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CALIBRATION OF REGRESSION-BASED MODELS FOR PREDICTION OF TEMPERATURE PROFILE OF ASPHALT LAYERS USING LTPP DATA

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Abstract. For analysis, design, and rehabilitation purposes of flexible pavements, the temperature profile of asphalt layers should be determined. The predictive models as an alternative to in-situ measurements, are rapid and easy methods to determine the temperature of asphalt layer at various depths. These models are developed based on limited field data. Hence, there is a need for developing new models for prediction of temperature profile of asphalt layers in various climatic regions. In this study, climatic data was retrieved from the Long-Term Pavement Performance (LTPP) database. The information of 33 asphalt pavement test sections in 16 states in the United States was employed for calibrating the predictive models. Using the prepared data, the temperature profile of asphalt layers was predicted utilizing four regression-based models, including Ramadhan and Wahhab, Hassan et al., Albayati and Alani, and Park et al. models. Existing prediction models were calibrated, and to predict the temperature profile of asphalt layer, new models were developed. Performance evaluation and validation of newly developed models showed an excellent correlation between predicted and measured values. Results show the ability of the developed models in predicting the temperature profile of asphalt layers with very good prediction precision (R^2 = 0.94) and low bias.

Keywords: asphalt pavement, temperature profile of asphalt layers, prediction models, regression-based models, long-term pavement performance (LTPP).

Introduction

In recent years, rising attention to climatic issues impacting transportation infrastructure has become one of the most important research topics (Zhang, 2012). The interaction between transportation system material components (including roads, traffic, etc.) takes place in an exterior environment. The transportation procedure seeks to acquire some positive results that can enhance the productivity of the transportation system (Podvezko & Sivilevičius, 2013).

Asphalt mixture is a viscoelastic material that has the characteristics of both viscous and elastic materials. One of the critical environmental factors that affect the deformation of asphalt pavements is the temperature of asphalt layers at various depths, which is due to the same viscoelastic behavior of the asphalt mixture (Shao et al., 1997; Kim & Lee, 1995; Park et al., 2002). The stiffness of the asphalt layers has a significant effect on the structural capacity of flexible pavements. This property is a function of the temperature of asphalt layer and changes daily and seasonally. As the temperature increases, the stiffness of the asphalt layer decreases, which increases the stresses in the base and subbase layers of the pavement. The asphalt mixture behaves like a viscous liquid by increasing the temperature and reducing it as an elastic solid (Diefenderfer et al., 2002, 2006). Therefore, the pavement response to the applied loads is affected by the temperature of asphalt layers at various depths. Measured deflections of the pavement through the application of the Falling Weight Deflectometer (FWD) represent the response of asphalt layers. For the possibility of comparing results and especially for asphalt pavement design objectives, temperature analysis is carried out at a reference temperature in the

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FWD backcalculation process using either a mechanistic-empirical (e.g., Evaluation of Layer Moduli and Overlay Design (ELMOD) software) or American Association of State Highway and Transportation Officials (AASHTO) empirical models (Solatifar et al., 2018).

Modeling pavement temperatures facilitate its maintenance in cold seasons. To schedule the defrosting of the road, and predict its weather, a vertical profile of the initial pavement temperatures is needed. In the study of Opara and Zieliński (2017), the average air temperature of seven previous days was used as a pseudo-observation of in-depth pavement temperature. Moreover, the benefit of digital surface models to assess the shadow effect has been scrutinized. Wang (2012) operated an analytical approach to predict the temperature in a multilayer pavement system based on surface temperature data. The proposed algorithm can efficiently predict the pavement temperature profile without employing climatic parameters, including air temperature, solar radiation, etc.

The temperature profile of asphalt layers is one of the essential and main factors in the analysis, design, and rehabilitation process of flexible pavements. In addition, Wang et al. (2014) study shows that daily variations in pavement temperature are very noteworthy and should be considered in the design of pavements. Several models and methods have been developed by various researchers to predict the temperature of asphalt layers at various depths. These models can be classified into three overall categories: The first one is the models with an analytical approach that developed based on heat transfer theory and thermal characteristics of asphalt pavement. The second one is the models based on soft computing, including Artificial Neural Networks (ANNs), Adaptive Neuro-Fuzzy Inference System (ANFIS), Group Method of Data Handling (GMDH), Genetic Expression Programming (GEP), etc. And finally, the last one is the statistical methods that utilize regression models to obtain the relationship between the temperature profile of asphalt layers and climatic parameters.

Temperature profile predictive models as an alternative to field measurements of this factor are low-cost, rapid, and uncomplicated methods to determine the temperature of asphalt layers at various depths (Minhoto et al., 2005). Because of the simplicity of working with statistical methods, and also the feasibility of obtaining a mathematical equation, these methods have been broadly used for prediction of temperature of asphalt layers by several researchers. In this regard, several studies have been carried out: Ramadhan and Wahhab (1997), Park et al. (2001), Diefenderfer et al. (2002, 2006), Hassan et al. (2005), Velasquez et al. (2008), Tabatabaie et al. (2008), Gedafa et al. (2014), Albayati and Alani (2015), Ariawan et al. (2015), Islam et al. (2015), Asefzadeh et al. (2017), Sedighian-Fard and Solatifar (2022), and the BELLS model by Stubstad et al. (1994). The specifications of temperature profile prediction models, such as input variables, the number of data points employed, and the goodness of fit statistics are given in Table 1.

Conventional regression-based models for prediction of temperature profile of asphalt layers have been investigated and scrutinized by Sedighian-Fard and Solatifar (2021). In these models, the temperature profile of asphalt layers has been modeled using climatic parameters, etc. Some remarkable biases of these models in predicting the temperature of asphalt layers led to the developing calibrated models that modified their original form based on the local climate conditions (Asefzadeh et al., 2017; Solatifar et al., 2018). Lukanen et al. (1998) have proposed models based on Seasonal Monitoring Program (SMP) data extracted from the Long-Term Pavement Performance (LTPP) database for the prediction of minimum and maximum pavement temperatures. The main goal of the LTPP program is to collect the high-quality information that is needed to interpret pavement performance precisely. In addition, the factors that affect pavements as well as create a comprehensive and worthy database for the research and development of valuable products in pavement analysis and design.

