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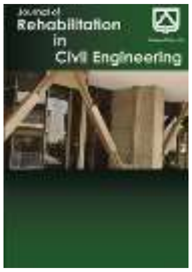

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Performance Evaluation of Dynamic Modulus Predictive Models for Asphalt Mixtures

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ABSTRACT

Dynamic modulus characterizes the viscoelastic behavior of asphalt materials and is the most important input parameter for design and rehabilitation of flexible pavements using Mechanistic–Empirical Pavement Design Guide (MEPDG). Laboratory determination of dynamic modulus is very expensive and time consuming. To overcome this challenge, several predictive models were developed to determine dynamic modulus of asphalt mixtures instead of laboratory testing. Present study utilizes a large database of 1320 dynamic modulus test results developed at the University of Maryland to evaluate the performance and accuracy of different dynamic modulus predictive models. For this purpose, six conventional dynamic modulus predictive models including Witczak, Modified Witczak, Hirsch, Al-Khateeb, Global and Simplified Global models were considered and dynamic moduli of asphalt mixtures were determined. These moduli were then compared with those determined from laboratory test results. Performance evaluation of the models showed high prediction accuracy and low prediction bias with good correlation between predicted moduli and measured values for Witczak and Global models.

1. Introduction

Asphalt dynamic modulus characterizes the viscoelastic time and temperature dependent behavior of asphalt materials and is used in Mechanistic–Empirical Pavement Design Guide (MEPDG) as an input design parameter [1].

Testing of dynamic modulus takes a lot of time and requires sophisticated equipment and trained specialists. Hence, besides measuring this modulus in laboratory, several predictive models were developed by researches to determine asphalt dynamic modulus from mixture properties. These developed models usually use aggregate

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gradation, mix volumetric properties and binder viscosity or stiffness to predict dynamic modulus of asphalt mixtures.

MEPDG uses two models, namely, Witczak model [2] and Modified Witczak model [3] to predict dynamic moduli of asphalt mixtures. Other researchers have also developed some predictive models including Hirsch model [4] and a modified version of this model, i.e. Al-Khateeb model [5]. In addition, Sakhaeifar et al. [6] developed two closed-form models employing viscoelastic behavior and time-temperature superposition principle of asphalt materials. New regression models were called Global and Simplified Global models [6].

Performance evaluation of developed models to different asphalt mixtures in local conditions varies with mixture properties and shows large bias in predictions [7]. In addition to these regression models, Artificial Neural Network (ANN) was utilized by Ceylan et al. [8-9] and Sakhaeifar et al. [10] to predict dynamic modulus with high goodness-of-fit and low bias based on laboratory test data.

Dynamic modulus of asphalt layers should be determined as the design parameter in structural evaluation and rehabilitation of in-service asphalt pavements using MEPDG [1]. This method was evaluated and, in some cases, lacked precision [11-13]. Other researchers have developed improved and simple methods based on MEPDG proposed procedure. Biswas and Pellinen [14], Seo et al. [15], Georgouli et al. [16] and Solatifar et al. [17] developed some practical methods using predictive models and field data to determine dynamic moduli of in-service asphalt layers.

Directly prediction of dynamic modulus of asphalt mixtures using mix volumetric properties and asphalt binder characteristics without need for laboratory testing, is the main advantage of predictive models. The objective of this paper is to apply and evaluate performance of six conventional dynamic modulus predictive models, namely, Witczak, Modified Witczak, Hirsch, Al-Khateeb, Global and Simplified Global models in determining dynamic moduli of asphalt mixtures.

2. Dynamic Modulus Predictive Models

Six conventional asphalt dynamic modulus predictive models have been investigated in this study as it follows:

2.1. Witczak Model

Witczak model [2] predicts asphalt dynamic modulus in terms of aggregate gradation, effective binder content, mix air voids, loading frequency and binder viscosity. This model was developed based on a nonlinear regression analysis and is presented in Equation 1 [2]. Witczak model is currently used in MEPDG analysis as described in protocol of NCHRP 1-37A [1].

$$\begin{aligned}\log|E^*| = 3.750063 + 0.02932\rho_{200} - 0.001767(\rho_{200})^2 - 0.002841\rho_4 - 0.058097V_a - 0.802208\left(\frac{V_{beff}}{V_{beff}+V_a}\right)\\ + \frac{3.871977 - 0.0021\rho_4 + 0.003958\rho_{38} - 0.000017(\rho_{38})^2 + 0.005470\rho_{34}}{1+e^{(-0.603313-0.313351\log(f)-0.393532\log(\eta))}}\end{aligned} \tag{1}$$

