**

This work is devoted to my parents, siblings, and beloved ones. This work is also dedicated to

Arab World countries, the heart of the desert.

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Great thanks to Allah (swt) for granting me this opportunity and experience throughout my life, and may the peace and blessings be on our Prophet Muhammad (peace be upon him).

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#### **CHAPTER 1: INTRODUCTION**

#### Overview

Asphalt mixture dynamic modulus  $(E^*)$  is one of the main factors in pavement design, especially in the mechanistic-empirical analysis and design method and estimating the layer coefficient of American Association of State Highway and Transportation Officials (AASHTO, 1993) empirical design method (Sakhaeifar et al., 2015). Due to this importance, laboratory testing is needed to characterize this parameter to provide the designer with flexibility in the material selection. However, characterizing the mixture would face multiple difficulties and determinants, such as having different sources of aggregate properties and gradation, having multi-types of asphalt binders, and the need for a large testing matrix that is not available at the design stage of the road. In order to overcome these difficulties, researchers come up with prediction models that forecast the mixture based on asphalt mixture volumetrics and asphalt binder properties such as Complex Modulus ( $G^*$ ). These prediction models are generally validated based on conventional mixtures of local materials and are not aimed to be generalized for all types of materials and mixtures (B. Zhang et al., 2019) (Apeagyei, 2011). Based on the literature, Hirsch, Witzack 1-37A (1999), Witzack 1-40D (2006), and Alkhateeb dynamic modulus prediction models are the most popular models studied and applied in practice among many prediction models developed around the world and considered as a proofed concept. However, these models vary in development technique, testing matrix, and calibration methods which result in different prediction performances due to a variety of material characteristics and mixture volumetrics from one region to another (Abu Abdo, 2012) (Ceylan, Schwartz, et al., 2009) (Mateosa & Soares, 2015).

Hirsch model (Christensen et al., 2003) is developed based on the mixture rule. It was considered in the early stages as a tool to define the sensitivity of volumetrics and their effect on the dynamic modulus (C. Zhang et al., 2017). As the Hirsch model relies on mechanistic concepts and regression results, it is considered a semi-empirical model and reduces the inputs compared to the entirely empirical models such as Witzack model (M Kim, 2010). However, the empirical part of the Hirsch model was built based on the conventional mixtures dataset resulting in questionable prediction performance of the model for the new modified type of mixtures that developed for other climatic conditions.

Witzack models rely on conventional multivariate regression analysis of a large dataset of laboratory testing results (Ceylan & Kim, 2007). These models were revised and developed through the last decades to improve their prediction performance for several mixes. First, a popular version was developed in 1999 and known as 1-37A Witzack Model, and then it was reviewed in 2006 and known as Witzack 1-40D (Yousefdoost et al., 2013). In the Witzack 1-40D model, the 1-37A version has been modified by widening the original dataset and introducing the complex modulus ( $G^*$ ) and the phase angle ( $\delta$ ) instead of the viscosity to include the loading frequency effect on the modulus (J. Bari & Witczak, 2006). Several researchers demonstrated that the 1-40D version has a good prediction performance (Ceylan, Schwartz, et al., 2009) (Yousefdoost et al., 2013) (J. Bari & Witczak, 2006). On the contrary, other studies show that the 1-40D Witzack model yields highly biased predictions (Khattab et al., 2014) (Andrei et al., 1999). Even though Witzack 1-40D is the latest model, several studies proved that Witzack 1-37A has better performance (Khattab et al., 2014) (Solatifar, 2020) (Robbins & Timm, 2011).

Alkhateeb Model defined the functional rheology of the asphalt layer as a combination of three phases of a parallel performance (Al-Khateeb et al., 2006). The research dataset included modified and unmodified asphalt mixtures with a wide range of performance grades (Al-Khateeb et al., 2006). Multiple studies showed that the Alkhateeb model resulted in biased prediction at low temperatures (Yousefdoost et al., 2013) (Far et al., 2009).

#### **Problem Statement**

Qatar has witnessed exponential growth in all infrastructure sectors and broad expansion in road networks in the past decade. The need to provide value-engineered and sustainable pavement structures has become a priority during this development. In Qatar, and to predict the dynamic modulus, Qatar Highway Design Manual (QHDM) (MOTC, 2015) and Interim Advice Note No. 101 (Public Work Authority, 2016) of the Public Works Authority (PWA) of Qatar have recommended using the Hirsch model without referring to a validation study. As this model was formed based on the USA mixtures (Christensen et al., 2003), the prediction performance of the Hirsch model of Qatar-based mixtures requires further verification and possibly recalibration in light of comparative study with other available models.

## Qatar Climate

The climate condition is an essential input in determining the properties of pavement materials. Qatar has a hot climate with high humidity levels during the summer. According to the Qatar Meteorology Department, Doha has a low average annual rainfall precipitation of 79mm(QMD, n.d.-a). Figure 1 shows the climatic temperature in Qatar for the period 1962 to 2013 collected in Doha city station (QMD, n.d.-b)

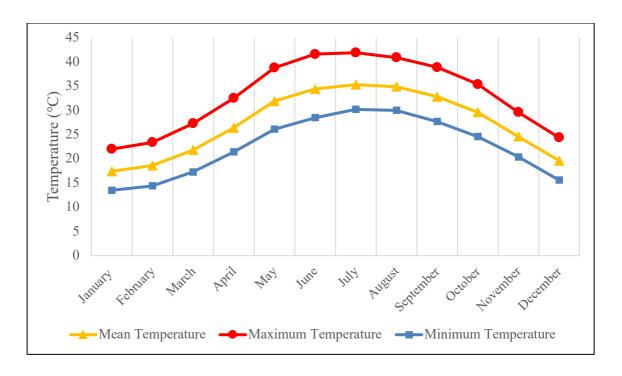


Figure 1. Climatic Temperature Normals in Qatar for the period 1962 to 2013 (Qatar Meteorology Department: Doha Station)

There is no significant deviation in the overall terrain and environment of the State of Qatar; thus, the data collected from the Doha station represents the entire country's climate. Figure 1 shows that the lowest temperature throughout the year is 13.5 °C. This explains that the State of Qatar does not experience air temperatures of 4 or 5 °C, which are typically used in dynamic modulus testing to construct the master curve.

## Objectives of the Study

This study aims to:

- Select the usable models in Qatar after reviewing the Hirsch, Witzack 1-37A (1999), Witzack 1-40D (2006), and Alkhateeb dynamic modulus prediction models.
- Conduct validation and calibration for the selected models based on local materials and testing practices.

• Evaluate the advantage of the calibration on the predicted functional performance of Qatar pavement structures.

#### Report Outline

The thesis contains five chapters. For ease of understanding, each chapter has an introduction that explains the chapter's content and presents the expected information. The chapters contents are briefly described below.

#### Chapter 1: Introduction

Chapter 1 of the thesis serves as a quick introduction and outlines its goal in light of the issue statement. This chapter also includes a description of the report's outline and the study's objectives.

#### Chapter 2: Literature Review

Chapter 2 offers an in-depth review of the Hirsch, Witzack 1-37A (1999), Witzack 1-40D (2006), and Alkhateeb dynamic modulus prediction models prediction bases, prediction performance, calibration techniques, limitations, and the latest technologies used to build dynamic modulus prediction models and highlight future developments needed to achieve better prediction performance. This chapter reviews sensitivity studies for the effect of dynamic modulus on the predicted functional operation of pavement structures. In the end, two prediction models have been chosen for the validation and the calibration based on their inputs after eliminating the other two reviewed models.

## Chapter 3: Research Methodology and Data Collection

Chapter 3 describes the research methodology developed to accomplish the targeted objectives. Also, the chapter presents the collected data and explains the calibration technique considered in this study. Lastly, the chapter shows the statistical measures considered to assess the results.

## Chapter 4: Results and Discussion

Chapter 4 presents the validation and calibration results in statistical terms, discusses them, and compares them with the reviewed literature. Also, the chapter presents the sensitivity analysis results of the Hirsch and Alkhateeb models. In the end, the chapter shows the result of the functional performance testing of Qatar pavement structures before and after calibration to highlight the importance of the conducted calibration.

## Chapter 5: Conclusion and Recommendations

Chapter 5 concludes this study's results and interconnects the outcomes with the study objectives. Also, the chapter includes recommendations that would be considered in future studies of dynamic modulus prediction models to improve the results.

#### **CHAPTER 2: LITERATURE REVIEW**

#### Introduction

Based on the above introduction, it is noticed that the evaluation studies for the four dynamic modulus prediction models resulted in contradicting results regarding the prediction performance. Therefore, this section gives a state-of-the-art review of the Hirsch, Witzack 1-37A (1999), Witzack 1-40D (2006), and Alkhateeb dynamic modulus prediction models to define the prediction bases, prediction performance, calibration techniques, limitations, and the latest technologies used to build dynamic modulus prediction models and highlight future developments needed to achieve better prediction performance. Also, this section reviews sensitivity studies on the dynamic modulus effect on the predicted functional performance of pavement structures and concludes the outcomes.

#### **Models Prediction Bases**

This section presents the Hirsch, Witzack 1-37A (1999), Witzack 1-40D (2006), and Alkhateeb prediction models prediction bases found in the literature. The section presents the theory behind each model and the dataset details that were considered to develop it.

#### Hirsch Model

The Hirsch model constructed by (Christensen et al., 2003) is among the most well-liked prediction models for asphalt layers modulus. This model can be categorized as a semi-empirical model that is rheologically developed based on Burger's model, which considers a synthesis of two mechanical responses for the material, parallel and series, as shown in Figure 2 (Huang, 2004)(Elseifi et al., 2002).

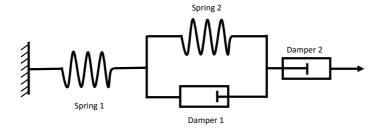


Figure 2. Burger's Model Concept Diagram

The parallel and series performance of the asphalt mixture is represented in Equations (1) and (2), respectively (Shu & Huang, 2008).

$$E_p = E_1 V_1 + E_2 V_2 (1)$$

$$\frac{1}{E_s} = \frac{V_1}{E_1} + \frac{V_2}{E_2} \tag{2}$$

Where:

 $E_p$  = Parallel performance modulus of the material

 $E_s$  = Series performance modulus of the material

 $E_1$  and  $E_2$  = Modulus of each material

 $V_1$  and  $V_2$  = Volume of each material in the mixture

Equation (3) represents the asphalt mixture modulus based on Burger's model (C. Zhang et al., 2017).

$$|E^*|_m = x \left( E_1 V_1 + E_2 V_2 \right) + (1 - x) \left( \frac{V_1}{E_1} + \frac{V_2}{E_2} \right)^{-1}$$
(3)

Where:

x =Parallel mechanical response ratio  $|E^*|_m =$ Asphalt mixture dynamic modulus

It is found that Hirsch Model has different versions compared with each other in the literature. (C. Zhang et al., 2017) found that the following version represented in Equations (4) and (5), known as an alternate, is the most accurate model and commonly referred to as Hirsch Model (K. L. Roja et al., 2020).

$$|E^*|_m = Pc \left[ 4,200,000 \left( 1 - \frac{VMA}{100} \right) + 3|G^*|_b \left( \frac{VFA * VMA}{10,000} \right) \right] +$$

$$\left( 1 - Pc \right) \left[ \frac{1 - \frac{VMA}{100}}{4,200,000} + \frac{VMA}{3VFA|G^*|_b} \right]^{-1}$$

$$(4)$$

Where:

$$Pc = \frac{\left(20 + \frac{VFA * 3|G^*|_b}{VMA}\right)^{0.58}}{650 + \left(\frac{VFA * 3|G^*|_b}{VMA}\right)^{0.58}}$$
(5)

Where:

 $|E^*|_m$  Predicted asphalt mixture dynamic modulus (psi)

VFA = Voids filled with asphalt (%)

VMA = Voids in the mineral aggregate (%)

 $|G^*|_b = \text{Complex modulus of binder (psi)}$ 

The constants (20, 0.58, and 650) are fitting parameters obtained from regression analysis and fitting with measured moduli of asphalt mixtures (C. Zhang et al., 2017). The regression constant (4,200,000) is an assumed aggregate young's modulus (in psi). The constant (3) multiplied with the  $|G^*|_b$  is obtained by assuming that asphalt is an incompressible material with a Poisson's ratio (v) of 0.5 substituted in the elastic modulus (E) equation:  $E = 2(1 + v)|G^*|_b$ , where ( $|G^*|_b$ ) is binder modulus (C. Zhang et al., 2017).

Hirsch model was created using a dataset collected from several projects in the US. A summary of the Hirsch model dataset details is presented in Table 1 (Christensen et al., 2003). Hirsch model dataset physical features are exhibited in Table 2 (Christensen et al., 2003).

Table 1. Summary of Hirsch Model Dataset Details

Source Project	FHWA ALF*	West Track	MN/Road	Variants Totals
Factor				
Binders	SBS Modified and PE- modified	PG 64-22	120/150- Pen	8
Mix Design Method	Marshall AC-5, 10, 20	Superpave	Marshall AC-20	2
Aggregate Size and Gradation	19mm Dense and 37.5mm Fine	19mm Fine and 19mm Coarse	9.5mm Fine	5
Number of Asphalt Mixes	7	6	5	18
No. of Data Point	78	69	59	206

<sup>\*</sup> ALF: Accelerated Load Facility

Table 2. Hirsch Model Dataset Physical Properties

Criteria	Value	
Air Voids (%)	5.6 to 12.2	
VMA (%)	13.7 to 21.6	
VFB (%)	38.7 to 68	
Loading Frequency (Hz)	0.1 and 5	
Dynamic Modulus (MPa)	183 to 20,900	
Complex Shear Modulus (MPa)	20 to 3,880	
Temperature (°C)	4, 21 and 38	
Phase Angle (degrees)	8 to 61	

## *Witzack 1-37A Model (1999)*

This empirical model was developed by Andrei Witzack et al. by collecting a database consisting of 205 asphalt mixtures tested at 2750 test points (C. Zhang et al., 2017). Shook and Kalas originally developed the model in 1969, which was modified by Fonseca and Witzack in 1996 (Li et al., 2012). A database contains 1430 data points obtained based on 149 conventional asphalt mixes initially utilized in the Fonseca and Witzack model, as well as a further 1320 test points from 56 asphalt mixtures the contains 34 mixtures have an enhanced asphalt binder, which was used to create the Witzack 1-37A model. The model inputs include volumetric characteristics, asphalt

mix grading, viscosity, and frequency. In Equation (6), the Witzack 1-37A model is displayed (Andrei et al., 1999).

Where:

 $|E^*|_m$  = Predicted Dynamic Modulus, in 0.72 MPa (105 psi)

 $p_{200} = \%$  Passing the sieve No.200

 $p_4 = \%$  Retained on sieve No. 4

 $V_a = \%$  Air voids

 $p_{38} = \%$  Retained on the 9.5 mm (3/8-inch) sieve by total aggregate weight (cumulative)

 $V_{beff} = \%$  Effective bitumen content, by volume

 $p_{34} = \%$  Retained on the sieve sized 19 mm (3/4-inch)

f = Loading frequency (Hz)

A summary of the Witzack 1-37A set of data is demonstrated in Table 3 (Garcia & Thompson, 2007).

Table 3. Summary of Witzack 1-37A Dataset Details

Criteria	Dataset
Frequency	0.1 to 25 Hz
Binder Types	9 Unmodified, 14 Modified
Temperature	-17.7 to 54.4 °C
Asphalt Mixtures	34 with modified binder, 171 with unmodified binder
Aggregate	39 grading type
Specimen Aging	Un-aged

The Witzack 1-40D model revised the previous Witzack 1-37A by expanding the database and introducing the  $G^*$  and  $\delta$  instead of viscosity. This model was

calibrated subject to 7400 modulus test points resulting from testing 346 Hot Mix Asphalt (HMA). The new data when compared with the Witzack 1-37A model data added aged and un-aged material of wider variety in the aggregate gradation, binder types, and mixture types (modified and unmodified) (Javed Bari et al., 2006).

The 1-40D model kept the same structure as the Witzack 1-37A model, but  $G^*$  and  $\delta$  were embedded in the equation (Robbins & Timm, 2011). The model is represented by Equation (7) (J. Bari & Witczak, 2006).

$$Log |E^*|_m = -0.349 + 0.754(|G_b^*|^{-0.0052}) x (6.65 - 0.032p_{200} + 0.0027p_{200}^2 + 0.011p_4 - 0.0001p_4^2 + 0.006p_{38} -0.00014p_{38}^2 - 0.08V_a - 1.06 \left(\frac{V_{beff}}{V_a + V_{beff}}\right))$$
(7)  
$$\frac{2.56 + 0.03 V_a + 0.71 \left(\frac{V_{beff}}{V_a + V_{beff}}\right) + 0.012p_{38} - 0.0001p_{38}^2 - 0.01p_{34}}{1 + e^{(-0.7814 - 0.578585 \log |G^*|_b + 0.8834log\delta_b)}}$$

Where:

 $|G^*|_b = \text{Complex modulus of the binder (in psi)}$ 

 $\delta_b$  = Phase angle of the binder (in degrees)

#### Alkhateeb Model

In addition to the Hirsch model, the Alkhateeb model (Al-Khateeb et al., 2006) has been applied in the practice due to its small number of inputs needed to predict the  $E^*$ . The model was constructed based on the rule of mixtures considering a three-component system of binder, aggregate, and air voids. (Al-Khateeb et al., 2006) determined the calibration parameters using mixtures from the State of Virginia in the USA. The set of mixtures included aging effect and modified binders. Equation (8) represents the Alkhateeb model (Al-Khateeb et al., 2006).

$$|E^*|_m = 3 \left(\frac{100 - VMA}{100}\right) \left(\frac{\left(90 + 1.45 \frac{|G^*|_b}{VMA}\right)^{0.66}}{1100 + \left(0.13 \frac{|G^*|_b}{VMA}\right)^{0.66}}\right) |G^*|_g$$
(8)

Where:

 $|G^*|_g$  = Binder glassy state shear modulus in Pa (assumed as  $10^9$  Pa)

VFA = Fraction of aggregate voids filled with asphalt (%)

VMA = Voids in the mineral aggregate (%)

 $|G^*|_b = \text{Binder complex modulus (asphalt) (psi)}$ 

The model was developed based on several material resources, production techniques, and binder types. Table 4 shows the Alkhateeb model dataset details, while Table 5 shows the physical properties of the Alkhateeb model dataset (Al-Khateeb et al., 2006).

