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PREDICTING ASPHALT PAVEMENT TEMPERATURE BY USING NEURAL NETWORK AND MULTIPLE LINEAR REGRESSION APPROACH IN THE EASTERN MEDITERRANEAN REGION

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Abstract

This study compares the feasibility of using artificial neural networks (ANN) and multi-linear regression (MLR) for predicting an hourly temperature of the pavement, considering the depth, time, and air temperature as independent variables. Accurate prediction of the pavement temperature is critical for road maintenance, pavement design, and near-surface microclimate environment to overcome the problems caused by the fluctuations in temperature such as rutting in higher temperature and thermal cracking in lower temperature. A dataset containing 7200 measurements of the pavement temperature was used. Thermal instruments were used to measure the asphalt pavement temperature every two hours with different variables during the four seasons of the year in an attempt to model pavement temperature by utilising MLR and ANN. The target used for prediction was modelling the pavement temperature profile. In autumn, the regression square (R^2) value predicted by the ANN model is 0.95, while the R^2 value predicted by the MLR model is 0.92 as the most significant value in autumn and the lowest value for MLR and ANN analysis is 0.83 and 0.85, respectively in the winter. Results show that the temperature predictions made by ANN are more accurate than those made by MLR. Nonetheless, these models are recommended to be used in the same region since both models presented in this study showed high correlation coefficients.

Keywords: Artificial neural networks; Multiple linear regression; Prediction; asphalt pavement; Temperature models.

1. Introduction

Flexible pavements play a dominant role in transportation and highway networks. They are more widely used than other pavement materials due to their superior in-service performance [1-3]. Lower maintenance cost and suitability for use over a range of climatic conditions and axle load limits [4]. These flexible pavements use bitumen, which is a thermoplastic material, as the main binder. The extreme temperatures can risk asphalt pavements and adversely affect pavement performance [5-7]. Therefore, the effect of temperature variations must be considered in the design of flexible pavements [8].

Mechanistic-Empirical (M-E) pavement design can provide a more accurate prediction of the performance of an asphalt pavement. The design can consider several parameters that may affect the performance of asphalt pavement during the different seasons [9-12]. One of the main parameters is temperature variation. An accurate model to predict variations in asphalt pavement temperature is vital to achieving a more reliable design and extending the operating life of road pavements [13, 14]. Many regression models have been developed to predict the temperature of asphalt pavements. While some models have good accuracy, they require several input parameters for each developed prediction equation, and each has its strengths and weaknesses [15, 16]. The accuracy of a statistical method can only be established within the range of the original data utilised to [17, 18] develop (MLR) models [19]. With technological advances, engineers are now using computers and software to analyse data.

Barber was one of the first researchers to develop a thermal conductivity model for calculating the internal temperature profile of asphalt pavements in 1957 [20]. Four decades later, Lytton et al. [21] developed an Enhanced Integrated Climatic Model (EICM) to predict the heat of pavement structures caused by climate parameters change. The Strategic Highway Research Program (SHRP) initiated the Long-Term Pavement Performance Program (LTTP) in 1987 as 20-year research to improve pavement characterisation at a particular site was selected as sections of the Seasonal Monitoring Program (SMP) [22-24]. In 1993, the researchers used heat transfer theory to develop and validate the model for the summer based on the highest pavement surface temperature [25]. In addition, the study included models for predicting the pavement temperature at a certain depth based on air temperature and other climate parameters [24].

More recently, a series of statistical models for predicting the minimum, maximum, and average pavement temperatures were developed using field-measured data collected from instrumentation road sections [26-29]. These statistical models were developed for predicting temperature at depths of more than 30 cm based on hourly measurements of the pavement temperature and meteorological data. These models were validated, and their applicability was verified by applying the model at other sites where the data are available [30, 31]. In Serbia, an artificial neural network (ANN) was used to develop models for predicting the minimum and maximum pavement temperatures as a function of pavement surface temperature and pavement depth [18].

This paper presents findings from a study determining the effect of changes in air and asphalt pavement temperatures during four climatic seasons. The pavement temperature prediction models for Mediterranean climate conditions have been developed based on MLR models and ANN analysis.

2. Methodology

The methodology employed to develop models for asphalt pavement temperature using the MLR and ANN methods consists of four steps. In the first step, the test site and data sorting for model prediction are determined. The second step involves the development and validation of the MLR and ANN models. The third step compares the two models. The fourth step is the development of the temperature profile prediction model. Finally, MLR and ANN analysis methods were used to define the relationship between measured climate data and measured pavement temperature and determine the temperature at various depths using the most appropriate models, a relation function of pavement depth, air temperature, and time.

The model development required a large amount of data gathered from their Gaza Strip throughout the year, where more than 7200 measurements were taken. These data were used to conclude models; three variables were assumed in a linear relation by considering the effect of air temperature, pavement depth, and the temperature of asphalt concrete at any depth. In this study, the prediction of asphalt temperature was made for different depths, with a greater focus on summer and winter since the maximum and minimum temperatures occur during these seasons. Thermocouples were used to record temperatures at three depths of 0, 2, 5.5, and 7 cm. This study analysed the accuracy of MLR and ANN models to predict pavement temperature variations for the east Mediterranean climate.

