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Flexible Pavement Distresses Prediction Models using AASHTOWare Pavement ME Design

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Keywords
Pavement Management Systems (PMS), AASHTOWare Pavement ME Design, Sensitivity analysis, Prediction distress models, Performance models.

Abstract

Pavement performance prediction is widely considered as a significant element of road infrastructure asset-management systems or Pavement Management Systems (PMS) by pavement researchers and practitioners. Predicting pavement performance significantly reduces the huge costs of constructing roads, especially in the case of countries that made incredible investments in road construction. This study mainly focuses on the implementation of the mechanistic-empirical (M-E) analysis method using the AASHTOWare Pavement ME Design (AASHTOWare PMED) software for flexible pavement distress prediction-models generation. To achieve that four steps were followed. First, the most accurate assessment that shows the combined impact of the most important parameters that affect flexible pavement performance was used to perform the AASHTOWare runs. In which, 378 design combinations of (3 traffic speed levels × 3 traffic load levels ×3 climatic zones ×7 Surface HMA mixes widely used in Egypt) at two input levels of the AASHTOWare PMED hierarchy (levels 1 &2) that typically are required for binders and hot-mix-asphalt (HMA) were used. Second, a sensitivity analysis to study the combined effect and impact of the investigated parameters on AASHTOWare PMED-predicted performance (cracking, rutting, and roughness) was conducted at the two input levels. Third, a Multiple Linear Regression (MLR) was implemented as a modeling approach to develop five performance prediction models for flexible pavements based on the AASHTOWare PMED software results. The proposed MLR models predicted each distress as a function of climatic factors, the surface HMA properties, different regions' speed levels, and traffic volume levels. Finally, a validation process of the proposed MLR prediction models was conducted. Results indicated that the proposed models yield an overall good prediction, asserting the robustness of the proposed process. Proposed MLR prediction models can be perceived as a function of Average Annual Daily Truck Traffic, Traffic speed, mean annual air temperature, and the percentage of air voids. This study provides a procedure to develop the performance prediction models of flexible pavements based on the AASHTOWare PMED approach and in accordance with different regions' input levels.

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1. Introduction

Due to the high maintenance cost associated with highway systems, the need to improve pavement performance has become one of the most important needs to decrease costs. Pavement performance is a representation of pavement behavior under traffic and climate conditions. In general, asphalt pavements are designed to resist cracking, rutting, and other distresses which, when they occur, increase the maintenance costs of the pavement and reduce the pavement service life [1]. The flexible pavement performance is governed by many factors including asphalt mixture components' properties as well as traffic and climate conditions [2,3,4]. The prediction of pavement distresses makes the expectation of pavement properties possible, thus improving it or selecting the most suitable HMA mixtures of flexible pavement design for several local conditions. Thus, to build roads to resist pavement distresses then decrease the maintenance cost and increase the pavement services life span, pavement engineers need to look for new predicting distress mechanisms.

The new Mechanistic-Empirical Pavement Design Guide (MEPDG) has been introduced by AASHTO based on the Mechanistic-Empirical (M-E) design method that is embedded in the AASHTOWare software. The AASHTOWare software considers the climate, material properties, subgrade type, traffic, etc. to compute the deflections, stresses, and strains, estimate the distresses, and predict the performance of pavements with the distress transfer functions for the entire service life of the pavement [5,6]. In many countries such as Italy [7] and Romania [8] as well as in the USA states such as Iowa [9], Oregon [10] and Kansas [11], usage of the AASHTOWare software gained significant popularity. Several studies have been performed to study the impact of inputs on the performance indicators using the MEPDG [12,13,14,15]. Thus initiate the development of new approaches to tackle the scarcity of the required input data in countries, e.g., Qatar [16]. While limited studies investigated the implementation of the MEPDG to provide long-term performance evaluations for road network investments in Middle East countries, e.g., Saudi Arabia [17]and [18], Qatar [19] and [16], and Egypt [15,20,21,22], Lebanon [23] as well as in the developed countries, e.g., India [24] and Turkey [25] and [26]. The scarcity of the required input data makes the implementation of the MEPDG in the Middle East region still in its early stages to reach an optimum design.

The main objective of this study is to initiate a procedure to develop prediction models of flexible pavement distresses based on the MEPDG approach and follow different regions' input. In this procedure, seven different types of HMA of the wearing layer materials at three weather stations representing climatic regions in Egypt: Alexandria, Cairo, and Aswan were analyzed optimizing 378 design combinations for the typical flexible pavement section. Furthermore, a sensitivity analysis to study the combined effect and impact of the investigated parameters on MEPDG-predicted performance (cracking, rutting, and roughness) was conducted at the two input levels. Moreover, Multiple Linear Regression (MLR) as a modeling tool was used to develop five distress prediction models for flexible pavements. The five distress performance prediction models that were developed include longitudinal cracking, alligator cracking, asphalt concrete (AC) rutting, total rutting, and the international roughness index (IRI). The proposed models predict each distress as a function of climatic factors and the surface HMA properties. Additionally, different regions' speed levels and traffic volume levels are also considered in those models. Finally, a validation process of the proposed MLR prediction models was conducted.

This study promotes predicting pavement performance to reduce the cost of construction of flexible pavements and help in preserving roads operated under an acceptable level of service. That may help decision makers to identify Maintenance and Rehabilitation (M&R) demands by predicting pavement performance and then plan rational budget and resource allocation in countries experiencing similar conditions in the future.

2. Background of AASHTOWare Pavement ME Design (AASHTOWare PMED)

The new MEPDG represents a comprehensive tool for the analysis and design of new and rehabilitated flexible and rigid pavement structures based on mechanistic-empirical fundamental engineering principles [27 and 28]. MEPDG was developed by Applied Research Associates (ARA) and Arizona State University (ASU) under the National Cooperative Highway Research Program (NCHRP1-37A and NCHRP 1-40D). A comprehensive set of procedures are provided by the MEPDG for the analysis of rehabilitated and new flexible and rigid pavements and then pavements can be designed lately. The MEPDG methodology predicts multiple performance indicators and provides more reliable predictions of pavement performance compared to the current design methods. Also, it provides a direct tie between daily, seasonal, and annual changes in local materials, climate, traffic, structural design, construction, and pavement management systems.

The MEPDG software, which was called “AASHTOWare”, is a tool to analyze and design pavements using a mechanistic-empirical approach. The stress-strains under various traffic loadings are determined for different seasonal conditions using the built-in numerical program in the software to predict different distresses with its service life. When the data for climate, traffic, materials, and proposed typical structure are start inputted by the designer, the pavement analysis and design are started. The software can mechanistically over the entire service life of the pavement calculates the structural responses (stresses, strains, and deflections) and estimates the damage accumulation, within a pavement system. The software also allows users to input defined calibration coefficients that reflected certain region conditions.

The AASHTOWare Pavement ME Design software uses a hierarchical approach from three levels of inputs for most of the parameters of the pavement conditions, traffic, climate, and material. This approach offers the designer a great deal of flexibility in selecting the project inputs based on their availability and the criticality of the project. These input levels are defined as follows :

- Input Level 1 input parameter is measured by the detailed testing of specific materials and thus it is typically the most accurate.
- Input Level 2 input parameter is a determined value from local average values, correlations, or regression equations with other more standard testing procedures thus it typically provides a moderate confidence level of performance.
- Input Level 3 input parameter has the lowest level of accuracy, it is the best-estimated national or regional default values.

