MODELING THE SURFACE STORED THERMAL ENERGY IN ASPHALT CONCRETE PAVEMENTS

by

Bojan J. MATIĆ**, Hasan Awadat SALEM, Vlastimir S. RADONJANIN, Nebojša M. RADOVIĆ, and Siniša R. SREMAC

Faculty of Technical Sciences, University of Novi Sad, Novi Sad, Serbia

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Regression analysis is used to develop models for minimal daily pavement surface temperature, using minimal daily air temperature, day of the year, wind speed and solar radiation as predictors, based on data from Awbari, Libya. Results were compared with the existing SHRP and LTPP models. This paper also presents the models to predict surface pavement temperature depending on the days of the year using neural networks. Four annual periods are defined and new models are formulated for each period. Models using neural networks are formed on the basis of data gathered on the territory of the Republic of Serbia and are valid for that territory.

Key words: *pavement, temperature, model, predicting, ANN, regression analysis, thermal energy*

Introduction

Pavement structure is a multi-layered system composed of diverse materials whose behaviour is more or less dependent on the temperature.

The main task, then, is to determine physical and mechanical properties of materials in the conditions equivalent to the conditions in the real pavement structure. In this sense, with the bitumen-bound materials, it is important to determine their characteristics in the range of temperatures in the pavement structure, with the special consideration on the impact of extreme temperature.

After several years long research (Long-Term Pavement Performance – LTTP) and Seasonal Monitoring program – SMP) on the behaviour of pavement structure under traffic load and in environmental conditions, the method for designing asphalt pavements, called SUPERPAVE, has been formed. The process of calculating pavement temperature from air temperature is as follows:

- Convert average 7-day maximum air temperature to pavement surface temperature;
- Calculate 7-day maximum pavement temperature at the design depth;
- Convert minimum air temperature to minimum pavement surface temperature; and
- Calculate minimum pavement temperature at the design depth.

Environmental conditions are specified in terms of average 7-day maximum pavement design temperature and minimum pavement design temperature. The average 7-day

* Corresponding author; e-mail: bojanm@uns.ac.rs

maximum pavement design temperature is the average of the highest daily pavement temperatures for the seven hottest consecutive days in a year. The lowest annual pavement temperature is the coldest temperature of the year. The asphalt binder specification uses the designation PG x-y, where PG = performance graded, x = high pavement design temperature, and y = low pavement design temperature [1].

Authors all around the world have provided models to predict pavement temperature both on local and on global level. Several models predicting the pavement temperature have been analysed, and it has been determined that the best predicting models are the ones formed using databases for the territory where they are intended to predict pavement temperature. Pavement temperature can be influenced, apart from latitude and other factors, by seasons as well, and by the time of a day. Until today, many authors have formed models using statistical data analysis to predict the surface pavement temperature (tab 1).

This paper presents two researches and formulates new models for predicting pavement temperature for two different locations with two different methods. The first model predicts minimum and maximum pavement surface temperatures using ANN (artificial neural network) for Serbian territory, and the second one predicts minimum surface pavement temperature for Awbary – a part of the Libyan desert (specific weather condition) by regression analysis.

Table 1. An overview of models for predicting pavement temperatures using regression analysis [1-6]

Author	Publishing year	Statistical data analysis
Strategic Highway Research Program (SHRP)	1987	Yes
Mohseni and Symons [2]	1998	Yes
Lukanen *et al.* [3]	1998	Yes
Bosscher *et al.* [4]	1998	Yes
Marshall *et al.* [5]	2001	Yes
Denneman E. [6]	2007	Yes

Abo-Hashema [7] discusses the feasibility of applying artificial neural network (ANN) technology in predicting the AC layer temperature. In his paper, the neural network is trained and tested using NeuroSolutions 5.0 software through the actual field data obtained from Long-Term Pavement Performance (LTPP) and Seasonal Monitoring Program (SMP) by DataPave3.0 software. Results indicate that the developed ANN-based pavement temperature prediction models can be used in predicting AC layer temperature with high accuracy in comparison to the measured values.

This outcome is considered crucial to the pavement design, especially followed by the second ANN model where some input parameters may not be available [7]. Matić *et al.*, [8] formulate a new model for predicting pavement temperatures at specified depth using neural networks, depending on the surface pavement temperature and depth.