Table 1. Specifications of the temperature profile predictive models of asphalt layers alongside their *goodness of fit statistics*

Model	Regression type	No. of used data, source (if applicable)	Model accuracy
Ramadhan and Wahhab (1997)	Linear	Two years (started in April 1989), King Fahd University of Petroleum and Minerals	R^2 = 0.94
Hassan et al. (2005)	Linear	445 days, Sultan Qaboos University (SQU)	R^2 = 0.85, SEE = 3.18 °C
Albayati and Alani (2015) model	Linear	24960, Baghdad University	R^2 = 0.98, SEE = 3.49 °C
Park et al. (2001) model	Non-linear	317, Michigan, USA	R^2 = 0.90
Diefenderfer et al. (2006)	Linear	2028, Virginia Smart Road, Virginia, USA	R^2 = 0.77 (Max temp. model), 0.80 (Min temp. model)
Gedafa et al. (2014)	Non-linear	65, Kansas, USA	R^2 = 0.94
Asefzadeh et al. (2017)	Non-linear	Two years, Alberta, Canada	R^2 = 0.92 (Max temp. model), 0.91 (Min temp. model)
BELLS (Stubstad et al., 1994)	Linear	10304, LTPP	R^2 = 0.97
Sedighian-Fard and Solatifar (2022)	Non-linear	34676, LTPP	R^2 = 0.95

Note: R^2 – coefficient of determination; SEE – standard error of estimate; and LTPP – long-term pavement performance.

LTPP consists of two types of studies: General Pavement Studies (GPS) and Specific Pavement Studies (SPS). GPS studies have been conducted on numerous in-service pavement sections to appraise the pavement performances, and also create and develop an exhaustive database. These studies have been used in developing pavement analysis and design procedures. SPS studies have been established and expanded to scrutinize the impact of different factors on pavement performance and specific characteristics, such as drainage, asphalt layer thickness, as well as maintenance and rehabilitation treatments. These pavement sections are uniquely designed for the LTPP program. LTPP consist of approximately 2581 flexible and rigid pavement sections in the United States and Canada. There are about 82 test sections for the climatic studies as categorized by SMP sections (Federal Highway Administration [FHWA], 2017; Solatifar & Lavasani, 2020).

Considering the importance of the perception of the temperature profile of asphalt layers in the analysis, design, implementation, evaluation, and rehabilitation of pavements, there is a need for developing new models for prediction of this parameter more accurately in different climatic conditions. The main purpose of this study is to employ and appraise four conventional temperature profile prediction models; namely, Ramadhan and Wahhab (1997), Hassan et al. (2005), Albayati and Alani (2015), and Park et al. (2001) models to determine the temperature of asphalt layers at various depths using LTPP data. Furthermore, newly calibrated predictive models are developed with high accuracy and low prediction bias.

1. Existing predictive models

Four conventional predictive models for determining the temperature of asphalt layers at various depths have been investigated in this study.

1.1. Ramadhan and Wahhab model

Ramadhan and Wahhab (1997) conducted two field experiments to scrutinize the temperature variations of asphalt and concrete pavement sections located in King Fahd University of Petroleum and Minerals in Saudi Arabia. The studied pavement consisted of a 25 cm asphalt layer with dense gradation on the subbase layer with a thickness of 20 cm and an overlay with a thickness of 5 cm. Pavement temperature data at depths of 2, 4, 8, 16, and 25 cm from the pavement surface and also air temperature information was measured. Data was collected during two years from April 1989 to April 1991 and the temperature of asphalt layer at depth of 2 cm is predicted based on air temperature (Eqn (1)):

$$PAV = 1.692 AIR + 12.670, \tag{1}$$

where PAV – asphalt layer temperature at depth of 2 cm (°C); and AIR – air temperature (°C). The results showed that the minimum measured temperature of the asphalt layer has a good correlation with the minimum air temperature (Ramadhan & Wahhab, 1997).

1.2. Hassan et al. model

A regression-based model has been developed by Hassan et al. (2005) to predict the minimum and maximum temperature of the pavement in Oman. Data on air temperature, pavement, and solar radiation for 445 days from the weather station located in the campus of Sultan Qaboos University were collected. Pavement temperature at a depth of 20 mm from the asphalt layer surface as well as air temperature for each day were measured. A stepwise linear regression analysis was performed applying the air temperature parameter as an independent variable and the temperature of asphalt layers at various depths as a dependent variable. Since the pavement temperature profile is affected by other parameters besides air temperature, solar radiation was used to enhance the accuracy of the model. The developed model is expressed as Eqn (2):

$$T_{20\text{ mm}} = 2.713 + 1.281 T_{air} + 0.00053 Solar, \tag{2}$$

where $T_{20\text{ mm}}$ = pavement temperature at 20 mm depth (°C); T_{air} – air temperature (°C); and $Solar$ – cumulative solar radiation from dawn to the time of occurrence of maximum air temperature (W.h/m^2).

1.3. Albayati and Alani model

The regression-based prediction model developed by Albayati and Alani (2015) predicts the temperature profile of asphalt layers based on the air temperature. Air temperature information was acquired from the Meteorological organization of Iraq, and also data of temperature at various depths was collected by conducting a field test in the parking lot of Baghdad University during April 27 to December 16, 2009. The thermometers have been installed at depths of 2, 7, and 12 cm from the asphalt pavement surface. The developed model is based on air temperature and depth of the pavement surface in the form of Eqn (3):

$$T_{pave} = 1.217 T_{air} - 0.354 Z, \tag{3}$$

where T_{pave} – pavement temperature at 20 mm depth (°C); T_{air} – air temperature (°C); and Z – depth from the pavement surface (cm).

1.4. Park et al. model

Park et al. (2001) developed a regression-based predictive model for estimating temperature profile of asphalt layers at any time of the day. The developed model has increased the accuracy of back-calculations of the structural characteristics of asphalt layers obtained from the FWD test. The model also has the advantage of lucidity by regarding only the pavement surface temperature and time of day as model inputs, as given in Eqn (4):

$$T_Z = T_{Surf} + \left(-0.3451z - 0.0432z^2 + 0.00196z^3\right) \times \sin\left(-6.3252t + 5.0967\right), \tag{4}$$

where T_Z – temperature at depth z (°C); T_{Surf} – pavement surface temperature (°C); z – depth from pavement surface (cm); and t – time of the day (decimal hours).

Table 2. Comparative review of four temperature profile predictive models

Prediction model	No. of input variables	Input variables					Regression type
		Air temperature	Surface temperature	Solar radiation	Time of day	Depth	
Ramadhan and Wahhab (1997)	1	✓					Linear
Hassan et al. (2005)	2	✓		✓			Linear
Albayati and Alani (2015)	2	✓				✓	Linear
Park et al. (2001)	3		✓		✓	✓	Non-linear

A comparative review of the differences between the four mentioned temperature profile prediction models is summarized in Table 2.

2. Data retrieving

Data extraction and preparation from LTPP database is presented in this section. The efficacy of four regression-based models for prediction of temperature profile of asphalt layers is appraised, then these models are calibrated to develop new prediction models. For developing the dataset, no specific consideration has been made during collecting information on pavement test sections (both GPS and SPS sections were included), and all available information on pavement test sections located in the United States has been extracted. Hence, the only applied filter in providing the primary data is rigid pavement sections.

