



Developing a Rutting Prediction Model for HMA Pavements Using the LTPP Database

Jolina Karam¹ · Hossein Noorvand¹

Received: 6 June 2021 / Revised: 3 May 2023 / Accepted: 13 May 2023

© The Author(s), under exclusive license of Chinese Society of Pavement Engineering 2023, corrected publication 2023

Abstract

Generally, asphalt concrete experiences permanent deformation due to its exposure to repeated traffic loading during its service life at high temperatures. The objective of this study was to provide an efficient and quick predictive model to easily assess the rutting potential in hot regions. The model was developed using materials properties, traffic, and climatic data gathered from the Long-Term Pavement Performance (LTPP) InfoPave database for 20 different sections in the Dry Freeze and Dry Non-Freeze regions. Performance prediction is one of the widely used methods to assess pavement performance during its service life. It is also used to in pavement management techniques to accommodate the pavement response for specific conditions. Thus, a multiple linear regression model was developed based on data collected from the LTPP database with an R^2 of 0.837 and a Se/Sy ratio of 0.47. This model predicts the rutting depth of Hot Mix Asphalt Concrete (HMA) pavements for given structure, climatic conditions, traffic levels and volumetrics properties of asphalt mixtures. The robustness of this model was also compared to two existing models in the literature and was shown to be accurate. In addition, the rutting resistance of various flexible pavement sections at hot and moderate climatic regions within the USA were compared. Based on the collected data, it was found that the maximum temperature had a significant impact on rutting, where higher temperatures increased the rutting development in pavements. On the other hand, some disparities in the measured rutting depth from different states (AZ vs TX) for similar traffic, climate conditions and mixture characteristics were noted. It was explained by the possible improvement in the mix design in certain location, as well as the different aggregates used and construction practices. For those reasons, the overall mechanical response of an HMA pavement is typically governed by the properties of its constituents.

Keywords HMA pavements · Rutting depth · Long term pavement performance (LTPP) · Prediction model · Temperature

1 Introduction

Several factors affect pavement design and performance over time. Historically, pavements are designed based on a climatic pattern, incorporating assumptions about reasonable ranges of temperatures and precipitation levels. Temperature causes several different modes of distresses along the pavement such as thermal cracking, permanent deformation (rutting), as well as shoving and corrugation [1, 2].

Rutting is one of the major distresses taken into consideration within hot climates such as Arizona. The presence of rutting on the pavement surface leads to different problems such as hydroplaning, which is the accumulation of water in the ruts. This phenomenon increases the likelihood of accidents, as cars would slide uncontrollably on wet surfaces [3]. Several studies have evaluated the effect of high temperatures on asphalt mixtures and binders. It has been found that high temperatures greatly affect the rutting behavior, as well as the stability of the mix. At higher temperatures and greater vehicle loading, the adhesive force between the binder and aggregates will be reduced [4]. In addition, premature rutting failures were noted with originally passing screening criteria in hot climates [5], requiring the revision of the pass-fail.

While designing a new pavement structure, having a quick method to assess the rutting behavior is helpful to

✉ Jolina Karam
jjkaram@asu.edu

Hossein Noorvand
hnoorvand@asu.edu

¹ Arizona State University, PO Box 875306, Tempe, AZ 85287-3005, USA

assign various design modifications and additions and tailor the structure and respond to the State's needs and remarkable issues. Several prediction models were previously developed based on the permanent strains and material properties to assess the potential distresses in asphalt pavements happening during their life span [6]. Such prediction models can allow state agencies to modify the pavement characteristics according to the expected traffic and climatic conditions. Rutting depth prediction can be modeled in different ways; this can be done by the means of regression analysis, or through material characterization parameters projecting future conditions. Many models have been developed, from purely empirical to mechanistic: asphalt institute (AI) model, shell model and those under the Federal Highway Administration (FHWA) LTPP program [1] and the FHWA/NCHRP WesTrack project [7]. However, these models were developed primarily for project-level applications, and their network-level applicability has not been examined. Furthermore, most of those models depend on testing methods in the laboratory and the field, by referring to the elastic and plastic strains as a function of number of load application and deviator stresses. It has also been determined that the effect of the underlying layers on rutting has not always been considered. In fact, rutting phenomena could occur in all the layers of pavement structures including asphalt layers and any of the underlying pavement layers. From a structural point of view, rutting is assumed to be the result of excessive strain in the subgrade, or permanent deformation from any layer under the surface within the pavement [8, 9]. A review of the rutting prediction models for flexible pavements is presented [10], where the major disadvantage of those models is the use of laboratory programs that limit the number of samples to be tested, leaving a big gap in the analysis. Other prediction tools were also developed to assess the pavement performance based on volumetric characteristics. The performance of the mixtures was evaluated based on the input parameters with respect to rutting, fatigue and thermal cracking [11].

Laboratory studies have developed a rutting model based on flow number test measurements, where the flow number is defined as the number of load repetitions till shear failure of the specimen [12]. The flow number test consists of the application of a dynamic load for several repetitions and the accumulated permanent deformation caused by the load repetition is recorded in terms of the number of cycles. The cumulative permanent strain versus the number of cycles denotes three different and major zones: primary, secondary, and tertiary. In the primary zone, the strain rate decreases. As the secondary zone follows, the permanent strain rate remains constant. Finally, in the tertiary zone, the

permanent strain rate increases rapidly, ending in material rupture or failure. The beginning of this zone is denoted by the Flow Number, or the number of repetitions until failure of the sample is reached [13]. An empirical model to determine the rutting depth of asphalt pavement layer based on 20 years of construction was developed at ASU [14]. It used the measured Flow Number (FN) values of the asphalt mixture, expected traffic (ESALs), and thickness of the asphalt layer. For evaluation of FN values, a predictive model based on the gradation of the aggregates used in the mix and the viscosity of the binder at the effective pavement temperature was developed. Other studies have developed a model relating the rutting depth to the Hamburg Wheel Tracking Test results [15]. This test is used by several state departments of transportation in the mixture design process. The test sections included Hot Mix Asphalt pavements (HMA) and Warm Mix Asphalt (WMA) under different traffic levels and climate conditions. Another study was carried out to predict rutting based on the Triaxial Repeated Load Test [16]. It refers to a quadratic modified Burger rheological model by considering dynamic loads to simulate the rutting depths through existing Burgers models. The triaxial test is carried out under different temperatures and loads.

Another prediction method for the behavior of asphalt mixtures within a pavement structure is the AASHTOWare Pavement Design Guide. It is a pavement design methodology based on engineering mechanics and has been validated with extensive road test performance data. It is also based on both mechanistic and empirical designs and represents a major change from the typical pavement design methods used nowadays. As it has been developed in the NCHRP Project 1-37A, it is able to predict the major distresses such as Permanent Deformation, Fatigue, Thermal Cracking and Roughness in terms of International Roughness Index (IRI) under given climatic and traffic conditions [17]. However, to have an accurate prediction, several input parameters from extensive laboratory testing are required to perform a level 1 analysis (most accurate). Studies have shown new and different approaches of rutting predictions using the AASHTOWare Pavement ME [18] showing better accuracy. This study showed the importance of the underlying layer's parameters for rutting prediction as well as the importance of traffic and accumulated strains in the layers. However, the accuracy also depended on laboratory testing. Other studies evaluated the performance of mixtures based on their placement within the pavement structure i.e., the wearing or binder course. A series of modified and unmodified binders were subjected to various tests such as performance grade and multiple stress creep and recovery. As for the mixtures, they were tested for dynamic modulus, flow time, flow number, and dry rut

wheel tests. The rutting performance varied depending on the test method and whether it was a binder or mixture. To evaluate pavement rutting performance, structural simulations were carried out using AASHTOWare software. The study found that there was no significant difference in rutting performance when different combinations of unmodified and modified mixes or modified mixes in both layers were used [19].

For this reason, an accurate and quick prediction model with handy input parameters, such as the ones presented in the LTPP Database, is needed. The aim of this study is to develop such a model based on data present on the LTPP Database to provide insight on the possible rutting values for different pavement mixture designs.

2 Objective

As the permanent deformation is not always recorded in the LTPP database, a rutting prediction model for flexible pavements per climate region and location is useful and may suggest tailoring the asphalt mixtures to increase the potential resistance to rutting. The early detection of rutting is imperative for optimal rehabilitation strategies and preventive maintenance programs. In addition, the material properties and mix design parameters could be re-evaluated and optimized by knowing the predicted rutting performance of the pavement. In other words, a prediction

model is useful for design agencies to enhance performance and make the necessary adjustments. In addition, previous studies have demonstrated the importance and effect of the underlying layers on permanent deformation. Based on the literature, the parameters of the underlying layers are often not considered [10]. Consequently, the main objective of this study is to develop a model for predicting the rutting depth of flexible pavements based on the input parameters from LTPP InfoPave database. **This will include parameters reflecting the underlying layer of the pavement structure and the asphalt layer parameters that can be obtained without rigorous laboratory testing.** All in all, this study includes the development of the model incorporating the entire asphalt pavement structure and the effect of high temperature on the rutting mechanisms of flexible pavements.

