Predicting Flow Number of Asphalt Mixtures Based on the Marshall Mix design Parameters Using Multivariate Adaptive Regression Spline (MARS)

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Received: 05.05.2019 Accepted: 04. 02. 2020

ABSTRACT

Rutting is one of the major distresses in the flexible pavements, which is heavily influenced by the asphalt mixtures properties at high temperatures. There are several methods for the characterization of the rutting resistance of asphalt mixtures. Flow number is one of the most important parameters that can be used for the evaluation of rutting. The flow number is measured by the dynamic creep test, which requires advanced equipment, notable cost, and time. This paper aims to develop a mathematical model for predicting the flow number of asphalt mixtures based on the Marshall mix design parameters using the Multivariate Adaptive Regression Spline (MARS). The required parameters for developing the model are as follows: percentage of fine and coarse aggregates, bitumen content, air voids content, voids in mineral aggregates, Marshall Stability, and flow. The coefficient of determination (R^2) of the model for training and testing set is 0.96 and 0.97, respectively, which confirms the high accuracy of the model. Moreover, the comparison of the developed model with the existing models shows the superior performance of the developed model. It should be noted that the developed model is valid only in the range of dataset used for the modeling.

Keywords: Flow number, rutting, marshall mix design parameters, multivariate adaptive regression spline (MARS)

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1. Introduction

Permanent deformation or rutting is one of the most commonly distresses in flexible pavements, which results in deformations of the road surface in the wheel's path. The main cause of rutting is the plastic deformation of pavement materials due to the repeated loading of vehicles [Kaloush 2001]. The rutting not only decreases the service life of the pavement due to longitudinal and transversal pavement surface distortions but also reduces the vehicle's safety due to increasing the potential of hydroplaning [Sousa et al. 1991; Alavi et al. 2010; Gandomi et al. 2011]. The rutting decreases the asphalt layer thickness, which leads to increase cracking potential of asphalt layer [Bahuguna 2003]. The previous studies showed that the rutting is the most common type of pavement distresses, and fatigue and thermal cracks were placed in the next ranks, respectively [FHWA 1998]. Therefore, the construction of asphalt mixtures with an acceptable level of resistance against rutting is essential [Sousa et al. 1991, Zhou et al. 2004, Alavi et al., 2010]. Characteristics of the aggregates, bitumen content, and volumetric specifications of asphalt mixtures are some of the key parameters that affect the rutting resistance. The most existing models for predicting the permanent deformation are empirical or semi-empirical that be developed for specific conditions and materials [Alavi et al. 2010]. The dynamic creep test is one of the best methods to investigate the rutting potential of asphalt mixtures [Kaloush and Witczak 2002]. The previous studies showed that the number of loading cycles to reach the third stage of the creep curve (flow number), is an appropriate index for evaluating the rutting resistance of asphalt mixtures [Alavi et al. 2010, Kim 2008]. Witczak (2002) defined the flow number as the number of loading cycles required to reach the third stage of the creep curve in the dynamic creep test. The flow number indicates the resistance against the shear deformation due to the dynamic loading [Williams et al. 2007]. The previous research also showed a logical relation between the permanent strain and the flow number. Therefore, most researchers have accepted the flow number as the best index of rutting potential for the asphalt mixtures [Zhou et al. 2004].

Application of the dynamic creep test to measure the flow number is time consuming and requires expensive and high technology equipment. Therefore, developing a model for predicting the flow number based on the Marshall mix design parameters is very useful and practical. The soft computing methods have emerged as powerful tools for modeling of complicated engineering problems during the last two decades. Some of these methods can be mentioned as the Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Support Vector Machine (SVM). These tools have been used in various fields of pavement engineering in recent years [Saltan and Terzi 2005, Fakhri and Ghanizadeh 2014, Ghanizadeh and Ahadi 2015, Ghanizadeh 2017, Gu et al. 2018, Ghanizadeh and Fakhri 2018, Georgiou et al. 2018, Kaya et al. 2018, Nivedya and Mallick 2018, Najafi et al. 2019]. Mirzahosseini et al. (2011) used the Multi Expression Programming (MEP) and Multilayer Perceptron (MLP) Neural Network to evaluate the rutting potential of asphalt mixtures. Gandomi et al. (2011) developed a model for predicting the flow number of asphalt mixtures using the Gene Expression Programming (GEP). Moreover, Alavi et al. (2010) employed the GP/SA method (hybrid genetic programming and simulated annealing) to predict the flow number of asphalt mixtures. In the most recent effort, Yan et al. (2014) implemented the Support Vector Machine (SVM) to predict the flow number. They showed that the performance of developed model based on the SVM is better than the multiple linear regression and gene expression programming models.