Experimental part

Data used for analyzing and forming the model for pavement temperature prediction by neural networks were taken from the pilot project by the public company (JP) *Putevi Srbije* and the Government of Sweden. Surface pavement temperature, as well as air conditions, were monitored using modern meteorological stations (Road Meteorological Information System) on six locations during the part of 2010, the entire 2011 and the part of 2012. The acquisition of all meteorological data in the base, including temperature, was performed every 30 minutes. Following values were measured: air temperature, air humidity, dew point temperature, type of precipitation, surface pavement temperature, and max wind speed [9]. Collected data: air temperature, surface pavement temperature, day of the year and humidity are used for the model for predicting the minimum and maximum surface pavement temperature by ANN.

The temperature data used in the regression analysis were collected in the period from 1st of January 2012 to 31st of December 2012 (data from Awbari-Libya). Awbari is situated in the desert of Libya, latitude 26°46'N and longitude 12°57'E.

The temperature of the air and pavement were registered each 15 seconds, as well as the wind speed and solar radiation. Minimal daily temperatures of the air and pavement were extracted for each day of the observing period. The selection of the best regression model was discussed by applying six criteria. Data were analyzed using the R programming language (R 3.1.2), and the statistical package Statistica 12 (StatSoft Inc., Tulsa, Okla., USA), university license for the University of Novi Sad.

In fig. 1, the scatter plot of minimal daily surface pavement temperatures against minimal daily air temperatures shows linear relationship. Thus, the first variable in the model is the minimal daily air temperature.

Figure 2 presents minimal daily pavement surface temperatures and air temperatures during the study period (1/1/2012 – 31/12/2012), and shows non-linear dependence on the day of the year, therefore time–day of the year, denoted by t, was included in the model as t and t_2. To establish the periodicity in the behavior of minimal daily pavement surface temperatures, periodogram [10] was calculated and the harmonic component that has the highest contribution to the mean of the total sum of squares of time series was singled out. Therefore, time t – day of the year, was included in the model as $\sin(2\pi t/182)$ and $(2\pi t/182)$. Days of the year were coded with codes: 0 for 1/1/2012, up to 366 for 31/1/2102.

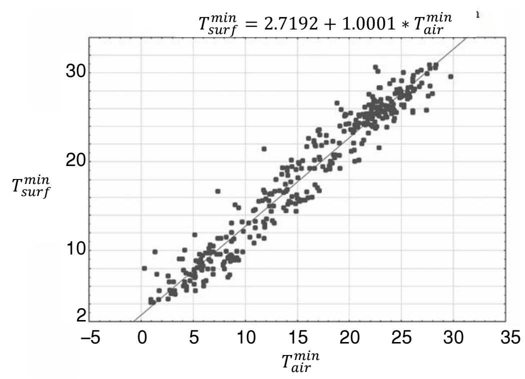

Figure 1. Minimal daily surface pavement temperature against minimal daily air temperatures

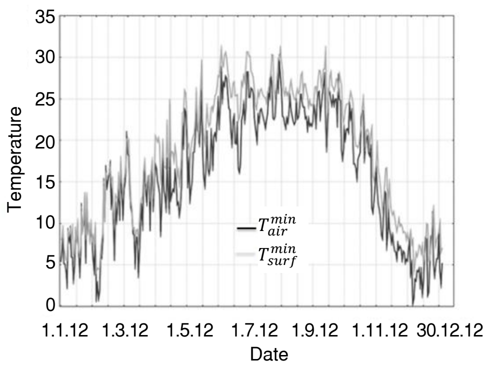

Figure 2. Minimal daily surface pavement temperature against minimal daily air temperatures

Since the daily minimal surface pavement temperature is affected by factors other than daily minimal air temperature and day of the year, other parameters were considered in order to improve the model, namely wind speed (m/s) and solar radiation (W/m^2). All considered models are listed in tab. 2.