2.1. Data acquisition

The pavement temperature was measured in the Gaza Strip Region Fig. 1, and the monitoring station was established to measure pavement temperature and air temperature at different depths (0, 2, 5.5, and 7 cm) and times in different seasons (winter, summer, spring, and autumn) Fig. 2. The data used in this study measured pavement temperature for 24 hrs based on one-year continuous data. Thus, the data were collected via hand measurements for the period from March 2012 to February 2013. The conditions of the data collection site must be known before the analysis is performed [32, 33]. The data were obtained from the data measuring station in the Gaza Strip and comprised three independent variables (air temperature, time, and depth) and one dependent variable (asphalt pavement temperature).

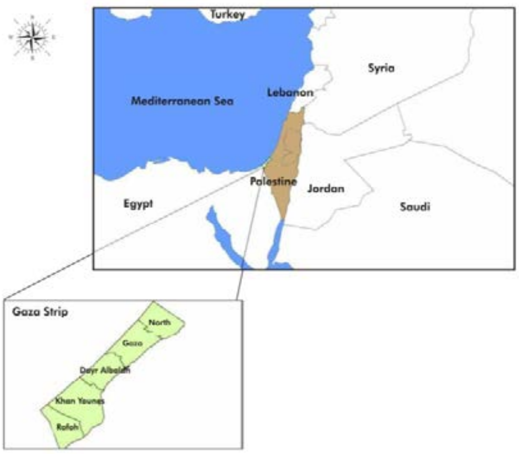


Fig. 1. Location of the study area [34].

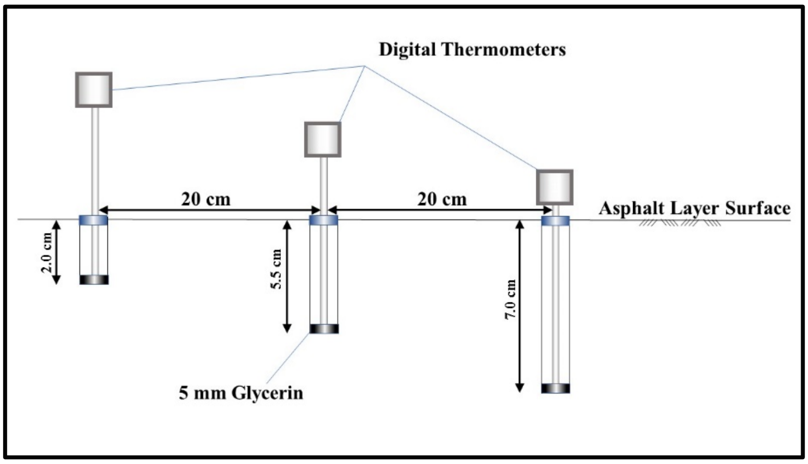


Fig. 2. Measurement depths of asphalt pavement temperature.

2.2. Developing pavement performance models

Two kinds of pavement temperature prediction models, traditional multiple linear regression (MLR) and artificial neural network (ANN) models, were developed to predict pavement temperature with ambient air temperature, depth within the asphalt pavement, and time variables. Therefore, the mean square error (MSE) and the coefficient of determination (R^2) were used to calculate and compare the model's efficiency [2]. Right model prediction should have low MSE and high R^2. R^2 values are the association between the actual and predicted values to determine model accuracy [3]. The MSE values calculate the differences between predicted and actual values. R^2 values range from 0 to 1, where 1 appears that the actual and predicted values are in accord and 0 indicates that they are not related [4]. The values of MSE and R^2 were calculated using equations 1 and 2, respectively [5].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}i - Yi)^2 \tag{1}$$

$$R^2 = \frac{\sum_{i=1}^{n}(Yi - \bar{Y}i)^2 - \sum_{i=1}^{n}(Yi - \hat{Y}i)^2}{\sum_{i=1}^{n}(Yi - \hat{Y}i)^2} \tag{2}$$

where Y_i is pavement temperature; $\bar{Y}i$ is the mean of measured pavement temperature; $\hat{Y}i$ predict pavement temperature, and n is the total number of observations.

2.3. Multiple linear regression (MLR)

MLR is a statistical technique that uses several explanatory variables to predict the outcome of a response variable [6]. The current study introduces the temperature prediction models as an hourly measurement based on differences in prediction seasons. The computer program SPSS version 20 for Windows was used as the statistical method to carry out the multi-linear regression analysis proposed. The stepwise regression analysis was used to determine and identify the value of variables that add considerable explanatory power to each regression model.