Table 4. Summary of Alkhateeb Model Dataset Details

<b>Mixture Production Types</b>	<b>Compaction Types</b>	Binder Types
Laboratory Produced Plant Produced Field Cores	Laboratory Compaction Field Compaction	PG 70-28 air blown PG 70-22 unmodified PG 70-28 modified by polymers PG 76-28 modified by crumb rubber PG 70-34 modified by polymers

Table 5. Alkhateeb Model Dataset Physical Parameters

	Grading	
75	Size (mm)	Percent Passing
2.965	37.5	100
12.5	9.5	84.6
3.001	12.5	93.6
5.3	4.75	56.7
Gyratory	2.36	34.9
100 x 150	1.18	24.8
4, 9, 31, 46, 58	0.6	18.2
0.6	0.3	13.1
$7\pm0.5$	0.15	9.3
0.1, 0.5, 1, 5, 10		
2.947		
	2.965 12.5 3.001 5.3 Gyratory 100 x 150 4, 9, 31, 46, 58 0.6 7±0.5 0.1, 0.5, 1, 5, 10	75 2.965 37.5 12.5 3.001 12.5 5.3 4.75 Gyratory 2.36 100 x 150 4, 9, 31, 46, 58 0.6 0.6 0.3 7±0.5 0.1, 0.5, 1, 5, 10

<sup>\*</sup> LPLC: Lab Produced – Lab Compacted

<sup>\*\*</sup> PPLC: Plant Produced – Lab Compacted

## **Models Comparison Summary**

Based on the review conducted in the previous sections, the comparative summary of the four models is presented in Table 6.

Table 6. Comparison of the four reviewed models

Criterion	Hirsch Model	Witzack 1-37A model	Witzack 1-40D model	Alkhateeb model
Prediction Type	Semi-empirical (C. Zhang et al., 2017)	Empirical (Ceylan & Kim, 2007), (Andrei et al., 1999)	Empirical (Ceylan & Kim, 2007), (Andrei et al., 1999)	Semi-empirical (Al-Khateeb et al., 2006)
Number of Test points	206 (Christensen et al., 2003)	2,750 (Yousefdoost et al., 2013), (Andrei et al., 1999)	7400 (Ceylan & Kim, 2007), (Andrei et al., 1999)	150 (Al-Khateeb et al., 2006)
Number of Mixtures	18 (Christensen et al., 2003)	205 (Yousefdoost et al., 2013), (Andrei et al., 1999)	346 (Ceylan & Kim, 2007), (Andrei et al., 1999)	6 (Al-Khateeb et al., 2006)
Type of Binders	2 Unmodified and 2 Modified (Christensen et al., 2003)	Unmodified and Modified (Yousefdoost et al., 2013), (Andrei et al., 1999)	Unmodified and Modified (Andrei et al., 1999)	6 Types of Modified and Unmodified (Yousefdoost et al., 2013), (Al- Khateeb et al., 2006)
Aggregate Gradation	1 Dense, 3 Fine, and 1 Coarse (Christensen et al., 2003)	39 Types (Yousefdoost et al., 2013), (Andrei et al., 1999)	Gap, Open, and Dense (Andrei et al., 1999)	1 Dense (Yousefdoost et al., 2013), (Al- Khateeb et al., 2006)
Aging	Aged	Un-aged (Yousefdoost et al., 2013), (Andrei et al., 1999)	Aged and Un-aged (Andrei et al., 1999)	Aged (Yousefdoost et al., 2013), (Al- Khateeb et al., 2006)
Assumed Rheology	Two Phases in parallel and series (Christensen et al., 2003)	Not Applicable	Not Applicable	Three phases in parallel (Al-Khateeb et al., 2006)

## **Models Performance Comparison**

As the above-mentioned prediction models relied on different techniques and datasets, the prediction performance varies from one region to another due to climatic and material differences. (C. Zhang et al., 2017) study evaluated the performance of the Hirsch model, the Witzack 1-40D model, and the modified Hirsch model proposed

through the study. The study also aimed to revise the Hirsch model by introducing the mixture's rule in addition to considering the elastic and viscoelastic properties. The study went through a rheological review for the Hirsch model and found that there are three sources of error in the model; (1) the model always assumes the aggregate modulus as a regression constant of 4,200,000 psi; (2) the model has been derived based on the assumption that asphalt mixture is elastic material so dynamic modulus was represented as  $E^* = 2(1 + v)|G^*|_b$ ; (3) the asphalt is assumed as incompressible with poisons ratio of 0.5. At first, the researchers conducted a sensitivity analysis to examine the influence of aggregate modulus on the forecasting performance of the Hirsch model by substituting the modulus of limestone, basalt, and tuff instead of the utilized 4,200,000 regression constant in the model and comparing it with a control limestone asphalt mixture modulus. The analysis showed that using a specific aggregate modulus is necessary due to the significant difference in the prediction when using a regression constant of 4,200,000. Figure 3 explains the aggregate modulus effect on predicted dynamic modulus based on the study outcomes (C. Zhang et al., 2017).

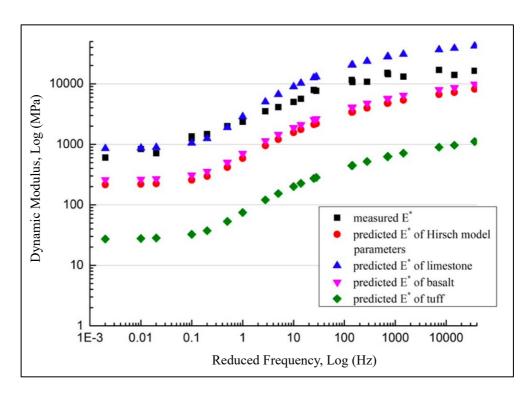


Figure 3. Measured Vs. Hirsch Predicted Mixtures Master Curve with Several Types of Aggregate

Figure 3 shows that the basalt modulus comes up in the closest prediction to the original Hirsch model values since the regression constant of 4,200,000 is close to the basalt modulus of ( 34,894 MPa) 5,061,000 psi (Stowe, 1969) so the prediction performance does not significantly vary. Also, the limestone resulted in the closest predicted modulus compared to the measured values since it is used in the control mixture.

(Yousefdoost et al., 2013) studied the appropriateness of the US (Alkhateeb, Hirsch, Witzack 1-37A, and Witzack 1-40D) models for Australian mixtures. In order to achieve the study goal, 28 asphalt mixtures used in Australia have been tested to define the modulus. The study concluded that the Hirsch, Witzack 1-37A (1999), and Alkhateeb models typically under-predict the dynamic modulus; meanwhile, Witzack 1-40D (2006) exaggerates the values. Bias and fitting errors were computed for each model and found high in the Hirsch, Alkhateeb, and Witzack 1-40D. The study also

came up with the conclusion that all models' prediction accuracy is sensitive to temperature. The study also included sensitivity analysis to check how the asphalt mix properties affect the prediction accuracy. It was found that binder type is the most sensitive characteristic. Therefore, the conclusion was interpreted that the studied prediction models are not accurate enough to be considered for Australian asphalt mixes. Table 7 shows the Goodness-of-fit of prediction models for Australian asphalt mixes.

Table 7. Goodness-of-fit of Prediction Models for Australian Asphalt Mixes

Statistics	Criteria	1-37A	1-40D	Hirsch	Alkhateeb
Se/Sy	5 °C	1.55	7.9	2.84	2.85
	20 °C	0.86	2.29	1.34	1.26
	35 °C	0.43	0.38	0.72	0.57
	50 °C	1	0.39	0.53	0.48
	Overall	0.49	2.29	0.88	0.87
$\mathbb{R}^2$	5 °C	-134.00%	-5998.00%	-702.00%	-709.00%
	20 °C	29.00%	-412.00%	-78.00%	-58.00%
	35 °C	82.00%	86.00%	49.00%	68.00%
	50 °C	2.00%	85.00%	73.00%	77.00%
	Overall	76.00%	-419.00%	1300.00%	24.00%
Other Statistics	SSE	1.75E+10	3.79E+11	5.59E+10	5.51E+10
	Average $ E^*_p $	5953	16555	3812	4000
	Average Error	-2007	8595	-4147	-3959
	Slope	0.618	2.688	0.342	0.332
	Intercept	1030.8	-4837.5	1090	1357.8
	Rating	Good	Very Poor	Poor	Poor

(Far et al., 2009) conducted a study to evolve an Artificial Neural Network (ANN) dynamic modulus prediction model and evaluated Alkhateeb, Hirsch, Witzack 1-37A, and Witzack 1-40D models. The study concluded that the Alkhateeb model has a significant bias at low temperatures compared to 1-40D Witzack and the Hirsch

models. In addition, the study modified all four models to improve the prediction performance. It was concluded that the newly modified Witzack and Hirsch models result in significant bias at high temperatures and low sensitivity of the two models to volumetric parameters.

(Solatifar, 2020) conducted a study to compare the performance of six dynamic modulus prediction models (Hirsch, Modified Witzack, Witzack, Alkhateeb, Global, and Simplified Global). The study includes a published database conducted by the University of Maryland. The testing consists of a broad extent of frequencies and temperatures. To evaluate the prediction performance of the studied models, the study considered two Measures for Effectiveness (MOE), which are goodness-of-fit and bias. The study concluded that the best prediction performance is arranged as Witzack 1-37A, Simplified Global, Global, Hirsch, Alkhateeb, and Modified Witzack 1-40D. The study highlighted that the Witzack 1-37A model has the best prediction performance because it was developed based on the same testing database utilized in this study. Although calibration is necessary, the study concluded that all models could be considered in the design and analysis process.

To establish the use of AASHTOWare software for the Pavement Mechanistic-Empirical (ME) design method in Saudi Arabia, (Khattab et al., 2014) analyzed Witzack 1-37A and 1-40D dynamic modulus prediction models. The modulus was measured for 25 different local mixtures. The results indicated that temperature and binder type impacted how well the two models worked. According to the data, MEPDG Level 3 binder inputs and the 1-37A Witzack model had the highest prediction performance and lowest biased prediction.

(Robbins & Timm, 2011) conducted a study evaluating Hirsch, Witzack 1-37A, and Witzack 1-40D on asphalt mixtures in the southeastern United States by testing 18

HMA. The Witzack model found to had the largest deviations from the measurements with overestimating  $E^*$  by about 61%.

### Models Calibration Techniques

Due to the importance of Dynamic Modulus ( $E^*$ ) prediction models in practical fields, several researchers focused on developing a methodology to calibrate the models (Goh et al., 2010). (C. Zhang et al., 2017), proposed to calibrate the Hirsch model with two major changes: (1) introducing Burger's model to describe binder viscoelastic properties and (2) considering design-specific aggregate elastic modulus instead of the regression constant. The study came up with a modified Hirsch model that includes the  $\delta$  of the mix. It was concluded that the modified Hirsch model in this study provides higher accuracy prediction than the original Hirsch and 1-40D Witzack models. In addition, it was found that the prediction performance is sensitive to the  $\delta$  value.

(Robbins & Timm, 2011) proposed the Hirsch model calibration methodology by substituting the actual aggregate modulus instead of the regression constant of 4,200,000. The used aggregate modulus considered in the mix has a modulus of 3,040,500 psi. In addition, the research proposed to use an error minimization tool in excel to find new regression factors instead of (20, 650, 0.58, 3). The calibration shows an improvement of 1.4% R<sup>2</sup> for the Hirsch model prediction, which was considered as minor improvement.

(Shen et al., 2013) proposed two calibration techniques for the Hirsch model based on Washington DC asphalt mixes using 42 samples. The first calibration technique considered replacing the 4,200,000 regression constant with an aggregate modulus of 4,800,000 psi and using error minimization to replace the regression coefficient (20, 650, and 0.58) with new values. The study resulted in a new regression coefficient of (0.2, 600, and 0.56), respectively. It was concluded that the quality of the

predictions improved but overestimated the modulus at high testing temperatures. In the second technique, the research proposed using asphalt mastic properties to calibrate the Hirsch model. The study suggested a factor of 68,947 MP (10,000,000 psi) instead of 4,200,000 regression constant and considered using mastic complex modulus ( $G_m^*$ ) instead of binder  $G^*$  and replacing the regression factors (650 and 0.58) with (10,000 and 0.67), respectively. Figure 4 shows the newly improved prediction performance based on the second technique (Shen et al., 2013).

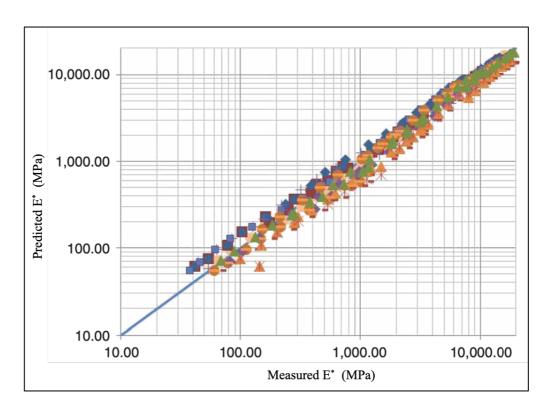


Figure 4. Predicted and Measured E\* based on Modified Hirsch Model of Shen et al. study

The trend of the predicted vs. measured  $E^*$  is going around the line of equality, and the performance appears consistent. Unfortunately, the published article did not present the statistical improvement of the prediction in the article.

#### Recent Developments and Future

New dynamic modulus prediction models have been developed with innovative techniques to overcome the shortcomings of conventional models (Ceylan, Gopalakrishnan, et al., 2009). Kim (Minkyum Kim, 2009) explained that empirical and semi-empirical models for predicting dynamic elastic moduli have significant shortcomings, especially when used for mixtures that vary significantly from those used to develop and calibrate the model. In the study, a proposed and experimentally validated a differential scheme micromechanics modeling framework for HMA modulus prediction was considered. Researchers have identified material micromechanics at the level of their individual components. After developing the new model, the predicted and measured E\* have been compared and a good agreement was found with reasonable accuracy.

(Ceylan & Kim, 2007) conducted a study to develop a simple dynamic modulus prediction model with less number of independent variables in comparison to the regression-based models such as Witzack models without negatively impacting the accuracy of the prediction. The Witzack 1-40D measured E\* dataset was considered for constructing Artificial Nural Network (ANN) based models. The obtained ANN-based models were checked against the MEPDG models. It was concluded that the ANN models with a smaller number of inputs have better performance and higher accuracy than regression-based MEPDG models.

(Far et al., 2009) constructed three ANN-based models based on the inputs of Alkhateeb, Hirsch, and 1-40D Witzack models. After validation of the three models, it was concluded that all three models have a high coefficient of determination (R<sup>2</sup>) and low bias. The ANN model with Hirsch model inputs had the best prediction for the modulus (Lu et al., 2009).

(El-Badawy et al., 2018) applied the ANN technique for dynamic modulus prediction based on 25 asphalt mixtures and considered the inputs of Hirsch, Witzack 1-37A, and Witzack 1-40D. After determining the most sensitive inputs using Global Sensitivity Analysis (GSA) and commercially available software, the ANN-based models were found to be more accurate than conventional models. The study concluded that the Hirsch model needs further aggregate characteristics inputs so, the model's accuracy will not be negatively affected.

(Moussa & Owais, 2020) developed a Deep Convolution Neural Networks (DCNNs) technique based on six convolution blocks and applied it on Witzack 1-37A and Witzack 1-40D. The study found that the developed models based on machine learning have a higher performance than conventional prediction models. In another research by the same researchers (Moussa & Owais, 2021), a prediction model-based Deep Residual Neural Networks (DRNNs) technique was developed based on comparing 8191 combinations of inputs. The study showed that the DRNNs model outperformed the conventional Witzack 1-37A, Witzack 1-40D, and Hirsch prediction models.

#### Dynamic Modulus Effect on Pavement Performance Predictions

(Cooper et al., 2015) performed research to define dynamic modulus impact on pavement performance predictions. For this purpose, ten asphalt mixtures moduli were obtained at the design, production, and construction stages. Consequently, Mechanistic-Empirical (ME) pavement analysis was conducted using AASHTOWare. The analysis showed that rutting distresses were sensitive to the modulus value. Moreover, it was found that the predicted alligator cracking between plant-produced laboratory-compacted (PL) samples and field cores of the same mixture reached a 60% difference due to changes in the modulus value.

(Cheng et al., 2021) studied the sensitivity of the loading wave types on the modulus value and, consequently, on the pavement layers distresses. The study considered three loading modes and found that field strain responses differ significantly by changing the modulus inputs within the MEPDG method.

#### Summary and Conclusion

Based on the above-presented literature review, it was found that all four models rely on modified and unmodified binders with datasets limited to a specific area region. In terms of models' performance, it was concluded that the models have varying performances based on the temperature, frequency, and country of application.

This section also presented recent calibration techniques found in the literature that opens the doors to develop prediction models with better accuracy by considering the effect of high and low temperatures on prediction performance.

Based on this section, the following can be concluded:

- Error minimization technique has been used in several studies to calibrate the models.
- Witzack models have many inputs that are not usually presented in Job Mix
   Formulas (JMFs) in Qatar, such as viscosity and effective binder content by volume.
- Witzack models have many regression-fitting factors that would result in overfitting once error minimization is applied over the model.
- Within the Hirsch model, the regression constant of 4,200,000 replaces the aggregate young modulus. The error resulting from this constant decreases significantly if the mixture aggregate young modulus in psi unit is close to this constant.

- Artificial Neural Network (ANN) and Machine Learning (ML) techniques were
  adopted in several studies to replace conventional models such as Hirsch and
  Witzack models. However, this practice needs a comprehensive dataset and
  many testing points.
- The effect of climate is introduced in the reviewed validation and calibration techniques by considering local materials and mixing practices of the targeted study area.
- The literature has no general agreement on the performance of the reviewed prediction models. Every model shows varying performance based on the temperature and materials.
- The reviewed studies evaluate the models' predictive performance solely based
  on statistical analysis. The effect of the prediction model calibration was not
  interconnected with the predicted functional performance of the pavement
  structures, such as fatigue and rutting.

Based on the above-drawn conclusion, Witzack 1-37A and 1-40D models will be eliminated from the validation and calibration part due to high numbers of needed inputs which are usually not presented in Qatar Job Mix Formulas (JMF) (sample is attached to Appendix B), and due to a high number of fitting factors needed to compute the dynamic modulus values. Accordingly, the following sections will focus on evaluating and calibrating the Hirsch and Alkhateeb models for Qatar.

#### CHAPTER 3: METHODOLOGY AND DATA COLLECTION

#### Introduction

This chapter describes the research methodology developed to achieve the stated study objectives. The chapter also goes into the considered calibration technique and displays the data acquired for this purpose. The chapter also shows the statistical metrics and their interpretations used to evaluate the results.