Table 2. List of all considered models

No.	Predictors
1	$Air_{min}, t, t^2, sin\left(\frac{2\pi t}{182}\right), cos\left(\frac{2\pi t}{182}\right)$
2	$Air_{min}, t, t^2, WS, sin\left(\frac{2\pi t}{182}\right), cos\left(\frac{2\pi t}{182}\right)$
3	$Air_{min}, t, t^2, SR, sin\left(\frac{2\pi t}{182}\right), cos\left(\frac{2\pi t}{182}\right)$
4	$Air_{min}, t, t^2\ cos\left(\frac{2\pi t}{182}\right)$
5	$Air_{\min}, t, t^2, WS, SR, \sin\left(\frac{2\pi t}{182}\right), \cos\left(\frac{2\pi t}{182}\right)$
6	$Air_{min}, t, t^2, WS, cos\left(\frac{2\pi t}{182}\right)$
7	$Air_{min}, t, t^2, SR, cos\left(\frac{2\pi t}{182}\right)$
8	$Air_{min}, t, t^2, WS, SR, cos\left(\frac{2\pi t}{182}\right)$
9	$Air_{min}, t, t^2\ sin\left(\frac{2\pi t}{182}\right)$
10	$Air_{min}, t, t^2, WS, sin\left(\frac{2\pi t}{182}\right)$

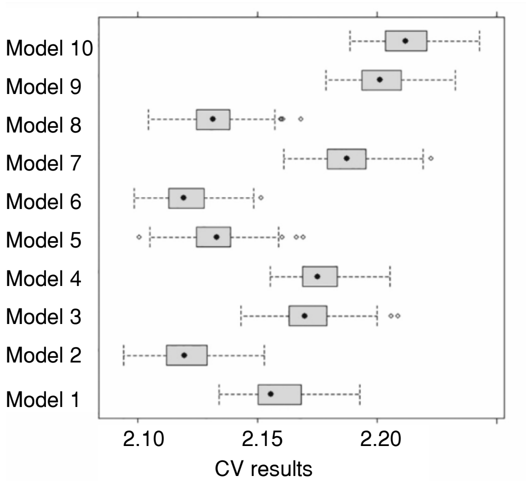

Figure 3. Distribution of repeated 15-fold CV with 100 replications

For repeating the 15-fold cross-validation, the empirical distributions of CV-test criterion for the applied methods were obtained and compared (fig. 3).

In order to select the best model, six criteria were applied. Adjusted R^2, Mallow's Cp, Akaike's information criterion (AIC), Bayesian information criterion (BIC), as well as two algorithms for cross-validation: leave one out cross-validation and 15-fold cross-validation. The split of 364 observations into 15 groups was done randomly with 100 replications. All criteria except Adjusted R^2 are based on balancing the model complexity against quality of model's fit. The results are given in tab. 3. The values in bold denote the best model according to corresponding criteria.

Table 3. The best models, according to six criteria

No	Mallows' Cp	Adj. R^2	AIC	BIC	CV1	CV15
6	**5.88**	0.9650	**1308.27**	**1335.55**	2.1184	2.1202
2	6.07	**0.9651**	1308.43	1339.61	**2.1179**	**2.1201**
8	7.87	0.9649	1310.26	1341.44	2.1293	2.1319
5	8.00	0.9650	1310.35	1345.43	2.1295	2.1325
1	12.30	0.9644	1314.75	1342.03	2.1566	2.1587
3	14.25	0.9643	1316.69	1347.88	2.1688	2.1716
4	14.94	0.9641	1317.35	1340.74	2.1749	2.1767
7	16.78	0.9640	1319.19	1346.47	2.1852	2.1878
9	19.60	0.9636	1321.92	1345.30	2.2001	2.202
10	21.27	0.9635	1323.60	1350.88	2.2108	2.2127

In order to compare our model with SHRP and LTPP low temperature prediction models for pavement surface temperature (tab. 4), the SHRP model is considered (1, 2):

$$T_{surf}^{min} = 0.859\, T_{air}^{min} + 1.7 \tag{1}$$

and LTPP model:

$$T_{surf}^{min} = -1.56 + 0.72\, T_{air}^{min} - 0.004\ \mathrm{Lat}^2 + 6.26\ \log_{10}(25) \tag{2}$$

Table 4. Coefficients of the best model to predict minimal daily surface pavement temperature