3. Objective and Methodology of Study

This study is considered a crucial attempt to develop pavement performance prediction models using AASHTOWare for the Middle East region due to the lack of resources that led to the unavailability of such models in most Middle East countries such as Egypt. So, this study focused on achieving the following objectives that are directly linked to the proposed implementation plan :

- Investigate the combined effect of climatic conditions, speed, HMA material properties, and traffic characteristics on pavement performance.
- Predict the pavement distresses for flexible pavements, taking into consideration the combined effect of the most important and common factors.
- Develop pavement distress prediction models for main roads located in Middle East countries experiencing the same regional conditions.
- Evaluate the input level in the AASHTOWare PMED on predicted performance to show the impact of the input level (1 and 2).

The adopted plan in this study is depicted in Fig. 1.

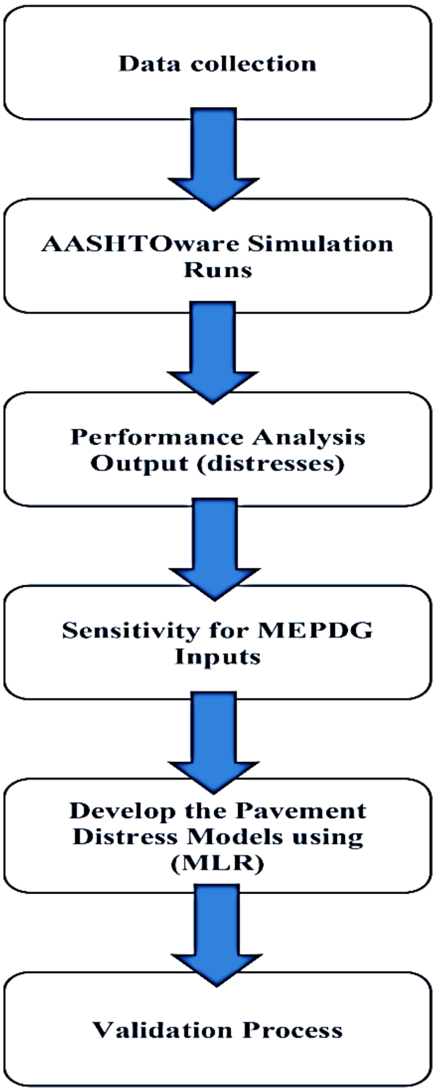


Fig. 1: A Scheme of this study plan

4. Data collection and processing

To assess the influence of the change in traffic, climate, and mixture properties of the wearing layer data on ME Design predicted performance, a study was conducted using to predict the field distresses of the typical flexible pavement cross section for a design life of 20 years. Figure 2 shows a typical flexible pavement cross-section used in all AASHTOWare PMED simulation runs. The required pavement material data of that pavement cross-section were collected by using the Egyptian code of practice [29] and the Egyptian General Authority for Roads, Bridges, and Land Transport (GARBLT) specifications [30]. Moreover, more detailed descriptions of the properties of the investigated AC mixtures in this study are presented in [31,32,33].

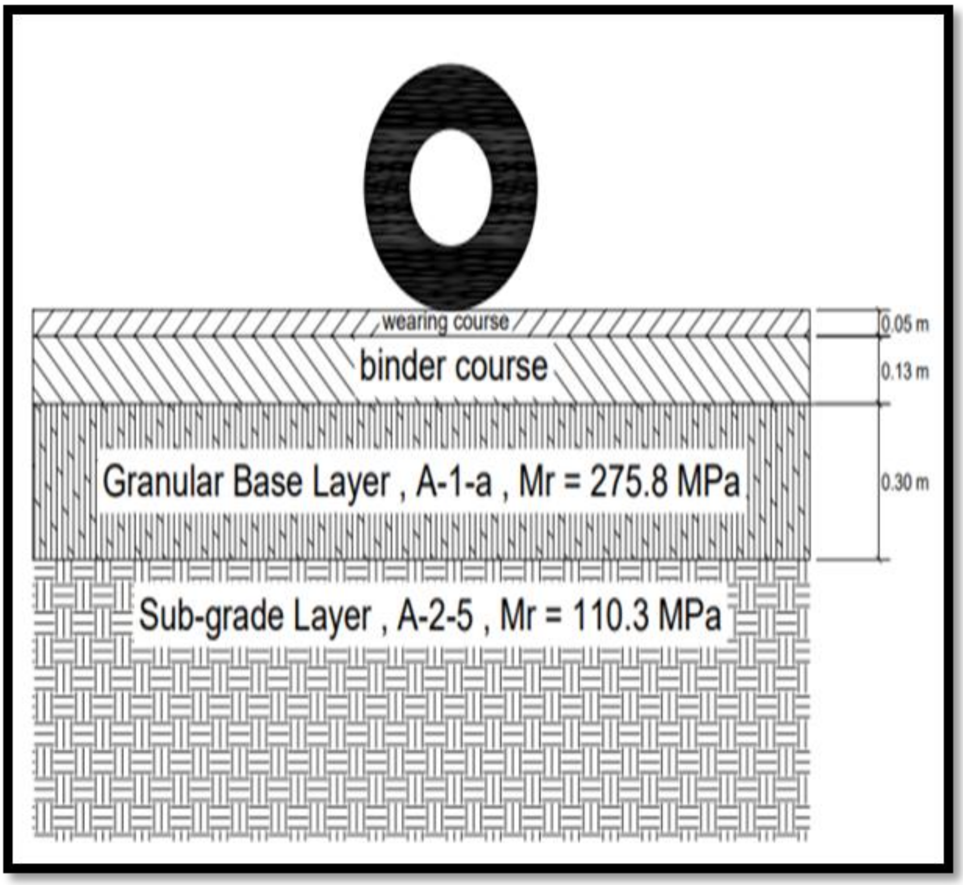


Fig. 2: Typical Flexible Pavement Section Used in the MEPDG Runs

A total of 378 AASHTOWare PMED simulation runs for the level 1 and level 2 analyses were conducted. In a level 1 analysis, HMA dynamic modulus, binder shear modulus, binder phase angle, effective binder content, air voids, and mix total unit weight measured in the laboratory were used. In a level 2 analysis, binder shear modulus, binder phase angle, effective binder content, air voids, and mix total unit weight measured in the laboratory were used.

The simulation runs were performed at the most three important locations and have a big difference in climate conditions in Egypt (Alexandria, Cairo, and Aswan) [34]. The depth of the water table was kept constant at 10ft. (3.048 m). There are nine changes was varied using the three traffic levels with 2-way annual average daily truck traffic (AADTT) (T1=2000, T2=4000, T3=7000) and 2.0% annual growth rate at the three different speeds values (S1=10 km/hr), (S2=55 km/hr) and (S3=95 km/hr) for each one of that traffic levels with the rest of the traffic inputs kept at the default values in AASHTOWare PMED was used in the analysis. Some of the major input data used for the AASHTOWare PMED simulation runs are summarized and presented in Table 1. After conducting the simulation runs, their outputs were used for a sensitivity analysis to study the combined effect and impact of the investigated parameters on AASHTOWare PMED-predicted performance (cracking, rutting, and roughness) at the two input levels. Then the simulation runs' outputs were divided into two sets; the first set (85% of the data) is used to create the MLR performance prediction models, and the second set (15% of the data) is used to validate those MLR models.

Table 1: A Summary of the major input data for the AASHTOWare PMED simulation runs.