3 Methodology

In this study, 20 test sections with a granular base from the Dry Freeze, Dry Non-Freeze regions from the LTPP database were selected. Data including the climatic conditions, traffic loading, material properties for both asphalt mixtures, binders and underlying layers, as well as measured rutting values were gathered and filtered. The effect of high temperatures on HMA pavements was studied according to the gathered information, and a multiple linear regression model was developed based on the data collected to

Fig. 1 Methodology flowchart

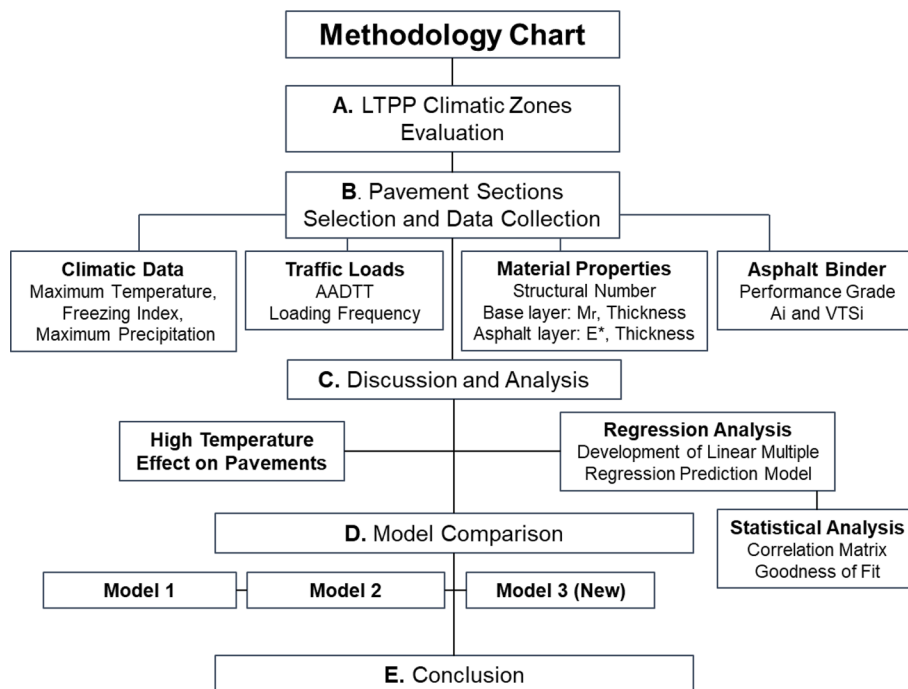


Table 1 Climatic data collected for the sections under study

State	Section	Max. temp., °F, (°C)		Freeze Index	Ave. precipitation, in, (mm)		Solar radiation (W/m ²)
Arizona	1025	74.8	(23.8)	25.3	13.0	(330)	174035
Arizona	1024	74.1	(23.4)	39.3	13.7	(348)	179796
Arizona	1022	84.8	(29.3)	9.3	9.0	(229)	177197
Arizona	1021	84.9	(29.4)	8.7	8.9	(226)	179206
Arizona	1018	85.4	(29.7)	0	12.7	(323)	180015
Arizona	1017	83.3	(28.5)	0.7	16.0	(406)	179206
Arizona	1006	90.1	(32.3)	0	13.3	(338)	181037
Arizona	1003	92.2	(33.4)	0	10.9	(277)	177764
California	8159	67.0	(19.4)	0	15.4	(391)	177216
California	8534b	93.4	(34.1)	0	2.1	(53)	178067
California	8535a	92.5	(33.6)	0	3.4	(86)	177890
California	0535b	93.5	(34.2)	0	2.4	(61)	176978
Colorado	1029	74.6	(23.7)	81	12.6	(320)	179548
Colorado	1053	70.1	(21.2)	530.5	12.0	(305)	178460
Idaho	1007	74.1	(23.4)	145.3	10.7	(272)	179035
Idaho	1020	73.6	(23.1)	295	8.6	(218)	175144
Montana	8129	72.2	(22.3)	414.6	11.1	(282)	176763
Nevada	1020	75.0	(23.9)	46	9.3	(236)	177998
New Mexico	1005	79.7	(26.5)	42.4	18.1	(460)	177482
Texas	1111	72.9	(22.7)	230.8	15.0	(381)	178323
Utah	1001	74.8	(23.8)	279	9.7	(246)	174706
Washington	1007a	70.9	(21.6)	499.3	9.7	(246)	178477
Washington	1005a	72.6	(22.6)	133.8	10.6	(269)	132779
Wyoming	7775	63.4	(17.4)	1019.8	8.3	(211)	135829

predict permanent deformation. The pavement structure's layer thicknesses are different for each section considered and are therefore considered in the model's development. Furthermore, the developed model was compared to existing prediction models present in the literature. In the following sections, the workplan is divided into data collection and methods followed. Figure 1 shows the development of the study in the form of a flowchart.

4 Data Collection and Input Parameters

One of the objectives of this study focuses on how temperature changes within different regions of the United States could affect the performance of flexible road pavement in terms of rutting. Dry Freeze and Dry Non-Freeze regions were selected from the LTPP database and only flexible pavements with an unbound granular base (GPS1) that have been actively monitored were considered. Therefore, a total of 20 sections were analyzed and the corresponding data gathered. It should be also mentioned that any rehabilitation methods were excluded to only compare the effects of temperature on the original asphalt layer of the pavement

structure. Furthermore, the data collected have been used to develop the suggested regression model later in the study.

4.1 Climate Data

Different ranges of climate data were obtained for the LTPP sections under study. To make an effective observation and study the external factors, the average annual temperature, precipitation, freezing index and solar radiation were obtained from the LTPP Database for each section. In addition, since rutting is significantly affected by high temperature, the maximum temperature within each year of pavement design was recorded for the purpose of the analysis. The temperature range considered is from 60 to 100°F (15°C to 37°C). The gathered climatic data is summarized in Table 1.

4.2 Traffic Loads

As previously discussed, rutting is the result of accumulated traffic loading. The sections were compared based on the measured accumulated traffic load during their design life by the LTPP. The Annual Average Daily Truck Traffic, which

is the total truck traffic volume divided by 365 days, was noted for the analysis of this study. In addition, the truck factor includes all varieties of vehicles including cars, single axle, tandem axles, and other types of trucks. It is the value that converts the volume of traffic into one reference truck and is also used as input for AASHTOWare Pavement-ME software. Therefore, to compare how traffic affects the performance of asphalt pavements in terms of rutting, the accumulated truck traffic was determined for the entire design lifetime of each section.

In addition, it was observed that the selected sections have different ranges of cumulative traffic loads. Therefore, knowing that rutting is very much dependent on traffic, sections were compared with similar ranges of traffic loads. It was found that accumulated truck traffic of the sections ranged from 500 to 25,000. However, after sorting and combining the sections, it was realized that accumulated traffic loads could be broken down into three groups as follows: 500–3000 with seven sections, 2000–6000 with six sections, and 12,000–25,000 with six sections.

4.3 Measured Rutting

The measured rutting is the key value needed in this study. This value has been collected for the surface layer before the implementation of any type of rehabilitation. The accumulated traffic, climate, material properties, and structure were collected accordingly. The data collected includes the latest rutting value recorded before the first maintenance/rehabilitation activity, changing the Construction Number “CN” from 1 to 2. Therefore, only the input variables contributing to such amount of rutting are included in the analysis to better assess the development of the distress as well as the accurate conditions the pavement was subjected to. Furthermore, the measured rutting values are needed for the development of the regression model later in this study.

4.4 Material and Structure Properties

Material properties of pavements play a very significant role with respect to their lifetime service performance. For example, good performing surface and binder layers must have sufficient stiffness to prevent rutting due to poor material selection and gradation. In addition, pavements must have sufficient thickness in order to resist distresses, such as rutting and fatigue cracking [20]. For this reason, parameters relating to the asphalt layer as well as the base layer such as the resilient modulus of the base layer, thicknesses of asphalt and base layers as well as structural numbers of the sections at the date of construction were collected for the analysis and development of the model. As each pavement structure

is different in terms of dimensions, those parameters were considered essential when developing the model. Table 2 summarizes all the values collected for this study.

4.5 Dynamic Modulus

It is well known that rutting is very much dependent on traffic and temperature [21]. However, to develop a regression model for prediction of HMA pavement performance terms of rutting, the materials properties of each section need to be identified for the accuracy and validity of the model. A mixture with a high resilient modulus of the base shows more resistance to permanent deformation than one with a lower modulus. Furthermore, the modulus values of asphalt binder/mixtures are useful to possibly define some contradictory trends observed within the sections. Although, the dynamic modulus values at different temperature and frequencies are available in LTPP InfoPave database, it is hard to locate a specific dynamic modulus in the model. To resolve this, one needs to find a specific temperature at a particular frequency that matches the climatic characteristics and the temperature of the asphalt of the particular pavement section. In other words, the evaluation of a particular test temperature for asphalt mixtures to analyze major distresses generally observed on flexible pavements (e.g., rutting, thermal cracking, and fatigue cracking) is of great importance in their analysis and design. It is apparent that using a single reference temperature for the analysis and development of model could greatly decrease the testing time as well as the required analytical efforts in the mixture assessment process and results in an increase in feasibility and effectiveness of models.

In this study, the dynamic modulus (E^*) was obtained from LTPP database and was chosen based on reference temperature 70°F (21°C) and frequency of 25 Hz. In the Mechanistic Empirical Pavement Design Guide (MEPDG), a frequency of 25 Hz is used as the reference frequency number for the design, and 70°F was selected as it was the closest value to the average annual temperature of the sections. The results are summarized in Table 2.