In this equation, $|E^*|$ is asphalt dynamic modulus (psi), η is binder viscosity (10^6 Poise), f is frequency (Hz), ρ_{200} is passing #200 Sieve (%), ρ_4 is cumulative amount retained on #4 Sieve (%), ρ_{34} is cumulative amount retained on #3/4 Sieve (%), ρ_{38} is cumulative amount retained on #3/8 Sieve (%), V_a is the air voids content (%), and V_{beff} is the effective binder content (% by volume).

For calculation of the viscosity (η) in using the model, MEPDG converts binder stiffness characteristics into viscosity-temperature susceptibility parameters, i.e. A, regression intercept and VTS, regression slope values as stated in ASTM-D2493 Standard [18].

2.2. Modified Witczak Model

This model was developed by modifying the Witczak model in NCHRP 1-40D protocol [3]. As with Witczak model, the Modified Witczak model is also based on a nonlinear regression analysis. Modified Witczak model, presented in Equation 2, is used in version 1.0 of MEPDG software [19-20].

$$\begin{aligned}\log|E^*| = {} & -0.349 + 0.754(|G_b^*|^{-0.0052}) \\ & \times \left\{6.65 - 0.032\rho_{200} + 0.0027(\rho_{200})^2 + 0.011\rho_4 - 0.0001(\rho_4)^2 + 0.006\rho_{38} - 0.00014(\rho_{38})^2 - 0.08V_a - 1.06\left(\frac{V_{beff}}{V_{beff} + V_a}\right)\right\} \\ & + \frac{2.56 + 0.03V_a + 0.71\left(\frac{V_{beff}}{V_{beff}+V_a}\right) + 0.012\rho_{38} - 0.0001(\rho_{38})^2 - 0.01\rho_{34}}{1 + e^{(-0.7814-0.5785\log|G_b^*|+0.8834\log\delta_b)}}\end{aligned} \tag{2}$$

where $|G_b^*|$ is dynamic shear modulus of binder (psi), δ_b is binder phase angle (°), and $|E^*|$, ρ_{200}, ρ_4, ρ_{34}, ρ_{38}, V_a and, V_{beff} are as previously defined in Equation 1.

For calculation of $|G_b^*|$ values from A and VTS viscosity-temperature susceptibility parameters, Modified Witczak model uses Cox-Mertz Rule. The processes of this rule are reported in Equations 3 to 5 as it follows:

$$|G_b^*| = 0.0051 f_s \eta_{f_s,T} (\sin\delta_b)^{7.1542-0.4929 f_s+0.0211 f_s^2} \tag{3}$$

$$\delta_b = 90 + (-7.3146 - 2.6162 * VTS') * \log(f_s * \eta_{f_s,T}) + (0.1124 + 0.2029 * VTS') * \log(f_s * \eta_{f_s,T})^2 \tag{4}$$

$$loglog(\eta_{f_s,T}) = 0.9699 f_s^{-0.0527} * A + 0.9668 f_s^{-0.0575} * VTS\ logT_R \tag{5}$$

where f_s is dynamic shear frequency (Hz), δ_b is binder phase angle predicted from Equation 4 (°), $\eta_{f_s,T}$ is viscosity of asphalt binder at a specific loading frequency (f_s) and temperature (T), determined from Equation 5 (cP), and T_R is temperature in Rankine scale.

2.3. Hirsch Model

Hirsch model was developed by Christensen et al. [4]. It is based on the law of mixtures parallel model that incorporates the binder dynamic shear modulus, voids in the mineral aggregate (VMA), and the voids filled with asphalt binder (VFA) to simply predict the dynamic moduli of asphalt mixtures [4-5, 21]. Hirsch model is expressed in Equation 6 to 8 as it follows:

$$|E^*|_m = P_c\left[4{,}200{,}000\left(1-\frac{VMA}{100}\right)+3\,|G^*|_b\,(\frac{VMA\times VFA}{10{,}000})\right]+\frac{(1-P_c)}{\frac{(1-{}^{VMA}/_{100})}{4{,}200{,}000}+\frac{VMA}{3\,|G^*|_b\,(VFA)}} \tag{6}$$