Data preparation has been conducted based on the input parameters of the temperature profile predictive models. All accessible information on the layer depth and surface temperature (the temperature at 2.5 cm depth) and also air temperature was extracted from the SMP section of the LTPP database climatic module. In addition, the rest of the information on other parameters, including pavement surface temperature and solar radiation, was extracted from the LTPP database Automatic Weather Station (AWS) section. The time interval of data acquisition is hourly. Moreover, due to major maintenance and preservation treatments like overlays, test sections with different construction numbers have been considered as new pavement sections (e.g., a pavement section with two consecutive construction numbers regarded as two test sections).

After preparing the data, the temperature at various depths of asphalt layers in each pavement test section was determined individually, and the data of some pavement test sections with low accuracy was removed from the final database. In sum, to construct the database, the information of 33 asphalt pavement test sections in 16 states in the United States has been employed. Table 3 reports the general characteristics of the pavement sites that were taken into consideration in the above states. It is notable that six pavement test sections have more than one construction number, as underlined in this table. These selected pavement sites are on different roads. So that they would include test sections with different characteristics such as layer thickness, age, and climatic information, etc. As it can be seen in Table 3, the age of pavement sections varied from 7 to 43 years. Their thickness varies from 53.5 to 276.3 mm. Moreover, most pavement sections have a low average annual temperature. It should be noted that 24 test sections are from GPS and 9 test sections are from SPS studies. Figure 1 shows the selected site locations in the USA and the descriptive statistics of the used data is presented in Table 4. As it can be observed from this table, the pavement temperatures ranges from –25.2 °C to 61.9 °C, and the dataset has a great variety of climates. On the other hand, the variation of air temperature from –33.60 °C to 43.90 °C demonstrates that the asphalt pavement test sections have experienced both cold and hot air temperatures.

In addition, the authors made many efforts to include the parameters of the material characteristics as input parameters of the models (these parameters include bulk specific gravity (coarse and fine aggregates), percentage of moisture absorption of coarse and fine aggregates, percentage of aggregates passing through different sieves (1”, $3/4$”, $1/2$”, $3/8$”, No. 4, No. 10, No. 40, No. 80, and No. 200 passings), binder penetration at 77 °F, specific gravity, binder absolute viscosity at 140 °F (Kinematic), binder content mean (optimum), and air voids mean). For this aim, alongside climatic data, material characterization was extracted from the pavement structure and construction module of LTPP database, asphalt concrete section. Using these characteristics besides climatic parameters, regression analysis was performed considering different scenarios and combinations of these variables. The results confirmed that the use of the material characteristics of the asphalt layers does not increase the accuracy of the proposed models; hence, to avoid the increase in complexity of the models, the parameters of material characterization were removed from the final modeling.

After extracting and preparing raw data, all the needed information were acquired from different data tables and linked to each other in a database. Therefore, all information including air temperature, wind speed, etc. matched with the temperature at various depths in terms of the State_Code, SHRP_ID, and different certain primary keys (e.g., construction number, data record time, etc.). Microsoft® Excel was used for the pre-processing phase. The time gaps in the temperature profile data were determined and removed through this phase. Moreover, asphalt pavement sites with limited information, have been dismissed.

Table 3. General characteristics of the utilized pavement sites

State	State_Code – SHRP_ID	Study type	SMP data	AWS data	Roadway functional class	Age (Since original construction) (Year)	Asphalt layer thickness (mm)	Annual temperature (°C)	Annual precipitation (mm)	Annual freezing index (°C* days)
Alabama	01-0102	SPS	✓	✓	Rural principal arterial – Other	12	106.7	17.6	1301.8	8
Arizona	04-0113	SPS	✓	✓	Rural principal arterial – Other	13	111.8	18.8	196.6	1
Arizona	04-0114	SPS	✓	✓	Rural principal arterial – Other	13	172.7	18.8	196.6	1
Arizona	04-1024	GPS	✓		Rural principal arterial – Interstate	43	276.3	12.4	360.6	43
Coloroda	08-1053	GPS	✓		Rural principal arterial – Other	35	116.8	10.7	216.5	253
Delaware	10-0102	SPS	✓	✓	Rural principal arterial – Other	13	109.2	13.6	1154.2	78
Maine	23-1026	GPS	✓		Rural principal arterial – Other	34	228.6	6.5	1242.4	722
Massachusetts	25-1002	GPS	✓		Urban principal arterial – Interstate	22	198.2	9.6	1246	333
Minnesota	27-1018	GPS	✓		Rural principal arterial – Other	32	145.9	6.8	683.1	977
Minnesota	27-6251	GPS	✓		Rural principal arterial – Other	39	233.7	4.3	684.6	1377
Nebraska	31-0114	SPS	✓	✓	Rural principal arterial – Other	7	167.6	11.3	775.8	372
Nevada	32-0101	SPS	✓	✓	Rural principal arterial – Interstate	14	182.9	10.3	229.7	228
New Hempshire	33-1001	GPS	✓		Urban principal arterial – Inrestate	36	213.4	8.4	1068.9	501
New Mexico	35-1112	GPS	✓		Rural principal arterial – Other	21	157.5	17.1	372.2	16
New York	36-0801	SPS	✓	✓	Rural minor arterial	14	127	9.6	906.7	374
Ohio	39-0901	SPS	✓	✓	Rural principal arterial – Other	21	106.7	11	1047.8	313
South Dakota	46-0804	SPS	✓	✓	Rural major collector	24	180.3	6.9	450.1	973
South Dakota	46-9187	GPS	✓		Rural minor arterial	9	149.9	8	464.4	718
Texas	48-3739	GPS	✓		Rural principal arterial – Other	24	53.5	23.1	662.2	0
Utah	49-1001	GPS	✓		Rural minor arterial	37	149.9	13.1	191	117