4.6 Binder Characterization

Another important aspect to consider in pavement design is the type of binder used within the pavement structure. As the viscosity of the asphalt binder chosen greatly affects the performance of the pavement, the Performance Grade (PG) type of each section has been selected from the LTPPBind V3.1, based on a 98% reliability. The binder type is a very important parameter, as choosing a soft binder for a high temperature location will cause a softening behavior, leading to extensive rutting. The opposite behavior is to be expected when a stiff binder is selected for cold temperature regions.

Table 2 General data collected and sections under study

State	Section	Road classification	SN	Max. temp. °F, (°C)	Accumulated truck traffic	E* psi, (MPa)	H _{AC} in, (mm)	H _{base} in, (mm)	Mr _{base} psi, (MPa)
Arizona	1018	Rural Principal Arterial—Interstate	4.5	84.2–87 (29–30)	3510–6972	1517194 (10461)	8.4 (213)	7.2 (183)	134.2 (3409)
Arizona	1017	Rural Principal Arterial—Interstate	5.2	81.5–85.1 (27.5–29.5)	3988–6533	1356603 (9353)	8.9 (226)	11.2 (284)	134.2 (3409)
Arizona	1003	Rural Principal Arterial—Interstate	6.4	90.5–93.2 (32.5–34)	17664–23328	1913877 (13196)	13.1 (333)	6 (152)	79.13 (2010)
Arizona	1006	Rural Principal Arterial—Interstate	4.1	89.6–93.2 (32–34)	19460–27815	1317756 (9086)	8.7 (221)	8.5 (216)	79.13 (2010)
Arizona	1024	Rural Principal Arterial—Interstate	5.5	72.5–76.1 (22.5–24.5)	10300–25269	1953837 (13471)	10.8 (274)	6.3 (160)	178.7 (4539)
Arizona	1025	Rural Principal Arterial—Interstate	3.7	72.5–76.1 (22.5–24.5)	12735–25483	2466438 (17005)	7.6 (193)	4.9 (124)	178.7 (4539)
California	8156	Rural Minor Arterial	3.8	65.3–69 (18.5–20.5)	2229–8503	712616 (4913)	3.9 (99)	15 (381)	170.93 (4342)
Colorado	1053	Rural Principal Arterial—Other	6.7	72.5–75.2 (22.5–24)	1712–6280	817329 (5635)	4.6 (117)	28.9 (734)	120 (3048)
Colorado	1029	Rural Principal Arterial—Other	3.8	67.1–70.7 (19.5–21.5)	1498–2659	1464096 (10095)	4.2 (107)	16.6 (422)	120 (3048)
Idaho	1007	Rural Principal Arterial—Other	4.6	71.6–74.3 (22–23.5)	2145–3072	904399 (6236)	3.6 (91)	19.4 (9493)	170.93 (94342)
Idaho	1020	Rural Principal Arterial—Other	4.4	73.4–74.3 (23–23.5)	715–3363	774909 (5343)	3.8 (97)	20.5 (521)	170.93 (4342)
Montana	8129	Rural Principal Arterial—Other	5	66.2–69.8 (19–21)	187–1975	1511681 (10423)	3.2 (81)	22.8 (579)	170.93 (4342)
Nevada	1020	Rural Principal Arterial—Other	3.2	78–80.6 (25.5–27)	845–3435	1471711 (10147)	7 (178)	4.7 (119)	120 (3048)
New-Mexico	1005	Rural Principal Arterial—Interstate	5	71.6–77 (22–25)	4374–28826	4347061 (29972)	8.7 (221)	8.5 (216)	79.13 (2010)
Texas	1111	Rural Principal Arterial—Other	3.9	79.7–83.3 (26.5–28.5)	3806–8070	1520936 (10486)	7.4 (188)	8.4 (213)	178.7 (4539)
Utah	1001	Rural Principal Arterial—Other	2.8	77–81 (25–27.2)	1943–5052	1164034 (8026)	5.5 (140)	5.8 (147)	170.93 (4342)
Washington	1007	Rural Principal Arterial—Other	4.9	71.6–77 (22–25)	234–3144	1411923 (9735)	6.4 (163)	13 (330)	61.96 (1574)
Washington	1005	Rural Principal Arterial—Interstate	6.7	69.1–73.4 (20.6–23)	12358–21230	1445014 (9963)	11.8 (300)	9.5 (241)	61.96 (1574)
Wyoming	7775	Rural Major Collector	2.5	60.8–66.2 (16–19)	411–1743	1307628 (9016)	4.7 (119)	6.8 (173)	61.96 (1574)

In addition, knowing the binder's temperature susceptibility is a great deal to this analysis. Based on the FHWA, each binder type has a corresponding "Ai" and "VTSi" parameter, related to the PG type where "Ai" is the intercept of the Temperature vs Viscosity curve, and "VTSi" is the slope of the curve. Having a flatter curve or smaller slope suggests that the binder is less susceptible to temperature fluctuations.

5 Methods and Discussion

5.1 Effect of High Temperature on Rutting

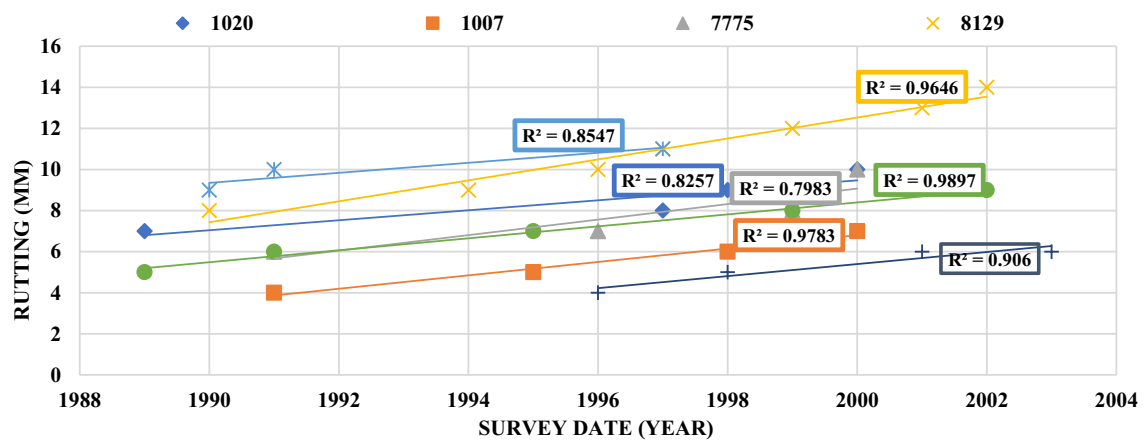
Figure 2 was plotted for all the selected sections to evaluate the trend of measured rutting at a specific year before any maintenance/rehabilitation activity. It can be seen that rutting increases with time regardless of the range of traffic and the unique characteristic of each designated section resulted from the accumulated traffic loads. This can be explained by the effect of temperature, as it affects the aging of asphalt binder causing an increase in embrittlement (cracking) of the surface. Furthermore, high temperatures cause the softening of the asphalt binder. In other words, it will cause a decrease in the viscous properties of the mix. With the repeated passing of traffic, the asphalt layer will be more susceptible to rutting. This also leads to a consequent loss of waterproofing, resulting surface water entering the pavement, which will ultimately cause potholing and a rapid loss of surface condition. Therefore, frequent maintenance and rehabilitation techniques are conducted to minimize this issue. For example, regions in the state of Arizona have more frequent rehabilitation activities when compared to moderate regions such as California. In this case, the climatic regions of these states also play a role. Studies have shown that potholing is enhanced by freeze–thaw cycles, which are present in Dry–Freeze and Wet–Freeze regions [22].

Not to mention that many factors can impact the maintenance and rehabilitation (M&R) frequency such as the available funding levels, M&R strategies, existing pavement conditions, materials, construction quality etc. One of the most common rehabilitation techniques in Arizona is mainly conventional cold milling, which is a common and safe type of rehabilitation to remove surface rutting [6]. It can also be seen in Fig. 2 that rutting values are different for each section with a similar range of traffic which should be attributed to different stiffness and thickness values of sections.