	Category	Input parameter	Symbol	Range	
				min	**max**
Material Characteristics	**Aggregate gradation of HMA surface layer**	% Aggregates passing #200 sieve	$\%P_{\#200}$	4	5.6
		% Aggregates passing #4 sieve	$\%P_{\#4}$	55	62
		% Aggregates passing #3/8" sieve	$\%P_{3/8''}$	68	89.5
		% Aggregates passing #3/4" sieve	$\%P_{3/4''}$	96	100
	Mix	% Air voids in the mix	$\%V_a$	6.05	7.34
		Effective asphalt content	V_{beff}	9.81	13.4
Climate Data	**Air Temperature**	Mean annual air temperature (°C)	T_{air}	21.75	24.29
Traffic Data	**Traffic Volume**	Annual average daily truck traffic	AADTT	2000	7000
	Traffic Speed	Operational speed (km/hr)	SPEED	10	95

5. Sensitivity Analysis for AASHTOWare PMED Inputs

Conducting sensitivity analyses is a powerful tool to achieve and facilitate the implementation of AASHTOWare PMED according to local conditions, understand the behavior of AASHTOWare PMED in Egypt, and allocate funds for the accurate estimation of the most important input variables. Several inputs were chosen to be included in this sensitivity analysis based on their high influence on performance predictions of AASHTOWare PMED. These inputs were Climate Condition, Traffic volume, Traffic speed, % Air Voids, Effective Binder Content, aggregate gradation, and HMA total unit weight.

In this study, the sensitivity of each parameter was evaluated according to the adopted sensitivity evaluation criteria [35]. Each selected AASHTOWare PMED input parameter was changed at 3 values. The sensitivity runs were conducted by varying one input under investigation at a time while keeping all other inputs under study at a constant level and then the AASHTOWare PMED predicted performance with these variations was observed in terms of terminal IRI, alligator cracking, longitudinal cracking, and rutting.The results of the sensitivity analyses and assigned sensitivity level of each distress for AASHTOWare PMED (Level 1) and (Level 2) runs are presented in Tables 2 and 3, respectively.

The following discussion summarizes each factor’s effect based on the results of the sensitivity analyses at AASHTOWare PMED (Level 1) and (Level 2) runs.

5.1. Climate Condition Effect

The air temperature had a significant effect on the AASHTOWare PMED (Level 2) total rutting, the AASHTOWare PMED (Level 1) longitudinal cracking, and the AASHTOWare PMED (Level 1 and Level 2) AC rutting predictions. The influence of air temperature was found to be not overly significant on both levels of the AASHTOWare PMED IRI and the AASHTOWare PMED (Level 1) alligator cracking. The influence of air temperature on the AASHTOWare PMED (Level 1) total rutting was found to be less than on AC rutting predictions. It was also found that the air temperature has an insignificant influence on the AASHTOWare PMED (Level 2) alligator and the longitudinal cracking predictions.

5.2. Traffic Volume Effect

At both levels of the AASHTOWare PMED (Level 1 and Level 2), the truck traffic volume had a significant effect on all distresses except IRI, with an extreme effect on alligator cracking.

5.3. Traffic Speed Effect

For the AASHTOWare PMED (Level 1), it was found that both alligator and longitudinal cracking were more sensitive to traffic speed than were the AC rutting and the total pavement rutting. However, at level 2 the traffic speed was only significant for the AC rutting.

5.4. % Air Voids in Mix Effect

For the AASHTOWare PMED (Level 1), the longitudinal cracking was found to be extremely sensitive to the percent air voids. Also, the influence of percent air voids was more significant on the AC rutting and the total rutting than on the IRI predictions and it was insignificant on the alligator cracking. For the AASHTOWare PMED (Level 2), the influence of percent air voids was more significant on the longitudinal cracking than on both the alligator cracking and the AC rutting, however, it was insignificant on both the IRI and the total rutting.

5.5. Binder Content Effect

For the AASHTOWare PMED (Level 1 and Level 2), the influence of binder content was found to be more significant on the longitudinal cracking than on the AC rutting, and it was insignificant on the IRI.

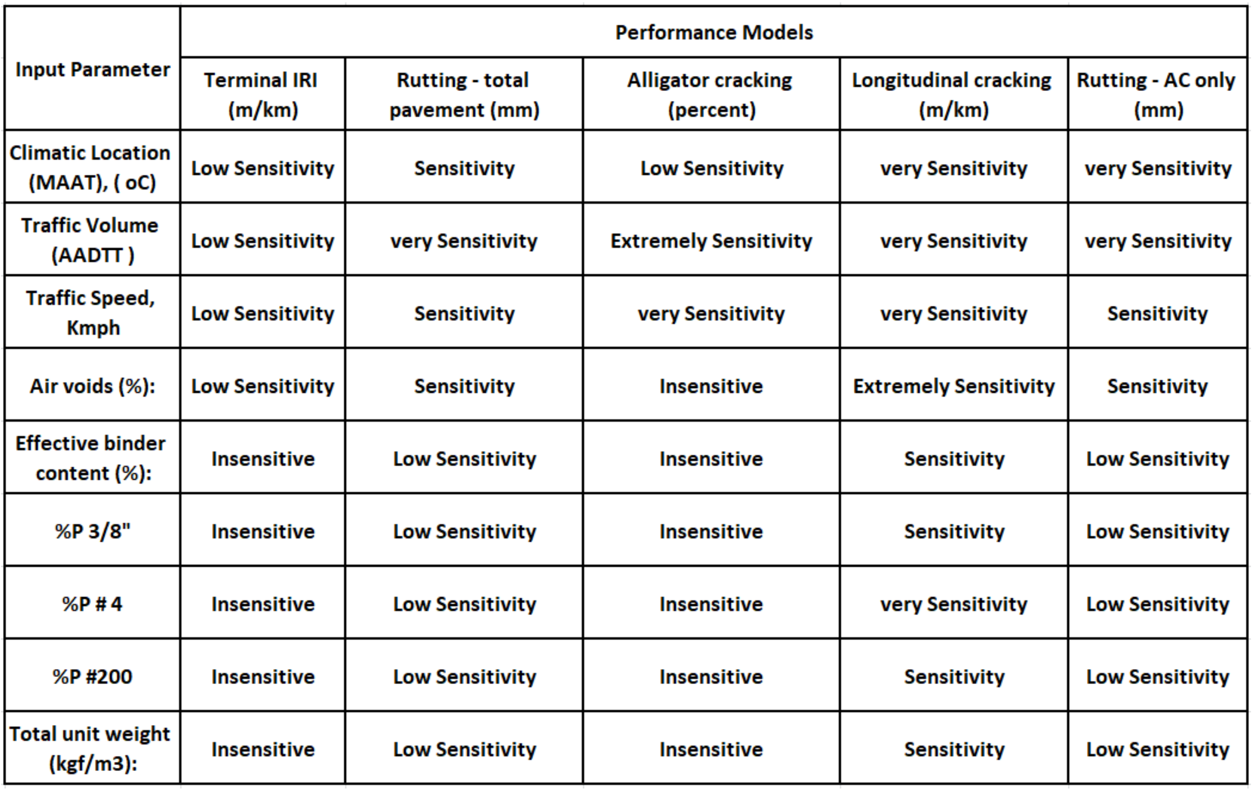
5.6. HMA Mixtures Aggregate Gradation Effect

For the AASHTOWare PMED (Level 1 and Level 2), the influence of percent aggregates passing from the 3/8” sieve and the NO.200 sieve was found to be more significant on the longitudinal cracking than on the rutting at AC and total pavement and it was insignificant on the IRI. For the AASHTOWare PMED (Level 1), the longitudinal cracking was found to be very sensitive to the percent aggregates passing from the NO.4 sieve versus what was found for the AASHTOWare PMED (Level 2). For the AASHTOWare PMED (Level 1), the influence of the percent aggregates passing from the NO.4 sieve was found to be not overly significant on the rutting at AC and total pavement.