Jerome H. Friedman (1991) introduced the Multivariate Adaptive Regression Spline (MARS) as one of the nonparametric regression methods. The main advantage of the MARS in comparison with the other computational intelligence methods (e.g., ANN, SVM, and ANFIS) is its ability to generate a simple regression equation for predicting unknown parameters. However, the required computations for simulation of ANN, SVM, and ANFIS are more complex and cannot be performed manually. In recent years, the MARS method is highly regarded by some researchers [Ghanizadeh and Fakhri 2014, Goh et al. 2018, Bhattacharya et al. 2018, Khadka et al. 2018, Ashrafian et al. 2018, Zhang and Goh 2018, Mohanty et al. 2018, Zhang et al. 2019]. In this study, a MARS model was developed to predict the flow number of asphalt mixtures based on the Marshall mix design parameters, including gradation, air void, voids in mineral aggregate, Marshall stability, and flow. The experimental dataset was adapted from Mirzahosseini et al. (2011) paper. After developing the model based on the MARS method, the results were compared with other models and the effects of Marshall mix design parameters on the flow number were evaluated by performing the parametric analysis.

2. Multivariate Adaptive Regression Splines (MARS)

The Multivariate Adaptive Regression Spline (MARS) is one of the nonparametric regression models [Friedman, 1991]. Compared to the other models, which only a set of coefficients are applied to the data, the MARS recognizes complex patterns for each subset of data by fitting the regional polynomial functions [Friedman, 1991]. In other words, the MARS divides the data into subsets, and according to the complexity of each subset, it tries to fit the functions called basis functions. The MARS model can be expressed as Equation 1 [Samui 2013]:

$$f(X) = \alpha_0 + \sum_{m=1}^{M} \alpha_m BF_m(X) \tag{1}$$

In which α_0 is the intercept parameter, and M is the number of non-zero terms, or the nodes. This function consists of an intercept parameter α_0 and the sum of weighted (by α_m) basis functions ($BF_m(X)$), which is determined by the following equation:

$$BF_m(X) = \prod_{i=1}^{k_m} \left[S_{i,m}(X_{v(i,m)} - t_{i,m}) \right]_+^q \tag{2}$$

In which K_m is the order of interaction between variables in the mth basis function, i is the number of independent input variables of the model, $S_{i,m} = \pm 1$, $X_{v(i,m)}$ is the vth variable where $1 \leq v(i,m) \leq k$, k is the number of variables, and $t_{i,m}$ is knot location in each of the variables that predict the dependent variable. For example, if m = 2 and K_m= 2, it means that in the second basis function a parabola (including two independent variables) is fitted to the independent input variables. Moreover, q is the basis function power. For example, if q = 1, a simple linear spline function is fitted to the data. The expression $[\, S_{i,m}\left(X_{v(i,m)} - t_{i,m}\right)]_+^q$ is as follow:

$$\left[S_{i,m}(X_{v(i,m)} - t_{i,m}) \right]_+^q = \begin{cases} S_{i,m}(X_{v(i,m)} - t_{i,m}) & \forall\ S_{i,m}(X_{v(i,m)} - t_{i,m}) > 0 \\ 0 & otherwise \end{cases} \tag{3}$$

Determining the number and location of the knots in the MARS is carried out in both the forward and backward stepwise. During the forward stepwise, the model starts with a constant term, and then the basis functions are repeatedly added to the fixed term. Only the basis functions, which will have the greatest effect on reducing the sum of squared residuals, can be added. The forward stepwise often leads to more-fitting to the data. In other words, a model is created, which has the greatest fit with the training data. To avoid over-fitting, the backward procedure is required. The purpose of this step is to summarize the model and remove the basis functions that have the least impact. To determine the sub-models with the least impact, validation is used to create a balance between the fitting ability and complexity of the model. In the forward stage, by increasing the number of basis functions, the fitting ability, as well as complexity, will be increased. But in the backward stage, by removing the basis functions with the least impact, the fitting ability, as well as complexity of the model, will be decreased. In the MARS method, the Generalized Cross Validation (GCV) is used to evaluate the error and measure the goodness of fit. The GCV is determined using the following equation [Hastie et al. 2009, Milborrow 2014].