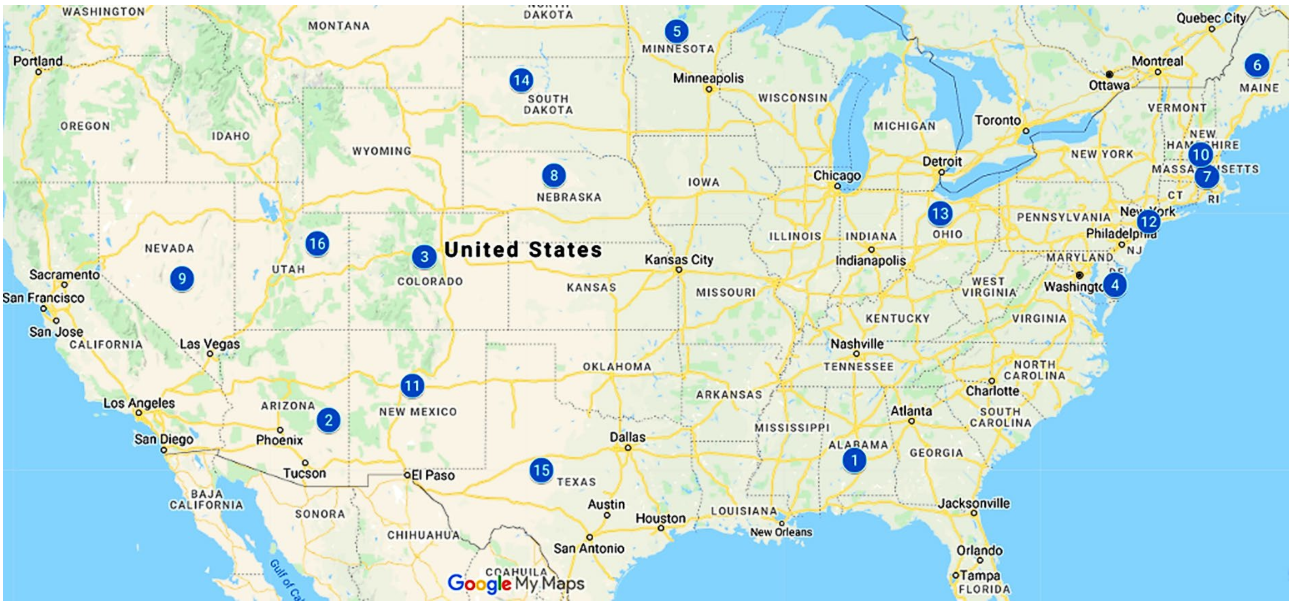

Figure 1. Location of 33 asphalt pavement test sections in 16 states in the USA

Table 4. Descriptive statistics of the variables

Parameter	Inputs					Output
	Air temperature (°C)	Surface temperature (°C)	Total solar radiation (W.h/m^2)	Time of day (decimal hours)	Depth (cm)	Temperature at various depths of asphalt layer
Mean	11.30	10.62	173.40	11.41	8	16.37
Median	10.40	10.48	5.78	12	7	15.40
Mode	5.10	4.90	0	15	2.5	–0.20
Skewness	–0.03	–0.06	0.13	0.05	–0.01	0.17
Kurtosis	–0.15	–0.16	1.43	0	0.25	–0.64
Range	–0.40	–0.37	0.76	–1.1	–1.09	–0.34
Minimum	–33.60	–33.40	0	1	1	–25.20
Maximum	43.90	41.20	1147	24	16	61.90

In general, according to the total thickness of the asphalt layers, the temperature profile information has been adopted at three different depths. It should be pointed out that the temperature at various depths information on the asphalt layers is available from August 1994 to October 2004 in the SMP program. Also, the AWS climatic information is available in the LTPP database from August 1994 to December 2008. Finally, for calibrating and developing new models, 837907 data points were used.

3. Prediction of temperature profile utilizing various models

Prediction of temperature of asphalt layers at various depths was conducted using the predictive models. For this purpose, the most famous pre-developed predictive models (as mentioned in the introduction section) were matched the developed database in this study, and the models that have the same data and input variables were specified. Using LTPP data, four predictive models, including Ramadhan and Wahhab (1997), Hassan et al. (2005), Albayati and Alani (2015), and Park et al. (2001), were used to predict the temperature profile of asphalt layers. Hence, according to the input variables of predictive models, prediction of temperature profile of asphalt layers has been conducted.

The predicted temperatures at various depths using the four predictive models and those in the LTPP database

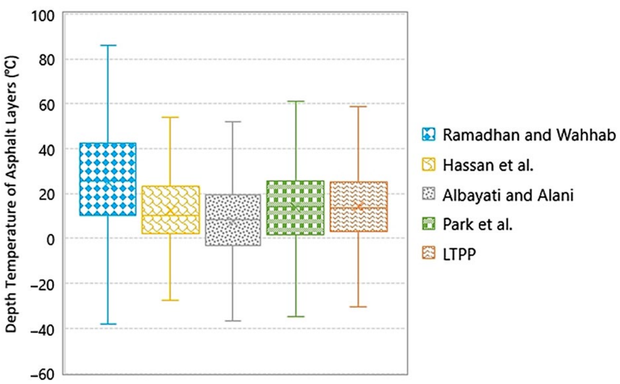

Figure 2. Measured temperatures at various depths of asphalt layers compared to the predicted values

in the form of statistical parameters, are shown in Figure 2. As it can be seen in this figure, the temperatures predicted by the Ramadhan and Wahhab (1997) model have larger values than the LTPP measured data and also than the other models. The reason may be that this model predicts the pavement temperature at 20 mm depth from the surface only based on the air temperature. Furthermore, Albayati and Alani (2015) model underpredicts the temperature profile. Moreover, Hassan et al. (2005) and Park et al. (2001) models have relatively predicted similar values. In the following, the performance and prediction accuracy of these models are investigated.

4. Performance evaluation

Figures 3a–3d show the predicted pavement temperature profile values by the models, including Ramadhan and Wahhab (1997), Hassan et al. (2005), Albayati and Alani (2015), and Park et al. (2001) versus the LTPP measured temperatures. Most of the predicted values by the first two models are spread around the line of equality (LOE). The most predicted values by Albayati and Alani (2015) model are below the LOE, which indicates that this model underpredicts the temperature profile of asphalt layers. However, the temperature values at various depths predicted by Park et al. (2001) model are some above the LOE, which indicates that the predicted values from this model are a little greater than the measured ones.

For calculation of prediction performance and accuracy, the coefficient of determination (R^2) with reference to the LOE, and the S_e/S_y, the ratio of the standard error to the deviation of measured values were used. Statistical criteria for correlation between the predicted and measured values, are given in Table 5 (Pellinen, 2001). A higher value of R^2 implies that the predictive model has higher accuracy. The lower ratio of S_e/S_y, and the closer to zero, the accuracy of the model (goodness-of-fit) enhances. On the other hand, the closer the slope of the trend line to 1, and also closer its intercept to zero, the lower the prediction model bias (Solatifar et al., 2021).

Table 6 reports the performance evaluation parameters of the investigated predictive models. As it can be observed from this table, the highest R^2 value with refer-