5.7. HMA Mix Total Unit Weight Effect

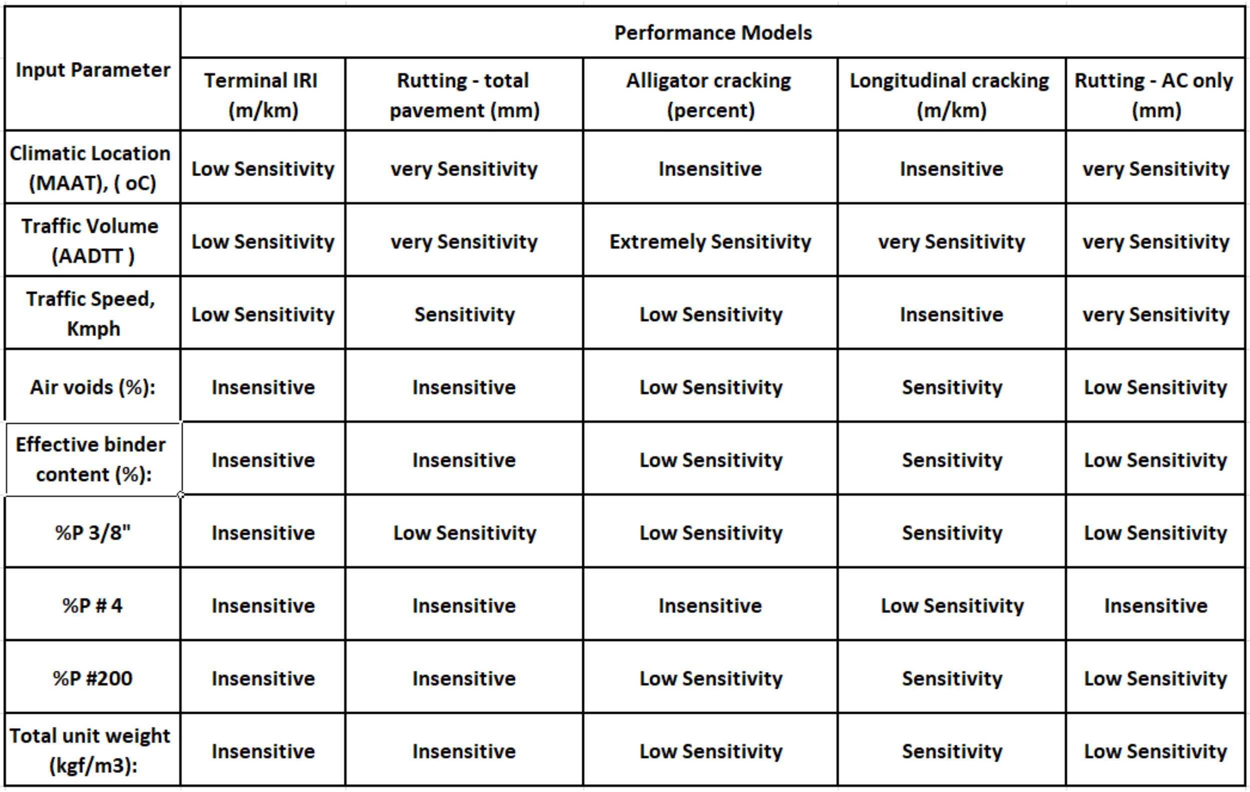
For the AASHTOWare PMED (Level 1 and Level 2), the total unit weight was found to be more significant on the longitudinal cracking than on the AC rutting and it was found to be insignificant on the IRI. For the AASHTOWare PMED (Level 2), it was found that the total unit weight is more sensitive to the alligator cracking than to the total pavement rutting versus what was found for the AASHTOWare PMED (Level 1).

Table 2: A summary of the sensitivity analyses results (level 1)



Input Parameter	Performance Models				
	Terminal IRI (m/km)	Rutting - total pavement (mm)	Alligator cracking (percent)	Longitudinal cracking (m/km)	Rutting - AC only (mm)
Climatic Location (MAAT), (oC)	Low Sensitivity	Sensitivity	Low Sensitivity	very Sensitivity	very Sensitivity
Traffic Volume (AADTT)	Low Sensitivity	very Sensitivity	Extremely Sensitivity	very Sensitivity	very Sensitivity
Traffic Speed, Kmph	Low Sensitivity	Sensitivity	very Sensitivity	very Sensitivity	Sensitivity
Air voids (%):	Low Sensitivity	Sensitivity	Insensitive	Extremely Sensitivity	Sensitivity
Effective binder content (%):	Insensitive	Low Sensitivity	Insensitive	Sensitivity	Low Sensitivity
%P 3/8"	Insensitive	Low Sensitivity	Insensitive	Sensitivity	Low Sensitivity
%P # 4	Insensitive	Low Sensitivity	Insensitive	very Sensitivity	Low Sensitivity
%P #200	Insensitive	Low Sensitivity	Insensitive	Sensitivity	Low Sensitivity
Total unit weight (kgf/m3):	Insensitive	Low Sensitivity	Insensitive	Sensitivity	Low Sensitivity

Table 3: A summary of the sensitivity analysis results (level 2).



Input Parameter	Performance Models				
	Terminal IRI (m/km)	Rutting - total pavement (mm)	Alligator cracking (percent)	Longitudinal cracking (m/km)	Rutting - AC only (mm)
Climatic Location (MAAT), (oC)	Low Sensitivity	very Sensitivity	Insensitive	Insensitive	very Sensitivity
Traffic Volume (AADTT)	Low Sensitivity	very Sensitivity	Extremely Sensitivity	very Sensitivity	very Sensitivity
Traffic Speed, Kmph	Low Sensitivity	Sensitivity	Low Sensitivity	Insensitive	very Sensitivity
Air voids (%):	Insensitive	Insensitive	Low Sensitivity	Sensitivity	Low Sensitivity
Effective binder content (%):	Insensitive	Insensitive	Low Sensitivity	Sensitivity	Low Sensitivity
%P 3/8"	Insensitive	Low Sensitivity	Low Sensitivity	Sensitivity	Low Sensitivity
%P # 4	Insensitive	Insensitive	Insensitive	Low Sensitivity	Insensitive
%P #200	Insensitive	Insensitive	Low Sensitivity	Sensitivity	Low Sensitivity
Total unit weight (kgf/m3):	Insensitive	Insensitive	Low Sensitivity	Sensitivity	Low Sensitivity

6. MLRs Pavement Distress Prediction Model Development

The multiple regression analysis techniques were applied to develop fatigue cracking, longitudinal cracking, Terminal IRI, AC, and total pavement deformation prediction models for different climate zones in Egypt using SPSS software [36].

6.1. Stepwise Regression:

Several trials were made to identify the independent variables that have the most significant impact on the various mentioned pavement distresses. Subsequently, reliable prediction models for the most accurate representation of the pavement distress relationships to the impacted factors were conducted with the estimated regression coefficients.

Through the analysis results examination, when the P-value for any test was found to be less than 0.05 at a 95% confidence level, this reinforces the significance of the inclusion of each one of the independent variables as a part of the model. Regarding the overall significance of the regression model, the F-values from the ANOVA test are less than the risk level (α=5%), meaning the regression model significance is verified [37].

6.2. Regression Analysis

6.2.1. Terminal IRI

Based on the P-value for all considered factors, the significance of the inclusion of the %air voids of the asphalt mix, % passing from the 3/8-in.sieve and No.4 sieve of the asphalt mix, mean annual air temperature, average annual daily truck traffic, and speed variables as a part of the terminal IRI model were reinforced, as shown in Table 4.