Analysis of variances (ANOVA) results, such as mean squared error (MSE) and the coefficient of determination (R^2), have been used to evaluate the prediction model of pavement temperature at different times and depths. It is necessary first to obtain a database to measure the pavement temperature with some other relevant parameters. The data for pavement temperature and other relevant data were obtained from the sites chosen for the pavement temperature database. The formula for MLR was determined using the following equation [7].

$$yi = \beta 0 + \beta 1x1 + \beta 2x2 + \ldots + \beta pxp + \epsilon \tag{3}$$

where, for $i = n$ observations: yi = dependent variable, $x1, x2\ldots..xk$ = Multiple independent variables, $\beta 0$ = y-intercept (constant term), βp = slope coefficients for each explanatory variable and ϵ = the model's error term (also known as the residuals).

2.4. Neural network

There are several neural network packages available. In this study, MATLAB version 2018, through the regression method, was used as a tool for designing and training the neural network. The MATLAB Builder software constructs the most common neural architectures. A sensitivity analysis of the trained ANN was conducted. Finally, testing and validation processes were performed on the four groups of trained ANN. The mean squared error MSE and plots were used to validate the prediction model of pavement temperature at different seasons, in normalisation, represented by restricted outputs to fit within the range from 0 to 1, so that the probability of class membership should represent. In ANN regression, outputs declare some of the required transformations and continuous values of input patterns. In ANN regression, a single hidden layer or multiple layers can learn to set the desired input and output if there were an adequate number of axons in the hidden layer (s) [36].

3. Results and Discussion

Asphalt pavements are heated to different depths during the day and the temperature drops during the night. The temperature in the asphalt pavement fluctuated, as shown in Figs. 3 and 4 in the summer and winter. Fig. 3 one of the summer days showing a seasonal manner of air and pavement temperatures at different depths. The minimum temperature occurred at around 6:00 am, and the maximum air temperature occurred just before midday (12 pm), and the maximum pavement temperature was achieved at about 2 pm. Figure 4 shows that the highest air temperature in the winter occurred in the afternoon (12:00 pm), and the minimum temperature occurred before sunrise (6:00 am). The daily maximum temperature was recorded at a deep depth of asphalt pavement at around 1:00 am. The temperature of asphalt pavements at all depths was considerably affected by air temperature, surface temperature, and pavement thickness. Determination of minimum, maximum, and average temperatures can provide an understanding of the behaviour of pavement temperature.

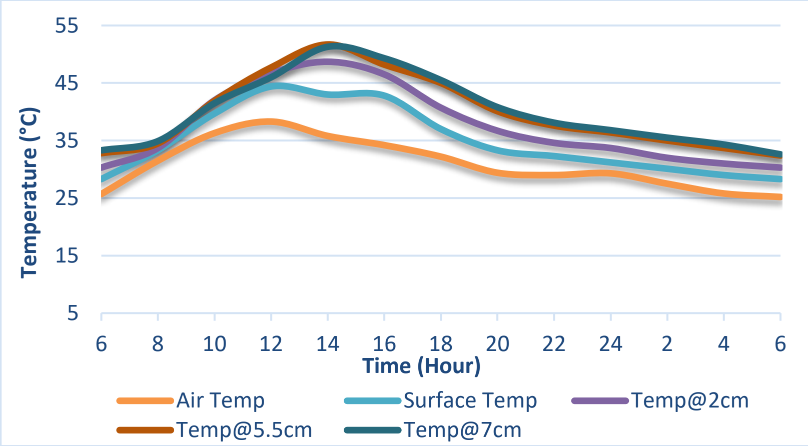


Fig. 3. Variation of summer air and asphalt pavement temperature.

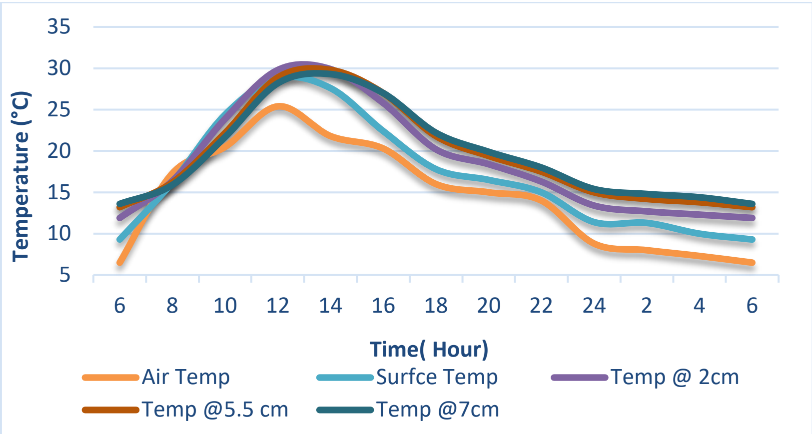


Fig. 4. Variation of winter air and asphalt pavement temperatures.

4. Model Development

4.1. Multi Linear Regression (MLR) Models

In MLR models, each value of x as the dependent variable correlates with the value of *y* as the independents variable [36, 37]. In this study, the MLR was utilised to model the independent variable's value, namely air temperature, measuring time, and depth of the asphalt pavement layer with a dependent variable. Stepwise regression is a technique for fitting regression models in which predictive variables are chosen employing an automatic procedure. This analysis technique was applied to identify the significant variables that would likely add significant explanatory power to each regression equation. The stepwise regression analysis was used to determine and identify the value of variables that add considerable explanatory power to a dependent variable based on a predetermined criterion in each stage. Stepwise regression allows addition if the value of R^2 increases or removes it if there is no significant correlation with the dependent variables.