### Methodology

Based on the reviewed literature and the defined gap in this study area, the following methodology has been considered.

- Collecting laboratory testing points of Qatar asphalt binder and mixtures modulus covering a wide range of local materials, temperatures, and frequencies tested based on Qatar guidelines.
- Substitute binder and mixture properties in Hirsch and Alkhateeb model and find the predicted dynamic modulus.
- Compare the predicted dynamic modulus with the measured values.
- Validate both Hirsch and Alkhateeb models based on bias and goodness-offit measures.
- Calibrate both models by using the error minimization tool in excel software and define new fitting factors.
- Study the effect of models' calibration on the predicted performance of asphalt pavement structures used in Qatar by performing mechanistic-empirical pavement analysis.

#### **Data Collection**

The master curve equation of the binder and mixture modulus considered in this study is represented in Equation (9) (AASHTO, 2017).

$$\log |M^*| = \delta + \frac{\alpha}{1 + e^{-\beta - \gamma \log f_r}}$$
(9)

Where  $|M^*|$  is the modulus value of either the mixture or binder,  $(\delta, \alpha, \beta, \beta)$  and  $(\delta, \alpha, \beta)$  are the fitting parameters, and  $f_r$  is the reduced frequency defined in Equation (10) (AASHTO, 2017).

$$f_r = f. a(T) \tag{10}$$

Where a(T) is the temperature shift coefficient that can be calculated using Equation (11) (AASHTO, 2017).

$$\log(a(T)) = a_1(T^2 - T_{ref}^2) + a_2(T - T_{ref})$$
(11)

Where  $(a_1 \text{ and } a_2)$  are the temperature shift factors and  $(T \text{ and } T_{ref})$  are the actual testing temperature and curve reference temperature, respectively.

Binder master curve parameters are collected from two studies conducted in Qatar (L. K. Roja et al., 2021) (L. K. Roja et al., 2022) to find the  $|G^*|_b$  that needed to predict the binder dynamic moduli in both Hirsch and Alkhateeb models at different frequencies and temperatures. The collected binder types represent the country's most common binders used in recently constructed road projects. The dataset includes an unmodified binder, Polymer Modified Binder (PMB) containing styrene-butadienestyrene (SBS), Crumb Rubber Modified Binder (CRMB), and Reclaimed Asphalt Binder (RAB) with different mixing percentages mixed with unmodified PEN 60/70 (PG64S-22) binder. All used materials are admitted for use in Qatar. The dataset represents a wide range of Superpave PG grading. The binder types and relevant master curve coefficients are presented in Table 8.

Table 8. Binder Types and Coefficients of Binder Master Curves

D: 1 T	Binder	Master curve coefficients								
Binder Type	Grade	δ	α	β	Y	<b>a</b> 1	<b>a</b> 2	Tref		
Unmodified	PEN 60/70*	-0.7380	8.8480	-0.0330	0.5880	0.0010	-0.1690	46.0		
PMB	PG 76E-10	-0.9450	10.4730	0.0960	0.3080	0.0007	-0.1430	46.0		
CRMB	PG 76E-10	1.5470	7.3020	0.5445	0.3925	0.0008	-0.1511	21.0		
15% RAB	PG 70S-22	0.0514	8.3672	0.2467	0.4401	0.0007	-0.1438	46.0		
25% RAB	PG 70S-16	0.7145	7.9034	0.0001	0.4414	0.0007	-0.1437	46.0		
35% RAB	PG 70S-10	0.0001	9.7364	0.0001	0.3399	0.0007	-0.1437	46.0		

<sup>\*</sup> PEN 60/70 binder is equivalent to grade PG64-22

Besides the binder dataset, twenty asphalt mixtures master curves are collected from several studies (L. K. Roja et al., 2021) (L. K. Roja et al., 2022) (Sebaaly et al., 2020) and construction projects in Qatar. The collected data set included mixtures used in the Wearing Course (WC) and Asphalt Base Course (ABC) with 19 and 25mm Nominal Maximum Aggregate Size (NMAS), respectively. The asphalt mixtures represented the materials and designs used in Qatar and were tested based on Qatar Construction Specification (QCS), 2014 (MOE, 2014). The binder content percentage (BC%) of the collected data ranges between 3.4% - 4.3%, while the Air Void ratio (V<sub>a</sub>) of the test specimens ranges between 5.2% - 7.0%. The master curve coefficients of the collected mixtures are presented in Table 9. The composition and volumetrics of the collected mixtures are shown in Table 10.

It is to be noted that each binder and mixture modulus master curve was constructed after conducting the testing on three replicates and finding the average value of the modulus after assuring the low variability in the modulus value between the replicates as per Qatar guidelines.

Table 9. Coefficients of Mixture Master Curves of the Study Dataset

HMA				Master c	urve coefficients		
No.	δ	α	β	Y	<b>a</b> 1	<b>a</b> 2	Tref (°C)
1	1.3309	3.1640	1.1334	0.3973	0.000610	-0.164685	20
2	1.8844	2.4852	1.0388	0.5557	0.000720	-0.164155	20
3	1.2225	3.1417	1.2301	0.5229	0.001994	-0.216857	20
4	-7.9430	12.8600	2.3860	0.1690	0.000831	-0.178000	21
5	-2.1850	6.9960	1.6330	0.2560	0.000737	-0.172243	20
6	-2.3190	6.9330	1.8690	0.2780	0.000899	-0.180347	20
7	-2.2800	6.8980	1.7860	0.2660	0.000948	-0.174775	20
8	-2.2210	6.8700	1.7580	0.2660	0.001050	-0.184469	20
9	-2.2280	6.7510	2.0530	0.2750	0.000920	-0.176847	20
10	-2.4620	7.0660	1.8630	0.2810	0.001206	-0.192653	20
11	-2.2700	6.9550	1.8850	0.2370	0.000952	-0.176755	20
12	-2.1560	6.8590	2.0260	0.2650	0.001154	-0.191043	20
13	-0.3760	4.9740	1.5660	0.2910	0.000510	-0.151924	20
14	-2.1410	6.7370	1.7590	0.2730	0.000720	-0.161181	20
15	-2.3330	6.8840	2.0900	0.3700	0.001066	-0.178346	20
16	-2.2560	6.8740	2.1550	0.2720	0.000691	-0.169981	20
17	4.3980	-1.8998	-0.1937	-0.5781	0.000376	-0.137171	20
18	4.3755	-2.0522	-0.6525	-0.5910	0.000664	-0.150427	20
19	4.4333	-2.2062	-0.6040	-0.4591	0.000118	-0.124096	20
20	4.4018	-1.9586	-0.7128	-0.4767	0.000263	-0.134852	20

Table 10. Mixtures Composition and Volumetrics of the Study Dataset

HMA	Binder	Binder	Mixture	NMAS	Aggregate	BC	Va	VMA	VFA
No.	Type	Grade	Rule	[mm]	Type	%	[%]	[%]	[%]
1	PMB	PG76E-10	ABC	25	Gabbro	4.10	6.10	16.20	62.60
2	PMB	PG76E-10	WC	19	Gabbro	4.30	6.00	15.80	61.90
3	Unmodified	PEN60/70	ABC	25	Gabbro	3.40	6.65	15.00	55.70
4	CRMB	PG76E-10	ABC	25	Gabbro	3.90	6.70	16.10	58.40
5	Unmodified	PEN60/70	WC	19	Gabbro	3.90	6.20	15.80	60.80
6	Unmodified	PEN60/70	WC	19	Gabbro	3.80	6.50	15.90	59.10
7	Unmodified	PEN60/70	WC	19	Gabbro	3.40	6.40	14.70	56.50
8	Unmodified	PEN60/70	WC	19	Gabbro	3.60	6.50	15.50	58.10
9	Unmodified	PEN60/70	WC	19	Gabbro	3.90	6.70	16.50	59.40
10	Unmodified	PEN60/70	WC	19	Gabbro	4.10	5.20	14.60	64.40
11	PMB	PG76E-10	WC	19	Gabbro	4.30	6.10	15.30	60.10
12	PMB	PG76E-10	WC	19	Gabbro	4.10	6.00	14.40	58.30
13	PMB	PG76E-10	WC	19	Gabbro	4.10	5.20	14.20	63.40
14	PMB	PG76E-10	WC	19	Gabbro	4.00	5.90	14.80	60.10
15	PMB	PG76E-10	WC	19	Gabbro	4.30	6.00	15.70	61.80
16	PMB	PG76E-10	WC	19	Gabbro	4.30	5.70	15.00	62.00
17	Unmodified	PEN60/70	ABC	25	Gabbro	3.90	6.90	14.70	53.20
18	15 % RAB	PG70S-22	ABC	25	Gabbro	3.70	6.80	14.70	53.40
19	25 % RAB	PG70S-16	ABC	25	Gabbro	3.50	6.90	14.70	53.10
20	35 % RAB	PG76S-10	ABC	25	Gabbro	3.50	6.90	15.40	55.20

In order to represent the aggregate grading in all 20 mixtures in this study, minimum and maximum percent passing at each sieve seize through the whole mixtures are collected and represented in Figure 5 versus grading envelop of Qatar Construction Specification (QCS) 2014. Based on Figure 5, it is clearly noticed that all mixtures follow a well-graded aggregate composition.

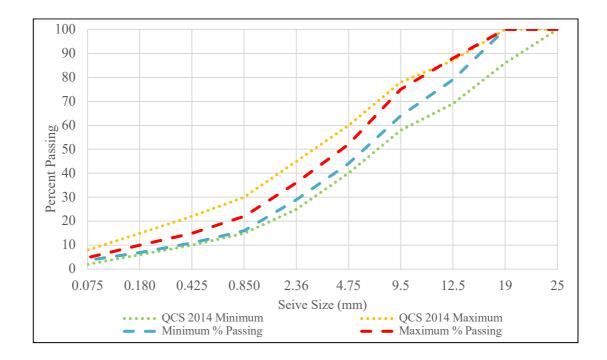


Figure 5. Aggregate Grading Envelop of QCS 2014 vs. Grading Envelop in the Study Dataset

Figure 6 below shows all PEN60/70 master curves of the collected dataset.

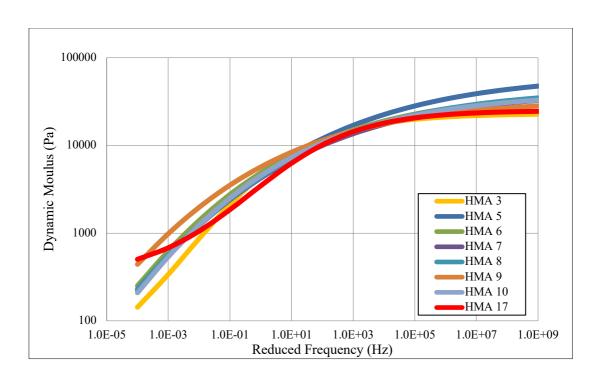


Figure 6. PEN60/70 Mixtures Master Curves of the Collected Dataset

Figure 7 below shows all PG67E-10 master curves of the collected dataset.

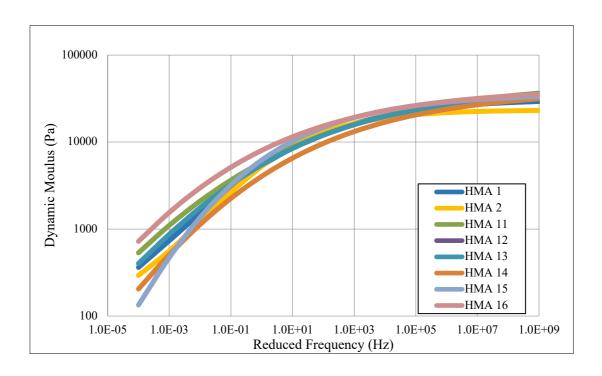
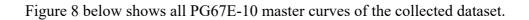


Figure 7. PG76E-10 Mixtures Master Curves of the Collected Dataset



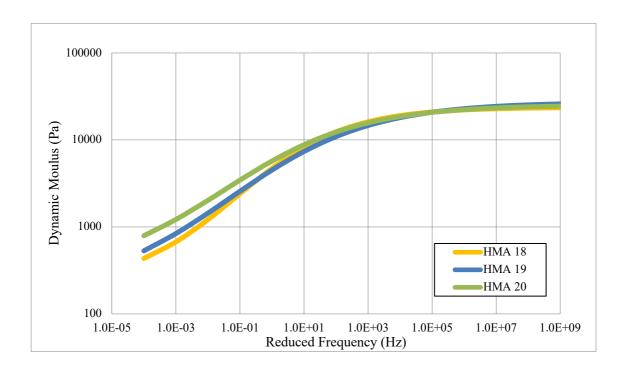


Figure 8. RAB Mixtures Master Curves of the Collected Dataset

Figure 9 below shows the only collected CRMB master curve of the collected dataset.

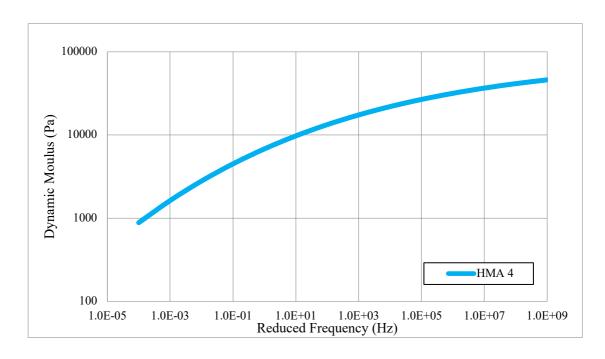


Figure 9. CRMB Mixture Master Curve of the Collected Dataset

# Validation and Calibration Technique

For the validation and calibration of the Hirsch and Alkhateeb models, 393 measured dynamic moduli for 20 mixtures are used for comparison with the predicted values from the two models. A broad spectrum of frequencies and temperatures is included in the collected dataset. Table 11 shows the testing temperatures and frequencies of the collected dataset of mixtures.

Table 11. Testing Temperatures and Frequencies of Mixtures Dataset

Group No.	HMA No.*	Temperature (°C)	Frequency (Hz)
Group 1	1, 2, 3, 4	4, 20, and 45	0.1, 1.0, and 10
Group 2	5, 6, 7, 8, 9, 10	4, 40, and 40	0.1, 0.2, 0.5, 1.0, 2.0, 5.0, 10.0, and 20.0
Group 3	11, 12, 13, 14, 15, 16	4, 20, and 45	0.1, 0.2, 0.5, 1.0, 2.0, 5.0, 10.0, and 20.0
Group 4	17, 18, 19, 20	5, 15, 25, 35, 45	0.1, 1.0, and 10.0

<sup>\*</sup> HMA numbers based on Table 9 and Table 10

After comparing the Hirsch and Alkhateeb models' predicted dynamic modulus values versus the measured ones, the coefficient of determination ( $R^2$ ) and  $S_e/S_y$  values were computed as goodness-of-fit measures using Equations (12), (13), and (14) (Yousefdoost et al., 2013).

$$R^{2} = 1 - \frac{(n-k-1)}{(n-1)} \left(\frac{S_{e}}{S_{v}}\right)^{2}$$
 (12)

Where:

n = Number of testing points

k =Count of regression coefficients in the prediction model

 $S_e$  = Standard error of estimation

 $S_y$  = Standard deviation of the measured values

Where:

$$S_{y} = \sqrt{\frac{\sum_{i=1}^{n} (E_{mi}^{*} - \bar{E}_{m}^{*})^{2}}{(n-1)}}$$

$$S_{e} = \sqrt{\frac{\sum_{i=1}^{n} (E_{pi}^{*} - \bar{E}_{mi}^{*})^{2}}{(n-k-1)}}$$
(13)

Where:

 $E_{mi}^*$  = Measured dynamic modulus value

 $\bar{E}_m^*$  = Average of dynamic modulus measured values

 $E_{pi}^* =$  Dynamic modulus predicted value

In order to interpret the computed values of  $R^2$  and  $S_e/S_y$ , the criterion in Table 12 is followed (Pellinen, Kristiina, 2001).

Table 12. Statistical Criterion for Association of Measured E\* versus predicted E\*

Criterion	R <sup>2</sup> (%)	S <sub>e</sub> /S <sub>y</sub>	
Excellent	> 90	< 0.35	
Good	70-89	0.36-0.55	
Fair	40-69	0.56-0.75	
Poor	20-39	0.76-0.90	
Very Poor	<19	>0.90	

Statistical bias has also been used to determine both models' predictive performance by finding the slope and intercept of the linear trend line of the measured vs. predicted plot. The higher prediction performance would be subjected to a slope closer to one and an intercept closer to zero (Solatifar, 2020).

To calibrate the models, the excel solver is utilized to minimize the error and maximize the fit by reducing the Route Mean Square Error (RMSE) that computed using formula shown in equation (15) (Cano-Ortiz et al., 2022).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (E_{mi}^{*} - E_{pi}^{*})^{2}}{n}}$$
 (15)

Where:

RMSE = Root Mean Square Error

Based on the error minimization results, new fitting parameters for the Hirsch model (i.e.,  $h_1$ ,  $h_2$ , and  $h_3$ ) are found instead of 20, 650, and 0.58, respectively, in Equation (5). The same approach is followed for the Alkhateeb model to find  $k_1$  -  $k_6$  coefficients instead of 3, 90, 1.45, 0.66, 1100, and 0.13, respectively, in Equation (8).

## Methodology Summary

The following steps represent the methodology summary that is explained in above sections:

- 1- Substitute the volumetrics (VMA/VFA) and G\* in both Hirsch (Equation (4) and Alkhateeb (Equation (5) models and find E\* using excel.
- 2- Calculate RMSE using Equation (15) after comparing predicted vs. measured E\*.
- 3- Use solver in excel in order to minimize the RMSE by changing the empirical fitting parameters of each model that is determined in the previous chapter.

- 4- Define the new fitting parameters after conducting the error minimization.
- 5- Calculate the R<sup>2</sup>, Se/Sy, Slope, and Intercept for each scenario.

#### **CHAPTER 4: RESULTS AND DISCUSSION**

#### Introduction

In this chapter, the validation and calibration results and the statistical findings are presented, discussed, and compared to the reviewed literature. The chapter also includes the aforementioned sensitivity study conducted on the Hirsch and Alkhateeb models. The chapter's conclusion displays the findings of functional performance analysis done on Qatari pavement sections before and after calibration to emphasize the significance of the calibration.

