Development of Regression Models to Estimate the Effect of Moisture on Performance of Asphalt Pavement

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***Abstract*-- Stripping is the separation of the asphalt cement film from the aggregate due to the action of water. Many methods were used to predict the stripping and the effectiveness of anti-stripping agents, but no sound procedure that takes into account all the relevant factors has been developed. So, researchers still look for a satisfactory procedure that can simulate the field conditions. Stripping resistance was found proportionally correlated with the resilient modulus of the mix. Regression models were developed to estimate the resilient modulus for different aggregate type and gradation, additive type and dosage and degree of saturation. These models were significant at the level of $\alpha \leq 0.05$. The developed model's considered suitable techniques to predict the stripping of asphalt, which could be used as a guideline to assess the water susceptibility for the aggregate type**.

Keywords-- Asphalt mixtures; Stripping; Anti-stripping additives; Resilient modulus; Modeling; Statistical analysis.

Highlights

- Stripping is a significant factor affecting pavement.
- Resilient modulus data are used for predicting asphalt mixture stripping resistance.
- Resilient modulus comparative between laboratory and estimated values.

I. INTRODUCTION / LITERATURE REVIEW

One of the most significant factors causing pavement stripping is the moisture susceptibility of asphalt concrete mixtures. Roberts et al. [1] defined stripping as the eventual loss of the adhesive bond between the aggregate surface and the asphalt cement due to the presence of moisture in a mixture or hot mix asphalt pavement.

Many factors affect stripping in asphalt concrete mixes, such as aggregate types, asphalt cement types, mixture design, construction methods, temperature variation, moisture and water presence, and traffic loads. Kandhal [2] concluded that many factors affect stripping in asphalt concrete mixes, such as aggregate types, asphalt cement types, mixture design, construction methods, temperature variation, moisture and water presence, and traffic loads. Each factor has its primary effect and the combined effect with others.

Cao et al. [3] used a simulation program for long-term fatigue performance pavement test on sections constructed in China. The obtained damage characteristic curves and failure criteria compared, it found that a small aggregate sizes mixtures, a dense gradation, and modified asphalt binder tended to exhibit the best fatigue resistance at the material level. The result of the 15-year finite element structural simulation test showed that the thickness of the asphalt pavements had a significant effect on fatigue performance.

Al-Swailmi and Terrel [4] defined the resilient modulus as the ratio of applied axial stress to recoverable axial strain was used. They found that resilient modulus test for specimens having length/depth (L/D) rates less than unity have shown greater variability and gave higher magnitudes than those having L/D greater than unity. They evaluated and developed the test system to induce and monitor moisture damage to asphalt concrete mixture. The procedure used computer M_R controlled closed-loop loading and data acquisition, a subsystem with moisture conditioning, and environmental control subsystem. The evaluation showed that many factors affect the reliability of subsystems, and the procedure considered as an efficient tool for finding factors causing variability in test results. The results showed that M_R at 60°C was higher than M_R at 25°C, and if the degree of saturation increased, the M_R decreased.

Pickering et al. [5] used resilient modulus and tensile strength ratios in the evaluation. The tests showed that the resilient modulus after moisture conditioning significantly improved with lime addition. Bozan [6] used resilient modulus (M_R) and indirect tensile strength (ITS) at 25ºC. The results indicated that the MR ratio decreased for high saturation, because of their exposure to water during the thawing stage, and that right with increasing saturation levels.

Kutay [7] searched about the fluid numerical modeling flow within the pores of asphalt pavements, which is a beneficial method to describe the directional hydraulic conductivity and the pore pressures. The author developed and validated fluid flow models with Three-dimensional lattice Boltzmann (LB) based on analytical solutions and laboratory experiments. By using X-ray CT technique, Three-dimensional, original pore structures of the specimens were generated and used as an input in the LB models. The analysis of hydraulic conductivity tensor, simplify the comparison between two horizontal directions with horizontal and vertical directions, the results showed that the first one is isotropic, where the second is anisotropic.

Kringos et al. [8] investigated new tools to develop a simulation of moisture infiltration due to pressure drove and moisture gradient driven processes. This research aimed to understand and quantify the physical processes leading to moisture induced damage in asphalt and combine them with the mechanical ones. A three dimensional visco-elastoplastic constitutive model for the mastic was presented, which showed a coupling with the moisture infiltration model. For the simulation of the response of the other components, the same formulation can use. A micro-scale simulation was developed to illustrate the damage generated in the mastic-aggregate interface, that could be due to both plastic strain and moisture induced damage.