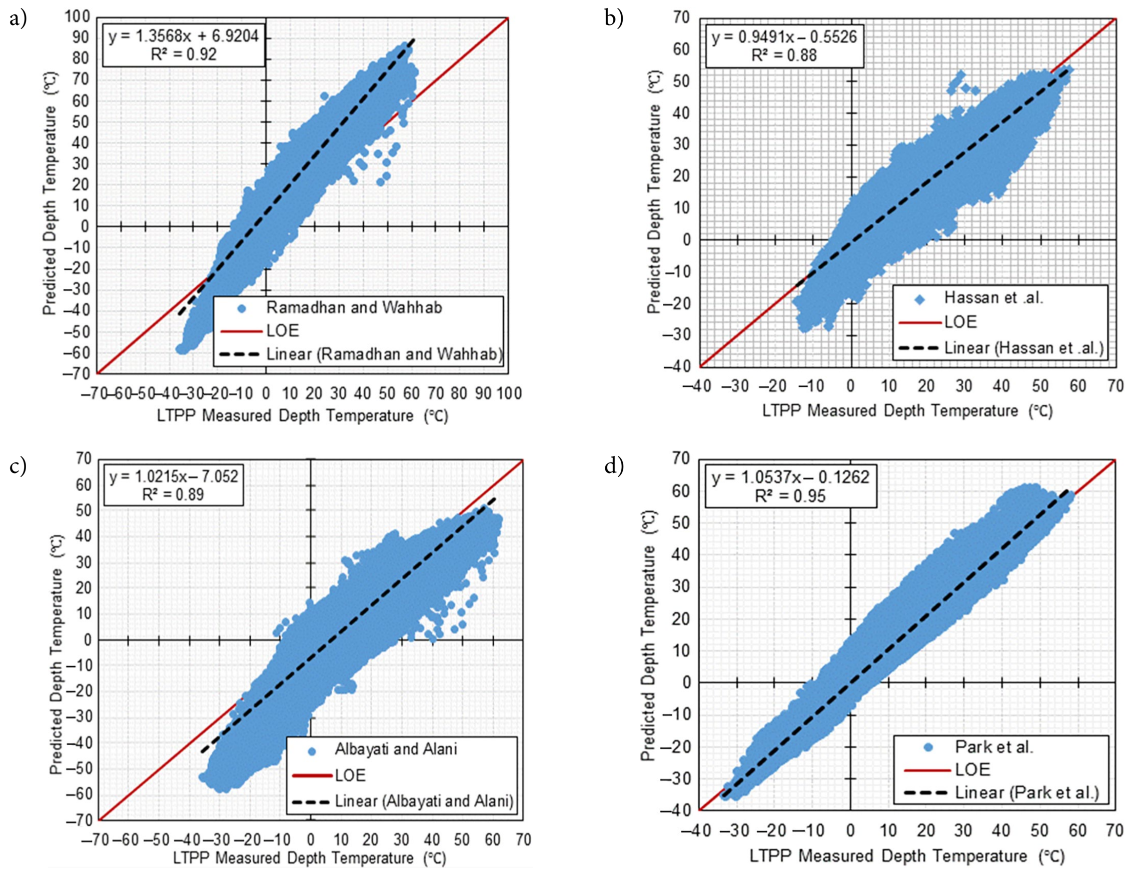

Figure 3. Predicted temperatures at various depths using original models versus measured values (LTPP data): a – Ramadhan and Wahhab (1997) model; b – Hassan et al. (2005) model; c – Albayati and Alani (2015) model; d – Park et al. (2001) model

Table 5. Statistical criteria for correlation between the predicted and measured values (Pellinen, 2001)

Criteria	R^2	S_e/S_y
Excellent	≥0.90	≤0.35
Good	0.70–0.89	0.36–0.55
Fair	0.40–0.69	0.56–0.75
Poor	0.20–0.39	0.76–0.90
Very poor	≤0.19	≥0.90

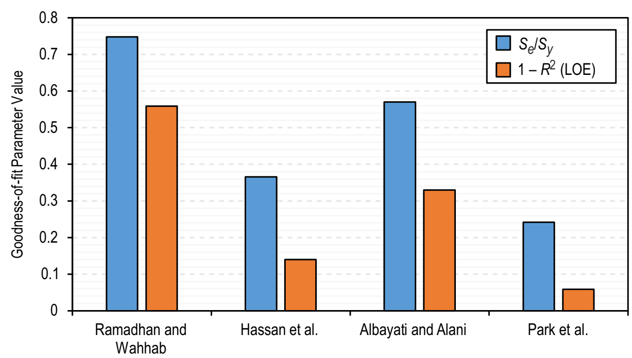

Figure 4. Goodness-of-fit parameters of the temperature profile predictive models for asphalt layers

ence to the LOE is for the Park et al. (2001) model with a value of 0.94 and the lowest value is for the Ramadhan and Wahhab (1997) model with a value of 0.44. Regarding S_e/S_y parameter, the minimum and maximum values are 0.24 and 0.74 for Park et al. (2001) and Ramadhan and Wahhab (1997) models, respectively. As noted in this table, Park et al. (2001) and Hassan et al. (2005) models showed excellent and good correlations, respectively; and both Ramadhan and Wahhab (1997), and Albayati and Alani (2015) models exhibited a fair correlation between the measured and predicted temperatures. Furthermore, the slope values of trend line varied from 0.9490 for the Hassan et al. (2005) to 1.3568 for the Ramadhan and Wahhab (1997) models. In addition, the intercept values of this line ranged from 0.1262 for the Park et al. (2001) to 7.052 for the Albayati and Alani (2015) models.

Using these data, Figure 4 shows the overall accuracy (goodness-of-fit) of the investigated predictive models. The $1 - R^2$ and S_e/S_y are considered as two parameters for evaluating the accuracy of models. According to Figure 4, Park et al. (2001) and Ramadhan and Wahhab (1997) models have the smallest and largest values of these parameters, respectively. Therefore, these models predict the temperature profile of asphalt layers with the highest and the lowest accuracy, respectively.

A comparison of prediction bias of the models is presented in Figure 5. With reference to this figure, two parameters of 1-Slope, as well as the intercept of the trend line (intercept), are defined to evaluate the bias of the pre-

Table 6. Statistical parameters for overall performance of investigated original models

Performance parameter	Prediction model			
	Ramadhan and Wahhab (1997)	Hassan et al. (2005)	Albayati and Alani (2015)	Park et al. (2001)
SSE	3177	15870	40280	161500
S_e	0.1794	5.0567	8.5398	3.7599
S_e/S_y	0.74	0.36	0.57	0.24
R^2 (LOE)	0.44	0.86	0.67	0.94
Correlation	Fair	Good	Fair	Excellent
Slope	1.3568	0.9490	1.0215	1.0537
Intercept	6.9204	0.5526	7.052	0.1262

Note: SSE – sum of squared errors; and LOE – line of equality.