## Validation and Calibration

The R<sup>2</sup> value of prediction performance for the Hirsch model before and after calibration is 87.2% and 89.2%, respectively. Figure 10 and 11 show measured versus predicted E\* before and after calibration of the Hirsch model, respectively. The R<sup>2</sup> value of prediction performance for the Alkhateeb model before and after calibration is 70.8% and 89.2%, respectively. Figure 12 and 13 show measured versus predicted E\* before and after calibration of the Alkhateeb model, respectively.

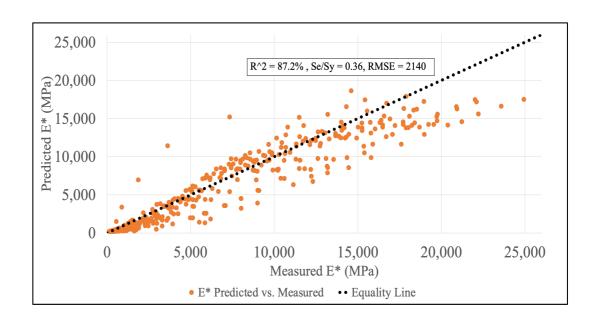


Figure 10. Predicted vs. Measured E\* before Calibration – Hirsch Model

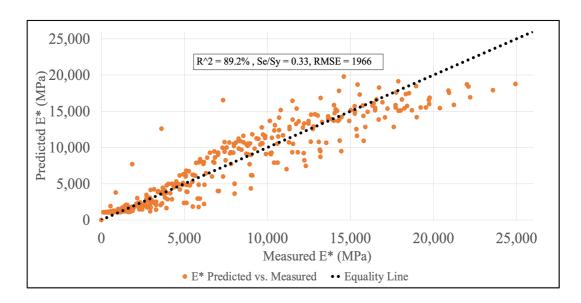


Figure 11. Predicted vs. Measured E\* After Calibration – Hirsch Model

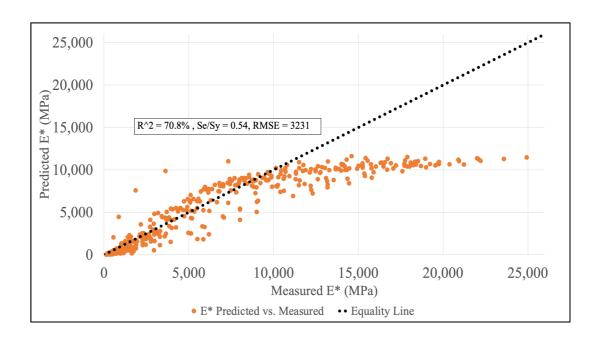


Figure 12. Predicted vs. Measured E\* before Calibration – Alkhateeb Model

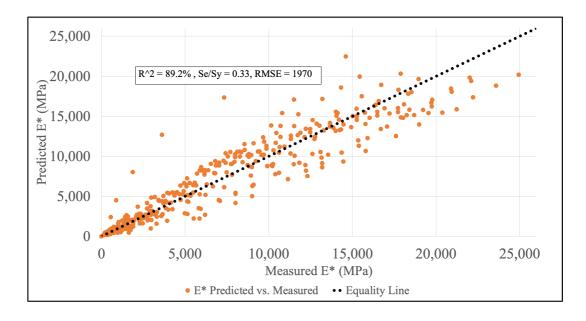


Figure 13. Predicted vs. Measured E\* after Calibration – Alkhateeb Model

Table 13 shows the goodness-of-fit measures and their correlation for both Hirsch and Alkhateeb models before and after calibration.

Table 13. Hirsch and Alkhateeb Overall Models Goodness-of-fit Values

Model		Before Ca	1	After Calibration				
	R <sup>2</sup>	Correlation	Se/Sy	Correlation	R <sup>2</sup>	Correlation	Se/Sy	Correlation
Hirsch	87.2%	Good	0.36	Good	89.2%	Good	0.33	Excellent
Alkhateeb	70.8%	Good	0.54	Good	89.2%	Good	0.33	Excellent

Table 14 shows bias measures for both Hirsch and Alkhateeb models before and after calibration.

Table 14. Hirsch and Alkhateeb Overall Models Bias Measures

Model	Be	fore Calibration	After Calibration		
Model	Slope	Intercept	Slope	Intercept	
Hirsch	0.848	214.37	0.900	716.98	
Alkhateeb	0.612	1116.10	0.900	652.75	

As presented in Table 13 and 14, the Hirsch model shows high prediction performance without calibration with an R<sup>2</sup> value of 87.2% and a slope of 0.848. After calibration, the R<sup>2</sup> value improved slightly to 89.2%, and the slope improved to 0.900. This improvement of 2.0% in R<sup>2</sup> value is close to the study of Robbins and Timm outcomes (Robbins & Timm, 2011) for the southeastern United States asphalt mixtures that used a similar error minimization approach to improve the Hirsch model R<sup>2</sup> value from 89.7% to 91.1%.

Alkhateeb model shows reasonable prediction performance prior to calibration over a wide variety of frequencies and temperatures. However, the findings show that the model underpredicts the  $E^*$  through a significant number of testing points with exponential trends resulting in a low  $R^2$  value of 70.8% and a high bias at the slope of 0.612. The calibration of the model improved the  $R^2$  value to become 89.2%.

The predictive performance of both the Hirsch and Alkhateeb models comes in contrary to Yousefdoost et al. (Yousefdoost et al., 2013) study, which concluded that none of the Hirsch and Alkhateeb models are suitable for use for Australian asphalt mixtures developed for a hot climate country.

It to be note that both models after calibration showed almost same goodnessof-fit and bias and this would be due to that both models derived from the rule of mixture and has quiet similar derivation, inputs, and assumptions.

## Sensitivity Analysis

Sensitivity analysis was conducted for the calibrated Hirsch and Alkhateeb models to investigate the sources of prediction errors and relate the results to the local Qatar conditions. R<sup>2</sup> and S<sub>e</sub>/S<sub>y</sub> were calculated for the prediction performance for both Hirsch and Alkhateeb models by varying one factor of binder type, temperature, or frequency at a time while keeping the other factors constants. Table 15 and 16 present the R<sup>2</sup> values of the Hirsch and Alkhateeb models for several binder types, respectively. Table 17 and 18 show the R<sup>2</sup> of the Hirsch and Alkhateeb models for several testing temperatures, respectively.

Table 19 and 20 present the R<sup>2</sup> of the calibrated Hirsch and Alkhateeb models for several frequencies, respectively.

Table 15. Binder Sensitive Predictive Performance of the Hirsch Model

Bind	ler Type		PEN 60/	70	PG 76E-	10	RAB (15, 2	5, 35)%
No.	of Data Po	ints	169		164		45	
00	. Before	$\mathbb{R}^2$	94.40%	Excellent	86.40%	Good	63.10%	Fair
rati	Delore	Se/Sy	0.24	Excellent	0.37	Good	0.63	Fair
Calibration	A 64 a	R <sup>2</sup>	94.60%	Excellent	90.50%	Excellent	50.90%	Fair
೭	After	Se/Sy	0.23	Excellent	0.31	Excellent	0.73	Fair

Table 16. Binder Sensitive Predictive Performance of the Alkhateeb Model

Bind	Binder Type		PEN 60/70		PG 76E-	PG 76E-10		25, 35)%
No.	of Data Po	ints	169		164		45	
uc	.5 Before	R <sup>2</sup>	78.6%	Good	65.9%	Fair	70.8%	Good
Calibration	before	Se/Sy	0.47	Good	0.59	Fair	0.58	Fair
alib	A 64	R <sup>2</sup>	95.1%	Excellent	91.1%	Excellent	41.2%	Fair
Ü	ਤੋਂ After Se		0.23	Excellent	0.30	Excellent	0.83	Poor

Table 17. Temperature Sensitive Predictive Performance of the Hirsch Model

Tem	Temperature		4 and 5 °C		15, 20 aı	nd 25 °C	35, 40 and	45 °C
No.	of Data Po	oints	122		134		137	
uc	Dafama	R <sup>2</sup>	35.6%	Poor	42.8%	Fair	17.5%	Very Poor
Calibration	Before	Se/Sy	0.81	Poor	0.77	Poor	0.92	Very Poor
Igip	A Ct	R <sup>2</sup>	51.0%	Fair	40.6%	Fair	36.9%	Poor
౮	After	Se/Sy	0.71	Fair	0.78	Poor	0.80	Poor

Table 18. Temperature Sensitive Predictive Performance of the Alkhateeb Model

Tem	Temperature		4 and 5 °C	C	15, 20 aı	nd 25 °C	35, 40 and	35, 40 and 45 °C		
No.	of Data Po	ints	122		134		137			
00	Before	R <sup>2</sup>	-94.8%	Very Poor	53.9%	Fair	15.0%	Very Poor		
rati	Delore	Se/Sy	1.41	Very Poor	0.69	Fair	0.93	Very Poor		
Calibration	A 64	R <sup>2</sup>	48.6%	Fair	44.4%	Fair	38.4%	Poor		
೭	After	Se/Sy	0.73	Fair	0.75	Fair	0.79	Poor		

Table 19. Frequency Sensitive Predictive Performance of the Hirsch Model

Frequency	*	Before Calibration				After Calibration			
(Hz)	n*	R <sup>2</sup>		Se/Sy		R <sup>2</sup>		Se/Sy	
0.1	68	78.30%	Good	0.48	Good	81.90%	Good	0.44	Good
0.2	39	81.70%	Good	0.45	Good	84.90%	Good	0.40	Good
0.5	36	88.50%	Good	0.36	Good	90.70%	Excellent	0.32	Excellent
1	68	89.00%	Good	0.34	Excellent	89.90%	Good	0.32	Excellent
2	36	90.00%	Excellent	0.33	Excellent	92.80%	Excellent	0.28	Excellent
5	36	89.40%	Good	0.34	Excellent	92.50%	Excellent	0.29	Excellent
10	68	83.40%	Good	0.42	Good	83.70%	Good	0.41	Good
20	39	84.60%	Good	0.41	Good	88.90%	Good	0.35	Excellent

<sup>\*</sup> n = Number of data points

Table 20. Frequency Sensitive Predictive Performance of the Alkhateeb Model

Frequency	n*	Before Calibration			After Calibration				
(Hz)		R <sup>2</sup>		Se/Sy	7	R <sup>2</sup>		Se/Sy	,
0.1	68	80.60%	Good	0.46	Good	83.80%	Good	0.42	Good
0.2	39	80.40%	Good	0.48	Good	86.50%	Good	0.40	Good
0.5	36	80.60%	Good	0.48	Good	91.20%	Excellent	0.33	Excellent
1	68	78.70%	Good	0.48	Good	89.00%	Good	0.35	Excellent
2	36	71.50%	Good	0.59	Fair	92.60%	Excellent	0.30	Excellent
5	36	63.70%	Fair	0.66	Fair	92.60%	Excellent	0.30	Excellent
10	68	59.70%	Fair	0.67	Fair	81.70%	Good	0.45	Good
20	39	47.30%	Fair	0.79	Poor	90.20%	Excellent	0.34	Excellent

<sup>\*</sup> n = Number of data points

Figure 14 below shows the HMA 9 measured master curve versus the predicted uncalibrated and calibrated master curves as a sample of binder PEN60/70 mixtures.

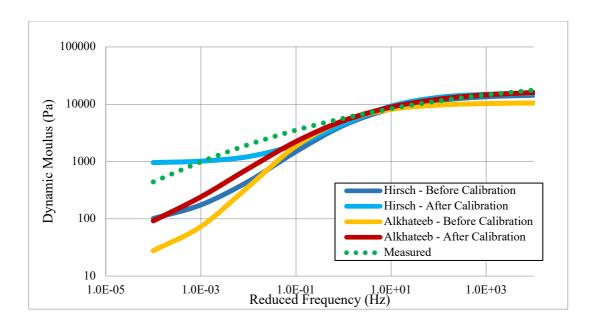


Figure 14. HMA 9 Measured and Predicted Uncalibrated and Calibrated Hirsch and Alkhateeb Models Master Curves

Figure 15 below shows the HMA 9 measured master curve versus the predicted uncalibrated and calibrated master curves as a sample of binder PG76E-10 mixtures.

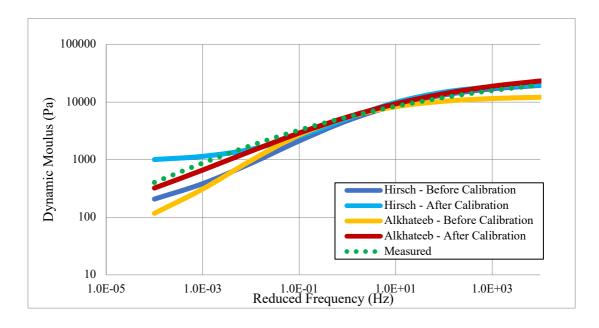


Figure 15. HMA 13 Measured and Predicted Uncalibrated and Calibrated Hirsch and Alkhateeb Models Master Curves

Figure 16 below shows the HMA 20 measured master curve versus the predicted uncalibrated and calibrated master curves as a sample of RAB mixtures.

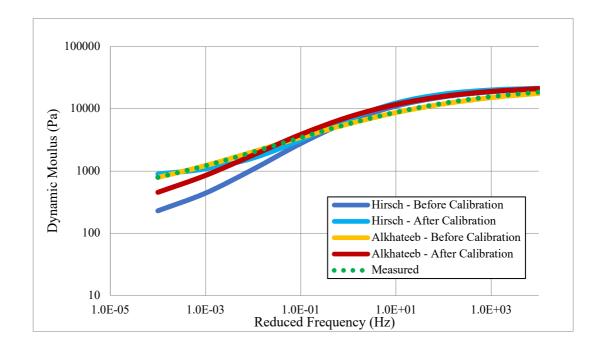


Figure 16. HMA 20 Measured and Predicted Uncalibrated and Calibrated Hirsch and Alkhateeb Models Master Curves

Figure 17 below shows the HMA 4 measured master curve versus the predicted uncalibrated and calibrated master curves as a sample of CRMB mixture.

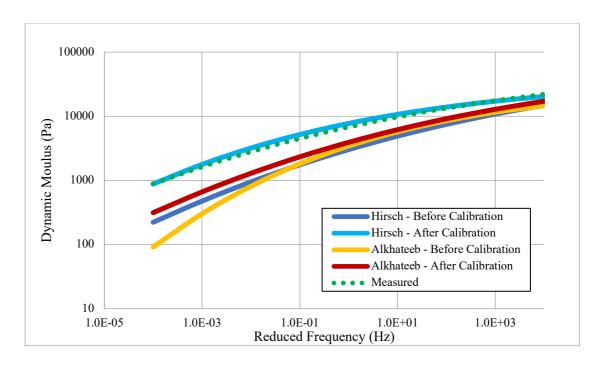


Figure 17. HMA 4 Measured and Predicted Uncalibrated and Calibrated Hirsch and Alkhateeb Models Master Curves

Sensitivity analysis results conclude that the calibrated Alkhateeb model shows equivalent performance to the calibrated Hirsch model for all types of binder mixtures. However, uncalibrated models offer superior performance to the Hirsch model in a PEN60/70 and PG 76E-10 but lower performance in RAB mixtures. This can be because the Alkhateeb model was developed based on a dataset of aged materials (Al-Khateeb et al., 2006). It is noticed that the calibration reduced the prediction performance of both models for RAB mixtures.

For testing frequency sensitivity, the uncalibrated Hirsch model shows superior performance over the Alkhateeb model, as the last has a significantly increasing bias toward higher frequencies. After calibration, the Alkhateeb model bias at high frequency is reduced significantly.

For temperature sensitivity, both uncalibrated models show very poor predictive performance at high testing temperatures of 35-45 °C, which has been improved after

calibration, which agrees with (Far et al., 2009) study that showed a noticeable bias of the Hirsch model at high temperatures. Looking at Figure 12, Tables 18 and 20, it can be inferred that the uncalibrated Alkhateeb model has poor prediction at testing temperatures 4 – 5 °C and 10 – 20 Hz testing frequency which is improved after calibration, as shown in Figure 13. This result agrees with the outcomes of (Yousefdoost et al., 2013) which was conducted on Australian Asphalt mixtures, and (Far et al., 2009) study, which was conducted on a comprehensive dataset of Witzack, Federal Highway Administration (FHWA), and others. The Hirsch model performance at low temperature was higher than the Alkhateeb model, which agrees with (Far et al., 2009) study outcome. However, the low predictability at such low temperatures is not a concern in Qatar because these temperatures are rare, as shown in Figure 1. Table 21 and 22 show the fitting parameters for Hirsch and Alkhateeb models, respectively.

Table 21. Fitting Parameters for the Hirsch Model (Equation (4)

Fitting Factor	Before Calibration	After Calibration		
${h_1}$	20	348		
$h_2$	650	897		
<u>h</u> <sub>3</sub>	0.58	0.63		

Table 22. Fitting Parameters for the Alkhateeb Model (Equation (8)

Fitting Factor	Before Calibration	After Calibration
${\mathrm{k_{1}}}$	3.00	6.76
$k_2$	90.00	92.69
$k_3$	1.45	2.67
$k_4$	0.66	0.42
$k_5$	1100.00	255.69
$k_6$	0.13	0.01

## Pavement Performance Analysis

This section compares the functional distresses of pavement profiles typically used in Qatar, considering the modulus of the Hirsch model before and after calibration. This was accomplished by evaluating the rutting and fatigue cracking performance using the Mechanistic-Empirical Asphalt Pavement Analysis (MEAPA) web application developed by (Kutay & Lanotte, 2020). This web-based application considers the same traffic inputs of the MEPDG (NCHRP, 2004). The MEAPA climatological inputs are equivalent to the MEPDG Enhanced Integrated Climatic Model (EICM). Equation (9) presented earlier in this report is considered in the MEAPA application to interpret the master curve. Calculations of the loading frequency are based on the concepts used by the MEPDG, where the stress pulse is assumed to be haversine, and its duration relies on the vehicle's speed and the depth from the wearing course top to the point of interest. In addition, the basic propagation of the thermal crack length within the depth of the pavement is found based on a simplified Paris law. MEAPA application has several climatological profiles covering several areas and climates worldwide that can be chosen as preliminary analysis to have a more accurate site-specific simulation.

Three pavement structures for different road hierarchies and traffic loading conditions are employed in the analysis to simulate the actual pavement structures used in Qatar.

Figure 18 shows pavement structures for the collected three pavement sections for different road reliabilities of 75%, 90%, and 97% corresponding to local, arterial, and expressway road hierarchies, respectively, based on Qatar Highway Design Manual (QHDM) (MOTC, 2015). The selected three pavement structures have three different

traffic loading levels indicated as Equivalent Single Axle Loads (ESALs).