Kringos [9] investigated improved material selection procedure and how numerical simulations competed for the damage-inducing processes within the asphalt mix. A computational tool was developed for the physical and mechanical moisture damage analysis on asphaltic mixes by mechanical and moisture induced damage together. In this research, the author concluded that it is essential to know the moisture susceptibility parameters of the components of the mix and the moisture susceptibility of its bond. It is shown that if the settings were varied, damage patterns might occur with entirely different. The recommendations for further researches were about moisture diffusion coefficients of the aggregates, changing material response, the bond strength of the aggregate-mastic combinations, and the loss of concentration of the mastic, in the presence of high water pressures.

Caro et al. [10] studied the effects of moisture on asphalt mixtures response by analyzing the impact of mechanical and physical material properties and loading conditions. The author aimed to couple the effects of moisture transport and mechanical loading by using a finite element, micromechanical model. The results showed that the asphalt matrix and aggregates diffusion coefficient and the aggregate–matrix interface bond strength have the most influence on the moisture susceptibility.

Al-Rub et al. [11] studied the moisture-induced damage model using continuum damage mechanics for predicting adhesive and cohesive moisture-induced damage. He proposed this model to capture all facets of realistic asphalt mix response, which will anticipate crack nucleation and propagation due to different mechanical loading conditions. The author investigated various aspects of the integrated continuum damage mechanics model to match the qualitative behavior of experiments. The results showed that current moisture-induced damage model could be used to predict the time frame over which moisture-induced damage may occur and to rank asphalt mixtures for moisture damage susceptibility.

Lu and Harvey [12] conducted in their statistical analysis in California that many factors affect the extent of moisture damage in pavements, that were air-void, pavement structure, cumulative rainfall, mix type, anti-strip additive (lime or liquid), and pavement age. High air-void contents reduce the fatigue resistance of mixes in wet conditions. They concluded that the use of the Hamburg Wheel Tracking Device (HWTD) test to determine the moisture sensitivity of asphalt mixes was effective, and the test can correctly identify the effect of anti-strip additives.

II. OBJECTIVE

The objective of this study is to develop regression models that can be used to estimate the effect of moisture on the performance of asphalt pavement.

III. DATABASE

The resilient modulus is considered a suitable measure of moisture susceptibility for asphalt concrete mixtures, and the degree of saturation can be used to represent the severity of conditioning. The five pulses indirect tensile test was used to find the resilient modulus for Marshall specimens. Several models were developed to estimate the resilient modulus and the effects of the following variables were included [13]:

1- Aggregate type (limestone, valley gravel, and basalt),
2- Aggregate gradation (wearing and binder course),
3- Saturation case (medium saturation, and high saturation),
4- A type of anti-stripping additive (lime and polyamine (Morelife)),
5- Five levels of additive dosages (0.0 to 2.0 with 0.5 increments for lime, and 0.0 to 1.0 with 0.25 increments for polyamine).

A. Description of Data Base

All variables listed above were considered qualitative, except the level of additive dosages, which can be treated as a quantitative variable. Covariance analysis performed on the different elements of the database, which obtained from laboratory tests on 360 specimens of asphalt concrete mixtures. Table 1 shows the resilient modulus for medium and high saturation, respectively. These tables present the values of resilient modulus for several combinations between the level of additive dosages on the one hand and aggregate type, aggregate gradation, and additive sort, on the other side. The value of resilient modulus in these tables was the average of three test results.

TABLE 1. Resilient Modulus Values (MPa) for Asphalt Concrete Mixtures*

a. Medium Saturation Degree								
Course Type	Additive %		Resilient Modulus (MPa)					
			Basalt		Valley Gravel		Limestone	
	Polyamine	Lime	Polyamine	Lime	Polyamine	Lime	Polyamine	Lime
Wearing	0.00	0.00	123	123	135	135	248	248
	0.25	0.50	160	134	147	154	239	235
	0.50	1.00	166	150	151	176	257	270
	0.75	1.50	178	170	169	230	267	319
	1.00	2.00	192	196	230	268	308	375
Binder	0.00	0.00	122	121	145	145	252	252
	0.25	0.50	124	139	149	176	257	255
	0.50	1.00	143	155	191	199	270	269
	0.75	1.50	156	163	217	219	276	293
	1.00	2.00	207	173	219	231	301	308
	b. High Saturation Degree							
	Polyamine	Lime	Polyamine	Lime	Polyamine	Lime	Polyamine	Lime
Wearing	0.00	0.00	106.5	106.0	116.4	116.4	233.3	233.3
	0.25	0.50	134.2	122.2	117.2	122.9	233.4	247.5
	0.50	1.00	147.0	142.5	146.1	132.7	244.7	262.3
	0.75	1.50	163.9	154.0	165.0	141.0	273.8	271.4
	1.00	2.00	175.1	185.0	198.2	220.0	291.9	344.4
Binder	0.00	0.00	94.5	94.5	127.8	127.8	206.5	206.0
	0.25	0.50	101.2	113.0	137.4	130.9	212.9	217.0
	0.50	1.00	115.2	134.4	149.0	144.9	221.4	219.0
	0.75	1.50	136.4	144.9	189.0	182.8	218.4	246.0
	1.00	2.00	175.2	157.3	196.0	197.9	285.7	295.0