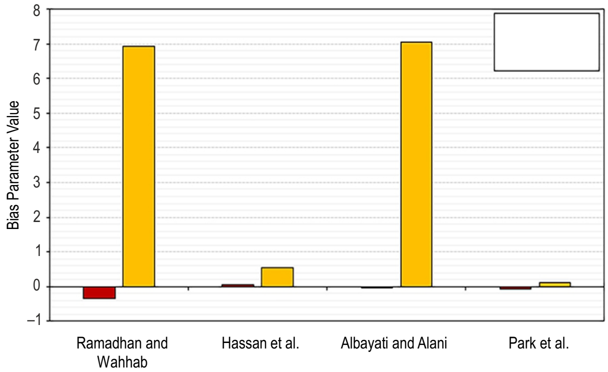

Figure 5. Bias parameters of the temperature profile predictive models for asphalt layers

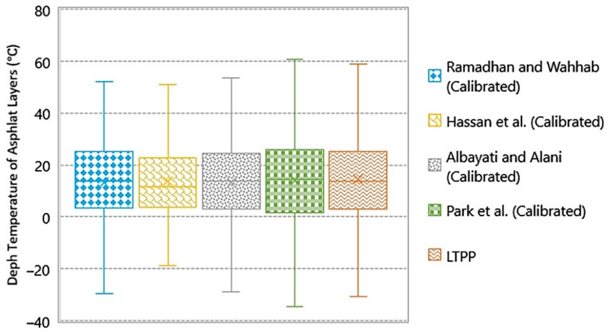

Figure 6. Measured and predicted temperatures at various depths of asphalt layers using calibrated models

dictive models (Solatifar et al., 2021). As it can be seen in this figure, Albayati and Alani (2015), and Ramadhan and Wahhab (1997) models predict the temperature profile of asphalt layers accompanied by the highest bias. As mentioned earlier, it may be associated with the use of limited variables besides temperature prediction in low or near depths from the pavement surface.

5. Calibration of predictive models using LTPP data

In this section, four temperature profile predictive models for asphalt layers called Ramadhan and Wahhab (1997), Hassan et al. (2005), Albayati and Alani (2015), and Park et al. (2001), have been calibrated using LTPP data. In addition, the accuracy and performance of the models have been assessed using parameters of the R^2 regarding the LOE, and S_e/S_y, slope, and intercept of the trend line.

5.1. Development of new predictive models

Evaluation of the performance of the predictive models in the previous section, showed the need for calibrating and developing new models with high accuracy and low bias in determining the temperature profile of asphalt layers. Hence, in this section, non-linear regression analysis was performed based on the calibration of the original models, and four new predictive models were developed. For this purpose, LTPP data in two categories of SMP (included 552411 data points) and SMP & AWS (included 285496 data points) consisting of climatic parameters were used. In sum, 837907 data points have been used to calibrate the predictive models. These data were divided into two categories of 80% (670327 data points) for modeling and 20% (167581 data points) for validation of new models. Before division, to distribute the data uniformly, all data points were randomized. The newly developed predictive models, named as calibrated Ramadhan and Wahhab (1997), calibrated Hassan et al. (2005), calibrated Albayati and Alani (2015), and calibrated Park et al. (2001) models, are given in Eqns (5)–(8) in their mathematical form, respectively:

$$PAV = b_1 AIR + b_2; \tag{5}$$

$$T_{20\ mm} = b_1 + b_2 T_{air} + b_3 Solar; \tag{6}$$

$$T_{pave} = b_1 T_{air} + b_2 Z; \tag{7}$$

$$T_Z = T_{Surf} + \left(b_1 z + b_2 z^2 + b_3 z^3\right) \times \sin\left(b_4 t + b_5\right), \tag{8}$$

where all the variables were defined previously. The analysis was performed, and the parameters of the new models were determined, as reported in Table 7. The predicted temperature ranges employing these new calibrated models besides the LTPP measured temperatures, exhibited in Figure 6. As it can be inferred from this figure, all the calibrated models predict the temperature profile of asphalt layers at similar ranges of the LTPP values. Such a result indicates that the developed models have a remarkable capability in predicting the temperature profile of asphalt layers. The performance evaluation of the developed models is presented in the next sub-section.

5.2. Performance evaluation of the proposed models

Similar to the evaluation of the original models, using accuracy and bias parameters, appraisal of performance and goodness-of-fit of the proposed calibrated models in predicting the temperature profile of asphalt layers was performed. Figures 7a to 7d show the predicted temperature values at various depths by the calibrated Ramadhan and Wahhab (1997), calibrated Hassan et al. (2005), calibrated Albayati and Alani (2015), and calibrated Park et al. (2001) models versus the LTPP measured temperatures. As it can be observed in this figure, the data points are spread densely around the LOE, which indicates that the calibrated models predict the pavement temperature with remarkable improvement in accuracy (compared to the original predictive models), and the prediction is well-performed.

The parameters of performance evaluation of the calibrated predictive models are given in Table 8. As it can be seen in this table, the highest and the lowest values of R^2 with reference to the LOE are 0.94 and 0.88 for the calibrated Park et al. (2001) and calibrated Albayati and Alani (2015) models, respectively. Regarding the S_e/S_y, the minimum and maximum ratios are 0.24 and 0.35 for calibrated Park et al. (2001) and calibrated Albayati and Alani (2015) models, respectively. As it can be inferred from this table, the calibrated Albayati and Alani (2015) model showed good, and other calibrated models exhibited an excellent correlation between the measured and the predicted temperatures at various depths. Furthermore, the slope of the trend line varied from 0.9124 for the calibrated Hassan et al. (2005) to 1.0539 for the calibrated Park et al. (2001) models. In addition, the intercept values ranged from

Table 7. Parameters of original and calibrated temperature profile prediction models

Parameter	Ramadhan and Wahhab (1997)		Hassan et al. (2005)		Albayati and Alani (2015)		Park et al. (2001)	
	Original	Calibrated	Original	Calibrated	Original	Calibrated	Original	Calibrated
b_1	1.692	1.1471	2.713	3.83693	1.217	1.1639	–0.3451	–9.915
b_2	12.670	4.96127	1.281	1.06232	–0.354	0.35277	–0.0432	231.476
b_3	–	–	0.00053	0.0117337	–	–	0.00196	–933.482
b_4	–	–	–	–	–	–	–6.3252	–5.382
b_5	–	–	–	–	–	–	5.0967	–25.2