Figure 19 shows a binder-type matrix for the collected pavement structures for the asphalt Wearing Course (WC), Asphalt Intermediate Course (AIC), and Asphalt Base Course (ABC) layers.

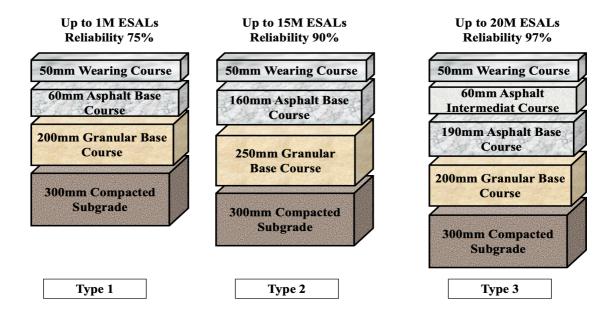


Figure 18. Illustration of Three Pavement Structures

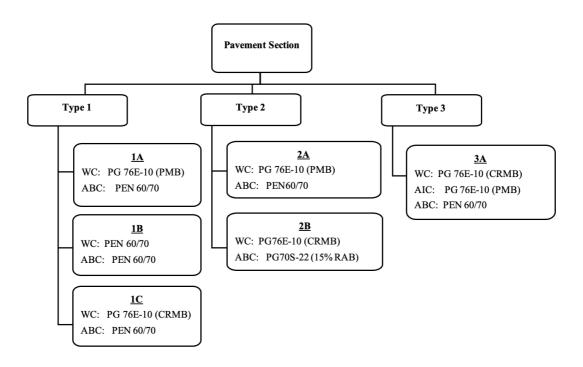


Figure 19. Binder Type Matrix for the Collected Pavement Structures

In the MEAPA web application, the nearest available climatological profile to the State of Qatar was for Dammam city, located in the eastern area of Saudi Arabia. Dammam city is a 180 km air distance from Doha city, the capital of Qatar. In order to validate the Dammam city climatological profile to represent Qatar, monthly mean temperatures data for Dammam was collected from the Saudi National Center for Meteorology (NCM) website (NCM, n.d.) and compared with the data collected from the Qatar Meteorology Department website (QMD, n.d.-a). Figure 20 shows the mean monthly temperature normals for Doha and Dammam cities. As shown in Figure 20, Doha and Dammam have similar mean temperature climatological normals with only minor differences. Accordingly, Dammam's climatological profile is considered valid to represent Qatar's climate. Table 23 shows the traffic inputs used in the ME analysis on the MEAPA website.

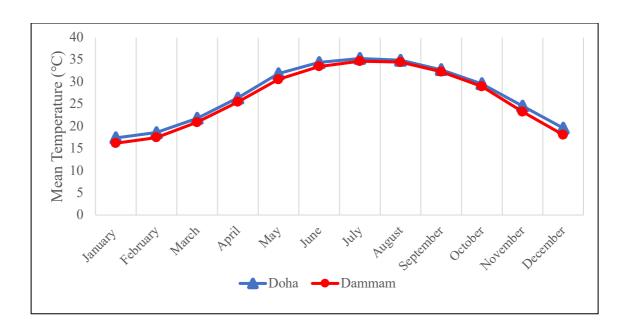


Figure 20. Mean monthly temperatures for Doha and Dammam cities

Table 23. Traffic Load Inputs for ME Analysis on the MEAPA Website

		Pavement Struc	ture*
Traffic Parameter	Type 1	Type 2	Type 3
AADT** (veh/day)	220	3344	6672
Lane Factor	1.00	0.90	0.60
Distribution Factor	0.55	0.55	0.55
Speed (kph)	50	60	100
Analysis Period (yrs)	20	20	20

<sup>\*</sup> Refer to Figure 18 and Figure 19 for pavement structures and binder types

It is to be noted that the vehicle fleet profile, monthly distribution, and other related entries were kept as default in the MEAPA software. Table 24 shows the performance results and percent change before and after calibration for pavement structures Type 1, 2, and 3. Detailed analysis results are attached to Appendix A.

<sup>\*\*</sup> AADT stands for Annual Average Daily Traffic

Table 24. Change in the Fatigue and Rutting due to Hirsch model Calibration

<b>Pavement Section*</b>	Fatigue (m/km)		Percent	Rutting (cm)		Percent	
<b>Calibration Status</b>	Before	After	Change	Before	After	Change	
1A	126.06	157.50	24.94%	0.51	0.58	13.73%	
1B	143.47	224.51	56.49%	0.51	0.53	3.92%	
1C	188.31	180.30	-4.25%	0.53	0.53	0.00%	
2A	662.23	892.19	34.73%	0.71	0.79	11.27%	
2B	870.40	746.44	-14.24%	0.71	0.66	-7.04%	
3A	578.69	615.22	6.31%	0.64	0.64	0.00%	
Average =			17.33%			3.65%	

<sup>\*</sup> Refer to Figure 18 and Figure 19 for pavement structures and binder types

As shown in Table 24, the difference in the predicted distress, whether a decrease or increase due to calibration, is more significant in the fatigue life predictions than the rutting predictions. For the case of fatigue life, the difference due to local calibrations reached more than 50%, with an average value of 17.33%. This result agrees with (Cooper et al., 2015) study, which concluded that the predicted alligator cracking would change by 60% with changing the dynamic modulus value. In addition, this result agrees with (Cheng et al., 2021) study, which concluded that changing the E\* value in the MEPDG analysis procedure would significantly change the predicted field strains. Accordingly, using locally calibrated is required to give more reliable pavement performance prediction and designs.

Despite that R<sup>2</sup> of the Hirsch model prediction performance was improved by around 2%, which is considered insignificant in another study (Robbins & Timm, 2011), the new dynamic modulus values have changed the predicted distresses of pavement structures. This implements the importance of investigating the practical effect of calibration in this field.

#### **CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS**

#### Conclusions

The study reviewed the Hirsch, Witzack 1-37A, Witzack 1-40D, and Alkhateeb models and evaluated and calibrated the Hirsch and Alkhateeb models based on local Qatari materials representing countries with hot and humid climates. The research study considered the empirical calibration method and highlighted the sensitivity of the models' calibration on the predicted functional pavement performance by conducting the MEAPA method analysis on pavement structures before and after calibration. The results of the investigation mentioned above lead to the following conclusions:

- Hirsch model showed high prediction performance for Qatar asphalt mixtures with an R<sup>2</sup> value of 87.2% prior to calibration. Alkhateeb model, however, showed lower performance with an R<sup>2</sup> value of 70.8%. The calibration improved the R<sup>2</sup> value of the Hirsch and Alkhateeb models to 89.2% for both.
- The sensitivity analysis showed that the Hirsch and Alkhateeb models had higher performance in PEN 60/70 and PG 76E-10 mixtures and lower performance in RAB mixtures.
- While the implemented calibration technique improved the overall performance of both models, more bias was introduced for RAB mixtures in both models after calibration.
- Both uncalibrated Hirsch and Alkhateeb models had a low predictive performance at test temperatures higher than 35°C, which improved with model calibration.
- Hirsch model showed consistent performance over-tested frequencies between
   0.1 and 20 Hz with an R<sup>2</sup> value ranging between 70 and 90%. However, the
   uncalibrated Alkhateeb model showed significant bias at high frequencies.

- The uncalibrated Alkhateeb model showed poor performance at low temperatures of  $4-5^{\circ}\text{C}$  and a frequency of 10-20 Hz. This performance was improved as a result of the model calibration.
- Mechanistic-Empirical analysis for pavement structures of Qatar showed significant change in the predicated fatigue distress, reaching more than 50% after considering the calibrated master curve of the asphalt mixtures with an average value of 17.33%. This result confirmed that using the locally calibrated models will give more reliable pavement performance prediction and designs.
- While the calibration changed the R<sup>2</sup> value of the Hirsch model only by 2%, there is a considerable variation in the predicted pavement performance using the MEAPA method. This result emphasizes the consideration of the practical effect of the calibration in this field.

#### Recommendations

Through this study, several challenges were determined that should be considered in the future as follows:

- It is recommended to use the calibrated Hirsch or Alkhateeb model in Qatar instead of the uncalibrated version of the models.
- Dynamic modulus testing practice in hot climate countries such as Qatar should consider testing temperatures higher than 45°C to simulate the hot climatic conditions.
- The public work authority should develop an organized database for all projects in the country, which will open doors for further calibration and value engineering studies in the region.
- It is recommended to introduce Artificial Neural Network (ANN) and Machine

  Learning techniques in developing dynamic modulus prediction models after

- collecting an extensive database from hot climate countries in the region.
- It is recommended to test the sensitivity of performed calibrations of prediction models on the predicted functional performance regardless of the improvement in the R<sup>2</sup>. Accordingly, the researcher would classify the significance of the calibration technique.

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# Appendix A

# MEAPA Output Reports

# **MEAPA**

Mechanistic Empirical Asphalt Pavement Analysis

# **Detailed Analysis Report**

1A - Before Calibration

User: AlTawalbeh

Report created on: 2022-03-12

Analysis run date/time: 03/12/2022 at 12:17 PM

## **Distress Summary**

Distress	Threshold	Target Reliability	Distress @ 20.0 year(s)	Pass /Fail
IRI (in/mile)	172.0	75.0%	102.3	PASS
AC Top-Down Fatigue Cracking (ft/mile)	2000.0	75.0%	665.6	PASS
AC Bottom-up Fatigue Cracking (%)	25.0	75.0%	0.8	PASS
AC Thermal Cracking (ft/mile)	1000.0	75.0%	113.3	PASS
Total Rutting (in)	0.75	75.0%	0.2	PASS
AC Rutting (in)	0.25	75.0%	0.08	PASS
AC Reflective Cracking (%)	25.0	75.0%	0.8	PASS

Figure A1. MEAPA Distress Summary for Section 1A – Before Calibration

Mechanistic Empirical Asphalt Pavement Analysis

### **Detailed Analysis Report**

1A - After Calibration

User: AlTawalbeh

Report created on: 2022-06-10

Analysis run date/time: 06/10/2022 at 02:20 PM

Distress	Threshold	Target Reliability	Distress @ 20.0 year(s)	Pass /Fail
IRI (in/mile)	172.0	75.0%	103.6	PASS
AC Top-Down Fatigue Cracking (ft/mile)	2000.0	75.0%	831.6	PASS
AC Bottom-up Fatigue Cracking (%)	25.0	75.0%	0.8	PASS
AC Thermal Cracking (ft/mile)	1000.0	75.0%	113.3	PASS
Total Rutting (in)	0.75	75.0%	0.23	PASS
AC Rutting (in)	0.25	75.0%	0.11	PASS
AC Reflective Cracking (%)	25.0	75.0%	0.8	PASS

Figure A2. MEAPA Distress Summary for Section 1A – After Calibration

Mechanistic Empirical Asphalt Pavement Analysis

### **Detailed Analysis Report**

1B - Before Calibration

User: AlTawalbeh

Report created on: 2022-03-12

Analysis run date/time: 03/12/2022 at 12:50 PM

Distress	Threshold	Target Reliability	Distress @ 20.0 year(s)	Pass /Fail
IRI (in/mile)	172.0	75.0%	102.4	PASS
AC Top-Down Fatigue Cracking (ft/mile)	2000.0	75.0%	757.5	PASS
AC Bottom-up Fatigue Cracking (%)	25.0	75.0%	0.8	PASS
AC Thermal Cracking (ft/mile)	1000.0	75.0%	113.3	PASS
Total Rutting (in)	0.75	75.0%	0.2	PASS
AC Rutting (in)	0.25	75.0%	0.08	PASS
AC Reflective Cracking (%)	25.0	75.0%	0.8	PASS

Figure A3. MEAPA Distress Summary for Section 1B – Before Calibration

Mechanistic Empirical Asphalt Pavement Analysis

#### **Detailed Analysis Report**

1B - After Calibration

User: AlTawalbeh

Report created on: 2022-06-10

Analysis run date/time: 06/10/2022 at 04:32 PM

Distress	Threshold	Target Reliability	Distress @ 20.0 year(s)	Pass /Fail
IRI (in/mile)	172.0	75.0%	118.6	PASS
AC Top-Down Fatigue Cracking (ft/mile)	2000.0	75.0%	1185.4	PASS
AC Bottom-up Fatigue Cracking (%)	25.0	75.0%	0.8	PASS
AC Thermal Cracking (ft/mile)	1000.0	75.0%	1878.0	FAIL
Total Rutting (in)	0.75	75.0%	0.21	PASS
AC Rutting (in)	0.25	75.0%	0.09	PASS
AC Reflective Cracking (%)	25.0	75.0%	0.8	PASS

Figure A4. MEAPA Distress Summary for Section 1B – After Calibration

Mechanistic Empirical Asphalt Pavement Analysis

# **Detailed Analysis Report**

1C - Before Calibration

User: AlTawalbeh

Report created on: 2022-03-12

Analysis run date/time: 03/12/2022 at 01:25 PM

Distress	Threshold	Target Reliability	Distress @ 20.0 year(s)	Pass /Fail
IRI (in/mile)	172.0	75.0%	103.3	PASS
AC Top-Down Fatigue Cracking (ft/mile)	2000.0	75.0%	994.3	PASS
AC Bottom-up Fatigue Cracking (%)	25.0	75.0%	0.8	PASS
AC Thermal Cracking (ft/mile)	1000.0	75.0%	113.3	PASS
Total Rutting (in)	0.75	75.0%	0.21	PASS
AC Rutting (in)	0.25	75.0%	0.09	PASS
AC Reflective Cracking (%)	25.0	75.0%	0.8	PASS

Figure A5. MEAPA Distress Summary for Section 1C – Before Calibration

Mechanistic Empirical Asphalt Pavement Analysis

# **Detailed Analysis Report**

1C - After Calibration

User: AlTawalbeh

Report created on: 2022-06-10

Analysis run date/time: 06/10/2022 at 04:41 PM

Distress	Threshold	Target Reliability	Distress @ 20.0 year(s)	Pass /Fail
IRI (in/mile)	172.0	75.0%	103.2	PASS
AC Top-Down Fatigue Cracking (ft/mile)	2000.0	75.0%	952.0	PASS
AC Bottom-up Fatigue Cracking (%)	25.0	75.0%	0.8	PASS
AC Thermal Cracking (ft/mile)	1000.0	75.0%	113.3	PASS
Total Rutting (in)	0.75	75.0%	0.21	PASS
AC Rutting (in)	0.25	75.0%	0.09	PASS
AC Reflective Cracking (%)	25.0	75.0%	0.8	PASS

Figure A6. MEAPA Distress Summary for Section 1C – After Calibration

Mechanistic Empirical Asphalt Pavement Analysis

# **Detailed Analysis Report**

2A - Before Calibration

User: AlTawalbeh

Report created on: 2022-06-11

Analysis run date/time: 06/11/2022 at 12:41 PM

Distress	Threshold	Target Reliability	Distress @ 20.0 year(s)	Pass /Fail
IRI (in/mile)	172.0	90.0%	121.5	PASS
AC Top-Down Fatigue Cracking (ft/mile)	2000.0	90.0%	3496.6	FAIL
AC Bottom-up Fatigue Cracking (%)	25.0	90.0%	1.5	PASS
AC Thermal Cracking (ft/mile)	1000.0	90.0%	215.3	PASS
Total Rutting (in)	0.75	90.0%	0.28	PASS
AC Rutting (in)	0.25	90.0%	0.15	PASS
AC Reflective Cracking (%)	25.0	90.0%	1.4	PASS

Figure A7. MEAPA Distress Summary for Section 2A – Before Calibration

Mechanistic Empirical Asphalt Pavement Analysis

# **Detailed Analysis Report**

2A - After Calibration

User: AlTawalbeh

Report created on: 2022-06-11

Analysis run date/time: 06/11/2022 at 12:32 PM

Distress	Threshold	Target Reliability	Distress @ 20.0 year(s)	Pass /Fail
IRI (in/mile)	172.0	90.0%	124.0	PASS
AC Top-Down Fatigue Cracking (ft/mile)	2000.0	90.0%	4710.8	FAIL
AC Bottom-up Fatigue Cracking (%)	25.0	90.0%	1.5	PASS
AC Thermal Cracking (ft/mile)	1000.0	90.0%	215.3	PASS
Total Rutting (in)	0.75	90.0%	0.31	PASS
AC Rutting (in)	0.25	90.0%	0.19	PASS
AC Reflective Cracking (%)	25.0	90.0%	1.4	PASS

Figure A8. MEAPA Distress Summary for Section 2A – After Calibration

Mechanistic Empirical Asphalt Pavement Analysis

# **Detailed Analysis Report**

2B - Before Calibration

User: AlTawalbeh

Report created on: 2022-06-09

Analysis run date/time: 06/09/2022 at 02:14 PM

Distress	Threshold	Target Reliability	Distress @ 20.0 year(s)	Pass /Fail
IRI (in/mile)	172.0	90.0%	122.6	PASS
AC Top-Down Fatigue Cracking (ft/mile)	2000.0	90.0%	4595.7	FAIL
AC Bottom-up Fatigue Cracking (%)	25.0	90.0%	1.5	PASS
AC Thermal Cracking (ft/mile)	1000.0	90.0%	215.3	PASS
Total Rutting (in)	0.75	90.0%	0.28	PASS
AC Rutting (in)	0.25	90.0%	0.16	PASS
AC Reflective Cracking (%)	25.0	90.0%	1.4	PASS

Figure A9. MEAPA Distress Summary for Section 2B – Before Calibration

Mechanistic Empirical Asphalt Pavement Analysis

# **Detailed Analysis Report**

2B - After Calibration

User: AlTawalbeh

Report created on: 2022-06-10

Analysis run date/time: 06/10/2022 at 05:12 PM

Distress	Threshold	Target Reliability	Distress @ 20.0 year(s)	Pass /Fail
IRI (in/mile)	172.0	90.0%	121.2	PASS
AC Top-Down Fatigue Cracking (ft/mile)	2000.0	90.0%	3941.2	FAIL
AC Bottom-up Fatigue Cracking (%)	25.0	90.0%	1.4	PASS
AC Thermal Cracking (ft/mile)	1000.0	90.0%	215.3	PASS
Total Rutting (in)	0.75	90.0%	0.26	PASS
AC Rutting (in)	0.25	90.0%	0.13	PASS
AC Reflective Cracking (%)	25.0	90.0%	1.4	PASS