Table 4: Summary of the hypothesis tests results for the regression coefficients of the terminal IRI model for (AASHTOWare PMED) level 1 and level 2

Parameters	**Level NO.**	**Coefficients**	**Standard Error**	**t-stat**	**P-value**
Intercept	level 1	-0.38	2.23E-01	-1.699	9.14E-02
	level 2	-0.01	2.23E-01	-0.031	9.76E-01
Air voids (%V_a)	level 1	0.07	1.76E-02	3.894	1.46E-04
	level 2	-----------	-----------	-----------	-----------
%P3/8"	level 1	-0.007	1.23E-03	-5.754	4.52E-08
	level 2	-0.01	1.40E-03	-7.196	2.45E-11
%P# 4	level 1	0.005	1.91E-03	2.809	5.62E-03
	level 2	0.005	2.16E-03	2.306	2.24E-02
Mean annual air temperature (T_{air})	level 1	0.12	6.81E-03	16.976	3.46E-37
	level 2	0.14	7.98E-03	17.016	2.22E-37
AADTT	level 1	9.03E-05	3.51E-06	25.739	7.64E-58
	level 2	1.01E-04	4.11E-06	24.634	1.22E-55
SPEED	level 1	-0.004	2.08E-04	-19.133	1.18E-42
	level 2	-0.005	2.43E-04	-18.802	6.14E-42

Also, it was noticed that the terminal IRI model significance was verified due to the F-values from the ANOVA test being less than the risk level (α=5%), as shown in Table 5.

Table 5: ANOVA results for terminal IRI regression model for (AASHTOWare PMED) level 1 and level 2

	Level NO.	**SS**	**df**	**MS**	**F**	**Significance F**
Regression	level 1	12	6	1.938	230	1.71E-74
	level 2	15	5	3.009	261	8.45E-74
Residual	level 1	1	155	0.008		
	level 2	2	156	0.012		
Total	level 1	13	161			
	level 2	17	161			

6.2.2. Rutting /deformation Distress

Based on the P-values for all considered factors, the inclusion of %air voids of asphalt mix, % effective binder content, % passing from the 3/8-in.sieve and No.4 sieve of asphalt mix, mean annual air temperature, average annual daily truck traffic and traffic speed variables as a part of one of the rutting/deformation distress model type were reinforced, as shown in Table 6.

Table 6: Summary of the hypothesis tests results for the regression coefficients of the rutting model for (AASHTOWare PMED) level 1 and level 2

Parameters	**Distress Type**	**Level NO.**	**Coefficients**	**Standard Error**	**t Stat**	**P-value**
Intercept	Total Rutting	level 1	-113.84	8.70E+00	-13.091	7.59E-27
		level 2	-98.59	9.51E+00	-10.364	1.78E-19
	AC Rutting	level 1	-148.49	7.65E+00	-19.400	1.99E-43
		level 2	-152.36	8.65E+00	-17.621	4.92E-39
Effective binder content (V_{beff})	AC Rutting	level 1	1.32	2.17E-01	6.079	8.94E-09
		level 2	2.23	2.91E-01	7.667	1.73E-12
Air voids ($\%V_a$)	Total Rutting	level 1	2.55	6.85E-01	3.724	2.74E-04
		level 2	-----------	-----------	-----------	-----------
	AC Rutting	level 1	3.15	6.36E-01	4.950	1.91E-06
		level 2	-----------	-----------	-----------	-----------
%P3/8"	Total Rutting	level 1	-0.28	4.77E-02	-5.790	3.80E-08
		level 2	-0.45	5.95E-02	-7.572	3.02E-12
%P# 4	Total Rutting	level 1	0.22	7.44E-02	3.010	3.05E-03
		level 2	0.24	9.22E-02	2.581	1.08E-02
Mean annual air temperature (T_{air})	Total Rutting	level 1	5.84	2.65E-01	22.015	1.43E-49
		level 2	6.72	3.40E-01	19.756	2.64E-44
	AC Rutting	level 1	5.79	2.56E-01	22.590	4.77E-51
		level 2	6.67	3.46E-01	19.288	2.90E-43
AADTT	Total Rutting	level 1	3.053E-03	1.37E-04	22.334	2.62E-50
		level 2	3.501E-03	1.75E-04	19.987	7.17E-45
	AC Rutting	level 1	2.869E-03	1.32E-04	21.712	5.25E-49
		level 2	3.304E-03	1.78E-04	18.559	1.98E-41
SPEED	Total Rutting	level 1	-0.15	8.09E-03	-18.248	1.94E-40
		level 2	-0.17	1.04E-02	-16.787	8.75E-37
	AC Rutting	level 1	-0.14	7.82E-03	-18.231	1.69E-40
		level 2	-0.17	1.05E-02	-16.009	8.09E-35

It was noticed that the rutting/deformation distress model significance was verified due to the F-values from the ANOVA test being than the risk level (α=5%), as shown in Table 7.

Table 7: ANOVA results for the rutting regression model for (AASHTOWare PMED) level 1 for (AASHTOWare PMED) level 1 and level 2

	Distress Type	**Level NO.**	**SS**	**df**	**MS**	**F**	**Significance F**
Regression	Total Rutting	level 1	17618	6	2936.264	230	1.82E-74
		level 2	23706	5	4741.110	226	1.56E-69
	AC Rutting	level 1	3332986	6	555497.623	73	1.38E-42
		level 2	5292146	4	1323036.501	783	1.43E-102
Residual	Total Rutting	level 1	1981	155	12.779		
		level 2	3274	156	20.984		
	AC Rutting	level 1	1182610	155	7629.743		
		level 2	265173	157	1689.001		
Total	Total Rutting	level 1	19598	161			
		level 2	26979	161			
	AC Rutting	level 1	4515596	161			
		level 2	5557319	161			

6.2.3. Fatigue Cracking

Based on the P-values for all considered factors, the inclusion of % passing from the 3/8-in.sieve of asphalt mix, mean annual air temperature, average annual daily truck traffic, and speed variables as a part of the alligator cracking model and the inclusion of % effective binder content, %air voids of asphalt mix, % passing from the No.200 sieve of asphalt mix in addition to the previous variables as a part of the longitudinal cracking model were reinforced, as shown in Table 8.

Table 8: Summary of the hypothesis tests results for the regression coefficients of the alligator cracks model for (AASHTOWare PMED) level 1 and level 2

Parameters	**Distress Type**	**Level NO.**	**Coefficients**	**Standard Error**	**t Stat**	**P-value**
Intercept	Alligator cracking	level 1	-2.39	6.74E+00	-0.355	7.23E-01
		level 2	5.58	3.99E+00	1.398	1.64E-01
	longitudinal cracking	level 1	290.38	2.46E+02	1.180	2.40E-01
		level 2	101.87	5.74E+01	1.775	7.78E-02
Effective binder content (V_{beff})	longitudinal cracking	level 1	-54.97	8.06E+00	-6.822	1.90E-10
		level 2	-63.89	2.58E+00	-24.773	4.08E-56
Air voids (%V_a)	longitudinal cracking	level 1	53.91	1.61E+01	3.351	1.01E-03
		level 2	143.09	7.56E+00	18.919	2.45E-42
%P3/8"	Alligator cracking	level 1	-0.08	3.97E-02	-2.131	3.46E-02
		level 2	-0.27	2.35E-02	-11.493	1.44E-22
%P# 200	longitudinal cracking	level 1	-68.59	1.92E+01	-3.567	4.80E-04
		level 2	-----------	-----------	-----------	-----------
Mean annual air temperature (T_{air})	Alligator cracking	level 1	0.60	2.53E-01	2.376	1.87E-02
		level 2	0.67	1.50E-01	4.494	1.35E-05
	longitudinal cracking	level 1	29.53	6.48E+00	4.554	1.06E-05
		level 2	-----------	-----------	-----------	-----------

Table 8: Summary of the hypothesis tests results for the regression coefficients of the alligator cracks model for (AASHTOWare PMED) level 1 and level 2 (Continue**)**

Parameters	Distress Type	Level NO.	Coefficients	Standard Error	t Stat	P-value
AADTT	Alligator cracking	level 1	3.387E-03	1.30E-04	25.975	1.02E-58
		level 2	3.595E-03	7.73E-05	46.525	9.61E-94
	longitudinal cracking	level 1	5.873E-02	3.34E-03	17.585	9.37E-39
		level 2	7.369E-02	1.57E-03	46.895	3.01E-94
SPEED	Alligator cracking	level 1	-0.04	7.72E-03	-4.836	3.13E-06
		level 2	-0.05	4.57E-03	-10.148	6.38E-19
	longitudinal cracking	level 1	-1.37	1.98E-01	-6.938	1.02E-10
		level 2	-0.45	9.30E-02	-4.868	2.72E-06

It was noticed that the fatigue cracking model significance was verified due to the F-values from the ANOVA test being less than the risk level (α=5%), as shown in Table 9.