N = 364	Residual standard error: 1.444 on 358 degrees of freedom Multiple R-squared: 0.9655, Adjusted R-squared: 0.965 F-statistic: 2005 on 5 and 358 DF,			
	b	Std. Err. of *b*	*t* (356)	p
Intercept	1.132758	0.242404	4.673	< 0.01
Air_min	0.759659	0.019343	39.273	< 0.01
T	0.088008	0.005708	15.417	< 0.01
t^2	–0.000228	0.000015	–14.858	< 0.01
WS	–0.09652	0.029012	–3.326	< 0.01
cos(2πt/180)	0.597117	0.133887	4.459	< 0.01

The predicted models and collected data are presented in fig. 4. It can be seen that the predicted minimal daily surface pavement temperatures by SHRP model are lower than the measured values and the minimal daily surface pavement temperature predicted by the best model. The LTPP model underestimates high minimal daily surface pavement temperatures both for the measured values and for predicted temperatures in relation to the best model.

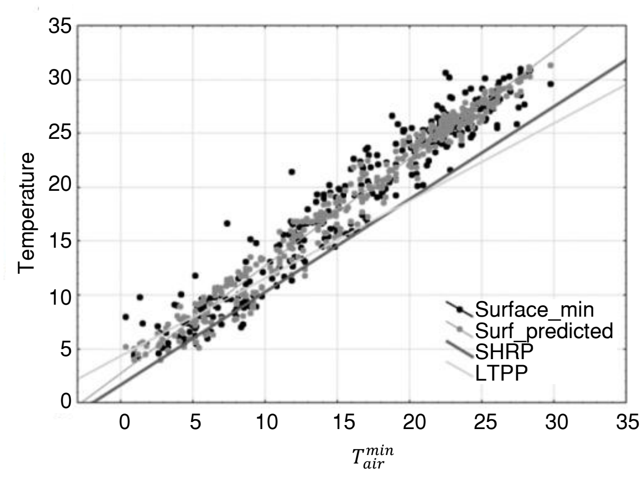

Figure 4. Comparison between the best selected model for predicting minimal daily surface pavement temperature and SHRP and LTPP models

The paper also formulates new models for predicting maximum and minimum pavement surface temperatures using ANN, depending on the ambient air temperature. The first one predicts maximum surface pavement temperatures based on maximum air temperature, as seen in tabs. 5 and 7. Mean Average Error (MAE) for this model is 3.82937757 °C.

The second one predicts minimum surface pavement temperatures based on minimum air temperature, as observed in tabs. 6 and 7. Mean Average Error (MAE) for this model is 1.40998219 °C.

Table 5. Model predicting maximum surface pavement temperature based on maximum air temperature by ANN

Index	Net. name	Training perf.	Test perf.	Training error	Test error	Training algorithm	Error function	Hidden activation	Output activation
1	MLP 1-5-1	0.944463	0.815718	0.004626	0.01596	BFGS 111	SOS	Logistic	Exponen.

Table 6. Model predicting minimum surface pavement temperature based on minimum air temperature by ANN

Index	Net. name	Training perf.	Test perf.	Training error	Test error	Training algorithm	Error function	Hidden activation	Output activation
1	MLP 1-5-1	0.974493	0.972041	0.001555	0.00161	BFGS 44	SOS	Logistic	Tanh

Table 7. Table overview of MAE of models predicting max and min surface pavement temperature by ANN

Mean average error, MAE, $^{\circ}$C	
maxTk	minTk
3.82937757	1.40998219

Based on previously completed research and developed models using regression analysis, it is concluded that models predict the minimum and maximum surface pavement temperature better than this models using ANN.

Furthermore, the paper formulates the models for predicting surface pavement temperature for diverse periods throughout a year based on air temperature, day of the year and humidity by ANN. The мean average errors (MAE) of these models are shown in tab. 8.

If we use humidity as one of the input variables in the model for predicting the surface pavement temperature, the MAE will not be less for all models. For some models MAE will be increased. Accordingly, it can be concluded that the model for predicting surface pavement temperature using ANN for the first two periods of the year (from January to March and from April to June) is better without humidity as an input variable (*i. e.* model where the input variables are air temperature and day of the year). For the other two periods (from July to September and October to December) the better model is with humidity as an input variable.