The analysis was performed to compare the association between the independent and dependent variables. The invalid hypothesis was no significant correlation. The alternative hypothesis was a significant correlation. As seen in the correlation (Table 1), there is a correlation between the independent variables and the dependent variable. The prefix (sig) value of the relationship among the dependent variable (Log TD) and the independent variables (Air, Time and Depth), Thus, we accept the alternative hypothesis that there is a significant correlation between the dependent and independent variables.

Table 1. Correlation between independent variables and the dependent variable.

Season		**(sig) value**		
		Air	**Time**	**Depth**
Summer	Log TD	0.000	0.000	0.000
	Air		0.845	0.326
	Time			0.318
Winter	Log TD	0.000	0.258	0.000
	Air		0.000	0.128
	Time			0.24
Spring	Log TD	0.000	0.031	0.02
	Air		0.000	1
	Time			1
Autumn	Log TD	0.000	0.035	0.023
	Air		0.000	1
	Time			1

The results of MLR analysis are presented in Table 2, which shows the best regression models (or parameters) and sample summary. The relationship in the models indicates a normal linear relationship between the independent parameters of air temperature, time, depth, and asphalt temperature parameters

Table 2. MLR model development for different seasons.

Season	Date	Model
Summer	21-6 to 22-9	logTD = 1.04202 + 0.016 A + 0.002 T + 0.007 d
Winter	23-12 to 20-3	logTD = 0.78399 + 0.022143 A + 0.003997 d + 0.000347 A T
Spring	21-3 to 20-6	logTD = 1.0634 + 0.013544 A + 0.007740 d + 0.000413 A T - 0.005193 T
Autumn	23-9 to 22-12	logTD = 0.97100 + 0.015877 A + 0.000385 A T + 0.003052 d - 0.005320 T

TD: Temperature at d depth (°C); *A*: Air Temperature (°C) *d*: Depth cm *T*: time (hour)

Goodness of MLR Model

One-way Analysis of Variance (ANOVA) was performed to estimate the four models for summer, winter, spring, and autumn; the results are shown in Table 2. The *P* values for all independent variables are approximately 0.000 and less than 0.05, which means a useful independent variable [38]. Therefore, the alternative hypothesis is accepted, and the null hypothesis is rejected. In order to evaluate the effectiveness of the MLR model in predicting asphalt pavement temperature, the coefficient of determination, R^2, for the independent variable data and the dependent variable are estimated. Table 3 shows that R^2 (coefficient of determination) in summer, spring, winter, and autumn are 0.84, 0.83, 0.84, and 0.92, respectively, indicating that there is an excellent relationship between the predicted asphalt pavement temperatures and independent parameters.

Table 3. ANOVA of multiple regression analysis outputs for season equations.

Season	Model	Sum of sq	*df*	SEE	*R*	R^2	Means SQ	*F*	*P*
Summer	Regression	8.360	3	0.0312	0.918	0.84	2.787	2846.11	0.0
	Residual	1.562	1595				0.001		
	Total	9.922	1598						
Winter	Regression	35.01	3	0.060	0.916	0.83	11.670	3316.66	0.0
	Residual	6.703	1905				0.004		
	Total	41.71	1908						
Spring	Regression	29.12	4	0.0491	0.919	0.84	7.281	3017.32	0.0
	Residual	5.393	2235				0.002		
	Total	34.51	2239						
Autumn	Regression	22.57	4	0.0379	0.964	0.92	5.656	4351.06	0.0
	Residual	1.702	1312				0.001		
	Total	24.28	1316						

4.2. Development of ANN model

4.2.1. Artificial neural network (ANN)

ANN can be regarded as a sophisticated general-purpose model that imitates the human brain. Considerable progress has been made since the introduction of ANN to be developed and applied for future growth [39, 40]. ANN was created as a multi-use arithmetic system for arranging and correlating data in a process that has been proven to be useful in solving complex problems by using computational methods. ANN involving in numerous tasks such as pattern recognition, an approximation of functions, prediction, data recovery, automatic control, and quick and easy information processing with a tolerance of errors of input data [6, 15, 41, 42]. However, ANN is a comparatively new method of statistical mapping that relies on learning from traditional statistical methods in its ability to generalise patterns that have not been successfully introduced before. ANN can learn and simulate the unanticipated and nonlinear features of a time series without having to identify the fundamental mechanisms [43]. ANN profiles have been used in various related civil engineering fields such as water resources, geotechnical engineering, coastal, structural, transportation, and engineering and for predicting pavement performance [17, 18]

In this study, MATLAB used the normalisation method for ANN modelling. The trial and error steps were adopted after extensive testing to determine the optimal number of neurons in the hidden layer. The data was trained using an LM backpropagation algorithm, and when generalisation ceases to progress, the training process would automatically stop. A three hidden layer network was chosen with 40 neurons per layer by repeating attempts, which obtained a better mean squared error (MSE) than two or four hidden layers, as shown in Table 4. The dataset is divided into training, testing, and validation (i.e. 70% for training, 15% for testing, and 15% for validation). Interpretation of the models was evaluated using the error criteria and goodness-of-fit standards. After the network has been trained, it can be used to compute network outputs. Hence, to calculate the output of the trained network for all inputs and determine the error and MSE. The ANN model was used to produce output based on specific inputs, as shown in Fig. 5.