* Alkofahi [13]

IV. DATA RESULTS AND DISCUSSION

A. Development of Models

The first step of development was the establishment of statistical correlation matrices for the different cases included in this study. These matrices are useful to know the degree of correlation between dependent and independent variables, and the multicollinearity among the independent variables. These matrixes help select the most significant independent variables. It is clear that aggregate type, aggregate gradation, and additive type highly correlated with the resilient modulus.

The resilient modulus (Y) used as the dependent variable in all regression models. In general, the repeated independent variables (dummy) in the developed models for all mixtures indicated, as shown below:

X_2 =1 if limestone,
= 0 if other (valley gravel and basalt).
X_3 =1 if valley gravel,
= 0 if other (limestone and basalt).
X_4 =1 if wearing course,
= 0 if other (binder course).

The other variables, which describe the additive type, additive level, or/and saturation degree, are presented as separate cases. The statistical Packages for Social Sciences (SPSS) software was used to find the statistical characteristics of different models. A linear regression method with (Enter) mode chosen.

1) The Case of High Saturation Degree

The objective of model development was to predict the effects of additive type and dosage value on the resilient modulus in the same condition of high saturation degree.

a) If lime additive is used:
X_1 = five levels (%) of lime = 0, 0.5, 1.0, 1.5, 2.0
The model of resilient modulus (Y lime) will be performed as follows:
$Y= b_0+b_1X_1+b_2X_2+b_3X_3+ b_4X_4$
$$Y\ lime = 88.447 +40.593X_1 +118.81X_2 +16.35X_3 +12.68X_4 \quad (1)$$
Table 2.a shows the regression model parameters of this equation.

b) If Polyamine additive is used :
X1 = five levels (%) of Polyamine = 0, 0.25, 0.5, 0.75, 1.0
The model of resilient modulus (Y Polyamine) will be performed as follows:
$Y = b_0+b_1X_1+b_2X_2+b_3X_3+ b_4X_4$
$$Y\ Polyamine = 80.95 +69.12X_1 +107.285X_2 +59.495X_3 +38.81X_4 \quad (2)$$
Table 2.b shows the regression model parameters of this equation.

c) If both additives are used:
X_1 =1 if lime,
= 0 if other (Polyamine)
X_5 = five levels (%) for each Additive
Lime = 0, 0.5, 1.0, 1.5, 2.0
Polyamine = 0, 0.25, 0.5, 0.75, 1.0
The model of resilient modulus (Y total) will be performed as follows:
$Y = b_0+b_1X_1+b_2X_2+b_3X_3+ b_4X_4 +b_5X_5$
$$Y\ total =104.163 -33.224X_1 +113.048X_2 +37.923X_3 +25.745X_4 +46.299X_5 \quad (3)$$
Table 2.c shows the regression model parameters of this equation.

TABLE 2. Statistical Characteristics of Models for High Saturation Degree

a. Lime Additive, Equation (1)				
Parameter	Parameter Estimation	Standard Error	t-value	Level of α
b0	88.447	7.870	11.283	.000
b1	40.593	5.544	8.934	.000
b2	118.81	7.870	15.096	.000
b3	16.35	7.870	2.077	.048
b4	12.68	6.426	1.973	.060
b. Polyamine Additive, Equation (2)				

Parameter	Parameter Estimation	Standard Error	t-value	Level of α
b0	80.95	7.766	10.429	.000
b1	69.12	8.967	7.708	.000
b2	107.285	7.766	13.815	.000
b3	59.495	7.766	7.661	.000
b4	38.81	6.341	6.121	.000
c. Both Additives, Equation (3)				
Parameter	Parameter Estimation	Standard Error	t-value	Level of α
b0	104.163	7.154	14.561	.000
b1	-33.224	6.508	4.334	.000
b2	113.048	7.276	-5.105	.000
b3	37.923	7.276	15.537	.000
b4	25.745	5.941	5.212	.000
b5	46.299	5.314	8.713	.000