Figure A10. MEAPA Distress Summary for Section 2B – After Calibration

Mechanistic Empirical Asphalt Pavement Analysis

# **Detailed Analysis Report**

1C - Before Calibration

User: AlTawalbeh

Report created on: 2022-03-12

Analysis run date/time: 03/12/2022 at 01:25 PM

Distress	Threshold	Target Reliability	Distress @ 20.0 year(s)	Pass /Fail
IRI (in/mile)	172.0	75.0%	103.3	PASS
AC Top-Down Fatigue Cracking (ft/mile)	2000.0	75.0%	994.3	PASS
AC Bottom-up Fatigue Cracking (%)	25.0	75.0%	0.8	PASS
AC Thermal Cracking (ft/mile)	1000.0	75.0%	113.3	PASS
Total Rutting (in)	0.75	75.0%	0.21	PASS
AC Rutting (in)	0.25	75.0%	0.09	PASS
AC Reflective Cracking (%)	25.0	75.0%	0.8	PASS

Figure A11. MEAPA Distress Summary for Section 1C – Before Calibration

Mechanistic Empirical Asphalt Pavement Analysis

# **Detailed Analysis Report**

1C - After Calibration

User: AlTawalbeh

Report created on: 2022-06-10

Analysis run date/time: 06/10/2022 at 04:41 PM

Distress	Threshold	Target Reliability	Distress @ 20.0 year(s)	Pass /Fail
IRI (in/mile)	172.0	75.0%	103.2	PASS
AC Top-Down Fatigue Cracking (ft/mile	2000.0	75.0%	952.0	PASS
AC Bottom-up Fatigue Cracking (%)	25.0	75.0%	0.8	PASS
AC Thermal Cracking (ft/mile)	1000.0	75.0%	113.3	PASS
Total Rutting (in)	0.75	75.0%	0.21	PASS
AC Rutting (in)	0.25	75.0%	0.09	PASS
AC Reflective Cracking (%)	25.0	75.0%	0.8	PASS

Figure A12. MEAPA Distress Summary for Section 1C – After Calibration

# Appendix B

# Job Mix Formula Sample Report

#### Fugro Peninsular Pavement Services Division Volumetric Mix Design Services



		Overseeing Engineer: Zahi Chamoun
T0: Preliminaries	Review of Applicable Specification Project Requirements (traffic type / surface te Production considerations (available material screens) Binder content restrictions Objective of the mix design Material sampling	Laboratory Volumetric Mix Design Stage
T1: Material Verification	Aggregate compliance testing (stock-piles / h     Binder testing (PEN / PMB)     Binder Mixing & Compaction temperature     Aggregate sieve analysis / specific gravities /	,
T2: Selection of Gradation	Contractor preference from past experiences     Bailey Aggregate Packing Method employed     Initial trials for volumetric feasibility / binder or indication     Gradation review by the Contractor	
T3: Selection of Binder Content	Volumetric curves at 4 – 6 binder contents     Verification of design binder content     Including expected volumetric property range given specification production tolerances	is
T4: Moisture Susceptibility	Tensile Strength Ratio (TSR) for Superpave Retained Stability for Marshall	
T5: Plant Verification	Can the designed aggregate structure be ach in the plant?     Does the binder content require adjustment for production?	
T6: Performance	Mechanistic Performance testing – Dynamic Modulus  E*      Rutting Indicators – Flow Number (repeated I triaxle testing)     Rutting Indicators – Hamburg Wheel Track T- (HWTT) at local climatic conditions (76degC)	esting
Notes:	<ul> <li>binders</li> <li>T5 and T6 are not required for a Volumetric I</li> </ul>	or Superpave Volumetric Mix Designs testing on plant produced material when using PMB asphalt Mix Design, but provide supplemental information beneficial to loads where mixture performance is more critical

Figure B1. JMF Testing Plan

Geotechnical, Material Testing, Engineers, Foundation Testing, Pavement Services



	SUF	PERPAVE MIX DE	SIGN REPORT	JMF		QTR/119
				Report		00038
	Plant:	MIDMAC COLAS	Design ES		licable (N.	(A)
į.	Designer:	Zahi Chamoun	Asphalt Gra			
	Date:	07-Jan-19	Aggregate Sou		rading G	oup
	NMAS:	25.0 mm	Asphalt Sou	rce: MEMBC	0	
Mate	rial Type:	Not Applicable (N/A)	Binder Cont	ent: 4.1%		
		Technical	2.6			
AASHTO PP60	Standard P		References and Applicable Standard Cylindrical Performance Test Specimens U		ve Gyrator	v Compactor
	(SGC)	rasass for t reparation of	eyimanoar i onormanoe rest opecimens e	sing the ouperpa	ve Gyrator	Compactor
AASHTO PP61	Standard P	ractice for Developing Dyr ce Tester (AMPT)	namic Modulus Master Curves for Asphalt M	Mixtures Using the	Asphalt N	1ixture
AASHTO R28			ing of Asphalt Binder Using a Pressurized		.V)	
AASHTO T19			nsity ("Unit Weight") and Voids in Aggregat	e		
AASHTO T44		lethod of Test for Solubility				
AASHTO T48			d Fire Points by Cleveland Open Cup			
AASHTO T55			Petroleum Products and Bituminous Mater	rials by Distillation	1	
AASHTO T228			Gravity of Semi-Solid Asphalt Materials			
AASHTO T240	Standard M	lethod of Test for Effect of	Heat and Air on a Moving Film of Asphalt I	Binder (Rolling Th	in-Film Ov	en Test)
AASHTO T283			sphalt (HMA) to Moisture-Induced Damage			
AASHTO T313	Standard M (BBR)	lethod of Test for Determine	ning the Flexural Creep Stiffness of Asphalt	Binder Using the	Bending E	Beam Rheometer
AASHTO T315	Standard M	lethod of Test for Determin	ning the Rheological Properties of Asphalt B	Binder Using a Dy	namic She	ar Rheometer
	(DSR)					
AASHTO T316			Determination of Asphalt Binder Using Ro			
AASHTO T350			Stress Creep Recovery (MSCR) Test of As	phalt Binder Usin	g a Dynam	ic Shear
A A CLUTO TDZC	Rheometer					
AASHTO TP79			ning the Dynamic Modulus and Flow Number	er for Asphalt Mix	tures Using	the Asphalt
ASTM D75		formance Tester (AMPT)				
ASTM C88		ractice for Sampling Aggre				
ASTM C88			of Aggregates by Use of Sodium Sulfate o			
	Standard Te	est Method for Materials F	iner than 75-µm (No. 200) Sieve in Mineral	Aggregates by V	/ashing	
ASTM C127 ASTM C128	Standard Te	est Method for Density, Re	elative Density (Specific Gravity) and Absor	ption of Coarse A	ggregate	
	Standard Te	est Method for Density, Re	elative Density (Specific Gravity), and Absor	rption of Fine Ago	regate	
ASTM C131			to Degradation of Small-Size Coarse Aggr	egate by Abrasio	and Impa	ct in the Los
ASTM C136	Angeles Ma	icnine	creen Analysis of Fine and Coarse Aggrega			
ASTM C130	Standard Te	act Mathed for Clay Lymn	s and Friable Particles in Aggregates	tes		
ASTM C142			ne Amount of Testing of Hydraulic Cement			
ASTM D546	Standard To	active for Sampling and the	ysis of Mineral Filler for Bituminous Paving	Mintunga		
ASTM C566	Standard Te	est Method for Total Evan	orable Moisture Content of Aggregate by Dr	vina		
ASTM D854			ravity of Soil Solids by Water Pycnometer	yirig		
ASTM D979		ractice for Sampling Bitum				
ASTM D1073	Standard St	necification for Fine Aggre	gate for Bituminous Paving Mixtures			
ASTM D2172	Standard Te	act Method for Quantitative	Extraction of Bitumen from Bituminous Pa	using Mistress		
ASTM D2419	Standard Te	est Method for Sand Equit	ralent Value of Soils and Fine Aggregate	iving ivilxtures		
ASTM D2716	Standard Te	et Method for Bulk Specif	ic Gravity and Density of Non-Absorptive C	omposted Ditumi	nava Mistr	
ASTM D2720	Standard To	est Method for Parcent Air	Voids in Compacted Dense and Open Bitu	minoue Povine *	livtures	162
ASTM D3203			it, Plastic Limit, and Plasticity Index of Soils		ixtures	
ASTM D4791			es, Elongated Particles, or Flat and Elongat		narea Age-	egate
ASTM D5731			the Percentage of Fractured Particles in C			zyale
ASTM D6925			and Determination of the Relative Density			nacimone by
	Means of the	e Superpave Gyratory Cor	mnactor	or riot with Aspire	ir (i livira) o	peciniens by
ASTM D6857		est Method for Maximum S	Specific Gravity and Density of Bituminous F	Paving Mixtures U	Ising Autor	natic Vacuum
ASTM E11	Standard Sr	pecification for Woven Wir	e Test Sieve Cloth and Test Sieves			
A.I. SP-2		Mix Design Manual				
NCHRP 648			s of Asphalt Binders in Hot-Mix Asphalt			
ASTM D242			er for Bituminous Paving Mixtures			
AASHTO M323		pecification for Superpave				
AASHTO M332			e-Graded Asphalt Binder Using Multiple St	ress Creen Reco	very (MSC	R) Test
	Standard Pr	actice for Grading or Verif	ying the Performance Grade (PG) of an As	phalt Binder	(14100	-, 1001
Specification	PROJECT S	SPECIFICATION; SECTION	N 02401; PLANT MIX BITUMINOUS PAVE 0. 25045-27-3PS-02401; Rev. 08 Dated 22-	MENT (AIRFIEL	D); NEW	ОНА
	141		23043-21-31 3-02401, Nev. 08 Dated 22-	Widi 2010	A	
	geal	Name .	30		naig	
Prepared By:	Zahi Cham Project En		Rev ( ) الدومة و فطي الدومة المطا	viewed By: Q	uality Ass	urance /
	r roject Eng		10500 0	Q	uality Cor	itroi Dept.
	17 107 5 1	2-1	Ontar / 1			
No.: 16522, P.O. Box 4	47 167, Doha, C	Qatar, pavements.fme@fugro.o	Om Doha-Qatar			
No.: 16522, P.O. Box 4	47 167, Doha, 0 must be in full, p	Qatar, pavements.fme@fugro.d prior written approval from Fugr	Opha-Qatar Opha-Qatar Ophaninsular is to be obtained.	_		V1R2 1504

Figure B2. Technical References and Applicable Standards

Geotechnical, Material Testing, Engineers, Foundation Testing, Pavement Services



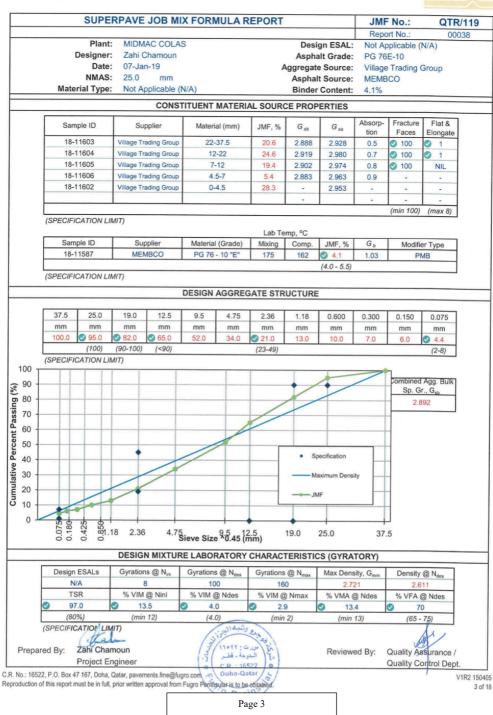


Figure B3. Material Source Properties

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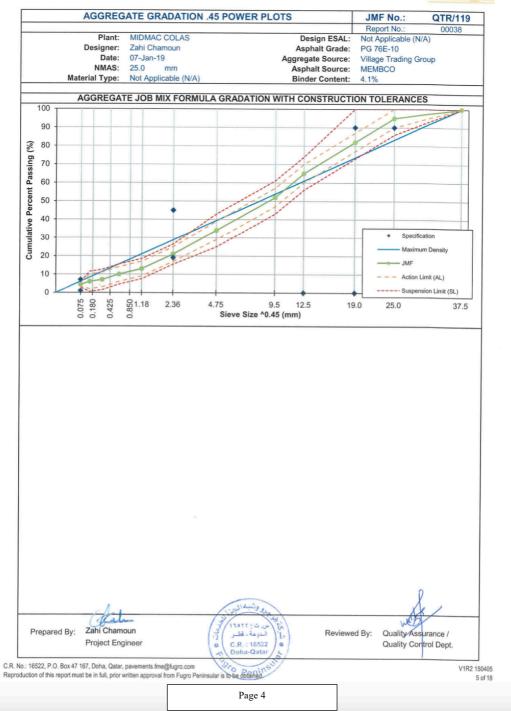


Figure B4. JMF Gradation Chart

Geotechnical, Material Testing, Engineers, Foundation Testing, Pavement Services



STC	CK-PILE AGGR	EGATE PHYS	SICAL P	ROPER	TIES		JMF	No.:	QTI	R/119	
							Repor	t No.:	00	0038	
Plant:	MIDMAC COLAS					Desig	n ESAL:	Not App	olicable (	N/A)	
Designer:	Zahi Chamoun					Aspha	It Grade:	PG 76E	-10	,	
Specification:	07-Jan-19					Aggregate	Source:	Village 1	Trading	Group	
NMAS:	25.0 mm						Source:	MEMBO		o.oop	
Material Type:	Not Applicable (N/	A)			Desig	gn Binder		4.1%			
Sample ID	Material (mm)	Stock-pil	е	T	Sampling			Producer Logo			
18-11593	32mm	Village Trading	Group	-	Date 01-Dec-1	0			-3-		
18-11594	20mm	Village Trading			01-Dec-1						
18-11595	10mm	Village Trading		-	01-Dec-1					~	
18-11596	0-5mm						midmac	مدماك	< co	LAC	
10-11030	0-011111	Village Trading	Group		01-Dec-1	0	Stand State	Art Mar Startle	60	LAJ	
						Line Control			Alla Santini ana alika		
	oile Grading (ASTM									ecs	
wetric	Sieve Size (mm) 37.5	32mm 100	20mm	10mm	0-5mm				Min	Ma	
	25.0	74	-	100	100	Sec. 2011				2201	
	19.0		100	100	100		(2) (2) (1)	10000		200	
		20	95	100	100					755	
	12.5 9.5	5	43	100	100	200000	\$500feet			15-1316	
	4.75	4	8	97	100						
		3	2	44	99						
	2.36	3	2	12	72	A 12 15 15		802.55			
	0.600	3	2	6	37						
	0.300	2	2	5	28		SALES FOR SALES				
	0.150	2	2	4	21		10,973011				
	0.075	1.9	1.4	3.9	16.3					1000	
	arameter			YSICAL F		IES			Specif		
	dard of Test)	32mm	20mm	10mm					Min	Max	
sb (C127/C128)	054)	2.897	2.930	2.882	2.854	10 March 10		RESERVE OF			
sa (C127/C128/D8		2.932	2.974	2.942	2.943						
sorption (C127/C		0.4	0.5	0.7	1.1						
odded Unit Wt (T1		1,720	1,710	1,630	1,510						
ovel Unit Wt (T19		1,640	1,650	1,610	1,320		Dill but			1	
astic Limit (D4318					NP						
quid Limit (D4318)					ND		5			25	
asticity Index (D43	,				ND	The same				6	
rcent Wear (C13	1)	<b>8</b>	12	17	1	WHO I'M				40	
undness (C88)		<b>②</b> 0	1	1	2		THE REAL PROPERTY.			12/1	
ay & Friable (C14)		·			None					1	
ind Equiv. (D2419					<b>5</b> 6				50		
ganic Impurities (C4	0)	etili Para a				Reserved to				None	
	tent (BS 1377 Part 3				<b>⊘</b> 0.04					0.1%	
id soluble SO3- c	ontent (BS 1377 Par	t 3)	4 - 4		<b>②</b> 0.13					0.5%	
at & Elongated (De		NIL	NIL	1		RECEIPT OF				8 (5:1	
actured Faces (D5	5821)	<b>100</b>	<b>100</b>	<b>100</b>		Charles I		A 1887 (SEE	75	, , ,	



Figure B5. Stockpile Aggregate Phyiscal Propoerites

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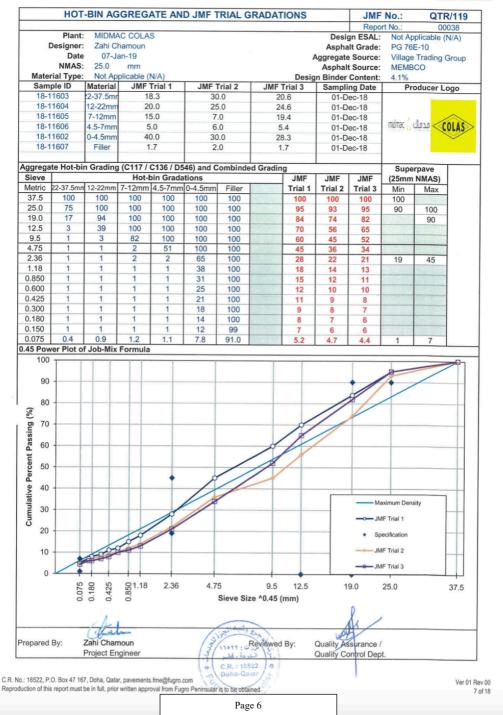