Table 4. Summary of optimum ANN model architecture.

Season		Summer	Winter	Spring	Autumn
No of inputs	Independent Variable	3	3	3	3
No-of output	Dependent Variable	1	1	1	1
	Rescaling Method	Normalise	Normalise	Normalise	Normalise
	Error Function	MSE	MSE	MSE	MSE
Hidden Layer		3	3	3	3

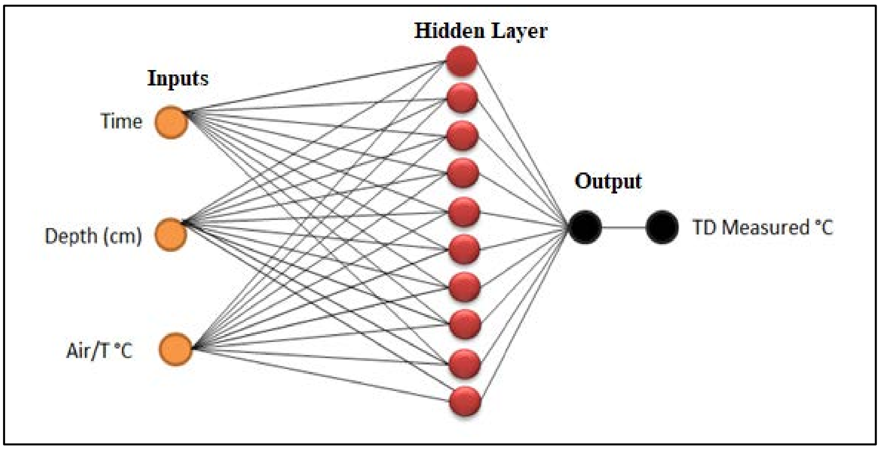


Fig. 5. ANN model frameworks for a temperature prediction model.

4.2.2. Goodness of ANN model

The ANN model was applied in the raw data as showing the result in a set of coefficient determination (R^2) for training between the actual temperature and prediction temperature in summer, winter, spring, and autumn in the model summary are 0.94, 0.85, 0.93 and 0.95, respectively in Table 5. The Accurate ANN models were based on the MSE as a minimum value and the maximum coefficient of Correlation R and coefficient of determination R^2 values [44]. The result is very satisfactory since the data is routinely collected at sites that are regularly exposed to unpredictable environmental and technical conditions, such as the pavement degradation process, ANN parameter estimation is derived from ANN training and testing. Therefore, it represents the knowledge that is extracted from the data set. The details of the optimal ANN architecture and model summary are given in Table 5.

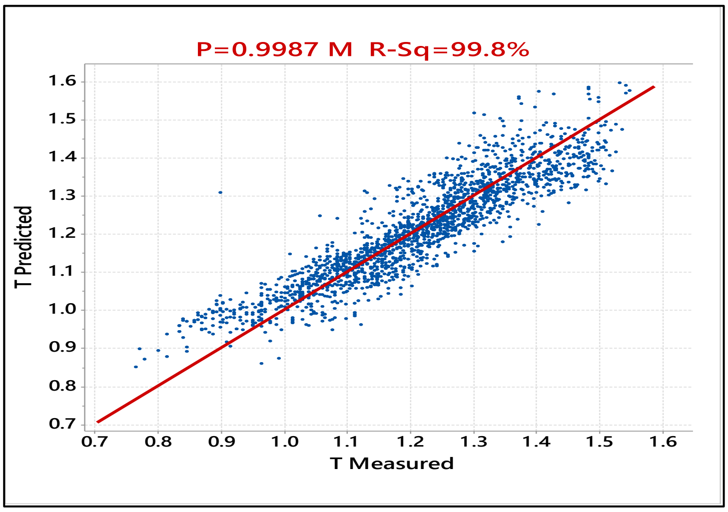
Table 5. ANN models Specifications, architecture, and their parameters.