$$\mathrm{GCV}\left(M\right)=\frac{\left(1/n\right)\sum_{i=1}^{n}\left[y_i-\hat{f}\left(X_i\right)\right]^2}{\left[1-\left(C\left(M\right)/n\right)\right]^2} \tag{4}$$

Where y_i is the actual value of the data, $\hat{f}(X_i)$ is the predicted value of the data, n is the total number of observations, and C (M) is the cost of the model, which includes the M basis functions. In other words, C (M) is the number of effective degree of freedom, according to which, the GCV adds a cost with increasing the input variables of the model. C (M) is determined as follows [Friedman 1991]:

$$C\left(M\right)=M\times d \tag{5}$$

In which, d is the penalty for adding a basis function that be selected between 2 and 4. Actually, the numerator in Equation 4, shows the amount of non-fit in the M fitted functions, and the denominator shows the cost of model complexity.

3. Dataset

In this study, the developed dataset by Mirzahosseini et al. (2011) was adopted for the modeling of asphalt mixtures flow number. This dataset consists of the dynamic creep test results on the various asphalt mixtures fabricated using nine different gradation types and different bitumen contents. The asphalt mix specimens were fabricated based on three grading systems presented by the Code 234 of IRAN Plan and Budget Organization, including the upper, middle, and lower limits of grading 3, 4, and 5. Moreover, the following percentage of the bitumen with the penetration of 60/70 were applied for the samples preparation:

1. Grading No. 3: 4%, 4.5%, 5%, 5.5% and 6%.
2. Grading No. 4: 4.5%, 5%, 5.5%, 6% and 6.5%.
3. Grading No. 5: 5%, 5.5%, 6%, 6.5% and 7%.

The asphalt specimens were compacted with 75 blows on each side, and then subjected to a dynamic creep test. The stress level was chosen as 300 kPa for the repeated creep tests. Before the creep tests, the specimens were put into the chamber for at least four hours, in order to have uniform temperature distributions. All of the repeated creep tests were carried out at 45 ^{o}C. The dynamic creep test was performed in accordance with the Australian Standard AS 2891.12.1 [Mirzahosseini et al. 2011]. According to the experiments conducted by Mirzahosseini et al., the dataset consists of 118 records with the different independent and dependent variables, including the percentage of coarse aggregates (C%), percentage of fine aggregates (S%), filler percentage (F%), air voids (V_a%), voids in mineral aggregate (VMA%), bitumen content (BP%), Marshall stability (M_{kN}), Marshall flow (F_{mm}), and flow number (F_n). Table 1 shows the statistical characteristics of the input, and output parameters in the dataset.

4. Predicting the flow number using the MARS

To develop and validate the MARS model, the STATISTICA program was employed and 70% of the data (83 records) were considered as the training set, and the remaining ones (35 records) were considered as the testing set. Using the trial and error method, the minimum number of basis functions, as well as the degree of interaction, were determined.

Table 1. Statistical characteristics of the input and output.

Statistical characteristics	Mean	Mode	Median	Minimum	Maximum	Variance
C (%)	57.3	68	57	33	81	205.32
S (%)	37.15	57	37	18	57	128.01
F (%)	5.54	10	6	1	10	10.06
BP (%)	5.5	5	5.5	4	7	0.66
V_a (%)	4.53	3.7	4.13	1.71	8.77	2.3
VMA (%)	15.55	16.25	16.6	13.2	19.04	1.99
M_{kN}	10.16	12.88	10.24	2.73	15.3	4.15
F_{mm}	3.5	3.3	3.44	2.1	4.75	0.38
F_n	227	60	240	22	510	20728.55