Figure B6. Hot-Bin Aggregate and Trial Gradations

Geotechnical, Material Testing, Engineers, Foundation Testing, Pavement Services



SUPE	RPAVE	DESIG	N BIND	ER CON	ITENT \	/ERIFIC	ATION				No.:		R/119
	Disert	MIDA	10.001	0							rt No.:		038
-	Plant:		AC COLA	S						gn ESAL:		oplicable (	N/A)
L	esigner:		hamoun							It Grade:	PG 76		
	Date:		an-19					1		Source:		Trading (	Group
Mater	NMAS:		mm plicable (	NI/AN						t Source:	MEMB	CO	
	ial Type:	esign Inp		N/A)				Desig	n Binder	Content:	4.1%		
		er / Standa		t	2-37 5m	12 22mn	7 12mm	4.5-7mm	0 4 Emm	Filler	7.72.97		2014
	SG (G <sub>sb</sub> )			/ C128	2.888	2.919	2.902	2.888	2.868	riller	-	Min	Max
	arent SG			128/D854	2.928	2.980	2.974	2.966	2.954	2.892		-	-
		ned Agg B			2.320	2.300	2.514	2.888	2.934	2.092			-
		ned Agg A						2.957					
		esign Inp						2.007				10-4-2-2-5	P. Committee
	Sam	ple ID	18-12213		Binder	Content	4.3	Gr	mm	2.713			
I	Dry	Weight in	SSD	G <sub>mb</sub> @	Height @		Height @	_		%G <sub>mm</sub> @	VIM @	VMA @	VFA @
	Weight	H <sub>2</sub> O	Weight	N <sub>compact</sub>	N <sub>9</sub>	N <sub>100</sub>	N <sub>160</sub>	N <sub>9</sub>	N <sub>100</sub>	N <sub>160</sub>	N <sub>compact</sub>	N <sub>100</sub>	N <sub>100</sub>
/1 N <sub>des</sub>	5090.1	3163.2	5099.2	2.629	124.2	112.6	100	87.9	96.9	-100	3.1	12.9	76.0
/2 N <sub>des</sub>	5096.2	3161.3	5104.4	2.623	125.3	113.7		87.7	96.7	-	3.3	13.1	74.8
/3 N <sub>des</sub>	5109.8	3172.9	5117.4	2.628	124.2	112.6		87.8	96.9	-	3.1	12.9	76.0
	Dry	Weight in	SSD	G <sub>mb</sub> @	Height @	Height @	Height @	%G <sub>mm</sub> @	%G <sub>mm</sub> @	%G <sub>mm</sub> @	VIM @	VMA @	VFA@
	Weight	H <sub>2</sub> O	Weight	N <sub>compact</sub>	N <sub>9</sub>	N <sub>100</sub>	N <sub>160</sub>	N <sub>9</sub>	N <sub>100</sub>	N <sub>160</sub>	N <sub>compact</sub>	N <sub>100</sub>	N <sub>100</sub>
4 Nmax		3193.6	5106.1	2.668	124.1	112.3	110.8	87.8	97.0	98.3	3.0	-	- 100
5 Nmax		3182.4	5092.7	2.664	123.4	112.7	111.3	88.6	97.0	98.2	3.0	-	-
		Average \	olumetric	Propertie	es @ Nde	S		87.8	96.8	-	3.2	-	-
	Averag	e Volumet	ric Prope	rties @ Ni	max			88.2	97.0	98.3	3.0	-	-
		esign Inp										QCS	2014
		r / Standa			2-37.5mr	12-22mm	7-12mm	4.5-7mm	0-4.5mm	Filler		Min	Max
	SG (G <sub>sb</sub> )			/ C128	2.888	2.919	2.902	2.888	2.868		Carlos de la companya della companya		
	rent SG (			28/D854	2.928	2.980	2.974	2.966	2.954	2.892			
		ned Agg B						2.891					
		ned Agg A						2.953					
/olumetr		esign Inp		2212									
	Samp	ole ID	18-12212		Binder	Content	4.3	Gn	nm	2.715			
	Dry	Weight in	SSD	G <sub>mb</sub> @	Height @	Height @	Height @	%G <sub>mm</sub> @	%G <sub>mm</sub> @	%G <sub>mm</sub> @	VIM @	VMA @	VFA@
	Weight	H <sub>2</sub> O	Weight	N <sub>compact</sub>	N <sub>9</sub>	N <sub>100</sub>	N <sub>160</sub>	N <sub>9</sub>	N <sub>100</sub>	N <sub>160</sub>	N <sub>compact</sub>	N <sub>100</sub>	N <sub>100</sub>
/1 N <sub>des</sub>	5071.0	3177.3	5078.5	2.667	125.3	113.6		89.1	98.2	-	1.8	11.7	84.6
/2 N <sub>des</sub>	5085.9	3189.5	5095.5	2.668	125.4	113.0		88.6	98.3	-	1.7	11.7	85.5
/3 N <sub>des</sub>	5090.9	3191.9	5098.3	2.670	126.4	113.3		88.2	98.3	-	1.7	11.6	85.3
	Dry	Weight in	SSD	G <sub>mb</sub> @	Height @	Height @	Height @	%G <sub>mm</sub> @	%G <sub>mm</sub> @	%G <sub>mm</sub> @	VIM @	VMA@	VFA@
	Weight	H <sub>2</sub> O	Weight	N <sub>compact</sub>	N <sub>9</sub>	N <sub>100</sub>	N <sub>160</sub>	Ng	N <sub>100</sub>	N <sub>160</sub>	N <sub>compact</sub>	N <sub>100</sub>	N <sub>100</sub>
4 Nmax	5090.9	3204.6	5098.9	2.687	126.7	114.3	112.7	88.0	97.6	99.0	2.4	-	-
5 Nmax	5105.6	3216.6	5112.1	2.694	125.2	112.6	111.2	88.1	98.0	99.3	2.0	-	-
		Average V				3	_	88.6	98.3		1.7	-	-
	Average	e Volumeti	ric Proper	ties @ Nr	nax			88.1	97.8	99.2	2.2	-	-
										0			
Prepared I		Zahi Char Project Er			O CHENTE	ارمند فطر رمند فطر C.R.: 165 Doha-Qa	22   0		-	isurance /	t.		
		7, Doha, Qata			com gro Peninsula		150/			1			Ver 01 F

Figure B7. Superpave Design Binder Content Verfication

Geotechnical, Material Testing, Engineers, Foundation Testing, Pavement Services



	ASPH	ALT BINDER PRO	PERTI	ES			JMF	No.:	QTF	2/119
							Repo	rt No.:		038
	Plant: MI	DMAC COLAS			Desig	n ESAL:		plicable (		
	Designer: Za	hi Chamoun			Aspha	It Grade:	PG 76	E-10		
	Date: 07	-Jan-19		Α	ggregate			Trading	Group	
	NMAS: 25	.0 mm				Source:	0			
		phalt Binder				Content:				
		-11587			Dilluci	Content	4.170			
			2 6 6 7 7	-NING T	FOT DE	OLU TO				
		AASHTO M33	Z SUKE	ENING I						
	Test Method	Parameter	Te	est	Te	est	S.	ecificat	ion	
			Tempe	erature	Re	sult	J.	ecilicat	IOII	
	AASHTO T44	Solubility	-	°C	100	%	99.0	%	min	0
	AASHTO T55	Water Content	-	°C		%	0.0	%	max	0
	250 μm Sieve Test	Particles	160	°C	0.80	No.	0.0	No	max	0
					0.00	110.	0.0	140	max	
	PG	VERIFICATION - AA	SHTO N	1332 (TA	BLE 1)	TEST RE	SULTS			
		T -	Te	est	Te	est				
	Test Method	Parameter		erature		sult	Sp	ecificat	ion	
	AASHTO T48	Temp	-	°C	318	°C	230	°C	po!-	
			135					-	min	00000000000
_	AASHTO T316	Viocosity		°C	2.2	Pa·s	3	Pa·s	max	$ \bigcirc $
_	AASHTO T315	G*/sinδ	76	°C	1.90	kPa	1.00	kPa	min	
	AASHTO T240	Mass ∆	163	°C	-0.08	%	1.00	%	max	
-	AASHTO T350	J nr3.2	76	00	0.261	kPa-1	1.0	kPa <sup>-1</sup>	max	0
		J nrdiff	76	°C	176.0	%	75	%	max	
	AASHTO R28	Temp	110	°C	110	-	110	°C	-	0
	AASHTO T315	G*sinδ	37	°C	998	kPa				0
			31				6,000	kPa	max	S.
	AASHTO T313	S	0	°C	37.0	MPa	300	MPa	max	
		m-value		°C	0.391	-	0.300		min	
	AASHTO T314	Fail ε			d, footno		1	%	min	0
A L	ote: As per speciifcation	on if Jnr3.2 < 0.5 then J	Inrdiff req	uirement	is waived					
140										
100	070010			3 AND A	ASHTO	T53 TES	T RESU	LTS		
140	STORAG	E STABILITY - AST	W D /1/							
140	STORAG				1.6					
100	STORAG	Top Residue	DSR	Test	1.6					
100	STORAG	Top Residue Bottom Residue			1.5					
700	STORAG	Top Residue	DSR		00 000					
140	STORAG	Top Residue Bottom Residue	DSR (G* v	alue)	1.5 4.7%	RESUL	т			
140	STORAG	Top Residue Bottom Residue Difference	DSR (G* v	alue) HTO T2	1.5 4.7%	RESUL	т			
140	STORAG	Top Residue Bottom Residue Difference	DSR (G* v	alue) HTO T2	1.5 4.7%	RESUL	т			
		Top Residue Bottom Residue Difference SPECIFIC GRAVIT	DSR (G* v.	HTO T2	1.5 4.7%					
		Top Residue Bottom Residue Difference	DSR (G* v.	HTO T2	1.5 4.7%			LE MET	HOD RE	SULT
		Top Residue Bottom Residue Difference SPECIFIC GRAVIT	DSR (G* v	HTO T2	1.5 4.7% 28 TEST	648 PHA		LE MET	HOD RE	SULT
	ATORY MIXING AN	Top Residue Bottom Residue Difference  SPECIFIC GRAVIT	DSR (G* v 1.0	HTO T2	1.5 4.7%	6 <b>48 PHA</b>		LE MET	HOD RE	SULT
	ATORY MIXING AN	Top Residue Bottom Residue Difference  SPECIFIC GRAVIT  D COMPACTION TE  Mixing Temperature (°	DSR (G* v 1.0	HTO T2	1.5 4.7% 28 TEST	6 <b>48 PHA</b>		LE MET	HOD RE	SULT
	ATORY MIXING AN	Top Residue Bottom Residue Difference  SPECIFIC GRAVIT  D COMPACTION TE  Mixing Temperature (°	DSR (G* v 1.0	HTO T2	1.5 4.7% 28 TEST	6 <b>48 PHA</b>		LE MET	HOD RE	SULT
	ATORY MIXING AN	Top Residue Bottom Residue Difference  SPECIFIC GRAVIT  D COMPACTION TE  Mixing Temperature (°	DSR (G* v 1.0	HTO T2	1.5 4.7% 28 TEST	6 <b>48 PHA</b>		LE MET	HOD RE	SULT
	ATORY MIXING AN	Top Residue Bottom Residue Difference  SPECIFIC GRAVIT  D COMPACTION TE  Mixing Temperature (°	DSR (G* v 1.0	HTO T2	1.5 4.7% 28 TEST	6 <b>48 PHA</b>		LE MET	HOD RE	SULT
BORA	ATORY MIXING AN	Top Residue Bottom Residue Difference  SPECIFIC GRAVIT  D COMPACTION TE  Mixing Temperature (°	DSR (G* v 1.0	HTO T2	1.5 4.7% 28 TEST	648 PHA 75 32	SE ANG	W	di	
BORA	ATORY MIXING AN	Top Residue Bottom Residue Difference  SPECIFIC GRAVIT  D COMPACTION TE  Mixing Temperature (* compaction Temperature	DSR (G* v 1.0	HTO T2	1.5 4.7% 28 TEST	6 <b>48 PHA</b>	SE ANG	Quality A	ssurance	,
	ATORY MIXING AN	Top Residue Bottom Residue Difference  SPECIFIC GRAVIT  D COMPACTION TE  Mixing Temperature (* compaction Temperature	DSR (G* v 1.0	HTO T2	1.5 4.7% 28 TEST	648 PHA 75 32	SE ANG	Quality A	di	,
BOR/	ATORY MIXING AN	Top Residue Bottom Residue Difference  SPECIFIC GRAVIT  D COMPACTION TE  Mixing Temperature (* compaction Temperature	DSR (G* v 1.0	HTO T2	1.5 4.7% 28 TEST	648 PHA 75 32	SE ANG	Quality A	ssurance ontrol Dep	vot.
BORA	By: Zahl Chamoun Project Enginee	Top Residue Bottom Residue Difference  SPECIFIC GRAVIT  D COMPACTION TE  Mixing Temperature (* compaction Temperature	DSR (G* v. 1.0	HTO T2	1.5 4.7% 28 TEST	648 PHA 75 32	SE ANG	Quality A	ssurance ontrol Dep	,

Figure B8. Asphalt Binder Properties - 1

Geotechnical, Material Testing, Engineers, Foundation Testing, Pavement Services



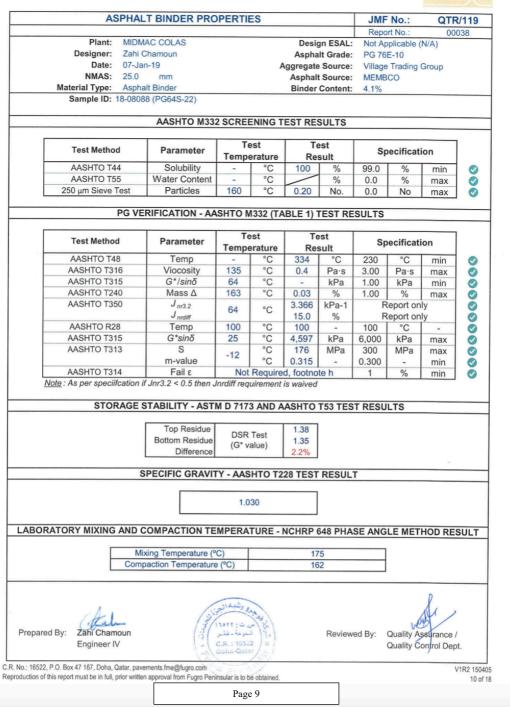


Figure B9. Asphalt Binder Properties - 2

Geotechnical, Material Testing, Engineers, Foundation Testing, Pavement Services



4.1 4.1 3.9 4.1 2.706 VIM @ N <sub>compact</sub> 3.1 3.0 3.3 3.1 2.680 VIM @ N <sub>compact</sub>	13.3 13.2 13.1 13.2 Avg VMA @ N <sub>des</sub> 13.4 13.3 13.6 13.4 VMA @ VMA @ 13.7	68.9 70.2 69.4 2.705 VFA @ N <sub>des</sub> 76.9 77.4 75.7 76.7 2.679 VFA @ N <sub>des</sub>
4.1 4.1 3.9 4.1 2.706 VIM @ N <sub>compact</sub> 3.1 3.0 3.3 3.1 2.680 VIM @	13.2 13.1 13.2 Avg VMA @ N <sub>des</sub> 13.4 13.3 13.6 13.4 Avg	68.9 70.2 69.4 2.705 VFA @ N <sub>des</sub> 76.9 77.4 75.7 76.7
4.1 4.1 3.9 4.1 2.706 VIM @ N <sub>compact</sub> 3.1 3.0 3.3 3.1	13.2 13.1 13.2 Avg VMA @ N <sub>des</sub> 13.4 13.3 13.6 13.4	68.9 70.2 69.4 2.705 VFA @ N <sub>des</sub> 76.9 77.4 75.7 76.7
4.1 4.1 3.9 4.1 2.706 VIM @ N <sub>compact</sub> 3.1 3.0 3.3	13.2 13.1 13.2 Avg VMA @ N <sub>des</sub> 13.4 13.3 13.6	68.9 70.2 69.4 2.705 VFA @ N <sub>des</sub> 76.9 77.4 75.7
4.1 4.1 3.9 4.1 2.706 VIM @ N <sub>compact</sub> 3.1 3.0 3.3	13.2 13.1 13.2 Avg VMA @ N <sub>des</sub> 13.4 13.3 13.6	68.9 70.2 69.4 2.705 VFA @ N <sub>des</sub> 76.9 77.4
4.1 4.1 3.9 4.1 2.706 VIM @ N <sub>compact</sub> 3.1	13.2 13.1 13.2 Avg VMA @ N <sub>des</sub> 13.4	68.9 70.2 69.4 2.705 VFA @ N <sub>des</sub> 76.9
4.1 4.1 3.9 4.1 2.706 VIM @ N <sub>compact</sub>	13.2 13.1 13.2 Avg VMA @ N <sub>des</sub>	68.9 70.2 69.4 2.705 VFA @ N <sub>des</sub>
4.1 4.1 3.9 4.1 2.706 VIM @	13.2 13.1 13.2 Avg VMA @	68.9 70.2 69.4 2.705 VFA @
4.1 4.1 3.9 4.1 2.706	13.2 13.1 13.2 Avg	68.9 70.2 69.4 2.705
4.1 4.1 3.9 4.1	13.2 13.1 13.2	68.9 70.2 69.4
4.1 4.1 3.9	13.2 13.1	68.9 70.2
4.1	13.2	68.9
4.1		
4.1		
N <sub>compact</sub>	N <sub>des</sub>	N <sub>des</sub>
		VFA @
2 724	Ava	2.725
5.8	13.6	57.0
5.8	13.5	57.0
6.0	13.7	56.2
5.7		N <sub>des</sub> 57.8
		VFA @
_		2.751
	13.0	46.5
_		47.8
7.4	13.8	46.4
7.7	14.1	45.4
		N <sub>des</sub>
_		VFA @
2 774	Ava	2.775
	Group	
	Group	
	(IV/A)	
		0038
9	2.774 VIM @ Noompact 7.7 7.4 7.1 7.4 2.749 VIM @ Noompact 5.7 6.0 5.8 5.8 2.724 VIM @	Description   Column   Colum