Season	Error	Summer	Winter	Spring	Autumn
Training	(MSE)	0.004	0.0059	0.0024	0.0025
	(RSE)	0.0095	0.00448	0.00393	0.00604
Testing	(MSE)	0.004	0.0075	0.0027	0.003

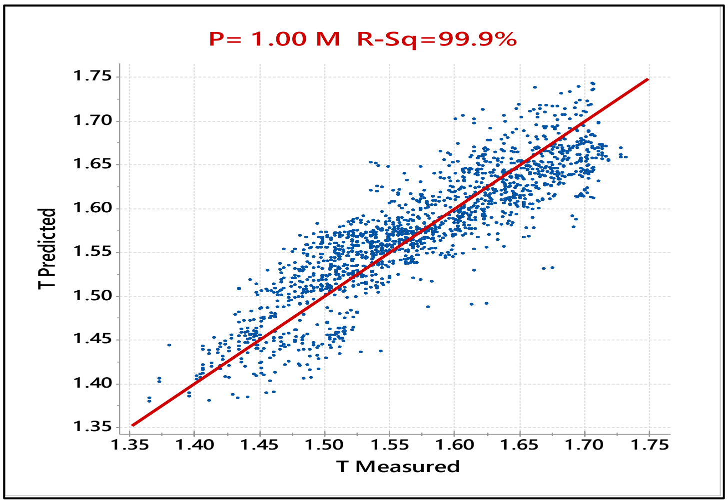
	(RSE)				
Validation	(MSE)	0.004	0.0085	0.00278	0.00278
R^2 Determination coefficient		0.94	0.85	0.93	0.95
R Correlation coefficient (ALL)		0.96	0.92	0.96	0.98

4.2.3. MLR validation

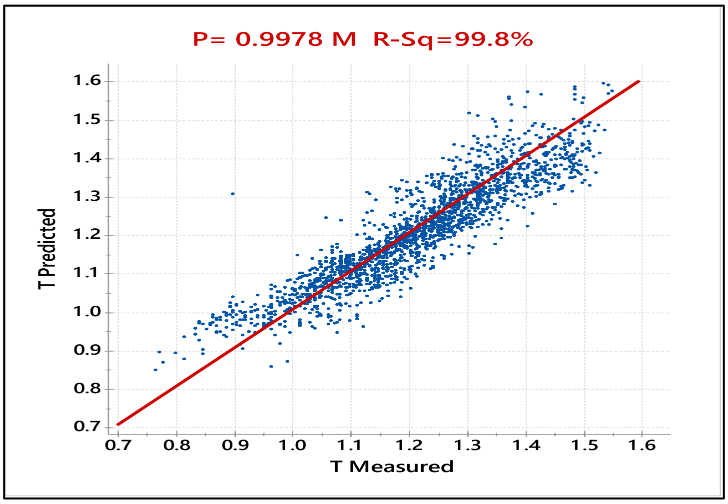
The validity of the model tested to determine its suitability indicates by Mean square error (MSE). Hence, the average squared difference between the predicted values and the actual value. The MSE value is always positive, zero in the ideal state. The MSE for summer, winter, spring, and autumn and are 0.001, 0.004, 0.002, and 0.001, respectively. These values indicate that the models are able to accurately predict asphalt pavement temperature at all depths and times, as shown in Table 3. The method of validation used in this study includes scattering plots of the predicted temperature against measured temperatures during the summer, winter, spring, and autumn. The measured temperatures were plotted on the *X*-axis while the predicted temperatures were plotted on the *Y*-axis. A diagonal line shows the distribution of the measured and predicted points of the pavement temperatures around the line axis, as shown in Figs. 6(a) to (d). The plotted measured and predicted temperatures show a similar trend around the 45° line, which confirms that the developed pavement temperature prediction models are valid, acceptable, and sufficiently accurate.



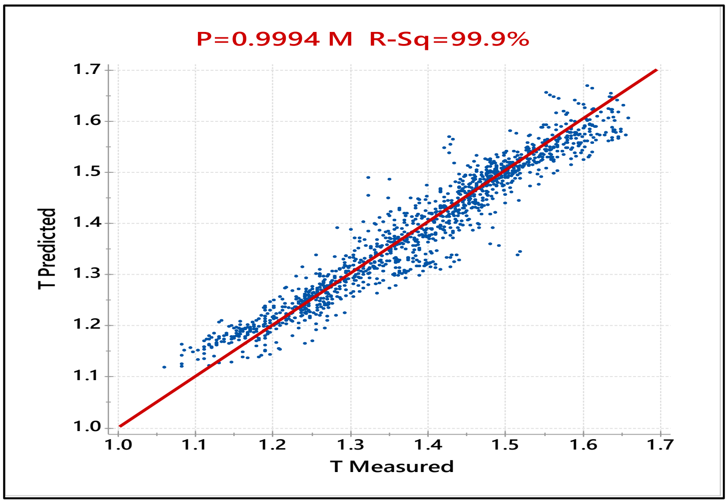
(a) Validation of summer: *T* predicted vs *T* measured.



(b) Validation of winter: *T* predicted vs *T* measured.



(c) Validation of spring: *T* predicted vs *T* measured.