In this study, the optimal number of basis functions (M), and the interaction parameter (K_m) were determined as 24 and 6, respectively. The developed equation for predicting the flow number based on the MARS method is as follows:

$$\begin{aligned}
F_n &= 1090.5593 - 72.7297\times Max(0,\ S_{\%}-48) + \\
&31.0679\times Max(0,\ 48-S_{\%}) - \\
&46.6933\times Max(0,\ C_{\%}-33) - \\
&0.8227\times Max(0,\ C_{\%}-33)\times Max(0,\ S_{\%}-37) + \\
&.2572\times Max(0,\ C_{\%}-33)\times Max(0,\ 37-S_{\%}) - \\
&33.9787\times Max(0,\ VMA_{\%}-15.25) - \\
&6.6023\times Max(0,\ C_{\%}-33)\times \\
&Max(0,\ S_{\%}-37)\times Max(0,\ F_{mm}-3.55) + \\
&11.3133\times Max(0,\ C_{\%}-33)\times Max(0,\ S_{\%}-37)\times \\
&Max(0,\ Va_{\%}-4.36)\times Max(0,\ F_{mm}-3.55) - \\
&214.0952\times Max(0,\ Va_{\%}-5.27)\times Max(0,\ F_{mm}-3.14) - \\
&13.4087\times Max(0,\ 5.27-Va_{\%})\times Max(0,\ F_{mm}-3.14) - \\
&.4987\times Max(0,\ C_{\%}-33)\times Max(0,\ S_{\%}-37)\times \\
&Max(0,\ M_{Kn}-9.71)\times Max(0,\ 3.55-F_{mm}) - \\
&.7950\times Max(0,\ C_{\%}-33)\times Max(0,\ S_{\%}-37)\times \\
&Max(0,\ 9.71-M_{Kn})\times Max(0,\ 3.55-F_{mm}) + \\
&19.7710\times Max(0,\ 5.53-Va_{\%}) + \\
&17.8303\times Max(0,\ VMA_{\%}-15.25)\times Max(0,\ F_{mm}-2.94)
\end{aligned} \tag{6}$$

As can be seen, in the final model, the bitumen content (BP) parameter is missing. In fact, for the preliminary stage of developing MARS model the bitumen content (BP) was considered as an input parameter, but during the backward pruning stage of MARS, the less significant factors or factors relates to other factors may be removed.

In order to evaluate the accuracy of the model, the results of the flow numbers obtained from the MARS model were plotted against the experimental values. The performance of the model related to the training, testing, and all data were presented in Figures 1 to 3, respectively. The coefficient of determination (R^2), and the Root Mean Square Error (RMSE) are also presented. These values can be determined using the following equations:

$$\text{RMSE}=\sqrt{\frac{1}{M}\sum_{i=1}^{M}(h_i-t_i)^2} \tag{7}$$

$$R^2=\left[\frac{\sum_{i=1}^{M}(h_i-\bar{h}_i)(t_i-\bar{t}_i)}{\sqrt{\sum_{i=1}^{M}(h_i-\bar{h}_i)^2\sum_{i=1}^{M}(t_i-\bar{t}_i)^2}}\right]^2 \tag{8}$$

Where M denotes the number of data, h_i and t_i shows the actual and predicted value of the output parameters, and $\bar{h}_i$ and $\bar{t}_i$ are the average of the real and predicted output, respectively. It is evident that the higher value of R^2 and lower value of RMSE confirm the higher accuracy of the model.

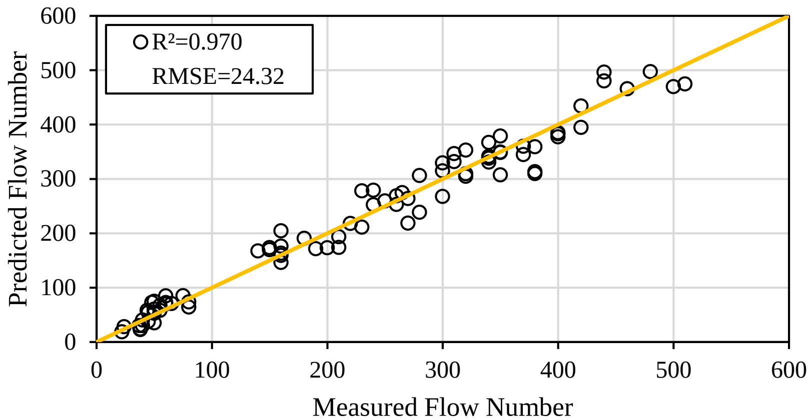

Figure 1. Performance of the MARS model for the training set.