$$\phi = -21(logP_c)^2 - 55logP_c \tag{7}$$

$$P_c = \frac{(20+3\,|G^*|_b\,(VFA)/(VMA))^{0.58}}{650+(3\,|G^*|_b\,(VFA)/(VMA))^{0.58}} \tag{8}$$

where $|E^*|_m$ is asphalt dynamic modulus (psi), P_c is aggregate contact volume, VMA is the percentage of voids in mineral aggregate (%), VFA is the percentage of voids filled with asphalt binder (%), $|G^*|_b$ is dynamic shear modulus of binder (psi), and ϕ is the phase angle of mixture (°). This model suffers from a weak dependence on volumetric parameters [21].

2.4. Al-Khateeb Model

This model as known as law of mixtures parallel model, was developed by Al-Khateeb et al. [5] based on the former Hirsch model. Equation 9 presents the mathematical form of the developed model.

$$|E^*|_m = 3\left(1-\frac{VMA}{100}\right)\left(\frac{\left(90+10{,}000\left({}^{|G^*|_b}/_{VMA}\right)\right)^{0.66}}{1{,}100+\left(900\left({}^{|G^*|_b}/_{VMA}\right)\right)^{0.66}}\right)|G^*|_g \tag{9}$$

where $|G^*|_g$ is the dynamic shear modulus of asphalt binder at the glassy state (assumed to be 145,000 psi (999,050 kPa)), and the other variables are as previously defined.

Al-Khateeb model is a simpler form of the Hirsch model and was developed to overcome on one of the Hirsch model problems, which is the inaccurately predicting dynamic modulus of asphalt mixtures at low and high temperatures [21].

2.5. Global and Simplified Global Models

As one of the latest regressions attempts to predict dynamic moduli of asphalt mixtures, Sakhaeifar et al. [6] developed two closed-form models based on viscoelastic and time-temperature superposition principles. These models can predict asphalt dynamic moduli at a wide range of temperatures (e.g. -10, 4.4, 37.8, and 54.4 ºC) as recommended in AASHTO T312 Standard [22].

In order to develop the models, a large database was generated to include different mixture properties and binder characteristics. The first model, named “Global Model”, is presented in Equation 10 [6].

$$\begin{aligned}\log|E^*| = {}& 6.1716 - 0.00269\rho_{34} - 0.00137\rho_{38} - 0.10641\rho_{200} - 0.05248V_a - 0.1774V_{beff} \\ & + 0.00618V_{beff}^2 + \frac{1.0154 + 0.08395\rho_{200} + 0.0142V_a + 0.17103V_{beff} - 0.00757V_{beff}^2}{1+e^{(-0.81189-0.54698X_G)}}\end{aligned} \tag{10}$$

$$X_G = log\left(\frac{2.4392 * 10^{-0.0004T^2+0.0135T-0.1003}}{\left[\left(\frac{145000}{|G^*|}\right)^{0.12332} - 1\right]^{7.72273}}\right) \tag{11}$$

where X_G is the predicted frequency by Equation 11, used in the main model (Equation 10) (Hz), T is temperature (ºC), and the other variables are as previously defined. The second model, named "Simplified Global Model", is presented in Equation 12 [6].

$$\begin{aligned}\log|E^*| &= 6.4197 - 0.00014\rho_{34}^2 - 0.00547\rho_{38} - 0.11786\rho_{200} - 0.05528V_a - 0.16266V_{beff} + 0.00487V_{beff}^2 \\ &+ \frac{0.57677 + 0.00713\rho_{38} + 0.16167\rho_{200} - 0.0052(\rho_{200})^2 + 0.01889V_a + 0.16031V_{beff} - 0.00592V_{beff}^2}{1 + e^{(1.8645 - 0.95991 log|G^*|)}}\end{aligned} \tag{12}$$

where all the variables are as previously defined.

3. Database

In this study, a published database developed based on various projects that were undertaken at the University of Maryland [1] was utilized for evaluation of dynamic modulus predictive models. This database consists of 1320 dynamic modulus test results from 66 asphalt mixes and covered a wide range of viscosity values, i.e. 20 binders at five test temperatures including -17.8, 4.4, 21.1, 37.8 and 54.4 ºC, and five aggregate gradations. All test samples used in the database were laboratory prepared by gyratory compaction. Cylindrical (2.75 in. diameter by 5.5 in. height) specimens were cored from each 6 in. diameter gyratory plug.