Table 9: ANOVA results for the alligator cracks regression model for (AASHTOWare PMED) level 1 and level 2

	Distress Type	**Level NO.**	**SS**	**df**	**MS**	**F**	**Significance F**
Regression	Alligator cracking	level 1	8239	4	2059.725	177	4.23E-57
		level 2	9882	4	2470.461	605	3.03E-94
	longitudinal cracking	level 1	3332986	6	555497.623	73	1.38E-42
		level 2	5292146	4	1323036.501	783	1.43E-102
Residual	Alligator cracking	level 1	1826	157	11.632		
		level 2	641	157	4.084		
	longitudinal cracking	level 1	1182610	155	7629.743		
		level 2	265173	157	1689.001		
Total	Alligator cracking	level 1	10065	161			
		level 2	10523	161			
	longitudinal cracking	level 1	4515596	161			
		level 2	5557319	161			

6.3. Regression models

6.3.1. Terminal IRI

The R^2 of the terminal IRI models were 0.895 and 0.890 based on AASHTOWare PMED data inputs at levels one and two, respectively. According to all the above, the proposed distress models of terminal IRI could be presented as follows:

Level (1) of AASHTOWare PMED data inputs:

Terminal IRI (m/km) = $- 0.38 + 0.07\ \%V_a - 0.007\ \%P_{3/8''} + 0.005\ \%P_{\#4} + 0.12\ T_{air} + 0.09*10^{-3}$ AADTT - 0.004 SPEED

Level (2) of AASHTOWare PMED data inputs:

Terminal IRI (m/km) = $- 0.01 - 0.01 \%P_{3/8''} + 0.005 \%P_{\#4} + 0.14 T_{air} + 0.101*10^{-3}$ AADTT $- 0.005$ SPEED

6.3.2. Total Pavement Rutting/deformation Distress

The R^2 of the rutting models were 0.895 and 0.875 for AASHTOWare PMED data inputs at levels one and two, respectively. The proposed distress models of the total pavement rutting/deformation distress are presented as follows:

Level (1) of AASHTOWare PMED data inputs:

Total Rutting (mm) $= - 113.84 + 2.55 \%V_a - 0.28 \%P_{3/8''} + 0.22 \%P_{\#4} + 5.84 T_{air} + 3.053*10^{-3}$ AADTT $- 0.15$ SPEED

Level (2) of AASHTOWare PMED data inputs:

Total Rutting (mm) = $- 98.59 - 0.45 \%P_{3/8''} + 0.24 \%P_{\#4} + 6.72 T_{air} + 3.501*10^{-3}$ AADTT $- 0.17$ SPEED

6.3.3. Alligator Cracks

The R^2 of the alligator cracks models were 0.814 and 0.938 for AASHTOWare PMED data inputs at levels one and two, respectively. The proposed distress models of fatigue cracking could be presented as follows:

Level (1) of AASHTOWare PMED data inputs:

Alligator Cracking (percent) = $- 2.39 - 0.08 \%P_{3/8''} + 0.6 T_{air} + 3.387*10^{-3}$ AADTT $- 0.04$ SPEED

Level (2) of AASHTOWare PMED data inputs:

Alligator Cracking (percent) = $5.58 - 0.27 \%P_{3/8''} + 0.67 T_{air} + 3.595*10^{-3}$ AADTT $- 0.05$ SPEED

6.3.4. Longitudinal Cracks

The R^2 of the longitudinal cracks model = 0.728 and 0.951 of AASHTOWare PMED data inputs at levels one and two, respectively. The proposed distress models of longitudinal cracks could be presented as follows:

Level (1) of AASHTOWare PMED data inputs:

Longitudinal Cracking (m/km) $= 290.38 - 54.97 V_{beff} + 53.91 \%V_a - 68.59 \%P_{\#200} + 29.53 T_{air} + 58.731*10^{-3}$ AADTT $- 1.37$ SPEED

Level (2) of AASHTOWare PMED data inputs:

Longitudinal Cracking (m/km) $= 101.87 - 63.89 V_{beff} + 143.09 \%V_a + 73.691 *10^{-3}$ AADTT $- 0.45$ SPEED

6.3.5. Rutting/deformation Distress on AC only

The R^2 of the AC rutting/deformation models = 0.895 and 0.865 of AASHTOWare PMED data inputs based on levels one and two, respectively. The proposed distress models of AC rutting/deformation distress could be presented as follows:

Level (1) of AASHTOWare PMED data inputs:

AC Rutting (mm) = $- 148.49 + 1.32\ V_{beff} + 3.15\ \%Va + 5.79\ T_{air} + 2.869*10^{-3}\ AADTT - 0.14\ SPEED$

Level (2) of AASHTOWare PMED data inputs:

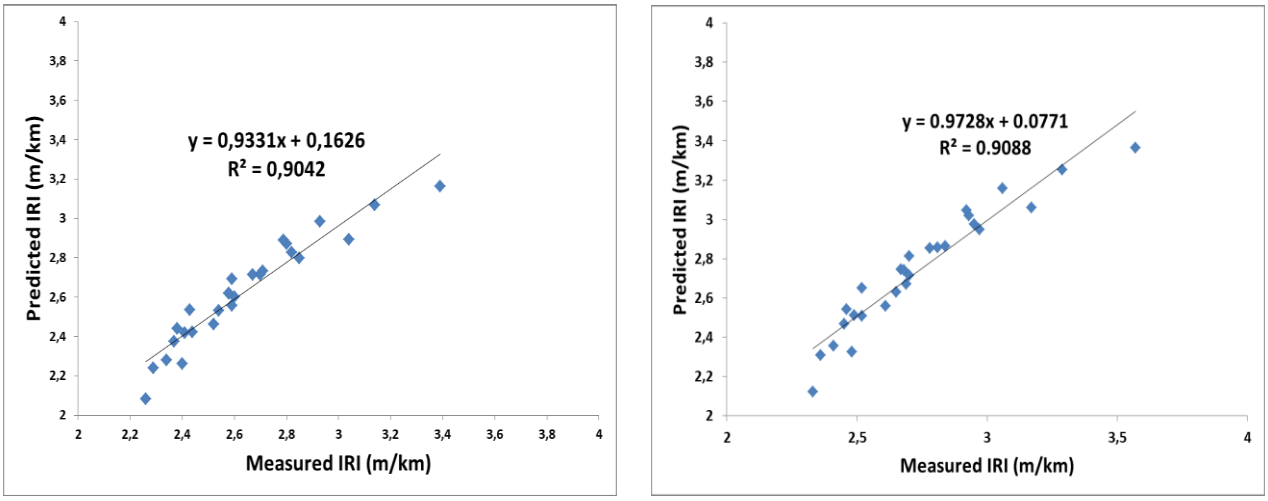
AC Rutting (mm) $= - 152.36 + 2.23\ V_{beff} + 6.67\ T_{air} + 3.304*10^{-3}\ AADTT - 0.17\ SPEED.$

7. Models Validation Process

To ensure the robustness of each proposed model, the model’s validation is considered a crucial process that starts once these models are developed. For all model validation processes in this study, the renaming database which represents 15% of all data was used to achieve this insurance. The model’s validation process is explained in subsections as presented below:

7.1. Validation of predicted IRI Models

For the AASHTOWare PMED (Level 1) and (Level 2) predictions, the results of measured and predicted IRI values are presented in Fig. 3.