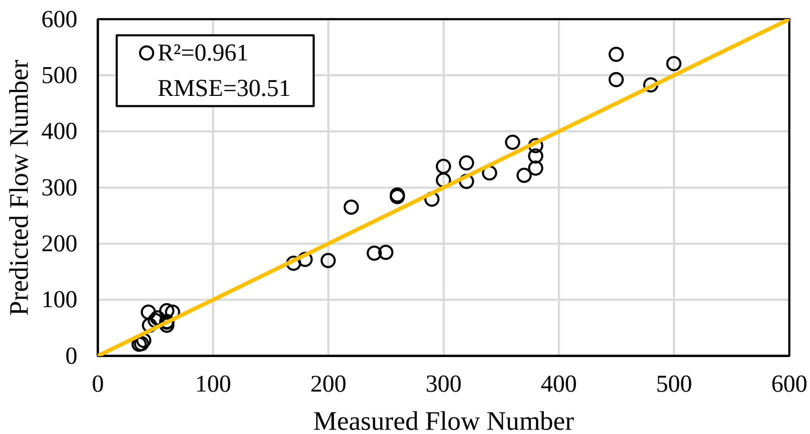

Figure 2. Performance of the MARS model for the testing set.

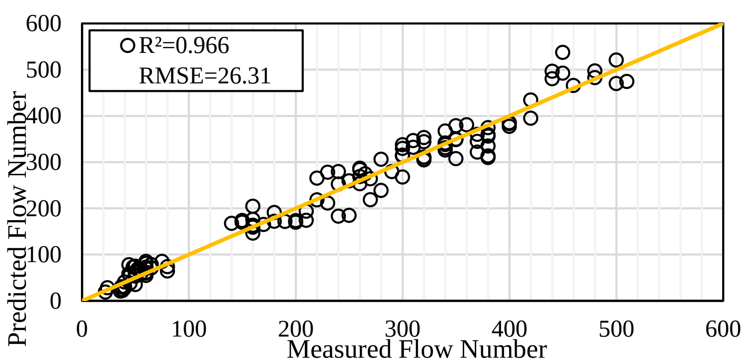

Figure 3. Performance of the MARS model for the tota

As can be seen from the figures, the coefficient of determination (R^2) is more than 0.96, which indicates the high accuracy of the developed model and the proper fitting of the predicted and measured flow numbers. It should be noted that the coefficient of determination for the training set (R^2= 0.970) is very close to the testing set (R^2 = 0.961), which indicates the generalizability of the developed MARS model. Table 2 summarizes the statistical results of the proposed model to predict the asphalt mixture flow number. As can be seen, the mean and standard deviation of the predicted and measured values are very close to each other and have a good match.

5. Parametric Analysis

The parametric analysis was performed to evaluate the effects of different Marshall mix design parameters on the flow number and validation of the MARS model. For this purpose, each independent variable was divided into nine intervals between the lowest and highest values, and the other values were assumed to be constant at three levels including the mean value, 10% less than the mean value and 10% more than the mean value. Figures (4) and (5) show the effects of the percentage of coarse and fine aggregates on the flow number of asphalt mixture, respectively. As can be seen from these figures, by increasing the coarse aggregates up to a certain value, the flow number will be increased and after that, it will be decreased. Therefore, to achieve asphalt mixtures with maximum rutting resistance, the fine and coarse aggregates content must be set to a certain values.

Table 2. Statistical Results of the MARS Model for Prediction of the flow number.

Data	Mean		Standard deviation		R^2	GCV
	Measured	Predicted	Measured	Predicted		
Training set	226.21	226.21	141.91	139.78	0.970	
Testing set	228.85	230.94	150.83	156.50	0.961	
Total data	227	227.62	143.97	144.28	0.966	1398.28