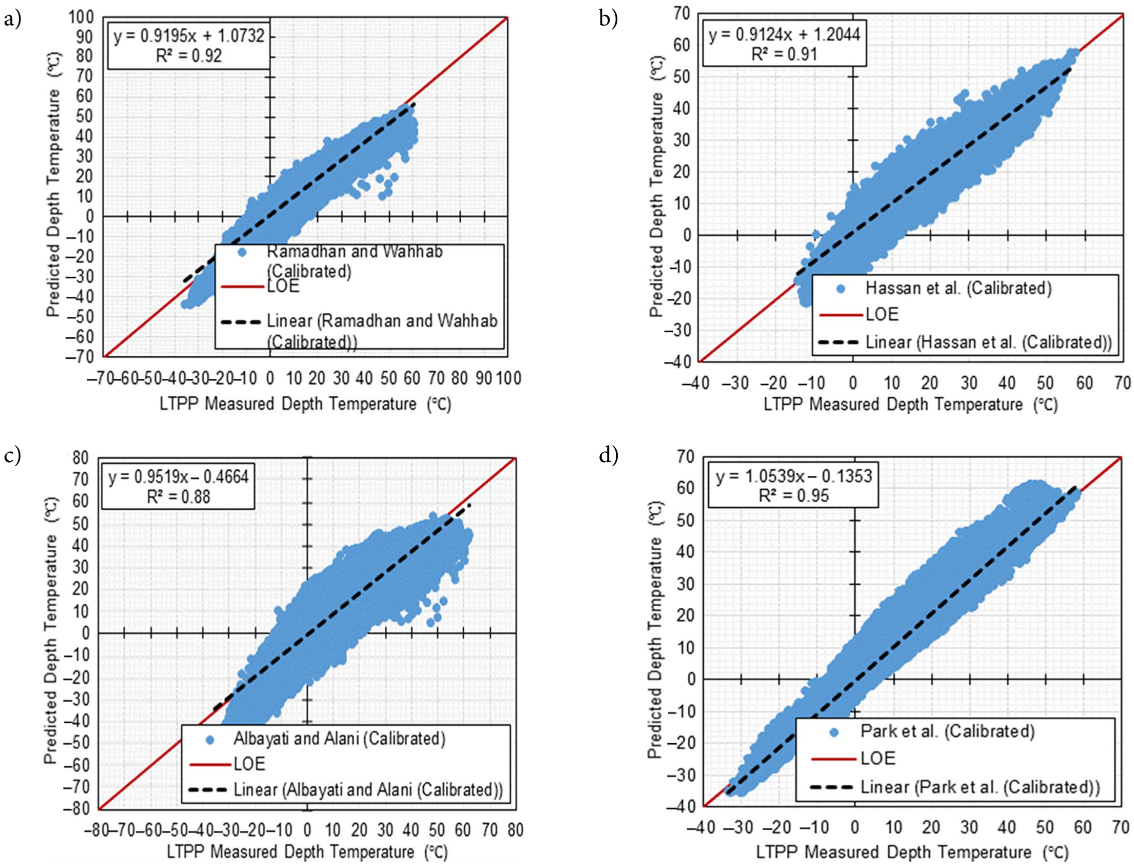

Figure 7. Predicted temperature at various depths using new models versus measured values (LTPP data): a – calibrated Ramadhan and Wahhab (1997) model; b – calibrated Hassan et al. (2005) model; c – calibrated Albayati and Alani (2015) model; d – calibrated Park et al. (2001) model

0.1353 for the calibrated Park et al. (2001) to 1.2044 for the calibrated Hassan et al. (2005) models.

As it can be seen in Figures 7a to 7d, the precision of the models has been boosted remarkably. So that, e.g., the accuracy (R^2) of Ramadhan and Wahhab (1997), Hassan et al. (2005), and Albayati and Alani (2015) models from 0.44, 0.86, and 0.67, have increased significantly to 0.92, 0.91 and 0.88, respectively. Owing to employing an extensive range of LTPP data, all new proposed models have been calibrated for application in regions with different climatic conditions.

In addition, the slope and intercept of the trend line parameters of the original models have also been improved. By comparing Table 5 and Table 7, it can be observed that the correlation of all models except Park et al. (2001) model has enhanced from fair and good to excellent. This increase in performance of the proposed models is evident by comparing Figure 2 and Figure 6 with each other. Furthermore, by comparing Figures 3a to 3d and 7a to 7d, it can be stated that by calibration of predictive models, the temperature values at various depths of asphalt layers are closer to the LOE line, hence, the precision of the proposed models has increased alongside their bias has decreased. In Figures 8, 9, 10, and 11, the evaluation parameters showed a notable improvement in the performance of calibrated models (compared to Figures 4 and 5).

Table 8. Statistical parameters for overall performance of developed calibrated models

Performance parameter	Calibrated prediction model			
	Ramadhan and Wahhab (1997)	Hassan et al. (2005)	Albayati and Alani (2015)	Park et al. (2001)
SSE	15580	82930	12030	12740
S_e	4.4455	4.0868	5.2175	3.7337
S_e/S_y	0.29	0.30	0.35	0.24
R^2 (LOE)	0.92	0.91	0.88	0.94
Correlation	Excellent	Excellent	Good	Excellent
Slope	0.9195	0.9124	0.9519	1.0539
Intercept	1.0732	1.2044	0.4664	0.1353

Note: SSE – sum of squared errors; and LOE – line of equality.

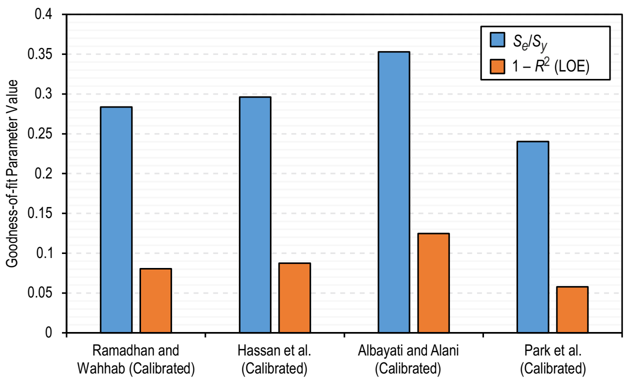

Figure 8. Goodness-of-fit parameters of new temperature profile predictive models for asphalt layers

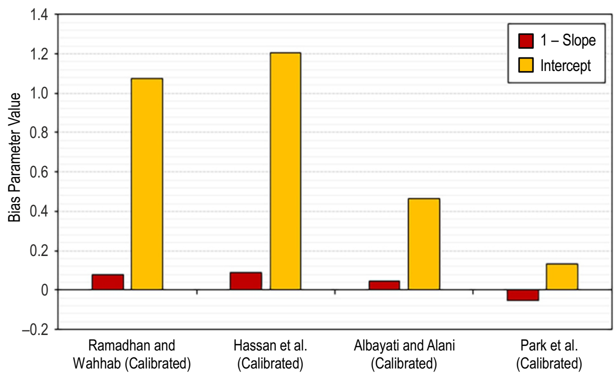

Figure 9. Bias parameters of new temperature profile predictive models for asphalt layers

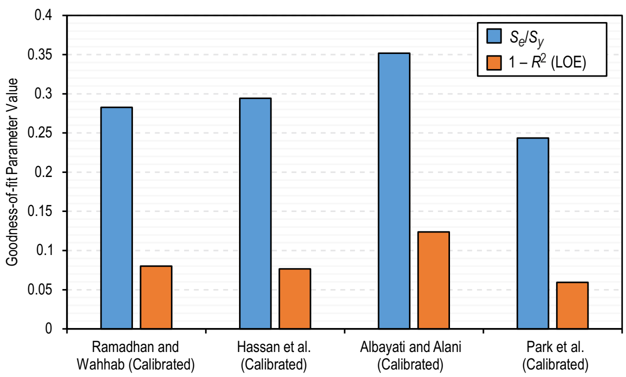

Figure 10. Goodness-of-fit evaluation of new temperature profile predictive models for asphalt layers using validation data