2) The Case of Medium Degree Saturation

The objective was to predict the effects of additive type and dosage value on the resilient modulus at the same condition of medium saturation degree.

a) If lime additive is used:

X1 = five levels (%) of lime =0, 0.5, 1.0, 1.5, 2.0

The model of resilient modulus (Y lime) will be performed as follows:

$Y = b_0+b_1X_1+b_2X_2+b_3X_3+ b_4X_4$

$Y\ lime =103.247 +47.427X_1 +128.255X_2 +39.325X_3 +7.463X_4$ (4)

In Equation (4), the regression model parameters corresponding to a high degree of saturation are shown in Table 3.a.

b) If Polyamine additive is used*:*

X1 = five levels (%) of Polyamine = 0, 0.25, 0.5, 0.75, 1.0

The model of resilient modulus (Y Polyamine) will be performed as follows:

$Y = Y = b_0+b_1X_1+b_2X_2+b_3X_3+ b_4X_4$

$Y\ Polyamine = 122.67 +66.787X_1 +116.385X_2 +26.525X_3 -7.567X_4$ (5)

In Equation (5), the regression model parameters corresponding to a high degree of saturation shown in Table 3.b.

TABLE 3. Statistical Characteristics of Models for Medium Saturation Degree

a. Lime Additive, Equation (4)				
Parameter	Parameter Estimation	Standard Error	t-value	Level of α
b0	103.247	7.524	13.723	.000
b1	47.427	4.344	10.918	.000
b2	128.255	7.524	17.047	.000
b3	39.325	7.524	5.227	.000
b4	7.463	6.143	1.215	.236
b. Polyamine Additive, Equation (5)				
Parameter	Parameter Estimation	Standard Error	t-value	Level of α
b0	122.67	5.344	22.956	.000
b1	66.787	6.170	10.824	.000
b2	116.385	5.344	21.78	.000
b3	26.525	5.344	4.964	.000
b4	-7.567	4.363	-1.734	.095

3) The Case of Different Degree Saturation (medium and high)

The objective was to predict the effects of additive type and dosage value on the resilient modulus for the variable condition of saturation degree (medium and high).

a) If lime additive is used:

X1 = five levels (%) of lime = 0, 0.5, 1.0, 1.5, 2.0

X6 = 1 if high saturation degree,

= 0 if other (medium saturation degree).

The model of resilient modulus (Y lime) will be performed as follows:

$Y = b_0+b_1X_1+b_2X_2+b_3X_3+ b_4X_4 +b_6X_6$

$Y\ lime = 110.762 +44.01X_1+123.533X_2 +27.838X_3 +10.072X_4 -29.832X_6$ (6)

In Equation (6), the regression model parameters corresponding to a high degree of saturation shown in Table 4.a.

b) If Polyamine additive is used:

X1 = five levels (%) of Polyamine = 0, 0.25, 0.5, 0.75, 1.0.

X6 = 1 if high saturation degree,

= 0 if other (medium saturation degree).

The model of resilient modulus (Y Polyamine) will be performed as follows:

$Y= b_0+b_1X_1+b_2X_2+b_3X_3+ b_4X_4 +b_6X_6$

$Y\ Polyamine = 106.514 +67.953X_1 +111.835X_2 +43.01X_3 +15.622X_4 -9.41X_6$ (7)

In Equation (7), the regression model parameters corresponding to a high degree of saturation shown in Table 4.b.

TABLE 4. Statistical Characteristics of Models for Different Saturation Degree (Medium and high)

a. Lime Additive, Equation (6)				
Parameter	Parameter Estimation	Standard Error	t-value	Level of α
b0	110.762	5.989	18.793	.000
b1	10.072	4.528	2.225	.003
b2	44.01	3.201	13.747	.000
b3	123.533	5.545	22.278	.000
b4	27.838	5.545	5.020	.000
b6	-29.832	4.528	6.589	.000
b. Polyamine Additive, Equation (7)				
Parameter	Parameter Estimation	Standard Error	t-value	Level of α
b0	106.514	7.213	14.766	.000
b1	15.622	5.453	2.865	.006
b2	67.953	7.711	8.812	.000
b3	111.835	6.678	16.746	.000
b4	43.01	6.678	6.440	.000
b6	-9.408	5.453	-1.725	.090

The models were compared depending on the following criteria:

1- The coefficient of multiple determination (R^2),
2- The level of significance of (α= 0.05),
3- F-Test,
4- The standard error of estimate

The results of regression modeling criteria listed in Table 5

TABLE 5. Summary of Models Criteria

Model Number and It's Case	Criterion				
	R^2	R^2 adjusted	Std.	F-value	Sig. F
1 (high saturation, lime)	0.934	0.923	17.59	87.88	0.000
2 (high saturation, Polyamine)	0.920	0.907	17.36	72.12	0.000
3 (high saturation, both additive)	0.866	0.853	23.01	69.54	0.000
4 (medium saturation, lime)	0.945	0.937	16.82	106.44	0.000
5 (medium saturation, Polyamine)	0.962	0.956	11.95	160.33	0.000
6 (different saturation, lime)	0.936	0.930	17.54	156.71	0.000
7 (different saturation, Polyamine)	0.874	0.862	21.12	74.85	0.000

Table 5 provides a summary of the regression characteristics of the models presented in Equations (1 through 7). All models were found to be significant due to the following reasons:

1-The differences between R^2 and R^2 adjusted were very small, indicating that the developed models could use for prediction purposes

2-The levels of significance were minimal (α= 0.000),

3-The F- values were tremendous,

4-The standard errors of estimate were minimal.

Model (5) found the most significant, which has $R^2 = 0.962$ and F=160.33. In general, five models have high values of multiple determination coefficients ($R^2 > 0.9$), where two models have lower amounts of multiple determination coefficients ($0.85 < R^2 < 0.9$). It found that all F-values were significant at the level of (α =0.000). It found that the standard error of estimate has a small value; the characteristics of independent variables listed in Table 6.

Table 6 shows that the most significant independent variable is aggregate type X_2 (limestone), which has the highest stripping potential. Through Tables (3 to 8), the parameters of the limestone variable were high (b2 >100) and were significant at the level of (α = 0.000). Where the course type was the lowest significant independent variable, and most of their parameters are (b4 < 20), their levels of α are more than 0.05, and their t-values are less than 3. It found that most variables were significant at the level of (α = 0.000), except for course type in Equations (4 and 5) where was not significant at the level of (α < 0.05).

TABLE 6. Summary of Independent Variables Characteristics for all Models

Independent Variable	Criterion	Model Number						
		1	2	3	4	5	6	7
Constant	t-value	11.24	10.42	14.56	13.72	22.96	18.49	14.77
	Level of α	0.000	0.000	0.000	0.000	0.000	0.000	0.000
X1 (Lime)	t-value	8.934	*	8.71	10.92	*	13.75	*
	Level of α	0.000	*	0.000	0.000	*	0.000	*
X1 (Polyamine)	t-value	*	7.708	*	*	10.82	*	8.81
	Level of α	*	0.000	*	*	0.000	*	0.000
X2 (Limestone)	t-value	15.096	13.82	15.54	17.05	21.78	22.78	16.75
	Level of α	0.000	0.000	0.000	0.000	0.000	0.000	0.000
X3 (Other)	t-value	2.08	7.66	5.21	5.23	4.96	5.02	6.44
	Level of α	.048	0.000	0.000	0.000	0.000	0.000	0.000
X4 (Wearing)	t-value	1.973	6.12	4.33	1.22	-1.73	2.23	2.87
	Level of α	.060	0.000	0.000	.236	.095	0.030	0.006
X5 (Additive)	t-value	*	*	-5.11	*	*	*	*
	Level of α	*	*	0.000	*	*	*	*
X6 (High)	t-value	*	*	*	*	*	6.59	-1.73
	Level of α	*	*	*	*	*	.000	.090

* Not included in the model

B. Implications of the Models

The covariance models were developed to determine how the aggregate type, aggregate gradation, additive type, additive dosage, and degree of saturation affect the stripping potential of asphalt mixtures. Figures (1 and 2) show the application of the models in Equations (1 and 2) in estimating the resilient modulus for any change in the variables. The difference between resilient modulus for limestone and other aggregates, as shown in Figures (1 and 2) is indicated to better resistance to stripping for limestone than others aggregate. The difference between the trend the increase of resilient modulus between these two figures represents the difference between the two models, which were used to estimate the resilient modulus for each case. Another application of the proposed models in Equations (1 through 7), is the estimation of additive dosage needed to obtain the suitable resilient modulus that can resist the stripping potential under a specific condition. Also, the saturation degree effect on the stripping potential can be estimated. The negative sign of high degree saturation variable in Equations (6 and 7) indicated that the high degree of saturation inversely affects the resilient modulus values. The positive sign of more independent variables represents the positive effect of these variables on the stripping potential resistance. The models in Equations (3) could be used to predict the impact of additive type on the resilient modulus, and therefore on the stripping potential resistance. It is clear from Figures 3 and 4 that limestone mixtures have the most significant values of resilient modulus for both laboratory and estimated values.