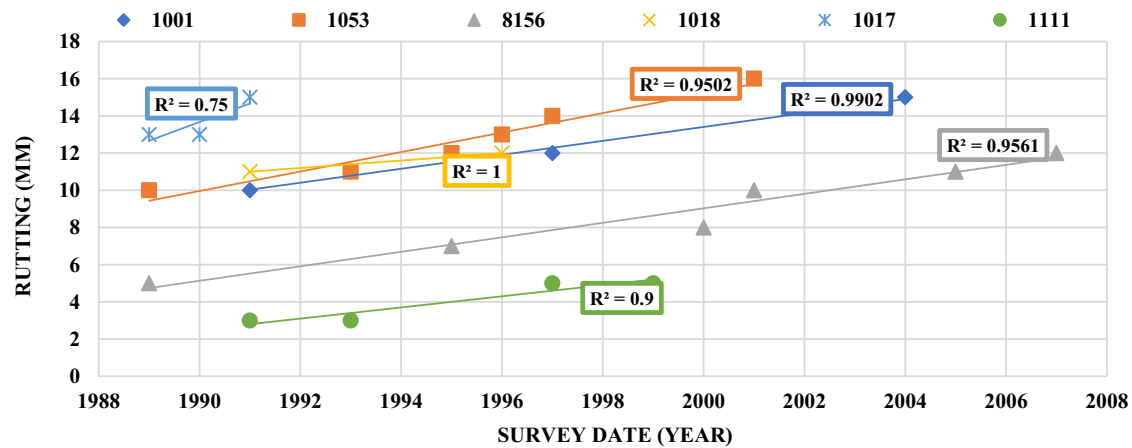
Figure 3 was therefore plotted to indicate the rutting values at different maximum temperature of the selected sections. It can be seen in the plot that there are three main clusters with respect to maximum temperature. The three different clusters can be explained as follows:

1. The first cluster indicates the increase in rutting values of sections with increasing temperature, which confirms the fact that higher temperature could adversely affect rutting.
2. The second cluster indicates that while temperature increases within the clusters, a slight increase in the rutting values was observed. This is explained by the fact that the sections located in Arizona have thicker layer thicknesses of the asphalt layer in the range of 8–11 in (20–28 cm) compared with the other sections with an asphalt layer thickness of range of 3–5 in (7.6–12.7 cm) (Refer to Table 2).
3. The third cluster is an exception to the rule. In fact, it was observed the sections within the state of Texas had lower rutting values in their service lifetime although the stiffness, traffic range, layer thickness, maximum temperature and the average annual temperature of the section were quite similar to those in Arizona, as shown in Tables 1 and 2.

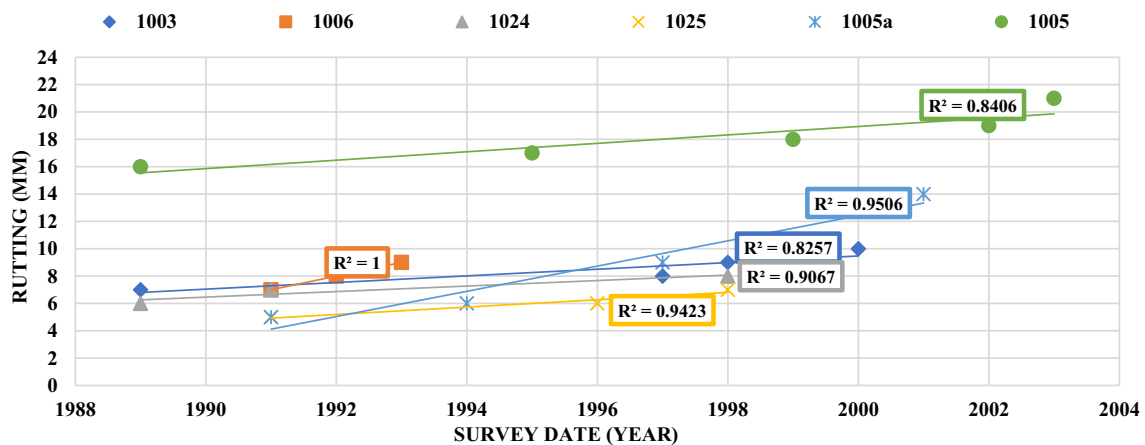
The contradictory trends within the sections can be explained by the presence of several external and internal factors such as properties of asphalt mixtures (i.e., gradation, asphalt binder content, and compaction level) which were not recorded in this study and could have an impact on the permanent deformation of asphalt pavements, as shown by Gopalipour in 2012 [23]. In addition, this could be explained by the fact that these sections' designs addressed the potential rutting problem in those states. In other words, as rutting is to be expected in those regions, the mix design has been improved to accommodate the conditions. Furthermore, the AC meso-structure could be affecting the rutting, since the coarse aggregates are enclosed by the Fine Aggregate Mixture/Matrix (FAM) that consist of fine fillers, fine aggregates, asphalt binder, and the air voids. According to Darabi [24], the overall mechanical response of an HMA pavement is governed by the properties of its constituents. Several studies have argued that the properties of aggregates are usually considered as the primary factors leading to rutting of HMA pavements [25, 26]. Stakston and Bahia [27] found that aggregate gradation rutting resistance is very dependent on gradation of aggregate. Asphalt binder content is another critical parameter which affects the shear resistance of asphalt mixtures. There should be an adequate film thickness to coat the aggregates providing better cohesion. However, the presence of excessive binder (high film thickness) can essentially have a lubricating impact, thus reducing the efficiency of the aggregate skeleton and generating an unstable mix that is susceptible to premature rutting [28]. It should also be noted that quite similar trends for traffic with the range of 500–3000 and 12,000–25,000 was



(a)



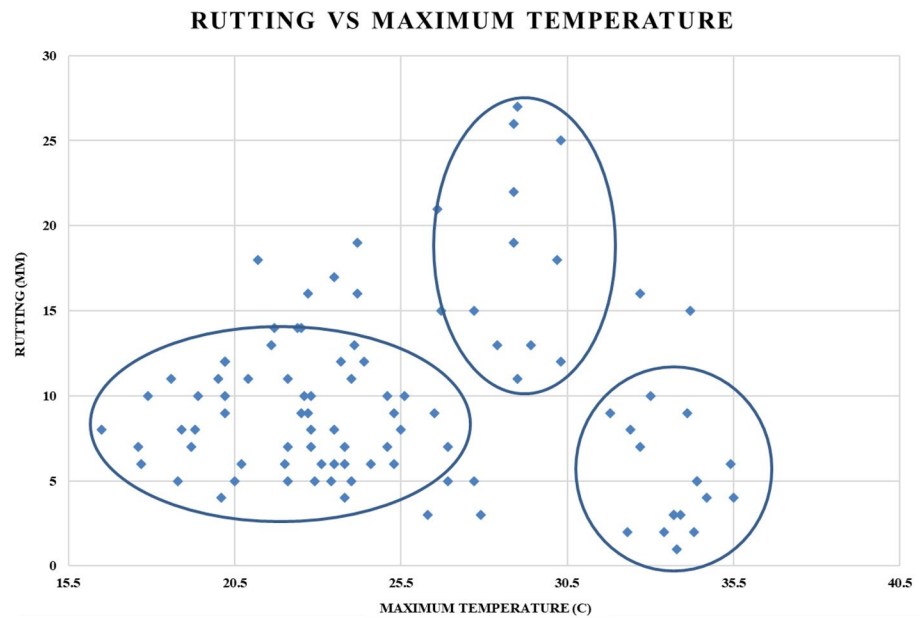
(b)



(c)

Fig. 2 Rutting measurement of selected section at their specific time with **a** truck traffic range of 500–3000, **b** 2000–6000, **c** 12,000–25,000

Fig. 3 Rutting values of all selected sections in this study vs their maximum temperature



also observed, which could be explained by the reasons mentioned above.

5.2 Development of a Regression Model

Two approaches have been considered for the mechanistic modeling of rutting. The first approach, typically referred to as the subgrade strain model approach, assumes that accumulated rutting depth is due to permanent deformation within the subgrade layer, and that the deformation within the HMA and base/subbase layers is negligible as the quality of these layers is controlled through mix design and construction specifications [29, 30]. The second approach considers permanent deformation within each layer of the pavement. Although several techniques have been proposed for the second approach, it has not been widely used because of the difficulty in obtaining elastoplastic or visco-plastic characterizations for the various HMA materials. The main challenge is to obtain those properties in the field in cheap and timely methods as they are related to the rutting performance of each layer. In most previous studies, the allowable number of load applications and resilient strain are considered as the input criteria for the development of a rutting prediction model. In addition, the models are mostly calibrated through empirical methods [31]. Barker et al. [32] also developed a statistical predictive model for rutting depth prediction on the basis of different properties of materials (i.e., thickness of the base material, surface deflection, resilient modulus of the subgrade, air void content), traffic

(ESAL), and climatic condition (i.e., average annual temperature, and freezing index).

Part of this study was to develop an accurate rutting prediction model defined by several input parameters such as the number of years when rutting needs to be evaluated, climatic factors, traffic loads and pavement mixture's volumetrics. The data collected earlier in this study was used to develop the model suggested for the 20 sections chosen in Dry Freeze and Dry Non-Freeze regions by linear regression analysis. The major parameters implemented in the development of the model were the structural number (SN) which represents the whole pavement structure, the resilient modulus (M_r) of the base and its thickness, the stiffness of the HMA layer (E^*) and its thickness, the Accumulated Daily Truck Traffic (AADTT), time (Y) after construction at which rutting is to be predicted and the maximum temperature (T_{max}) at the location of the pavement.

One other important parameter needed is the loading frequency, which relates to the traffic volume to which the pavement will be subjected to during its life span. The analysis behind the importance of this parameter is explained below. As the LTPP database does not provide such information and that one of the goals is to solely use LTPP input data, the following analysis has been carried:

- As the LTPP specifies the functional classification of each road, this data has been collected according to the sections under this study.

- The FHWA report SA-16-076 [33] suggests limit posted speed for each road classification as follows:
 - a. The Interstate System, having the highest classification of roadways in the United States, provides the highest level of mobility and the highest speeds over the longest uninterrupted distance. They usually have posted speeds between 55 and 75 mph (88 and 120 km/hr).
 - b. Collectors are major and minor roads that connect local roads and streets with arterials. Collectors provide less mobility than arterials at lower speeds and for shorter distances. The posted speed limit on collectors is usually between 35 and 55 mph (56 and 88 km/hr).
 - c. Other Arterials include freeways, multilane highways, and other important roadways that supplement the Interstate System. They connect, as directly as practicable, the Nation's principal urbanized areas, cities, and industrial centers. Land access is limited. Posted speed limits on arterials usually range between 50 and 70 mph (80 and 112 km/hr).
 - d. Local roads provide limited mobility and are the primary access to residential areas, businesses, farms, and other local areas. Local roads, with posted speed limits usually between 20 and 45 mph (32 and 72 km/hr), are the majority of roads in the U.S.