Laboratory dynamic modulus test was performed at these five temperatures and at four loading frequency including 0.1, 1, 10 and 25 Hz. In order to apply the predictive models to these data, binder viscosity values were needed for each mix at the temperatures at which the tests were actually performed. These values were obtained by using the linear relationship between log-log viscosity (cP) and log temperature (degrees Rankine), also known as the A and VTS relationship. The developed database, including mixture volumetric properties and binder viscosity parameters for all samples is presented in MEPDG, Appendix CC-4 [1].

4. Dynamic Modulus Prediction

Using the data in the mentioned database, asphalt dynamic moduli were predicted. For this purpose, six conventional asphalt dynamic modulus predictive models including Witczak, Modified Witczak, Hirsch, Al-Khateeb, Global and Simplified Global models were used. Predicted dynamic moduli for all samples at different temperatures and frequencies using these predictive models as well as laboratory measured ones are shown in Fig. 1. As it can be seen in this figure, the moduli predicted with Modified Witczak model are greater than the laboratory measured and the values predicted with the other models and has shown a large difference with them. Moduli predicted with Witczak and Global models are similar to the measured values to some extent.

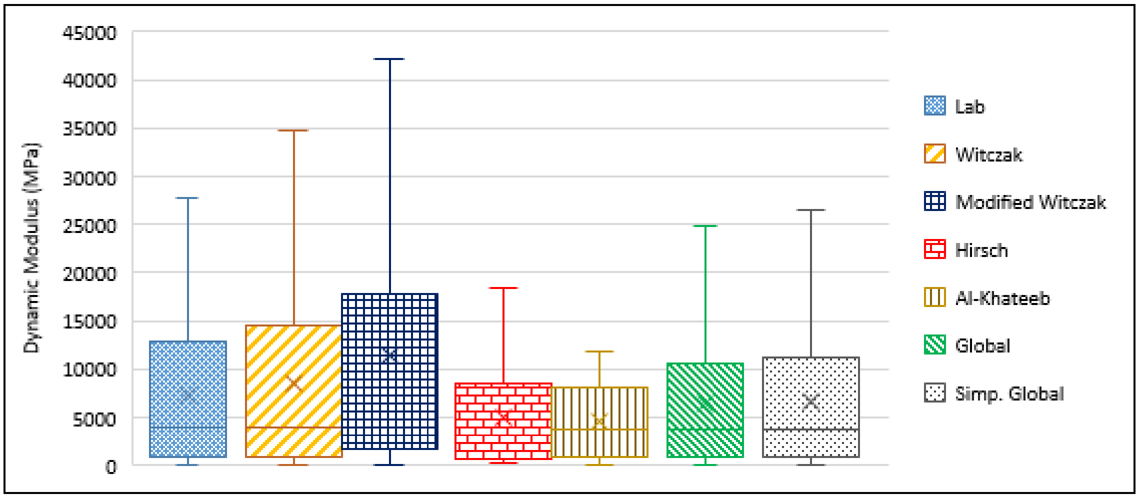

Fig. 1. Predicted moduli versus laboratory measured values for all samples.

5. Performance Evaluation

Fig. 2(a) through 2(f) show the predicted moduli versus laboratory measured values using six predictive models. These figures are presented in arithmetic space. As it can be seen in these figures, Witczak and Modified Witczak models overpredict the asphalt dynamic moduli; while the other models underpredict this parameter to some extent. For evaluation of prediction performance and accuracy of the mentioned models, two statistical criteria including goodness-of-fit and bias have been utilized in this study. For this purpose, the dynamic modulus was considered as the independent variable, the errors about the line of equality (LOE) were defined as it follows:

$$SSE = \sum [|E^*|_P - E_m]^2 \tag{13}$$

$$S_e = \sqrt{\frac{SSE}{n-1}} \tag{14}$$

$$S_y = \sqrt{\frac{\sum [E_m - \bar{E}_m]^2}{n-1}} \tag{15}$$

where SSE is sum of squared error, $|E^*|_P$ is predicted dynamic modulus, E_m is measured modulus, S_e is standard error (standard deviation of errors), S_y is standard deviation of the measured values about the mean dynamic modulus, and n is the number of observations.