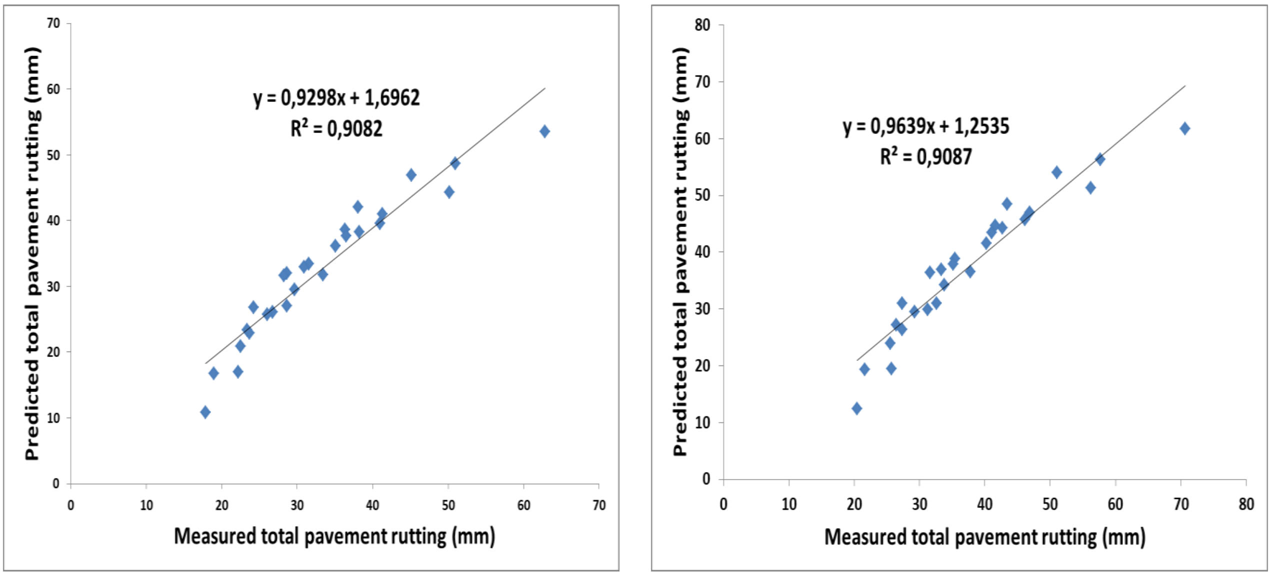
(a) Level 1 (b) Level 2

Fig. 3: The results of measured and predicted IRI values for the model validation

The results indicated that the goodness-of-fit statistics in terms of R^2 are 0.9042 and 0.9088 for the AASHTOWare PMED (Level 1) and (Level 2) predictions, respectively. So, it can be indicated that the proposed models of IRI yield acceptable IRI predictions, asserting the robustness of the proposed models.

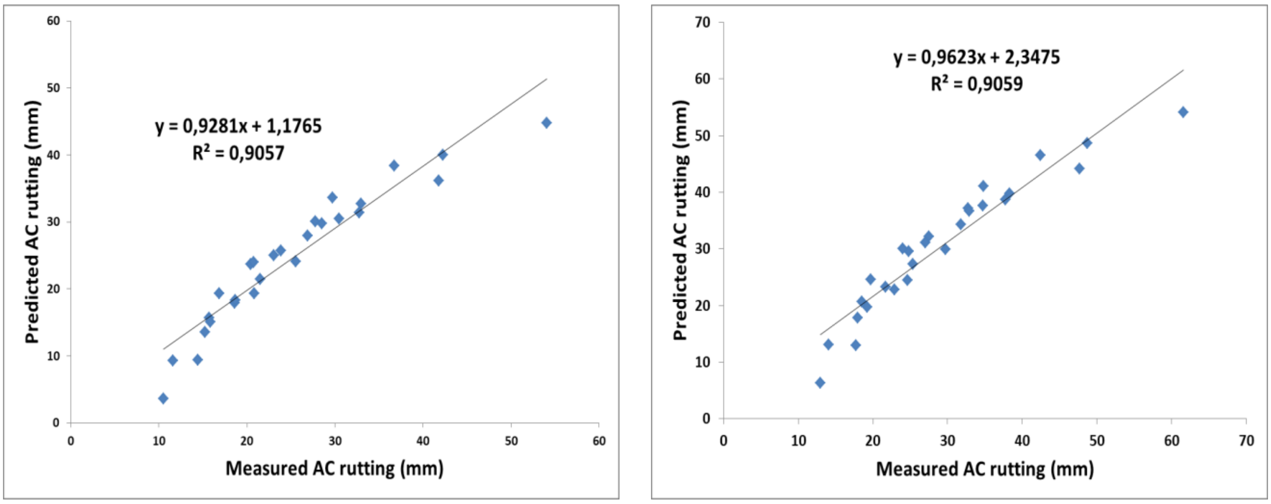
7.2. Validation of predicted pavement rutting Models

For the AASHTOWare PMED (Level 1) and (Level 2) predictions, the results of measured and predicted pavement rutting values for the model validation are presented in Fig. 4 and Fig. 5.



(a) Level 1 (b) Level 2

Fig. 4: The results of measured and predicted total pavement rutting values



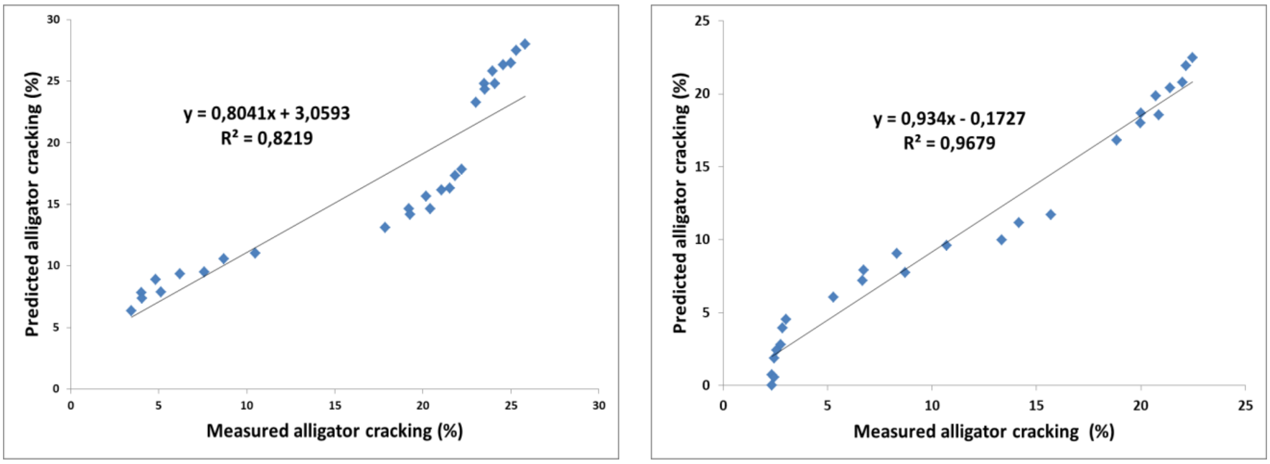
(a) Level 1 (b) Level 2

Fig. 5: The results of measured and predicted AC rutting values for the model validation

The results indicate that the goodness-of-fit statistics in terms of R^2 are 0.9082, 0.9087, 0.9057, and 0.9059 for the AASHTOWare PMED (Level 1 and Level 2) rutting predictions, respectively, for both types of pavement rutting. So, it can be indicated that the proposed models of pavement rutting yield an acceptable rutting prediction, asserting the robustness of the proposed models.