Having this in mind, the following frequency ranges were selected with respect to the accumulated AADTT collected earlier. The higher the AADTT, the higher the frequency. As a high traffic volume relates to the biggest functional classification, it is safe to assume a high loading frequency with a high vehicle speed as discussed earlier. The following ranges have been selected for the development of the model:

- For Accumulated AADTT < 10,000: 5–15 Hz
- For Accumulated AADTT between 10,000 and 20,000: 20–25 Hz
- For Accumulated AADTT > 20,000: 25–30 Hz

By having all the previous data collected for the 20 sections sorted and filtered in Microsoft Excel, a *multiple linear regression analysis* was carried, and the following model (Eq. 1) has been developed:

$$\begin{aligned}
 R = & 2.93 + (0.0011 \times Y) + (1.74 \times 10^{-5} \times A_{AADTT}) \\
 & + (0.211 \times SN) + (-0.0414 \times Freq) \\
 & + (9.69 \times 10^{-8} \times |E^*|) + (-0.1 \times H_{AC}) + (-0.034 \times H_{Base}) \\
 & + (0.002 \times M_{RBase}) + (0.0181 \times T_{Max}) \\
 & + (-6.26 \times A_i) + (-17.68 \times VTS_i)
 \end{aligned} \quad (1)$$

where R = rut depth (in), Y = time where rutting is to be predicted since construction year, A_{AADTT} = accumulated

average annual daily truck traffic, SN = structural number, $Freq$ = loading frequency (Hz), E^* = dynamic modulus of the asphalt layer, psi, H_{AC} = thickness of asphalt layer, in., H_{Base} = thickness of the base layer, in., $M_{r,base}$ = resilient modulus of the base layer, psi, T_{Max} = maximum temperature in the year, °F, A_i and VTS_i being the intercept and slope of the temperature vs viscosity curve for each PG-Binder (pre-defined by LTPP)

The developed model has an R^2 of 0.837, and an adjusted R^2 of 0.822. Figure 4 shows the measured and the predicted rutting values, and how they are related based on the suggested model. The model was generated by including 75% of the data collected and was verified for the remaining 25% of the data.

It was noticed that the prediction model is slightly overestimating the rutting values. This could be considered as conservative, as predicting more rutting will induce more tedious modifications in the pavement design. The prediction model appears to be effective in predicting the values of RD as they are within 3% standard deviation of the measured ones. This model is considered to be robust as it includes the effects of the underlying base layer, asphalt layer, traffic volume and frequency as well as time without the need of in-situ and lab measurements.

The limitations of the model were identified as it was developed using the temperature ranges (Sect. 4.1) and the defined frequency ranges (Sect. 4.2). The sections that serve as basis for this model are all principal arterials with granular base, which limits the use of the model to higher road classifications and narrower pavement structure types.

5.3 Statistical Analysis

The goodness of fit for this model was calculated to make sure that it is statistically reasonable. The Se/Sy ratio yielded a value of 0.47, which is good. The significance and relevance of each parameter were evaluated based on the p -values of each independent parameters along with the standardized regression parameters “ β ”, shown in Table 3. A “ β ” value of X indicates that a change of one standard deviation in the independent variable results in X standard deviations increase in the dependent variable. A p -value less than 0.05 was considered to indicate strong evidence against the null hypothesis which shows no correlation was identified between the dependent and independent variables. p -Values by themselves may not be very indicative of the importance of the parameters, as low p -values may have high regression coefficients, and vice versa. This was observed for the “ A_i ” parameter that reflects the behavior of asphalt binder at lower temperatures. This parameter has a p -value of 0.99 and a β -coefficient of approximately 17. In addition, the time “ Y ” parameter had a p -value of 0.4, and a β -coefficient of 0.1. This parameter influences the rutting values in the prediction

Fig. 4 Measured vs predicted Rutting Values (mm)

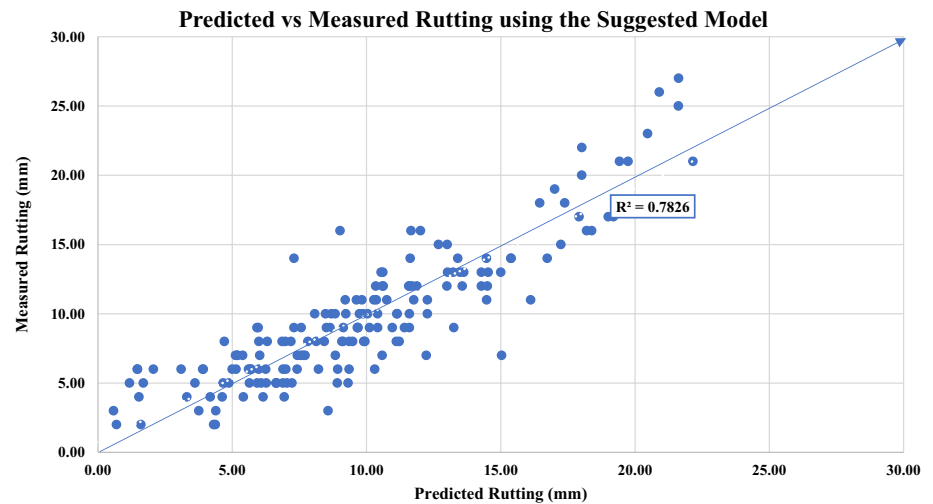


Table 3 p -Value and standardized coefficients

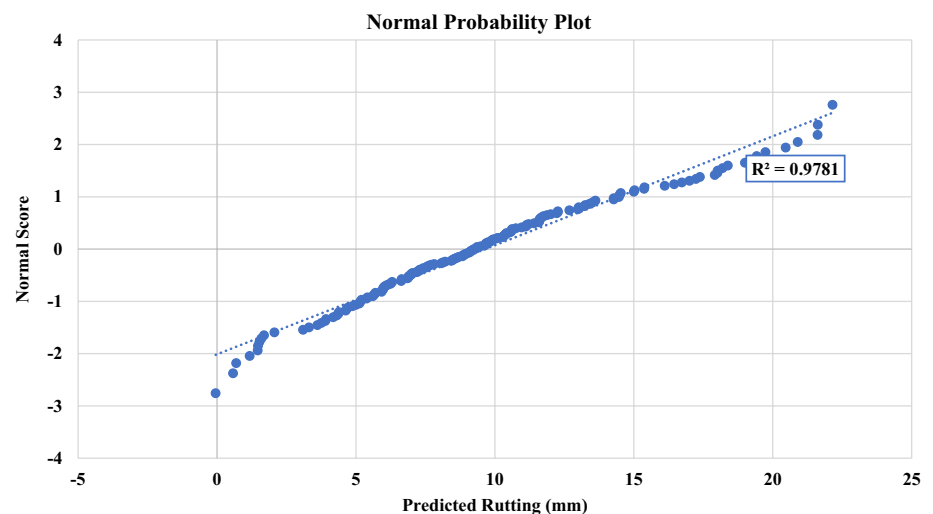
Standardized (Std) variables	Standardized coefficients	p -Value
Std SN	1.95	3.02E-09
Std Y	0.05	4.14E-01
Std A_{ADTT}	0.70	9.17E-09
Std Freq	-0.76	3.20E-20
Std E^*	0.16	2.48E-04
Std H_{AC}	-1.77	3.27E-10
Std H_{Base}	-1.67	2.02E-08
Std $M_{r,base}$	0.37	2.93E-07
Std T_{Max}	0.70	4.08E-14
Std A_i	-16.86	9.91E-01
Std VTS_i	-17.34	4.20E-13

and in practice as the age of the pavement directly affects its behavior and contributes to the development of rutting.

Furthermore, a normal probability plot was generated to make sure that the resulting values follow a normal distribution, showing that the model is statistically sound and normal. The regression statistics using ANOVA showed a Standard Error of 0.084, reflecting a good fit of the values and a p -value of $1.0 \times E^{-39}$ compared to an F value of 49.5. This means that the hypothesis is not rejected, and that the populations are the same (Fig. 5).

Table 4 shows the correlation matrix calculated for the developed model. With respect to the rutting depth, the parameters' correlations were identified: the rutting depth is expected to increase with an increase in AADTT and maximum temperature. On the other hand, rutting is to decrease with a higher frequency (faster traffic), viscosity (softening of the binder) and an increase in layers thicknesses and construction year. One important correlation is the one for maximum temperature and stiffness as they are directly

Fig. 5 Normal distribution plot



correlated. This refers to the fact that at higher temperatures, higher stiffness is needed to sustain higher loads and prevent rutting. Similarly, for high rutting values, higher stiffness values are recommended. Even though the coefficient of temperature is low compared to the others, it is greatly correlated to the mixture's parameters such as E^* , thickness and structural number. All in all, the structural number represents an indication of the strength of the pavement layers and of the total pavement structure. Having a correlation factor of 0.45 with SN, temperature shows a great effect on the strength of the pavement which in turn affects rutting. Furthermore, as most models depend on the surface mixtures (refer to Sect. 1), involving the whole pavement structure is important as rutting depends on the underlying layers. This also supports the benefit of including the SN and how it relates to temperature.