Table 8. Table overview of models predicting surface pavement temperature for diverse periods during a year by ANN

Independent Variables	Mean average error, MAE, $^{\circ}$C			
	January-March	April-June	July-September	October-December
Air temperature, day of the year	0.894487	2.226435	1.690075	0.869849
Air temperature, day of the year, humidity	1.033865	2.470103	1.683501	0.852367

The tables below present the ANN models that predict seasonal asphalt concrete surface pavement temperature with the highest accuracy using ANN for four different periods of the year (tabs. 9-12).

Table 9. Model predicting surface pavement temperature by ANN based on air temperature and day of the year for the period January-March

Index	Net. name	Training perf.	Test perf.	Training error	Test error	Training algorithm	Error function	Hidden activation	Output activation
1	RBF 2-63-1	0.895316	0.889872	0.002	0.0021	RBFT	SOS	Gaussian	Identity

Table 10. Model predicting surface pavement temperature by ANN based on air temperature and day of the year for the period April-June

Index	Net. name	Training perf.	Test perf.	Training error	Test error	Training algorithm	Error function	Hidden activation	Output activation
1	MLP 3-6-1	0.946513	0.964050	0.002701	0.0039	BFGS 47	SOS	Logistic	Logistic

Table 11. Model predicting surface pavement temperature by ANN based on air temperature and day of the year for the period July-September

Index	Net. name	Training perf.	Test perf.	Training error	Test error	Training algorithm	Error function	Hidden activation	Output activation
1	MLP 3-3-1	0.961315	0.955025	0.00	0.002	BFGS 50	SOS	Tanh	Identity

Table 12. Model predicting surface pavement temperature by ANN based on air temperature and day of the year for the period October-December

Index	Net. name	Training perf.	Test perf.	Training error	Test error	Training algorithm	Error function	Hidden activation	Output activation
1	MLP 3-4-1	0.978898	0.972124	0.000711	0.00091	BFGS 70	SOS	Exponent.	Logistic

Conclusions

Regression models (for desert Libyan aria) for predicting minimal daily pavement surface as a function of minimal daily air temperature, day of the year and wind speed are considered. The best model was selected using adjusted R2, Mallows' Cp, AIC, BIC and cross-validation. The comparison of the best formulated model with SHRP and LTPP models indicates that the presented models would estimate lower minimal daily surface pavement temperatures for Awbari, Libya. Therefore, these models would be conservative in the selection of performance grade (PG) binders.

The paper also formulates new models for predicting minimum and maximum pavement surface temperatures using ANN, depending on the ambient air temperature (for Serbian territory). The paper formulates new models for predicting day surface pavement temperature, including seasonal influences by ANN. Furthermore, model validation has been conducted. Based on the mean absolute error (MAE) and standard deviation error (SDE) between measured and predicted pavement temperatures, it can be concluded that the models formed with two variables (air temperature and day of the year) using ANN predict pavement temperatures for the period January-March and April-June with better accuracy than the models [3] formed by regression analysis.

Likewise, it can be concluded that the models formed with three variables (air temperature, day of the year and humidity) using ANN predict pavement temperatures for the period July-September and October-December with higher accuracy than the models formed by two variables, tab 13.

Table 13. Table overview of models predicting surface pavement temperature for diverse periods during a year using regression analysis and ANN

Independent Variables	Type of analysis	Mean average error, MAE, °C			
		January-March	April-June	July-September	October-December
Air temperature, day of the year	Regression analysis [3]	1.284492	2.799148	2.158237	1.123356
	ANN	0.894487	2.226435	1.690075	0.869849
Air temperature, day of the year, humidity	Regression analysis [3]	1.283519	2.613486	2.162538	1.082358
	ANN	1.033865	2.470103	1.683501	0.852367

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Nomenclature

$T_{air}^{\min}$ – minimum air temperature, [C°]
$T_{surf}^{\min}$ – minimum surface temperature, [C°]
${}^{\max}T_k$ – maximum surface temperature, [C°]
${}^{\min}T_k$ – minimum surface temperature, [C°]
Lat – latitude [for Awbari-Libya and it is equal to 26.767 (26°46'N)]
Air_min – minimal daily air temperature, [C°]
t – day of the year,
SR – solar radiation [W],
WS – wind speed [m/s],
CV1 – leave on out cross-validation,
CV15 – 15-fold cross-validation.

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