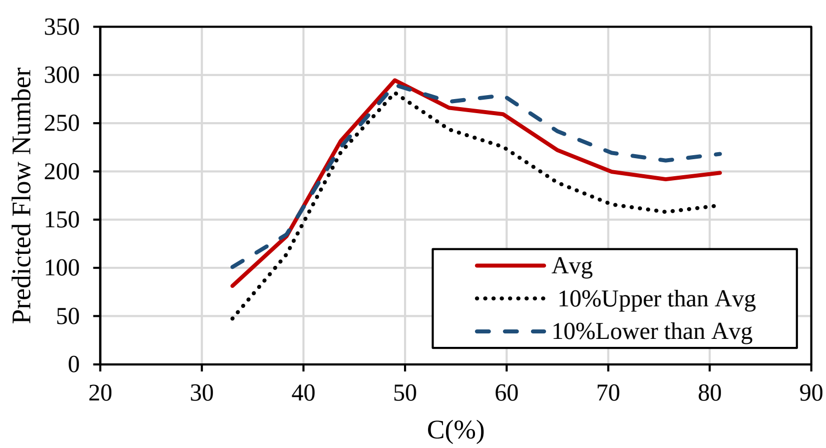

Figure 4. The effect of coarse aggregates on the flow number of asphalt mixtures.

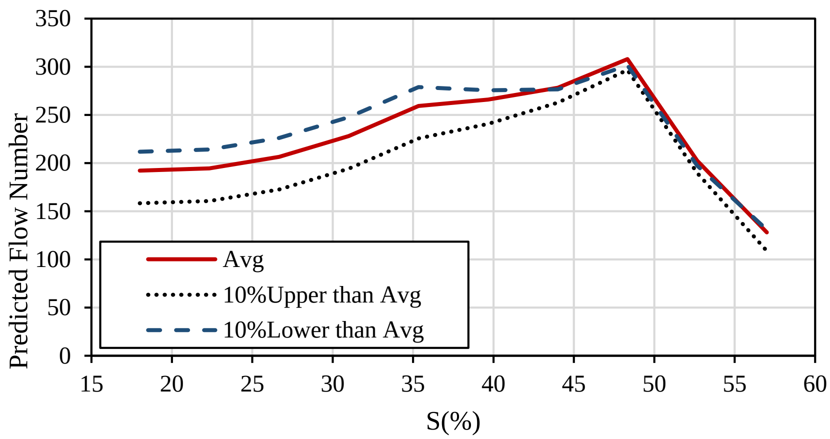

Figure 5. The effect of fine aggregates on the flow number of asphalt mixtures.

Figure 6 shows the effect of Void in mineral aggregate (VMA) on the Flow number of asphalt mixtures. It is evident that with increasing the VMA, up to a certain value (e.g., 15%), the flow number remains constant, and after that, the flow number decreases. Several studies have also shown that the asphalt mixtures with high rut resistant should have a low VMA [Cooper et al. 1985, Sousa et al. 1991, Pardhan 1995, Lavin 2003]. Figure 7 shows that by increasing the ratio of Marshall Stability to flow (M/F), the flow number was increased. Some studies have shown that, increasing the M/F ratio, resulted in better distribution of loads, and consequently, the rutting resistant of asphalt mixtures was increased [Zoorob and Suparma 2000, Hınıslıoglu and Agar 2004, Lavin 2003]. Figure 8 shows the effect of air voids on the flow number of asphalt mixture. As can be seen, the flow number decreases as the air voids of asphalt mixtures increases. In fact, due to air voids reduction, the asphalt mixtures becomes stiffer, leading to increased rutting resistance [Lavin 2003].

It should be noted that in all parametric analyzes all parameters are assumed to be constant and only one parameter is changed, whereas this is not possible in practice. In fact, changing one mixing parameter causes other parameters to change and one parameter cannot be changed individually without changing other parameters.

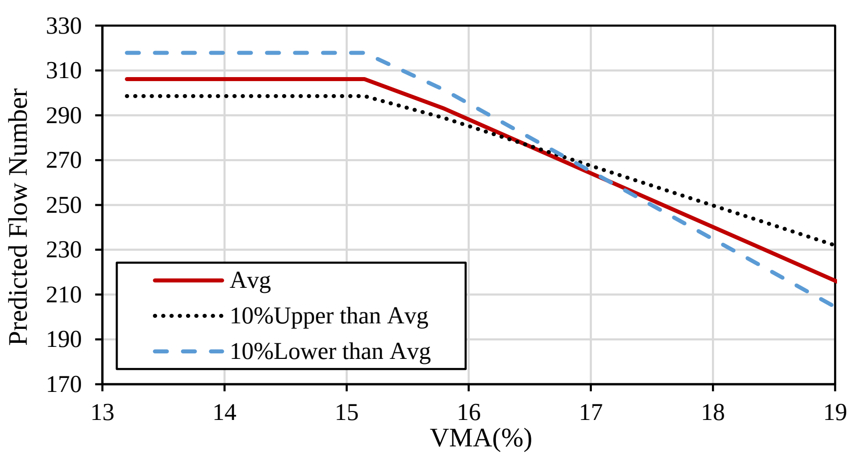

Figure 6. The effect of voids in mineral aggregate on the flow number of aphalt mixtures