Based on the correlation matrix, the potential parameters that may be of interest to the designer related to the temperature and affecting rutting are the SN and thickness of the asphalt layer having correlation factors of 0.45 and 0.66 respectively. As the asphalt layer thickness increases, the temperature will increase as well. As the structural number also highly depends on the layer thicknesses, the same analysis is suggested. This is explained by the fact that more material is going to be present in the layer, leading to a higher thermal mass. In addition, the binder's parameters as well as mixture's stiffness (E^*) are affected by temperature change. This is expected as the asphalt properties are greatly affected by the temperature in terms of viscosity (softening, hardening).

5.4 Sensitivity Analysis

An important part of the model evaluation is to conduct a sensitivity analysis to assess the effect of each variable on the rutting prediction, and to check if the model reasonably

responds to the changes within each variable's range of values. This can be accomplished by varying one variable at a time within its full range and keeping the other variables constant.

- In terms of Structural Number, SN, it is evaluated as part of the thicknesses of the pavement layers. For the asphalt layer thickness and base layer thickness, an increase of 17% for both resulted in a decrease of rutting by 24% and 9%, respectively. An increase in thickness will induce an increase in SN.
- For the time “Y”, an increase in 67% (i.e., from 9 years to 15) yielded to a predicted value increase by 3%.
- For the accumulated AADTT, an increase from 1943 to 5000 (157%) yielded an increase of 12% in terms of rutting.
- For the loading frequency, an increase from 15 to 20 Hz (33%) decreased the rutting value by 50%.
- For the dynamic modulus of the asphalt layer, an increase of 29% slightly increased rutting by 8%.
- For the resilient modulus of the base, an increase of 5% increased rutting by 5%.
- In terms of the maximum temperature, as it is also related to the binder viscosity; an increase in temperature by 3% (decrease in viscosity by 25%) increased rutting by 10%.
- In terms of “ A_i ” and “VTS_i”, the change has been noted in three cases:
 - For 1 grade higher in terms of upper bound temperature (i.e., from PG64-22 to PG70-22), rutting is noted to decrease by 55%. On the other hand, for 1 grade lower, (PG64-22 to PG58-22), an increase of 64% in rutting is noted.
 - For 1 grade lower in terms of lower bound temperature (PG64-22 to PG64-28), rutting decreased by 17%.

Table 4 Correlation matrix

	Predicted rutting	SN	Design year	Acc. AADTT	Loading freq	E^*	H_{AC}	H_{Base}	$M_{r,base}$	T_{Max}	A_i	VTS _i
Predicted rutting	1.00											
SN	−0.25	1.00										
Year	−0.26	0.36	1.00									
A_{AADTT}	0.21	0.27	0.24	1.00								
Freq	−0.27	0.12	0.08	0.67	1.00							
E^*	0.19	−0.04	−0.28	0.50	0.35	1.00						
H_{AC}	−0.12	0.59	0.36	0.61	0.35	0.29	1.00					
H_{Base}	−0.27	0.60	0.21	−0.34	−0.25	−0.36	−0.23	1.00				
$M_{r,base}$	0.25	0.14	0.17	−0.10	−0.21	−0.28	−0.18	0.39	1.00			
T_{Max}	0.02	0.45	0.37	0.27	−0.01	0.24	0.66	0.04	0.14	1.00		
A_i	0.45	−0.57	−0.15	0.15	0.15	−0.05	−0.05	−0.66	−0.1	−0.2	1.00	
VTS _i	−0.45	0.58	0.17	−0.14	−0.15	0.05	0.07	0.65	0.12	0.27	−1.0	1.00

Based on this analysis, traffic and temperature had the highest impact on the predicted rutting values. Followed by the moduli, the pavement structure's thicknesses, and loading frequency.

5.5 Model Comparison

5.5.1 Model Selection

Another way to reflect the advantages of the proposed model is to compare its results with other models present in the literature. Two pre-existing rutting models were selected in this study to predict the rutting depths for the sections considered in this study based on the LTPP database. The respective data was collected and filtered.

The first model (Model 1) depends on the Flow Number of the mixture, expected traffic (ESALs) and thickness of the asphalt layer. The flow number was determined based on a developed predicted model [14]. The advantage of this model refers to the parameters needed to obtain the predicted rutting performance of HMA mixtures. In other words, it relies on the gradation of the mixture, effective pavement temperature, and viscosity of the binder. This model was selected as it was validated and solely uses the asphalt mixture's volumetrics for the prediction, which are available in the LTPP database. Ninety-four mixtures were evaluated and a total of 1759 Flow Number test results were available when developing both models. The accuracy of the flow number prediction model was found to be $R^2 = 0.62$, with a Se/Sy ratio of 0.60 which are fair statistical measures of model accuracy, considering the wide range of each variable. As for the rutting model developed from the flow number prediction model, the accuracy was $R^2 = 0.86$ and Se/Sy = 0.36, which is considered to be acceptable.

The second model (Model 2) chosen was developed. [34] using 39 in service pavements and more than 760 data locations. It includes variables such as the layer's stiffness, strains of the base and subgrade layers, resilient moduli of the asphalt layer and subgrade, and surface deflection measured by the Falling Weight Deflectometer (FWD). This model was also selected as all the required parameters are available in the database and provides good comparison to the suggested model in this study. It accounts for the rut contribution of the subgrade, subbase, base, and HMA layers. It also addressed inventory-type variables like pavement cross section, ambient temperature, and asphalt consistency properties, which is relative to the model being developed in this study. In terms of accuracy, the applicability of the model was validated by using data from 24 LTPP sites. For 19 of the 24 GPS sites, the predicted rut depth was within 0.2 in (5 mm) of the measured rut depth. The R^2 was found to be 0.905.

However, it relies on measured data from the field sections, such as surface deflection (SD).

Overall, those two models were selected since they depend on the temperature parameter, as well as stiffness, binder characteristics and traffic loading which make them comparable to the proposed model in this study. Moreover, their accuracy was considered to be consistent and effective with respect to this study with respect to the parameters involved from the LTPP.

5.5.2 Comparison and Analysis

All the mentioned data has been collected for the sections studied and the results are summarized in Tables 5 and 6 respectively. Based on the results obtained, the suggested model showed an improved prediction trend compared to the two other models, as seen in Fig. 6. In addition, the data required to be able to use those models requires field testing (such as FWD for measured surface deflection, kinematic viscosity of the binder (Model 2) and may not include the effect of the underlying layers (Model 1). It is also important to note that the type of data used to develop those models is different in traffic type and climate and may affect the predictions and not suit the sections chosen in this study. For example, Model 2 was validated by using sections located in a different location and climate, whereas Model 1 was developed for higher ranges of traffic volumes, which favors the prediction model suggested in this study. Those reasons reflect why the predictability of those models is not ideal in those conditions as seen in Fig. 6. Overall, by comparing the three models in this study, the parameters involved were all gathered from the LTPP successfully and were relatable in terms of analysis. Model 1 included parameters such as traffic, HMA layer thickness and climate in terms of temperature, whereas Model 2 accounted for the effect of the underlying pavement structure. The new suggested model showed promising prediction results, while considering parameters such as climate, traffic, underlying layers effect and mixture volumetrics for dry freeze and non-freeze regions.

6 Conclusion

This research initially focused on how the temperature changes within different regions of the United States could affect the performance of flexible road pavements in terms of permanent deformation or rutting as per the following:

- Four different climatic regions were identified in the LTPP Database as Dry Freeze, Dry Non-Freeze, Wet Freeze and Wet Non-Freeze. The Dry Freeze and Dry Non-Freeze regions were selected for analysis.