For calculation of prediction accuracy, S_e/S_y, the standard error over the standard deviation of laboratory measured values ratio, and R^2, coefficient of determination with reference to the line of equality (Equation 16) were used. Higher R^2 indicates higher accuracy. The S_e/S_y is an indicator for the relative improvement in accuracy and that means smaller value points out better accuracy. In Table 1, statistical criteria for correlation between the measured and the predicted values are reported [23].

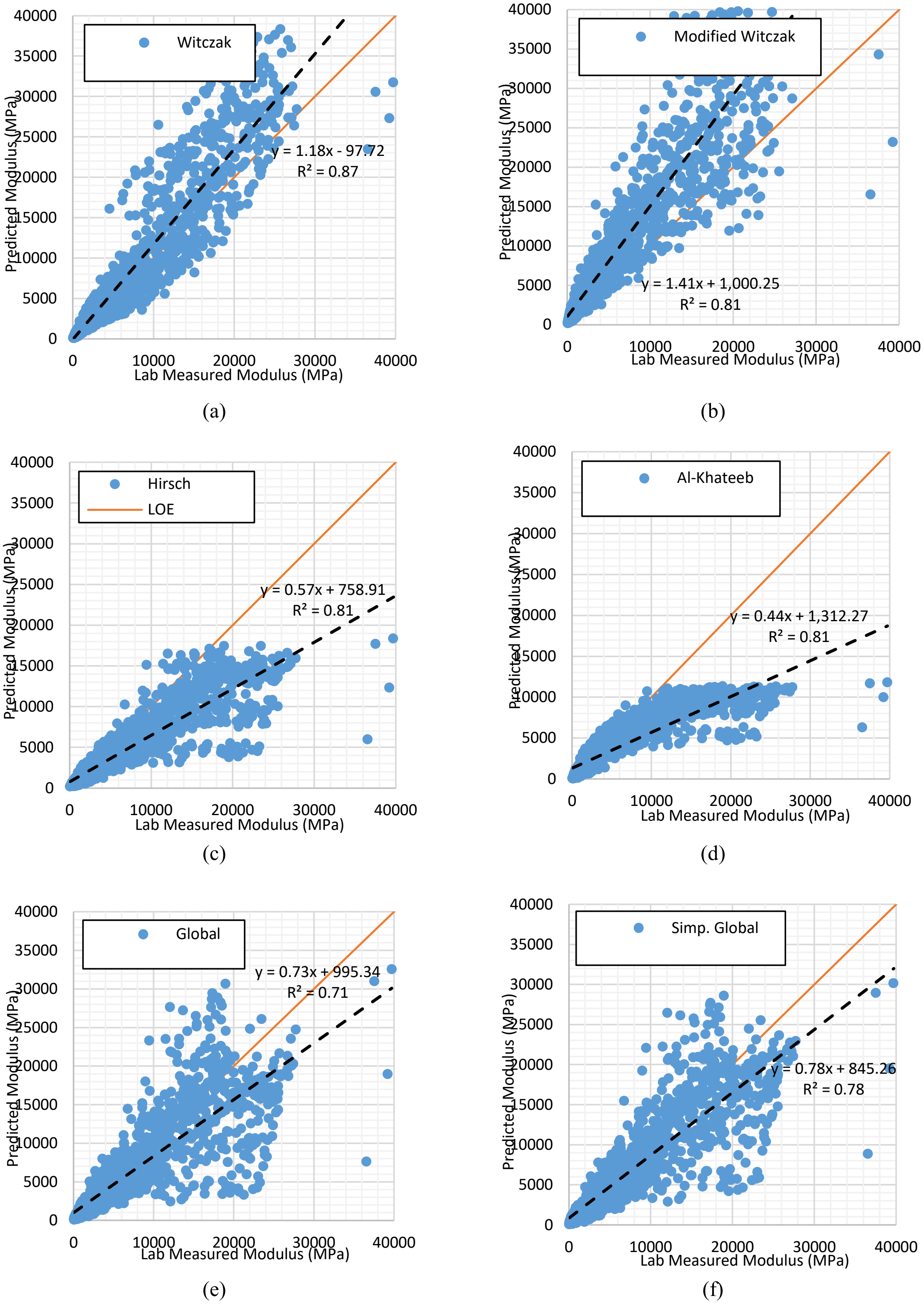

Fig. 2. Predicted dynamic moduli versus laboratory measured values.

$$R^2 = 1 - \frac{n-p}{n-1}\left(\frac{S_e}{S_y}\right)^2 \quad (16)$$

where p is the number of model parameters.