Figure B10. Mix Design Volumitric Data - 1

Geotechnical, Material Testing, Engineers, Foundation Testing, Pavement Services



. Jaconori (	and report i	DO III IUII	, prior writter	approvar itu	r ugru nell	Page 1							11 of
	2, P.O. Box 4	Project Er 7 167, Doha,	ngineer Qatar, pave	ments.fme@f		حة - قطـر C.R.: 10 Doha-Qa	atar a character			,	Quality C	ontrol Dep	ot. V1R2 1504
Prepar	ed By:	Zahi Char	moun		13	11011:0	200		Review	ed Bv	Quality A	ssurance	/
		1.4	De I Callo	1.7	1.4	وشبه الم		0.9	0.6 -	1.2	1.3	1.2	1.1
		Dust to F	A @ N <sub>des</sub>	46.5	57.0	69.4	76.7	85.5 0.9	65 -		66.3	70.2	73.9
		VMA	A @ N <sub>des</sub>	13.8	13.6	13.2	13.4	13.8	≥ 13		13.3	13.3	13.
			√ @ N <sub>des</sub>	7.4	5.8	4.1	3.1	2.0	4 9		4.5	4.0	3.
			M @ N <sub>ini</sub>	16.2	14.8	12.9	12.4	11.2	> 11		13.5	13.0	12.
			G <sub>mm</sub>	2.775	2.751	2.725	2.705	2.679			2.731	2.722	2.71
		G <sub>m</sub>	@ N <sub>des</sub>	2.570	2.590	2.615	2.621	2.625			2.608	2.614	2.61
		Binder	Content	3.0	3.5	4.0	4.5	5.0	Specifi	cation	3.9	4.1	4.3
		S	SUMMAR	RY OF G	YRATOR	RY CURV	/E DATA	\			DESIG	SN ESTI	MATE
						Α	verage V	olumetric	Propertie	s @ N <sub>des</sub>	2.0	13.8	85.5
Spec 3	5033.9	3118.3	5035.2	2.626	124.7	112.9	-	88.7	98.0	-	2.0	13.7	85.4
Spec 2	5083.4	3145.4	5084.5	2.622	124.8	113.3	-	88.9	97.9	-	2.1	13.9	84.9
Spec 1	5038.7	3124.4	5042.0	2.628	123.6	111.9	- max	88.8	98.1	- INmax	1.9	13.7	N <sub>des</sub> 86.1
JMF	Weight	in H <sub>2</sub> O	Weight	N <sub>compact</sub>	Height @ N <sub>ini</sub>	Height @ N <sub>des</sub>	Height @ N <sub>max</sub>	%G <sub>mm</sub> @ N <sub>ini</sub>	%G <sub>mm</sub> @ N <sub>des</sub>	%G <sub>mm</sub> @ N <sub>max</sub>	VIM @ N <sub>compact</sub>	VMA @ N <sub>des</sub>	VFA@
	Dry	Weight	SSD	G <sub>mb</sub> @			G <sub>mm</sub>	/1 %C	2.678	/2	2.680	Avg	2.679
Blend	Samp	le ID T	18.1	1832	P <sub>b</sub> , %	5.0							
							verage V		Propertie	s @ N <sub>dee</sub>	3.1	13.4	76.7
Spec 3	5085.5	3150.3	5093.2	2.617	126.1	114.1 114.9		87.8 87.5	97.0 96.7	-	3.0	13.3 13.6	77.4 75.7
Spec 1 Spec 2	5075.2 5078.2	3148.2 3150.5	5083.6 5086.0	2.622 2.624	125.9 126.1	113.8	-	87.6	96.9	-	3.1	13.4	76.9
	Weight	in H <sub>2</sub> O	Weight	N <sub>compact</sub>	@ N <sub>ini</sub>	@ N <sub>des</sub>	@ N <sub>max</sub>	@ N <sub>ini</sub>	@ N <sub>des</sub>	@ N <sub>max</sub>	N <sub>compact</sub>	N <sub>des</sub>	N <sub>des</sub>
JMF	Dry	Weight	SSD	G <sub>mb</sub> @	Height	Height	Height	%G <sub>mm</sub>	%G <sub>mm</sub>	$%G_{mm}$	VIM @	VMA@	VFA@
Blend		ole ID		1831	P <sub>b</sub> , %	4.5	G <sub>mm</sub>	/1	2.704	/2	2.706	Avg	2.705
							verage V	olumetric	Propertie	s @ N <sub>des</sub>	4.1	13.2	69.4
Spec 3	5098.1	3161.2	5107.7	2.619	126.5	114.8	-	87.2	96.1	- 0 11	3.9	13.1	70.2
Spec 2	5089.1	3156.9	5103.6	2.614	128.0	115.8	-	86.8	95.9	-	4.1	13.2	68.9
Spec 1	5098.4	3162.0	5114.2	2.612	127.6	116.2	-	87.3	95.9	-	4.1	13.3	69.2
	Weight	in H <sub>2</sub> O	Weight	N <sub>compact</sub>	@ N <sub>ini</sub>	@ N <sub>des</sub>	@ N <sub>max</sub>	@ N <sub>ini</sub>	@ N <sub>des</sub>	@ N <sub>max</sub>	N <sub>compact</sub>	N <sub>des</sub>	N <sub>des</sub>
JMF	Dry	Weight	SSD	G <sub>mb</sub> @	Height	Height	Height	%G <sub>mm</sub>	%G <sub>mm</sub>	%G <sub>mm</sub>	VIM @	VMA@	VFA @
Blend	Sam	ple ID	18-1	1830	P <sub>b</sub> , %	4.0	G <sub>mm</sub>	/1	2.726	/2	2.724	Avg	2.725
						-	verage V	olumetric	Propertie	s @ N <sub>des</sub>	5.8	13.6	57.0
Spec 3	5093.2	3150.6	5116.0	2.591	128.4	116.4	-	85.4	94.2	- O N	5.8	13.5	57.0
Spec 2	5095.4	3147.8	5118.7	2.585	129.2	117.0		85.1	94.0	-	6.0	13.7	56.2
Spec 1	5097.5	3152.6	5118.2	2.593	128.2	115.9	-	85.2	94.3	-	5.7	13.5	57.8
JMF	Weight	in H <sub>2</sub> O	Weight	N <sub>compact</sub>	@ N <sub>ini</sub>	@ N <sub>des</sub>	@ N <sub>max</sub>	@ N <sub>ini</sub>	@ N <sub>des</sub>	@ N <sub>max</sub>	N <sub>compact</sub>	N <sub>des</sub>	N <sub>des</sub>
IME	Dry	Weight	SSD	G <sub>mb</sub> @	Height	Height	Height	%G <sub>mm</sub>	%G <sub>mm</sub>	%G <sub>mm</sub>	VIM @	VMA @	VFA (
Blend	Sam	ple ID	18-1	1829	P <sub>b</sub> , %	3.5	G <sub>mm</sub>	/1	2.752	/2	2.749	Avg	2.751
						/	Average \	olumetric	Propertie	es @ N <sub>des</sub>	7.4	13.8	46.5
Spec 3	5097.2	3160.6	5138.2	2.577	130.5	117.6	-	83.7	92.9	-	7.1	13.6	47.8
Spec 2	5090.6	3153.6	5134.2	2.570	129.2	117.2	-	84.0	92.6	-	7.4	13.8	45.4 46.4
Spec 1	5092.1	3153.3	5140.7	N <sub>compact</sub>	@ N <sub>ini</sub> 129.5	@ N <sub>des</sub>	@ N <sub>max</sub>	@ N <sub>ini</sub> 83.8	@ N <sub>des</sub>	@ N <sub>max</sub>	N <sub>compact</sub>	N <sub>des</sub>	N <sub>des</sub>
JMF	Dry Weight	Weight in H <sub>2</sub> O	SSD Weight	G <sub>mb</sub> @	Height	Height	Height	%G <sub>mm</sub>	%G <sub>mm</sub>	%G <sub>mm</sub>	VIM @	VMA @	VFA @
Blend		ple ID		11828	P <sub>b</sub> , %	3.0	G <sub>mm</sub>	/1	2.775	/2	2.774	Avg	2.775
	,		_	oplicable (	_		_		Content:				
	Mato	NMAS: rial Type:		mm	NI/A)				t Source:		3CO		
		Date:					A		Source:		Trading	Group	
	I	Designer:		Chamoun					It Grade:		E-10		
		Plant:		AC COLA	S			Desi	gn ESAL:		oplicable		000
										Repo	ort No.:	00	038
				IGN VO						01111	No.:	OC 11	₹/119

Figure B11. Mix Design Volumitric Data - 2

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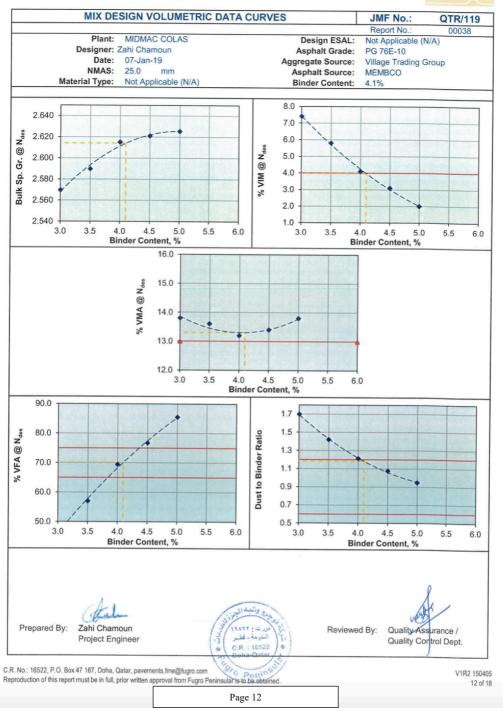


Figure B12. Mix Design Volumtric Data Curves

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		DE	SIGN B	INDER	CONTE	NT VEF	RIFICAT	ION				No.:		<b>R/119</b>
		Plant: Designer: Date: NMAS: erial Type:	Zahi Cha 07-Jar 25.0					A	Aspha Aggregate Asphalt	gn ESAL: It Grade: Source: Source: Content:	Not Ap	oplicable ( E-10 e Trading	(N/A)	
N <sub>des</sub> =100	Sar	nple ID	18-1	2114	Binder	Content	4.1		G <sub>mm</sub>	/1	2.723	/2	2.718	2.721
I <sub>max</sub> =160	Dry	Weight in	SSD	G <sub>mb</sub> @			Height @	%G <sub>mm</sub> @	%G <sub>mm</sub> @		VIM @	VIM @	VMA @	VFA@
	Weight		Weight	N <sub>compact</sub>	N <sub>ini</sub>	N <sub>des</sub>	N <sub>max</sub>	N <sub>ini</sub>	N <sub>des</sub>	N <sub>max</sub>	N <sub>des</sub>	N <sub>max</sub>	N <sub>des</sub>	N <sub>des</sub>
/1 N <sub>des</sub>	5084.4		5099.8	2.610	128.7	115.9	-	86.4	95.9	-	4.1	-	13.5	69.6
/2 N <sub>des</sub> /3 N <sub>des</sub>	5080.2 5082.0		5094.9 5098.8	2.614	128.2 129.6	115.7 116.8	-	86.7 86.4	96.1 95.9		3.9	-	13.3	70.7
/4 N <sub>max</sub>	5103.6		5116.0	2.642	129.5	117.0	115.5	86.6	95.9	97.1	4.1	2.9	13.5 12.4	69.6
/5 N <sub>max</sub>	5068.1		5076.1	2.645	128.3	115.7	114.2	86.5	96.0	97.1	4.0	2.8	12.4	66.9 67.5
G <sub>b</sub>	1.03	P <sub>ba</sub>	0.4	P <sub>be</sub>	3.7	F/A	1.2		/ol Properti		4.0	-	13.4	70.0
G <sub>sb</sub>	2.892	G <sub>se</sub>	2.926	G <sub>sa</sub>	2.892	P <sub>0.075</sub>	4.4		ol Propertie	0 000		2.9	-	-
				SUM	MARY (	OF GVR	ATORY \	/EDIEIC	ATION D	ΑΤΛ				
				- 501	IIIIAKI	JI GIIO	HIOKIY	LKIFIC				14		
				Desi	ign Param	neter	Specifi 25045-2	7-3PS-	Res	ge Test sult				
					A 1 #5	0/	024			2114				
					, Avg VIM		> 1			3.5	0			
					, Avg VIN		4			.0	0			
					, Avg VM		> 1			3.4	0			
					, Avg VFA		65%	75%		0.0	0			
					, Avg VIN	1, %	> 2		_	.9	0			
					P <sub>0.075</sub> /P <sub>be</sub>		0.6	1.2	1.	.2				
A design t	binder c at N <sub>max</sub> ).	ontent of 4	.1% was	selected v	BIN with the in	DER CO	NTENT S	SELECT g the targ	TON et volume	tic proper	ties (VIM	, VMA, ar	nd VFA at	N <sub>design</sub>
\ design t	binder c at N <sub>max</sub> ).	ontent of 4	.1% was	selected v	BINI with the in	DER CO	NTENT:	SELECT g the targ	TION et volume	etic propert	ties (VIM	, VMA, ar	nd VFA at	N <sub>design</sub>
design I	binder c at N <sub>max</sub> ).	ontent of 4	.1% was	selected v	BIN with the in	DER CO	NTENT S	SELECT g the targ	TION et volume	tic propert	ties (VIM	, VMA, ar	nd VFA at	N <sub>design</sub>
design I	binder c at N <sub>max</sub> ).	ontent of 4	.1% was	selected v	BINN the in	DER CO	NTENT (	SELECT g the targ	TION et volume	tic properi	ties (VIM	, VMA, ar	VFA at	N <sub>design</sub>
design I	binder c	ontent of 4	.1% was	selected v	BINI with the in	DER CO	NTENT :	SELECT g the targ	TION et volume	tic properi	ties (VIM	, VMA, ar	nd VFA at	N <sub>design</sub>
design I	bbinder c	ontent of 4	.1% was	selected v	BINI with the in	DER CO	NTENT :	SELECT the targ	TION et volume	tic properi	ties (VIM	, VMA, ar	nd VFA at	N design
design I	binder c	ontent of 4	.1% was	selected v	BINI with the in	DER CO	NTENT :	SELECT the targ	TION et volume	tic properi	ties (VIM	, VMA, ar	nd VFA at	N design
design to the de	at N <sub>max</sub> ).	ontent of 4	A	selected v	BINI with the in	sisterion of	balancing	SELECT The targ	Review		ud			Ndesign
Prepare	at N <sub>max</sub> ).	Zahi Char Project Er	moun		with the in	tention of	balancing balancing	SELECT the targ	et volume	ed By: (	W. Quality A		1	Ndesign
Prepare	ed By:	Zahi Char	noun igineer	mants frac@	with the in	tention of	balancing وشد در در د	SELECT the targ	et volume	ed By: (	W. Quality A	ssurance	/ pt.	N design

Figure B13. Design Binder Content Verification

Geotechnical, Material Testing, Engineers, Foundation Testing, Pavement Services



	TENSILE STRENGT	H RATIO	(AASHT	O T283	)		JMF	No.:	QTR/119
							Repo	rt No.:	00038
	Plant: MIDMAC CO	LAS			Desig	gn ESAL:	Not Ap	plicable (I	
	Designer: Zahi Chamou	ın			Aspha	It Grade:	PG 76	E-10	
	<b>Date:</b> 07-Jan-19			Α	ggregate	Source:	Village	Trading (	Group
	NMAS: 25.0 mm				Asphalt	Source:	MEMB	CO	
Mat	erial Type: Not Applicab	le (N/A)			Binder	Content:	4.1%		
	VOLUI	METRIC PR	OPERT	IFS OF T	FST SP	ECIMEN	S		
		8-12214	l Liki	120 01 1	L01 01	LOINILIN	3		
	Sample Number		1	2	3	4	5	6	
t	Sample Height, mm		94.9	94.9	94.9	94.9	95.0	94.9	95 ± 5 mm
D	Sample Diameter, mm		150.0	150.0	150.0	150.0	150.0	150.0	
A	Dry Mass		3997.8	4011.9	4017.0	4009.1	4013.6	4015.4	
C	Mass in Water		2446.7	2443.9	2452.1	2453.7	2455.1	2462.9	
В	SSD Mass		4026.6	4034.2	4044.3	4036.4	4042.0	4043.5	
E	Volume of Sample (B - C		1579.9	1590.3	1592.2	1582.7	1586.9	1580.6	
G <sub>mb</sub>	Bulk Specific Gravity (A)	(E)	2.53	2.523	2.523	2.533	2.529	2.540	
$G_{mm}$	Maximum Density		2.721	2.721	2.721	2.721	2.721	2.721	
$P_a$	%VIM [100*(G <sub>mm</sub> - G <sub>mb</sub> )		7.0	7.3	7.3	6.9	7.1	6.7	7 ± 0.5 %
Va	Vol. of Air Voids (P <sub>a</sub> *E /	100), cc	110.6	116.1	116.2	109.2	112.7	105.9	
	SATII	RATION O	F COND	ITIONED	SPECIA	IEN SET			
			00110		JI LUIN				
	Sample Number		1	2	3	4	5	6	
B'	SSD Mass after Saturation		-	-	-	4087.8	4098.9	4093.4	
C'	Mass in Water after Satu	ration	-	-	-	2505.7	2513.2	2510.3	
E'	Vol. of Sat. Sample (B' -		-		-	1582.1	1585.7	1583.1	
J'	Vol. of Abs. Water (B' - A		-	-	-	78.7	85.3	78.0	
S"	% Saturation (100*J'/V <sub>s</sub>	)	-	-	-	72.1	75.7	73.7	70 - 80 %
	1	ENSILE S	TRENGT	H RATIO	RESUL	TS			
	Sample Number		1	2	3	4	5	6	
P'	Recorded Load (@ 25°C)		15,989	13,977	15,471	14,696	14,517	15,047	
S	Indirect Tensile Strength,		715.1	625.1	691.9	657.2	648.5	672.9	
	Average ITS for each set	, kPa		677			660		
	CoV for each set, %			6.9			1.9		Specification
<u> </u>	Tensile Strength Ratio (T	SR), %			9	7			> 80%
	Feb		شبه البحر.	9 24				Var	
Prepared By:	Zahi Chamoun Project Engineer		المرازية المرازية C.R.: 1 Doha-0	الدوء الدوء 6522 علما	1	Review	,	Quality As Quality Co	ontrol Dept.
No.: 16522, P.O. Box	47 167, Doha, Qatar, pavements.fm	e@fugro.com	gro po	mine"					V1R2 150
	47 167, Doha, Qatar, pavements.fm t must be in full, prior written approva		insular is to b	e obtained.					V1R2 150 14 o
			Page	e obtained.					

Figure B14. Tensile Strength Ratio (AASHTO T283)

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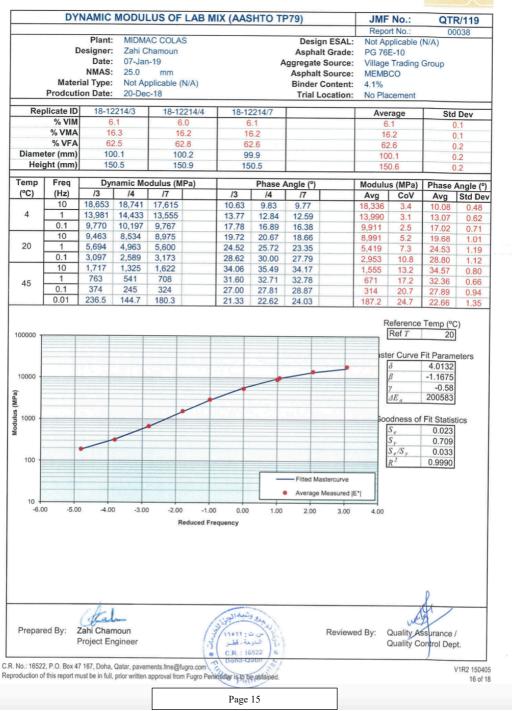


Figure B15. Dynamic Modulus of Lab Mix (AASHTO TP79)