Table 5 Data collected for model comparison

State	Sect.	Kinematic viscosity (cSt)	S.D. in. (mm)	Annual temp., °F, (°C)	ESAL	H_{AC} in. (mm)	$Mr_{Asphalt}$ psi, (MPa)	Mr_{Base} psi, (MPa)	Strain Base	$Mr_{Subgrade}$ psi, (MPa)
Arizona	1003	350	0.0145	72 (22.2)	3573000	13.1	(332.7)	1290500 (8898)	11474 (79)	0.00084 10715 (74)
Arizona	1006	350	0.0156	72 (22.2)	3586000	8.7	(221.0)	1493500 (10297)	10324 (71)	0.00084 7909 (55)
Arizona	1017	350	0.0167	66 (18.9)	2454000	8.9	(226.1)	839550 (5788)	19459 (134)	0.0007 16277 (112)
Arizona	1018	350	0.0161	70 (21.1)	2436000	8.4	(213.4)	839550 (5788)	19451 (134)	0.0007 16277 (112)
Arizona	1021	350	0.0158	65 (18.3)	3485000	5.3	(134.6)	1228150 (8468)	25912 (179)	0.00054 7275 (50)
Arizona	1022	234	0.0155	65 (18.3)	3501000	8.3	(210.8)	1595000 (10997)	25912 (179)	0.00054 7275 (50)
Arizona	1024	234	0.0150	52 (11.1)	4447000	10.8	(274.3)	1194800 (8238)	25327 (175)	0.00054 15931 (110)
Arizona	1025	273	0.0151	52 (11.1)	3619000	7.6	(193.0)	1232500 (8498)	25912 (179)	0.00054 15931 (110)
California	8156	447	0.0151	59 (15.0)	143000	3.9	(99.1)	462550 (3189)	24785 (171)	0.001 8449 (58)
California	8534	447	0.0150	73 (22.8)	504000	10.6	(269.2)	462550 (3189)	24785 (171)	0.001 8449 (58)
California	8535	429	0.0149	73 (22.8)	982000	10.3	(261.6)	416150 (2869)	25912 (179)	0.001 5738 (40)
Colorado	1029	649	0.0150	43 (6.1)	133000	4.2	(106.7)	913500 (6298)	17400 (120)	0.00053 9421 (65)
Colorado	1053	649	0.0153	47 (8.3)	264	4.6	(116.8)	855500 (5898)	25943 (179)	0.00053 9421 (65)
Idaho	1007	649	0.0158	49 (9.4)	80000	3.6	(91.4)	649600 (4479)	24785 (171)	0.001 7691 (53)
Idaho	1020	649	0.0160	50 (10.0)	129000	3.8	(96.5)	649600 (4479)	24781 (171)	0.001 7691 (53)
Montana	8129	649	0.0151	45 (7.2)	145000	3.2	(81.3)	867100 (5978)	24785 (171)	0.001 16273 (112)
Nevada	1020	860.7	0.0159	56 (13.3)	290000	7	(177.8)	1083150 (7468)	17400 (120)	0.0007 9135 (63)
New Mexico	1005	860.7	0.0194	53 (11.7)	386000	8.7	(221.0)	1290500 (8898)	23956 (165)	0.00055 11448 (79)
Texas	1111	860.7	0.0152	61 (16.1)	161000	7.4	(188.0)	1112150 (7668)	21315 (147)	0.00062 8239 (57)
Utah	1001	860.7	0.0148	55 (12.8)	46000	5.5	(139.7)	1300650 (8968)	24785 (171)	0.001 7238 (50)
Washington	1005	649	0.0155	50 (10.0)	444000	11.8	(299.7)	907700 (6258)	8984 (62)	0.00084 13127 (91)
Washington	1007	810	0.0159	53 (11.7)	145000	6.4	(162.6)	784450 (5409)	8984 (62)	0.00084 7012 (48)
Wyoming	7775	649	0.0152	39 (3.9)	30000	4.7	(119.4)	3842500 (26493)	8984 (62)	0.00084 5649 (39)

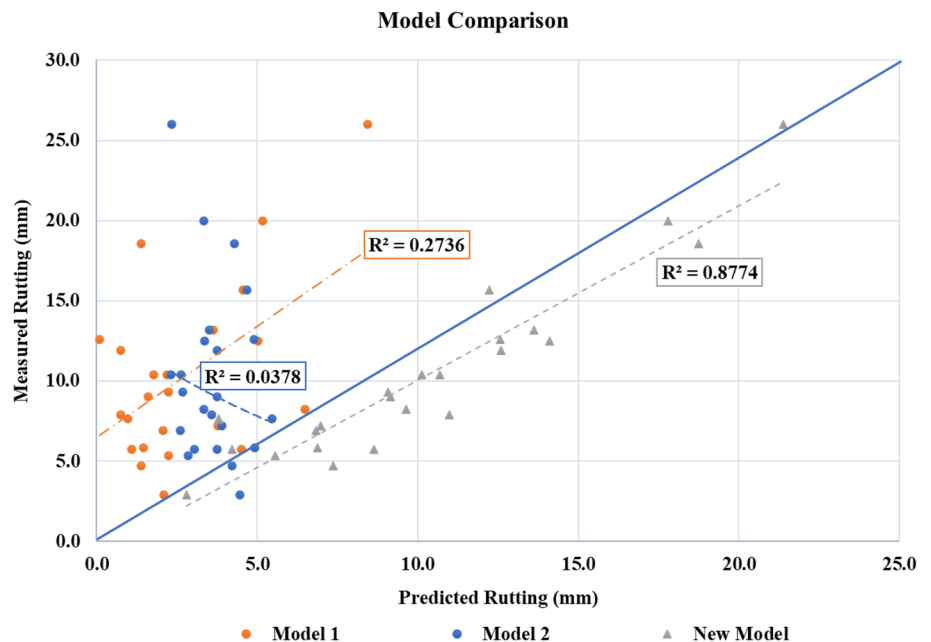
Table 6 Model comparison: rutting depth results from the three models

State	Section	Measured Rutting (average) in, (mm)	Model 1 in, (mm)	Model 2 in, (mm)	New Model in, (mm)
Arizona	1003	0.62 (15.748)	0.18 (4.572)	0.18 (4.572)	0.5 (15.748)
Arizona	1006	0.32 (8.128)	0.26 (6.604)	0.13 (3.302)	0.4 (8.128)
Arizona	1017	0.52 (13.208)	0.14 (3.556)	0.14 (3.556)	0.5 (13.208)
Arizona	1018	0.49 (12.446)	0.20 (5.08)	0.13 (3.302)	0.6 (12.446)
Arizona	1021	1.02 (25.908)	0.33 (8.382)	0.09 (2.286)	0.8 (25.908)
Arizona	1022	0.79 (20.066)	0.20 (5.08)	0.13 (3.302)	0.7 (20.066)
Arizona	1024	0.28 (7.112)	0.15 (3.81)	0.15 (3.81)	0.3 (7.112)
Arizona	1025	0.23 (5.842)	0.18 (4.572)	0.12 (3.048)	0.3 (5.842)
California	8156	0.37 (9.398)	0.09 (2.286)	0.11 (2.794)	0.4 (9.398)
California	8534	0.23 (5.842)	0.06 (1.524)	0.19 (4.826)	0.3 (5.842)
California	8535	0.11 (2.794)	0.08 (2.032)	0.18 (4.572)	0.1 (2.794)
Colorado	1029	0.21 (5.334)	0.09 (2.286)	0.11 (2.794)	0.2 (5.334)
Colorado	1053	0.50 (12.7)	0.00 (0)	0.19 (4.826)	0.5 (12.7)
Idaho	1007	0.41 (10.414)	0.07 (1.778)	0.10 (2.54)	0.4 (10.414)
Idaho	1020	0.27 (6.858)	0.08 (2.032)	0.10 (2.54)	0.3 (6.858)
Montana	8129	0.41 (10.414)	0.09 (2.286)	0.09 (2.286)	0.4 (10.414)
Nevada	1020	0.35 (8.89)	0.06 (1.524)	0.15 (3.81)	0.4 (8.89)
New Mexico	1005	0.73 (18.542)	0.05 (1.27)	0.17 (4.318)	0.7 (18.542)
Texas	1111	0.19 (4.826)	0.05 (1.27)	0.17 (4.318)	0.3 (4.826)
Utah	1001	0.47 (11.938)	0.03 (0.762)	0.15 (3.81)	0.5 (11.938)
Washington	1005	0.30 (7.62)	0.04 (1.016)	0.22 (5.588)	0.1 (7.62)
Washington	1007	0.22 (5.588)	0.04 (1.016)	0.15 (3.81)	0.2 (5.588)
Wyoming	7775	0.31 (7.874)	0.03 (0.762)	0.14 (3.556)	0.4 (7.874)

- Only flexible pavements with unbound granular base (GPS1) that have been actively monitored were considered for a total of 20 sections. Any rehabilitation of over-

lay design was excluded to only compare the effects on original HMA pavement.

Fig. 6 Model comparison: Model 1, Model 2 and the new suggested model



- The relevant data for each section was collected and their rutting performance was compared.
- The collected data was used to develop a regression model to predict the rutting depth of the flexible pavements.
- It was observed that increasing temperature leads to an increase in rutting, which agrees with previous studies.
- The results suggest that higher thickness values of asphalt layer at the beginning of the construction date with higher stiffness could extend the service lifetime and sections in hot climate regions.

The second objective of this research was the development of a regression model that includes the effect of underlying layers and the pavement structure as whole. For this reason, a multiple linear regression model was developed based on the data collected from the LTPP Database to predict the rutting performance of flexible pavements. The model gave the accuracy of $R^2 = 0.83$, with a good fit and normal distribution. The developed model was compared to two existing and validated prediction models. The developed model showed promising accuracy while not requiring field measurements and lab testing.

Being able to have an indication of this potential distress will allow better design of the pavement mixture and increase its resistance to it. State agencies will be able to tailor their mixtures with respect to the climate, traffic, pavement structure, as well as asphalt binder type to be used.

7 Recommendations

In some cases, it was found that although the traffic load and stiffness were relatively in similar range, sections with higher temperature recorded lower rutting than lower temperature, even though sections with higher temperature had a lower asphalt layer thickness in comparison with those of lower temperatures. To fully explain this, further data collection on the gradation of the sections are recommended to explore the conflicts. Having the collected parameters from the LTPP, the model is expected to behave in an accurate manner, responding to one of the biggest distresses developed in the Hot climate areas, such as Arizona.

Acknowledgements The authors would like to thank Dr. Kamil Kaloush for his guidance, support, and input on this study.

Author Contributions The authors confirm contribution to the paper as follows: study concept and layout: JK, and HN; data collection, analysis, and interpretation of results: HN and JK; draft manuscript preparation: JK and HN. All authors reviewed the results and approved the final version of the manuscript.

Funding Not applicable.

Data availability The data used to support the findings of this study are included in this document. Other data used in this study are available in a repository or online in accordance with funder data retention policies: - Long Term Pavement Performance: InfoPave Database: <https://infopave.fhwa.dot.gov/Data/DataSelection>.