Table 1. Statistical criteria for correlation between the measured and the predicted values [23].

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

The overall goodness-of-fit statistics including S_e/S_y and R^2 do not show the whole story about the model accuracy. Hence, prediction bias, in terms of slope and intercept of the trend line of predicted versus measured moduli were utilized. The goodness-of-fit statistics in Equations 13 through 16 are defined about the line of equality. This line is a linear trend line for which the intercept is constrained to pass through the origin and the slope is constrained to unity. One measure of the overall bias in the model predictions is how closely the unconstrained linear trend line matches the line of equality. That means how close the unconstrained intercept and slope are to 0 and 1, respectively. The closer the intercept is to zero and the slope is to unity, the lower the bias [9].

Using data of asphalt mixtures, the overall performance of the investigated predictive models is presented in Table 2. As it can be seen in this table, the R^2 values ranged from 0.09 for Modified Witczak model to 0.77 for Simplified Global model. The other statistic, i.e. S_e/S_y ranged from 0.48 for Simplified Global model to 0.96 for Modified Witczak model. As it is mentioned in this table, Witczak, Global and Simplified Global models have “Good”, Hirsch and Al-Khateeb models have “Fair”, and Modified Witczak model has “Very Poor” correlations between predicted and laboratory measured moduli. Moreover, the parameters of trend line show that the slope values ranged from 0.438 for Al-Khateeb model to 1.408 for Modified Witczak model and the intercept values ranged from 98 for Witczak model to 1312 for Al-Khateeb model.

Table 2. Statistical parameters for overall performance of investigated models.

Performance Parameter	Predictive Model					
	Witczak	Modified Witczak	Hirsch	Al-Khateeb	Global	Simplified Global
SSE	2.0E+10	7.2E+10	2.8E+10	3.9E+10	2.4E+10	1.8E+10
S_e	3910	7364	4607	5433	4241	3712
S_e/S_y	0.51	0.96	0.60	0.70	0.55	0.48
R^2 (LOE)	0.74	0.09	0.64	0.50	0.70	0.77
Correlation	Good	Very Poor	Fair	Fair	Good	Good
Slope	1.179	1.408	0.571	0.438	0.733	0.784
Intercept	98	1000	759	1312	995	845

Figs. 3 and 4 compare respectively the overall accuracy (goodness-of-fit) and bias for all investigated dynamic modulus predictive models using laboratory measured moduli from the database used in this study. According to Fig. 3, Witczak and Simplified Global predictive models with the smaller values for $1-R^2$ and S_e/S_y, have the highest accuracy and the Modified Witczak model with the largest values, has the lowest prediction accuracy among the other models. In addition, Fig. 4 shows that Witczak model with the smallest values for $1 - Slope$ and $Intercept$ has the lowest bias among the other models. On the other hand, the highest bias belongs to the Modified Witczak model with the greater values for the mentioned statistics. This figure shows that the other models yield biased predictions to some extent. This result is expected due to the fact that Witczak model was developed based on the utilized database [2].

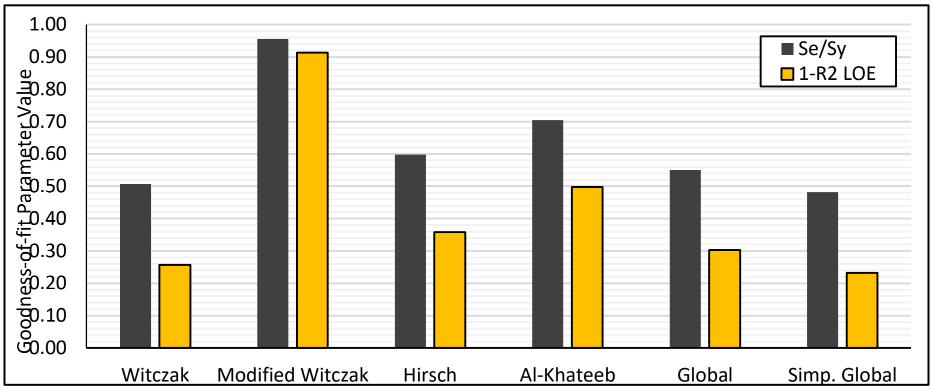

Fig. 3. Goodness-of-fit evaluation of dynamic modulus predictive models.