In general, it is clear that the effect of Polyamine additives was found more significant at both degrees of saturation than lime additive. The relationship between these variables and resilient modulus found statistically significant. The assessment of the effect of additives and the degree of saturation is essential applications of these models. The predicted models in Equations (1 and 2) can be employed to estimate the resilient modulus at high saturation degree. Table 7 shows the estimated resilient modulus values for aggregate mixtures using the described statistical models.

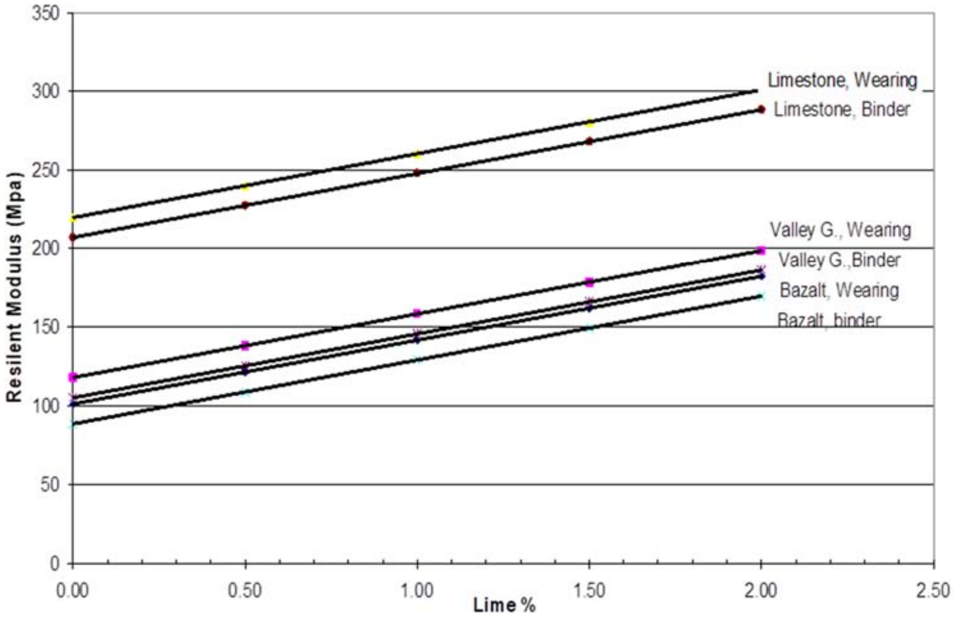

Fig 1. The estimated resilient modulus for lime additive using equation (1)

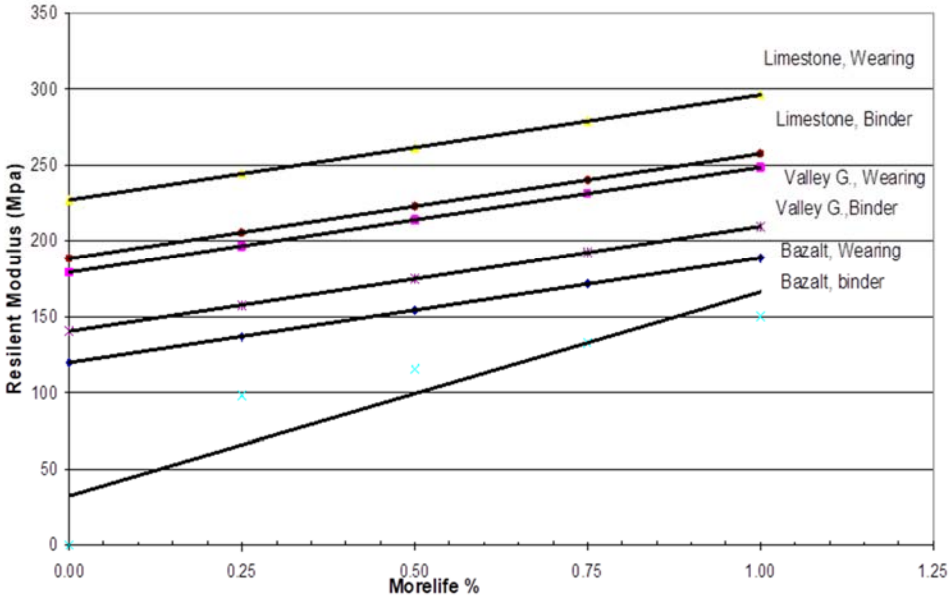

Fig 2. Estimated Resilient Modulus for Polyamine Additive Using Equation (2)