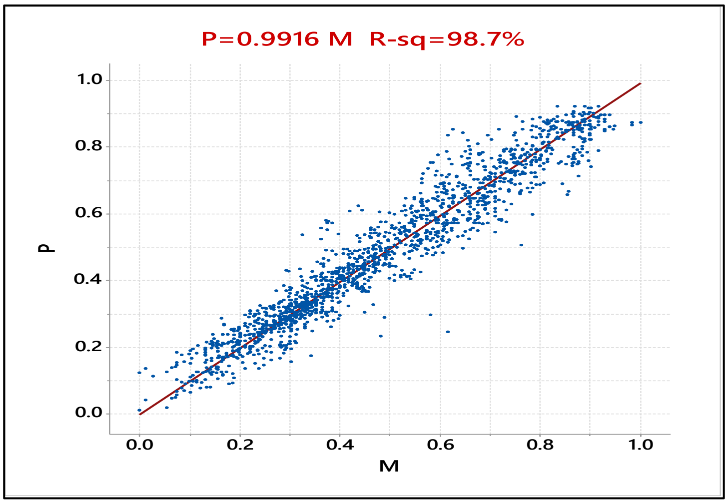


(d) Validation of autumn: *T* predicted vs *T* measured.

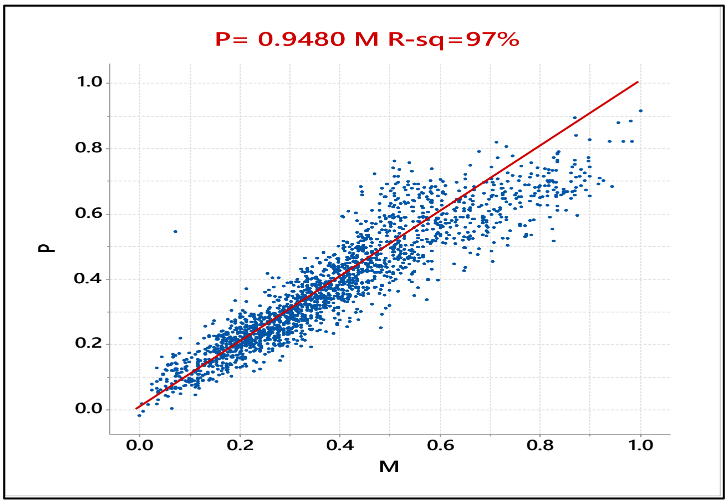
Fig. 6. MLR Validation of an equation using measured field data.

4.2.4. ANN validation

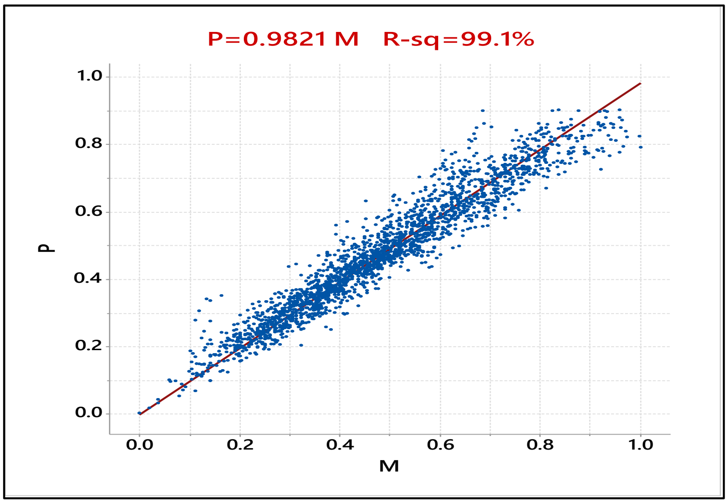
The validation was conducted using the data sets selected from the created database. The predicted pavement temperatures of the four seasons were compared. A low accuracy indicates that the network has not been appropriately trained, and other training groups must be created to retrain the network. Moreover, the ANN is reliable for executing the model used to predict the pavement temperatures at the specified depth. The models were evaluated by comparing the predicted pavement temperatures with the measured temperatures at different depths and times. The MSE for summer, winter, spring, and autumn are 0.0045, 0.008585, 0.00278, and 0.00278, respectively, for the validation shown in Table 5. These values indicate that the models can accurately predict asphalt pavement temperature by knowing explanatory variables: air temperature, measuring depths, and measuring time. The MSE value for each season was accurate, and this indicates the accuracy of the models used. Besides, a correlation analysis was conducted between the predicted asphalt pavement temperatures and the measured temperatures for the four seasons. This analysis examines the null hypothesis, where the direction of the effect is not determined in advance. Furthermore, the target output data sets of the four seasons have been drawn according to the measured temperature as the x-axis and the expected temperature as the y-axis, as shown in Fig.7(a) to (d). Spread of relationship points between the measured and predicted values showing a similar distribution around the 45° line, confirming that the development models of pavement temperature prediction are acceptable and sufficiently accurate.