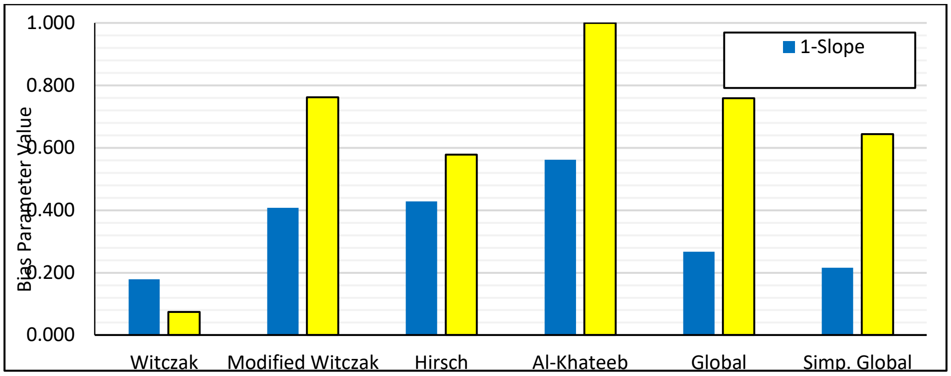

Fig. 4. Bias evaluation of dynamic modulus predictive models.

6. Conclusions

In this study six conventional dynamic modulus predictive models were investigated and following findings were obtained:

- Feasibility investigation of using six dynamic modulus predictive models including Witczak, Modified Witczak, Hirsch, Al-Khateeb, Global and Simplified Global models showed that it is possible to determine dynamic moduli of asphalt mixtures using these models; although improvement of prediction accuracy is necessary.
- The best prediction performance ordinary belonged to Witczak, Simplified Global, Global, Hirsch, Al-Khateeb and Modified Witczak models.
- Among the all investigated predictive models, the best prediction performance was belonged to "Witczak model" with high prediction accuracy and low prediction bias. It should be noted that, this result was expected due to the fact that Witczak model was developed based on the utilized database.

REFERENCES

[1] ARA. (2004). "Guide for mechanistic-empirical design of new and rehabilitated pavement structures" (NCHRP 1-37A, National Cooperative Highway Research Program). Transportation Research Board, National Research Council, Washington, D.C.

[2] Andrei, D., Witczak, M. W. and Mirza, M. W. (1999). "Development of a revised predictive model for the dynamic (complex) modulus of asphalt mixtures" (Inter Team Technical Rep. prepared for the NCHRP 1-37A Project). Department of Civil Engineering, University of Maryland, College Park, MD.

[3] Bari, J. and Witczak, M. W. (2006). "Development of a new revised version of the Witczak E* predictive model for hot mix asphalt mixtures", Journal of Association of Asphalt Paving Technology, 75, 381-417.

[4] Christensen, D. W., Pellinen, T. and Bonaquist, R. F. (2003). "Hirsch model for estimating the modulus of asphalt concrete", Journal of the Association of Asphalt Paving Technologists, Vol. 72, pp. 97-121.

[5] Al-Khateeb, G., Shenoy, A., Gibson, N. and Harman, T. (2006). "A new simplistic model for dynamic modulus predictions of asphalt paving mixtures", Journal of the Association of Asphalt Paving Technologists, Vol. 75, pp. 1254-1293.

[6] Sakhaeifar, M. S., Kim, Y. R. and Kabir, P. (2015). "New predictive models for the dynamic modulus of hot mix asphalt", Construction and Building Materials, No. 76, pp. 221-231. doi: http://dx.doi.org/10.1016/j.conbuildmat.2014.11.011

[7] Solatifar, N. (2018). "Analysis of Conventional Dynamic Modulus Predictive Models of Asphalt Mixtures", Amirkabir Journal of Civil Engineering. doi: http://dx.doi.org/10.22060/ceej.2018.15006.5811

[8] Ceylan, H., Gopalakrishnan, K. and Kim. S. (2008). "Advanced approaches to hot-mix asphalt dynamic modulus prediction", Canadian Journal of Civil Engineering, Vol. 35, No. 7, pp. 699-707. doi: http://dx.doi.org/10.1139/L08-016