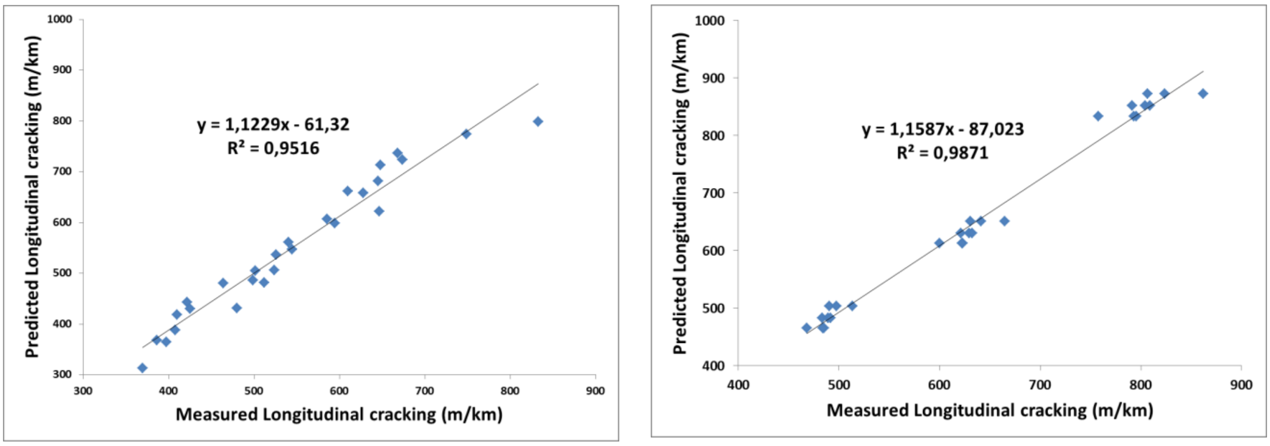
7.3. Validation of predicted fatigue cracking Models

For the AASHTOWare PMED (Level 1) and (Level 2) predictions, the results of measured and predicted each type of fatigue cracking (alligator and longitudinal) values are presented in Fig. 6 and Fig. 7.



(a) Level 1 (b) Level 2

Fig. 6: The results of measured and predicted alligator cracking values for the model validation



(a) Level 1 (b) Level 2

Fig. 7: The results of measured and predicted longitudinal cracking values for the model validation

The results indicate that the goodness-of-fit statistics in terms of R^2 are 0.8219, 0.9679, 0.9516, and 0.987 for the AASHTOWare PMED (Level 1) and (Level 2) predictions, respectively. So, it can be indicated that the proposed models of fatigue cracking (alligator and longitudinal) yield an acceptable cracking prediction, asserting the robustness of the proposed models.

8. Discussions and Conclusions :

Based on the results and analyses, the main observations and conclusions of this research can be summarized as presented below:

1. The AASHTOWare PMED (Level 1) longitudinal cracking predictions were found to be more sensitive to most of the investigated parameters than the AASHTOWare PMED (Level 2) longitudinal cracking predictions.

2. The AASHTOWare PMED (Level 1), alligator cracking was very sensitive to the traffic speed. While, at both levels (1 and 2), the AASHTOWare PMED alligator cracking was very sensitive to the truck traffic volume, the remaining investigated parameters have little effect on the alligator cracking.
3. It was found that total pavement rutting was more sensitive to traffic volume and speed than to other parameters.
4. Among all investigated parameters, it was found that the Average Annual Daily Truck Traffic is the most influencing input on the AASHTOWare PMED (Level 1 and Level 2) predicted performance of flexible pavements. The traffic speed and the Mean Annual Air Temperature were also the most influencing inputs on the AASHTOWare PMED (Level 1) predicted performance of flexible pavements.
5. Five MLR prediction models were proposed for the AASHTOWare PMED Level1 and Level2 performance predictions.
6. For all proposed AASHTOWare PMED (Level 1) and (Level 2) MLR distress prediction models, the R^2 values were more than 0.70 indicating a good model performance.
7. The results of the validation process reveal that the predicted values were close to the measured ones for the developed models with R^2 values greater than 0.8.
8. Despite the good quality of the developed prediction models using the MLR approach, other techniques such as machine learning can produce more precise prediction models for pavement performance.
9. To increase the applicability of the proposed process, more parameters need to be considered such as; the thickness of both asphalt and base layers and properties of asphalt underneath layers (base and subgrade).

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الملخص العربي:

يُنظر إلى التنبؤ بأداءِ الرصفِ على نطاق واسع كعنصر هام في أنظمةِ الإدارة لتقييم البنية التحتية للطريق أَو ما يسمى بأنظمةِ إدارةِ الرصفِ (PMS) مِن قِبل الباحثين في مجال الرصفِ، ليقلل ذلك بشكل كبير وملحوظ من التكاليف الضخمة اللازمة لانشاء الطرقِ، لا سيما في حالة البلدان التي بها إستثمارات هائلة في مجال بناءِ الطرقَ. تركز هذه الدراسة بشكل أساسي على تنفيذ طريقة التحليل الميكانيكي التجريبي (M-E) باستخدام برنامج الـ AASHTOWare لتكوين معادلات للتنبؤ بعيوب الرصف المرن . و لتحقيق ذلك تم اتباع أربع خطوات. أولاً ، تم إجراء التقييم الأكثر دقة الذي يوضح التأثير المشترك لأهم العوامل المؤثرة على أداء الرصف المرن بواسطة تنفيذ عمليات تشغيل لبرنامج .AASHTOware التي تمت باستخدام ، ٣٧٨ مجموعة تصميمية من (٣ مستويات سرعة حركة المرور × ٣ مستويات حمل مرور × ٣مناطق مناخية × ٧ أنواع من الخلطات الأسفلتية للطبقة السطحية المستخدمة على نطاق واسع في مصر) عند مستويين من مستويات الادخال في دليل تصميم الرصف الجديد MEPDG (المستويان ١ و ٢) المطلوبان عادةً لتوصيف مادة الأسفلت الرابطة وخلطات الاسفلت الساخنة (HMA) . ثانيًا ، تم إجراء تحليل الحساسية لدراسة التأثير المشترك للعوامل التي تم فحصها على الأداء الذي تنبأ به AASHTOWARE PMED(الشروخ ، والتخدد ، والخشونة) على مستويين من المدخلات. ثالثًا ، تم تنفيذ طريقة الانحدار الخطي المتعدد (MLR) كنهج نمذجة لتطوير خمسة معادلات للتنبؤ بأداء الأرصفة المرنة بناءً على نتائج برنامج MEPDG. تنبأت معادلات MLR المقترحة بكل عيب من العيوب المذكورة كدالة في العوامل المناخية ، وخصائص HMA السطحية ، لمختلف مستويات سرعة و مختلف مستويات الحجم المروري. أخيرًا ، تم إجراء عملية التحقق من صحة معادلات التنبؤ MLR المقترحة. أشارت النتائج إلى أن المعادلات المقترحة تعطي تنبؤًا جيدًا بشكل عام ، مما يؤكد متانة العملية المقترحة. توفر هذه الدراسة إجراءً لتطوير معادلات التنبؤ بأداء الرصف المرن بناءً على نهج AASHTOWARE PMEDووفقًا لمستويات إدخال المناطق المختلفة على أداء الرصف. قد يساعد ذلك صانعي القرار على تحديد متطلبات الصيانة والتأهيل من خلال التنبؤ بأداء الرصف ثم التخطيط لميزانية عقلانية وتخصيص الموارد في البلدان التي تواجه ظروفًا مماثلة في المستقبل.