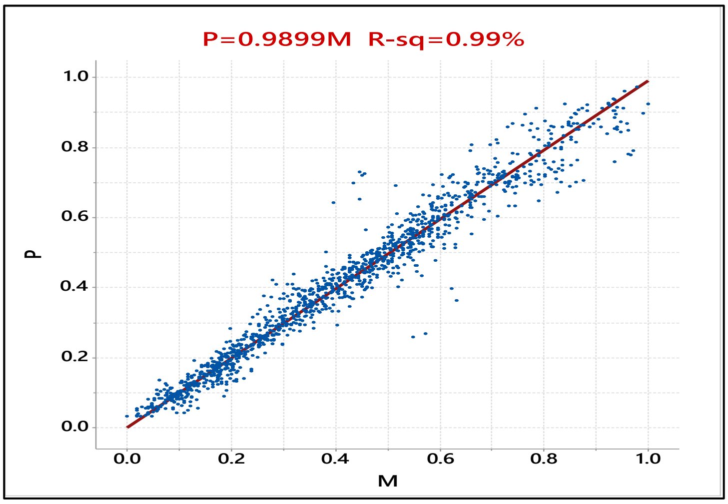
(a) Validation of summer: *T* predicted vs. *T* measured.



(b) Validation of winter: *T* predicted vs. *T* measured.



(c) Validation of spring: *T* predicted vs. *T* measured data.



(d) Validation of autumn: *T* predicted vs. *T* measured.

Fig. 7. ANN validation using measured field data.

5. Comparisons between ANN and MLR

A comparison of the results generated by the ANN and MLR models Figs. 6 and 7 show the scatter plots of the measured temperature against the temperatures predicted using MLR and ANN for summer, winter, spring, and autumn, respectively. The performance of the models was calculated and compared with the values R^2 and MSE. Active prediction models should have high R^2 and low MSE. Survey data both on ANN and MLR models were used to predict asphalt pavement temperature for four seasons in the whole year in the Eastern Mediterranean Region. These models were predicted based on air temperature, time, and depths within asphalt pavement. Through asphalt temperature prediction, decision-makers may evaluate individual distress for any pavement and decide which time and depth would have a more significant effect on the overall pavement condition. MATLAB software randomly classified the database by training (70%) and validation and test (30%) data sets for each season after determining the architecture of each ANN model. The training process results provided the weight matrices, which are already preserved in links within layers and could also be used to collect information on the role of each input in the model output. Table 6 summarises values in terms of the squared correlation coefficient (R^2) and MSE between the two models. It is noted that the value of the coefficient of determination (R^2) in the winter season is lower than it is in the rest of the seasons using both MLR and ANN, due to the cold precipitation in the winter season, which falls and seeps to the surface and the depth of the pavement, affecting the temperature of the asphalt and a change the real temperature of the asphalt

The accuracy of ANN models produced better results than MLR. In terms of the error parameters, the MSE of the ANN models is significantly lower. This comparative study has clearly shown that the ANN models were able to make a more accurate prediction of pavement temperature compared to the MLR models. The explanation may be that the nonlinear relationship between the input variables is involved in both ANN models, but the relationship between the variables is linear in the MLR model [35, 45]. This conclusion agrees with the results published in previous studies. For instance, Legube et al. [46] declare that the ANN model is entirely satisfactory to facilitate prediction and better predictive efficiency than the MLR models.

Chandra et al. [42] evaluated the accuracy of ANN and MLR models developed to predict pavement roughness from various forms of distress and stated that the ANN model was substantially more accurate than the MLR model with an MSE of 18% lower than the MLR model. Likewise, Alharbi [33] stated that pavement performance was predicted in the ANN models with greater accuracy than the MLR model [44].

Table 6. Comparison of the prediction among MLR and ANN models.

Season	**MLR**		**ANN**	
	R^2	MSE	R^2	MSE
Summer	0.84	0.001	0.94	0.0045
Winter	0.83	0.004	0.85	0.0086
Spring	0.84	0.002	0.93	0.0027
Autumn	0.92	0.001	0.95	0.0028

6. Conclusion

This study has developed ANN and MLR models for predicting asphalt pavement temperature. The neural network was trained using the data obtained through field measurement. The training and validation processes were conducted using the developed ANN and MLR models. Both models predicted asphalt temperature based on air temperature and other related parameters, such as time and depth of asphalt pavement. Using only air temperature to predict asphalt pavement temperature produced acceptable results. The models were based on an instrumental section in Gaza, which is considered as a coastal area; the typical night and the midday temperature in Gaza change from low to high, respectively. Therefore, the temperature at night should also be considered. The outcomes of this study show that ANN was able to produce a prediction model with higher accuracy compared with the MLR model. Based on the results gained from this study, it is considered that the models will be able to accurately predict the temperature of flexible pavement within various depths in road location at Eastern Mediterranean region conditions. It is recommended to use these models for other countries in the same region, subject to validation of the models against the field data of the respective countries.

Acknowledgement

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Abbreviations

ANN	Artificial Neural Networks
EICM	Enhanced Integrated Climatic Model
SMP	Seasonal Monitoring Program
ANOVA	Analysis of Variances
LTTP	Long-Term Pavement Performance Program
M-E	Mechanistic-Empirical
MLR	Multi-Linear Regression
MSE	Mean Squared Error
R^2	Coefficient of Determination
SHRP	Strategic Highway Research Program

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