TABLE 7. Estimated Resilient Modulus Values (MPa) for Asphalt Concrete Mixtures by Using Equations (1, 2)

Course Type	Additive %		Resilient Modulus (MPa)					
			Basalt		Valley Gravel		Limestone	
	Polyamine %	Lime %	Polyamine	Lime	Polyamine	Lime	Polyamine	Lime
Wearing	0.00	0.00	93.6	93.6	110.2	110.2	212.4	212.4
	0.25	0.50	103.8	103.8	120.3	120.3	222.6	232.7
	0.50	1.00	113.9	113.9	130.5	130.5	232.7	253.0
	0.75	1.50	124.1	124.1	140.6	140.6	242.9	273.3
	1.00	2.00	134.2	134.2	150.8	150.8	253.0	293.6
Binder	0.00	0.0	81.0	81.0	97.5	97.5	199.8	199.8
	0.25	0.5	91.1	91.1	107.6	107.6	209.9	220.1
	0.50	1.0	101.2	101.2	117.8	117.8	220.1	240.4
	0.75	1.5	111.4	111.4	127.9	127.9	230.2	260.6
	1.00	2.0	121.5	121.5	138.1	138.1	240.4	280.9

Figures (3 through 6) illustrate the comparisons between the estimated resilient modulus values and that obtained by the laboratory experiments. These figures indicated that the calculated values were less than laboratory values, especially at a high additive dosage; this may be because the relationships were assumed linear, but the correlations for the laboratory values were found polynomial. The differences between the statistical and laboratory results were minimal. In general, the polynomial relationships were better in representing the results than linear relationships. The regression models were assumed to be linear because most variables considered as qualitative variables. There was only one variable that considered a quantitative variable, which is the dosage of the additive.

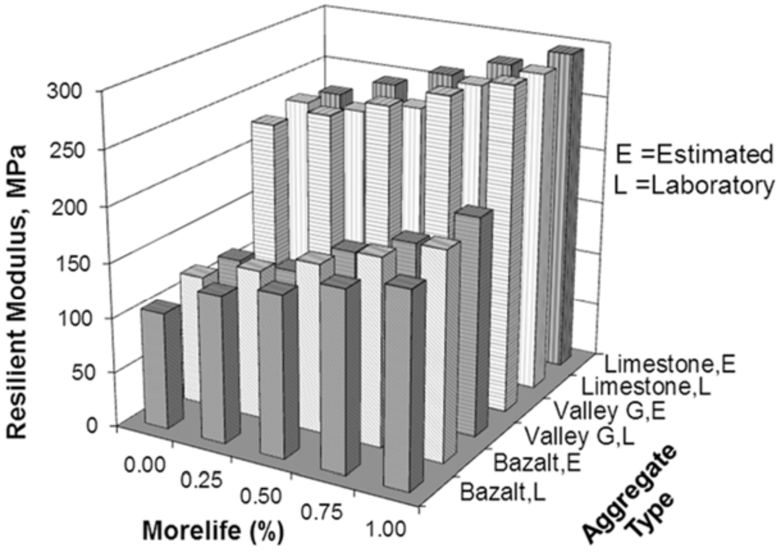

Fig. 3. Effect of lime (%) on resilient modulus for wearing course (Laboratory and estimated values) using equation (1).

V. CONCLUSION

The study has revealed the following findings related to the material and testing program:

1) The developed regression models were found significant with high values of R^2.
2) The established models could be used to estimate the resilient modulus for different aggregate types and gradations, additive type and dosage and degree of saturation.