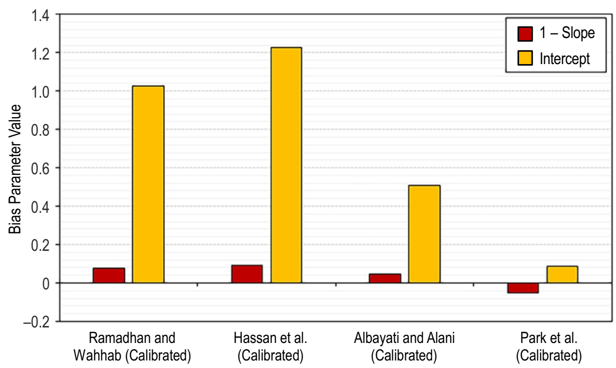

Figure 11. Bias evaluation of new temperature profile predictive models for asphalt layers using validation data

Table 9. Statistical parameters for validation of the newly developed models

Performance parameter	Calibrated prediction model			
	Ramadhan and Wahhab (1997)	Hassan et al. (2005)	Albayati and Alani (2015)	Park et al. (2001)
SSE	39604	021516	30050	32450
S_e	4.4686	4.0656	5.2152	3.7681
S_e/S_y	0.28	0.29	0.35	0.24
R^2 (LOE)	0.92	0.91	0.88	0.94
Correlation	Excellent	Excellent	Good	Excellent
Slope	0.9215	0.9104	0.9517	1.0523
Intercept	1.0245	1.2256	0.507	0.0889

Note: SSE – sum of squared errors; and LOE – line of equality.

Figure 8 presents the overall accuracy (goodness-of-fit) of the calibrated predictive models. According to this figure, calibrated Park et al. (2001) and calibrated Albayati and Alani (2015) models predict the temperature profile of asphalt layers with the highest and the lowest accuracies, respectively. In addition, calibrated Ramadhan and Wahhab (1997), and calibrated Hassan et al. (2005) models also had satisfying prediction accuracy. Figure 9 presents the all-inclusive comparison of predicting bias of calibrated models. As it can be perceived from this figure, calibrated Hassan et al. (2005) and calibrated Ramadhan and Wahhab (1997) models have the highest bias in predicting the temperature profile of asphalt layers. However, the calibrated Park et al. (2001) model yielded the lowest prediction bias.

6. Validation of the proposed models

After calibrations, 20% of the data points were used to validate the newly developed models. For validation goals, performance appraisal of the new models in predicting the temperature profile of asphalt layers was carried out. Table 9 reports the evaluation results. As it can be seen in this table, the highest R^2 value regarding the LOE is for the calibrated Park et al. (2001) model with a value of 0.94 and the lowest value is for the calibrated Albayati and Alani (2015) model with a value of 0.88. Furthermore, similar to the previous section, the minimum and maximum ratios of S_e/S_y are 0.24 and 0.35 for calibrated Park et al. (2001) and calibrated Albayati and Alani (2015) models, respectively. Again, the calibrated Albayati and Alani (2015) model showed good, and other calibrated models exhibited an excellent correlation between the measured and the predicted temperature at various depths. Moreover, the slope values differed from 0.9104 for the calibrated Hassan et al. (2005) to 1.0523 for the calibrated Park et al. (2001) models. In addition, the intercept values ranged from 0.0889 for the calibrated Park et al. (2001) to 1.2256 for the calibrated Hassan et al. (2005) models. Hence, it can be argued that these values show very good accuracy with low bias for the performance of the new models.

Comparison of the overall accuracy and bias for validation purposes of all proposed temperature profile predictive models are exhibited in Figure 10 and Figure 11, respectively. Similar results, conferred in Figures 8 and 9, were acquired. According to these figures, calibrated Park et al. (2001) and calibrated Albayati and Alani (2015) models predict the temperature profile of asphalt layers respectively with the highest and the lowest accuracies among the other models. Consequently, the calibrated Park et al. model yielded the lowest prediction bias.

Using validation data points, except calibrated Albayati and Alani (2015) model, all the newly developed models, specially calibrated Park et al. (2001) model, predict the temperature at various depths of asphalt layers with considerably low bias. Hence, validation of the developed models shows that these models well satisfy all of the requisite requirements. Therefore, these new models have remarkable accuracy for predicting the temperature profile of asphalt layers with low predictive bias and can be as an alternative to in-situ measurements.

Conclusions

The data was extracted from the pavement international database (LTPP) to determine the temperature profile of asphalt layers. Based on all available data collected by the Automatic Weather Stations (AWS) and the Seasonal Monitoring Program (SMP), available in the LTPP database, calibrating the four famous temperature profile prediction models has been well done. Using these data, the performance of these models was evaluated. By interpreting this study, the following conclusions are drawn:

- Original prediction models predict the temperature profile of asphalt layers with low, and in some rare cases satisfying accuracy. In addition to the model accuracy, high prediction bias was observed using the original models. The results of the evaluating these models, show the need for calibrating and developing new models for utilization in local climatic conditions.
- Comparing the measured temperatures at various depths and those predicted using new calibrated models showed that the proposed models predict the temperature profile of asphalt layers with high accuracy and low prediction bias.

- Temperature measurements at various depths for pavement design, analysis, and rehabilitation purposes require in-situ (i.e., drilling) testing; this is very time-consuming and high-priced. The chief benefit of the newly developed models is precisely predicting the temperature profile without conducting direct measurements in any local conditions.
- The best prediction performance belongs to calibrated Park et al. (2001), calibrated Ramadhan and Wahhab (1997), calibrated Hassan et al. (2005), and calibrated Albayati and Alani (2015) models, respectively. Among the developed models, the calibrated Park et al. (2001) model yielded the best prediction accuracy and performance with R^2 of 0.94, as well as the lowest prediction bias.
- Because of the use of large data (837907 data points) of asphalt pavement test sections in different regions of the US with different climatic conditions (such as average annual temperature, annual precipitation, etc.), the proposed models in this research have the generalizability for advantage in different areas. Whereas the original models are based on limited data and local conditions. Similar results for the validation data of the calibrated models also confirm the applicability of these models in different regions.
- The use of such large and diverse data for the development of calibrated models has been performed for the first time in this research. By using these models, the determination of the temperature profile of asphalt layers in different areas can be conducted with satisfying accuracy without direct and in-situ measurements. In addition, providing mathematical and simple hand-operated formulas of the proposed models accelerates their application for easy, fast, safe, and low-cost use.
- It should be noted that one of the limitations of the research is the restricted application of the new models presented for benefit in areas with hot climate regions. According to Table 4, in areas with air temperatures higher than about 50 °C, the proposed models will have low accuracy and performance. To solve this problem, it is suggested to count the data of asphalt pavements located in hot and tropical areas in the final dataset. However, Solatifar et al. (2018) calibrated the BELLS model for pavements experiencing air temperatures up to 59 °C and developed the new BELLS model.

Disclosure statement

No potential conflict of interest was reported by the authors.

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