Declarations

Conflict of Interest The authors declare that they have no conflict of interest.

References

1. Epps, J. S. (2000). *Accelerated field test of performance-related specifications for hot-mix asphalt pavement construction, part II: Performance-related specification*. Final report for NCHRP Project 9-20. Transportation Research Board.
2. Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement. (2004). *Structures appendix II-1: Calibration of fatigue cracking models for flexible pavements*. Final report for NCHRP Project National Cooperative Highway Research Program Transportation Research Board National Research Council.
3. National Highway Institute (NHI). (2001). *HMA pavement evaluation and rehabilitation: Reference manual*. NHI Course No. 131063. Federal Highway Administration.
4. Van Thanh, D., & Feng, C. P. (2013). Study on Marshall and Rutting test of SMA at abnormally high temperature. *Construction and Building Materials*, 47, 1337–1341. <https://doi.org/10.1016/j.conbuildmat.2013.06.032>
5. Walubita, L. F., Faruk, A. N. M., Zhang, J., Hu, X., & Lee, S. I. (2016). The Hamburg rutting test—Effects of HMA sample sitting time and test temperature variation. *Construction and Building Materials*, 108, 22–28. <https://doi.org/10.1016/j.conbuildmat.2016.01.031>
6. Khedr, S. A. (1986). Deformation mechanism in asphaltic concrete. *Journal of Transportation Engineering, American Society of Civil Engineers*, 112(1), 29–45.
7. Ali, H. (1998) *mechanistic evaluation of test data from LTPP flexible pavement test sections, Volume I: Final report*. FHWA-RD-98-012. Federal Highway Administration.
8. Van Deusen, C. (1979). *Cold planning of asphalt pavements*. Proceedings, Association of Asphalt Paving Technologists (Vol. 48). Association of Asphalt Paving Technologists.
9. Mallick, R. B., & El-Korchi, T. (2013). *Pavement engineering. Principles and practice* (2nd ed.). Taylor & Francis.
10. Singh, A. K., & Sahoo, J. P. (2021). Rutting prediction models for flexible pavement structures: A review of historical and recent developments. *Journal of Traffic and Transportation Engineering (English Edition)*, 8(3), 315–338.
11. Karam, J., Salim, R., Kaloush, K. (2022). Using Mixture Design Data and Existing Prediction Models to Evaluate the Potential Performance of Asphalt Pavements. *Journal of Materials in Civil Engineering*, 34(7), 04022151.
12. Witczak, M. W. (2007). *Specification criteria for simple performance tests for rutting*. NCHRP Report 580. TRB, National Research Council.
13. AASHTO, TP79. (2009). *Standard method of test for determining the dynamic modulus and flow number for hot mix asphalt (HMA) using the asphalt mixture performance tester (AMPT)*. American Association of State Highway and Transportation Officials.
14. Rodezno, M. C., Kaloush, K. E., & Corrigan, M. R. (2010). Development of a Flow Number Predictive Model. *Transportation Research Record: Journal of the Transportation Research Board*, 2181(1), 79–87. <https://doi.org/10.3141/2181-09>

15. Zhang, W., Shen, S., Wu, S., & Mohammad, L. N. (2017). Prediction model for field rut depth of asphalt pavement based on Hamburg wheel tracking test properties. *Journal of Materials in Civil Engineering*. [https://doi.org/10.1061/\(ASCE\)MT.1943-5533.0001946](https://doi.org/10.1061/(ASCE)MT.1943-5533.0001946)
16. Ji, J., Chen, M., Suo, Z., Wei, J., Wang, J., & Chen, L. (2021). Rutting prediction model of asphalt mixture based on the triaxial repeated load test. *Advances in Civil Engineering*, 2021, 1–9.
17. American Association of State Highway and Transportation Officials. (2020). *Mechanistic-empirical pavement design guide: a Manual of Practice*. American Association of State Highway and Transportation Officials.
18. Gong, H., Sun, Y., Mei, Z., & Huang, B. (2018). Improving accuracy of rutting prediction for mechanistic-empirical pavement design guide with deep neural networks. *Construction and Building Materials*, 190, 710–718. <https://doi.org/10.1016/j.conbuildmat.2018.09.087>. ISSN 0950-0618.
19. Nivitha, M. R., Jain, P. K., & Krishnan, J. M. (2023). Rutting performance of modified binders based on laboratory tests and structural simulations. *International Journal of Pavement Research and Technology*, 16, 343–355. <https://doi.org/10.1007/s42947-021-00135-w>
20. American Association of State Highway and Transportation Officials. (1993). AASHTO guide for design of pavement structures, 1993. The Association.
21. Alkaissi, Z. A. (2020). Effect of high temperature and traffic loading on rutting performance of flexible pavement. *Journal of King Saud University Engineering Sciences*, 32(1), 1–4. <https://doi.org/10.1016/j.jksues.2018.04.005>. ISSN 1018-3639.
22. Grogg, M. G. (2001). *HMA pavement evaluation and rehabilitation: Reference manual*. U.S. Dept. of Transportation, Federal Highway Administration.
23. Golalipour, A., Jamshidi, E., Niazi, Y., Afsharikia, Z., & Khadem, M. (2012). Effect of aggregate gradation on rutting of asphalt pavements. *Procedia-Social and Behavioral Sciences*, 53, 440–449.
24. Darabi, M. K., Abu Al-Rub, R. K., Masad, E. A., Huang, C.-W., & Little, D. N. (2012). A modified viscoplastic model to predict the permanent deformation of asphaltic materials under cyclic-compression loading at high temperatures. *International Journal of Plasticity*, 35, 100–134. <https://doi.org/10.1016/j.ijplas.2012.03.001>
25. Button, J. W., Perdomo, D., & Lytton, R. L. (1990). Influence of Aggregate on Rutting in Asphalt Concrete Pavements. *Transportation Research Record*, 1259. <https://trid.trb.org/view/348222>
26. Ahlrich, R. C. (1996). *Influence of aggregate gradation and particle shape/texture on permanent deformation of hot mix asphalt pavements*. Army Engineer Waterways Experiment Station Vicksburg MS Geotechnical Lab.
27. Stakston, A. D., & Bahia, H. U. (2003). *The effect of fine aggregate angularity, asphalt content and performance graded asphalts on hot mix asphalt performance* (Vol. 92, No. 45–98). Wisconsin Highway Research Program.
28. Brosseau, Y., Delorme, J. L., & Hiernaux, R. (1993). Use of IPC wheel-tracking rutting tester to select asphalt pavements resistant to rutting. *Transportation Research Record*, 1384, 59.
29. Bari, J., & Witczak, M. (2006). *Development of a new revised version of the Witczak E* Predictive Model for hot mix asphalt mixtures (with discussion)* (pp. 381–423). Transportation Research Board.
30. Ramsamooj, D. V., Ramadan, J., & Lin, G. S. (1998). Model prediction of rutting in asphalt concrete. *Journal of Transportation Engineering*, 124(5), 448–456.
31. Dongre, R., D'Angelo, J., Paugh, C., & Gudimettla, J. (2005). *Field evaluation of Witczak and Hirsch models for predicting dynamic modulus of hot-mix asphalt (with discussion)* (pp. 381–442). Transportation Research Board.
32. Barry Barker, J. et al. (2011). *A performance-related specification for hot-mixed asphalt*. Final report 704 NCHRP Project National Cooperative Highway Research Program. Transportation Research Board National Research Council.
33. Safer speeds: Considerations for speed limits and management. https://calsta.ca.gov/-/media/calsta-media/documents/safetrec_grembek_ab2363_06252019-a11y.pdf. Accessed 8 Mar 2021.
34. Kim, H. B., Buch, N., Park, D. Y. (2000). *Mechanistic-empirical rut prediction model for in-service pavements* (pp. 99–109). Transportation Research Record 1730, Paper no. 00-0165.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.



Jolina Karam M.S Graduate Research and Teaching Associate at Arizona State University Jolina Karam is currently a full-time Ph.D. Candidate at Arizona State University (ASU) in Civil, Environmental and Sustainable Engineering. More specifically, her research is focused on Transportation, Pavement and Materials. Jolina is originally from Lebanon, where she pursued her Bachelor of Engineering in Civil and Environmental Engineering with a Minor in Engineering Management at Notre Dame University (NDU). Recently, she has completed her master's degree in civil, Environmental and Sustainable Engineering at ASU. Her current research focuses on studying the effects of different modifiers introduced into asphalt crack sealants. By adding different modifiers, their effect on the sealant with respect to climate is of interest.



Hossein Noorvand is an Assistant Research Professor in the School of Ira A. Fulton Schools of Engineering at Arizona State University (ASU). He received his Ph.D. in Civil, environmental, and sustainable engineering (2020) from Arizona State University, M.Sc. in Structural Engineering (2014) from Universiti Putra Malaysia, and B.Sc. in Civil Engineering (2009) from Azad University of Zanjan in Iran. Since 2023, He has worked with the pavement and materials group on several research projects, related to sustainable concrete materials, fiber-reinforced composites, and pavement design and evaluation. Dr. Noorvand also works as a research Engineer for ViaSun Corporation in Phoenix where he develops ideas and solutions related to pavement preservation technologies in partnership with ASU to help create materials with improved durability, sustainability, energy efficiency, and cost-effectiveness.