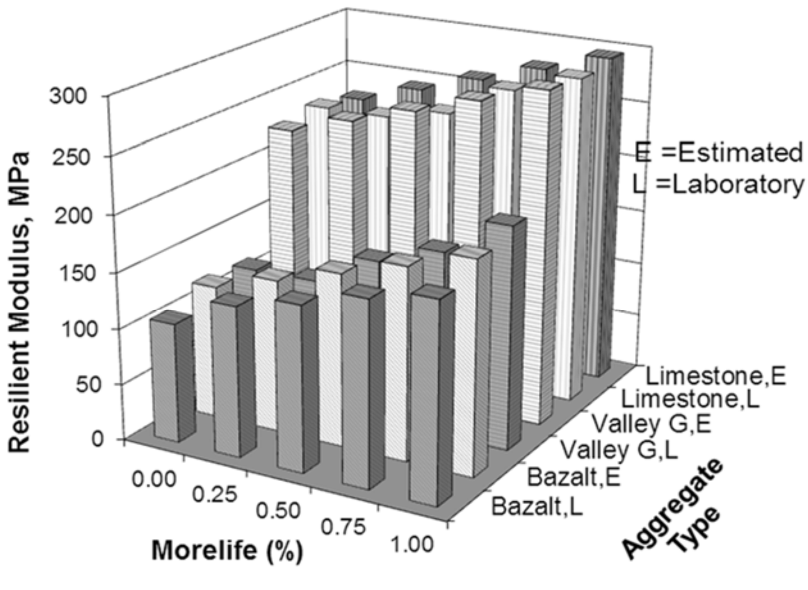

Fig 4. Effect of Polyamine (%) on resilient modulus for wearing course (Laboratory and estimated values) using equation (2)

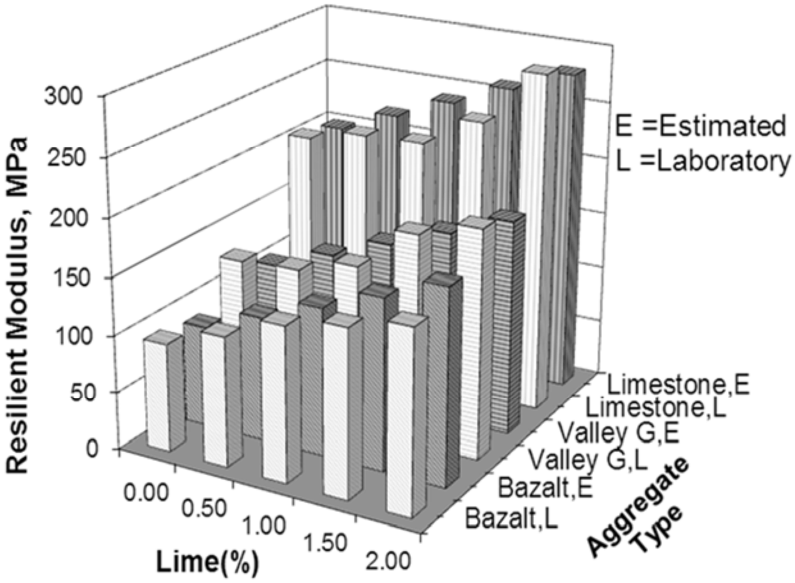

Fig 5. Effect of lime (%) on resilient modulus for binder course (Laboratory and estimated values) using equation (1)

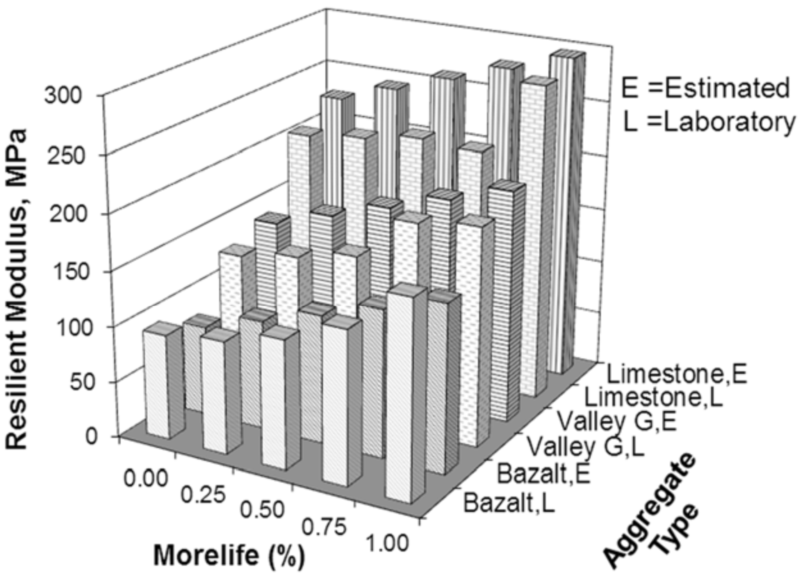

Fig 6. Effect of Polyamine (%) on resilient modulus for binder course (Laboratory and estimated values) using equation (2)

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests regarding the publication of this paper.

DATA AVAILABILITY

The data used to support the findings of this study are available from the corresponding author upon request.

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