[9] Ceylan, H., Schwartz, C. W., Kim. S. and Gopalakrishnan, K. (2009). "Accuracy of predictive models for dynamic modulus of hot-mix asphalt", Journal of Materials in Civil Engineering, Vol. 21, No. 6, pp. 286–293. doi: http://dx.doi.org/10.1061/(ASCE)0899-1561(2009)21:6(286)

[10] Sakhaeifar, M. S., Underwood, B. S., Kim, Y. R., Puccinelli, J. and Jackson, N. (2010). "Development of artificial neural network predictive models for populating dynamic moduli of long-term pavement performance sections", Transportation Research Record: Journal of Transportation Research Board, No. 2181, pp. 88–97. doi: http://dx.doi.org/10.3141/2181-10

[11] Loulizi, A., Flintsch, G. W. and McGhee, K. (2007). "Determination of the in-place hot-mix asphalt layer modulus for rehabilitation projects by a mechanistic-empirical procedure", Transportation Research Record: Journal of the Transportation Research Board, 2037, 53-62. doi: http://dx.doi.org/10.3141/2037-05

[12] Kavussi, A., Solatifar, N. and Abbasghorbani, M. (2016). "Mechanistic-empirical analysis of asphalt dynamic modulus for rehabilitation projects in Iran", Journal of Rehabilitation in Civil Engineering, Vol. 4, No. 1, pp. 18-29. doi: http://dx.doi.org/10.22075/jrce.2016.488

[13] Solatifar, N., Kavussi, A., Abbasghorbani, M. and Katicha, S. W. (2019). "Development of dynamic modulus master curves of in-service asphalt layers using MEPDG models", Road Materials and Pavement Design, 20(1), 225-243. doi: https://doi.org/10.1080/14680629.2017.1380688

[14] Biswas, K. G. and Pellinen, T. K. (2007). "Practical methodology of determining the in situ dynamic (complex) moduli for

engineering analysis", Journal of Materials in Civil Engineering, 19(6), 508-514. doi: http://dx.doi.org/10.1061/(ASCE)0899-1561(2007)19:6(508)

[15] Seo, J., Kim, Y., Cho, J. and Jeong, S. (2013). "Estimation of in situ dynamic modulus by using MEPDG dynamic modulus and FWD data at different temperatures", International Journal of Pavement Engineering, Vol. 14, No. 4, pp. 343–353. doi: https://doi.org/10.1080/10298436.2012.664274

[16] Georgouli, K., Pomoni, M., Cliatt, B. and Loizos, A. (2015). "A simplified approach for the estimation of HMA dynamic modulus for in service pavements", 6th International Conference 'Bituminous Mixtures and Pavements', Thessaloniki, Greece: 10-12 Jun.

[17] Solatifar, N., Kavussi, A., Abbasghorbani, M. and Sivilevičius, H. (2017). "Application of FWD data in developing dynamic modulus master curves of in-service asphalt layers". Journal of Civil Engineering and Management, 23(5), 661-671. doi: http://dx.doi.org/10.3846/13923730.2017.1292948

[18] ASTM. (2009). "Standard viscosity-temperature chart for asphalts" (D2493/D2493M-09). West Conshohocken, PA. doi: http://dx.doi.org/10.1520/D2493_D2493M-09

[19] El-Badawy, S., Bayomy, F. and Awed, A. (2012). "Performance of MEPDG dynamic modulus predictive models for asphalt concrete mixtures: local calibration for Idaho", Journal of Materials in Civil Engineering, 24(11), 1412-1421. doi: http://dx.doi.org/10.1061/(ASCE)MT.1943-5533.0000518

[20] Witczak, M. W., El-Basyouny, M., & El-Badawy, S. (2007). "Incorporation of the new (2005) E* predictive model in the MEPDG", (NCHRP 1-40D Inter-Team Technical Rep.). Tempe: Arizona State University.

[21] Kim, Y. R., Underwood, B. S., Sakhaeifar, M. S., Jackson, N. and Puccinelli, J. (2011). "LTPP computed parameter: dynamic modulus", Final Report for Project: DTFH61-02-D-00139, Federal Highway Administration, Washington, D.C.

[22] AASHTO. (2012). "Standard method of test for determining the rheological properties of asphalt binder using a dynamic shear rheometer (DSR)", AASHTO Designation: T 315-12.

[23] Pellinen, T. K. (2001). "Investigation of the use of dynamic modulus as an indicator of hot-mix asphalt performance", Thesis (PhD). Arizona State University.