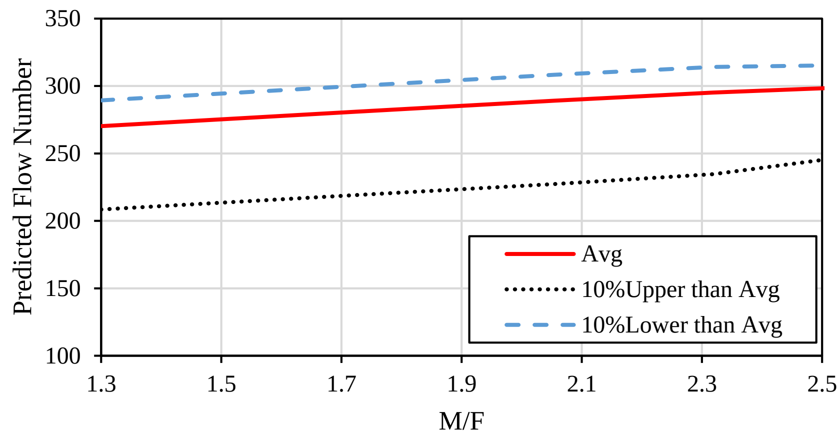

Figure 7. The effect of Marshall stability to flow ratio on the flow number of asphalt mixtures.

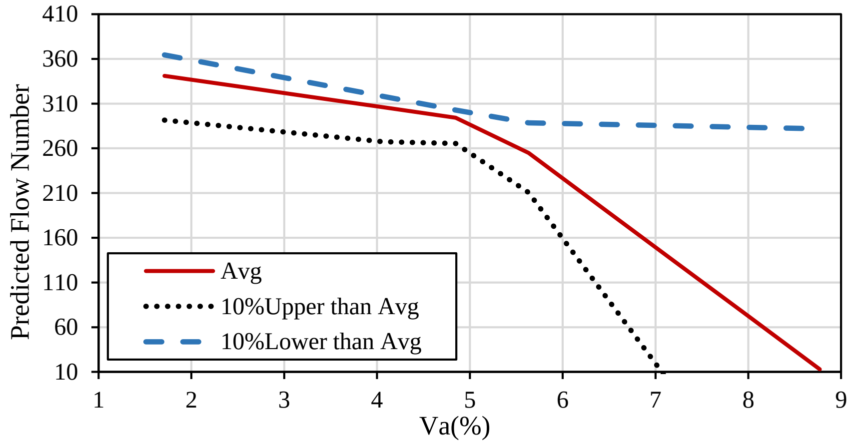

Figure 8. The effect of air voids on the flow number of asphalt mixtures.

6. Comparison of the MARS with the other models

In order to evaluate the ability of the MARS model to predict the flow number of asphalt mixtures, the results were compared with the other developed models for predicting flow number of asphalt mixtures based on the Marshall mix design parameters. These models include Multi Expression Programming (MEP) model developed by Mirzahosseini et al. (2011), the Gene Expression Programming (GEP) model, and the Multiple Least Squares Regression (MLSR) model developed by Gandomi et al. (2011) and the Support Vector Machine (SVM) model developed by Yan et al. (2014).

In each case, the best model developed by these researchers is selected and its results including the coefficient of determination (R^2) and RMSE are compared with the developed MARS model.

6.1. Multi Expression Programming (MEP)

The general form of the MEP model developed by Mirzahosseini et al. (2011) is as follows:

$$\log(F_n) = \frac{-4\times F_{\%} - B_{\%}{}^2}{VMA_{\%}\times Exp(F_{\%})} + \frac{F_{\%} + 2\times VMA_{\%} + 1/M_{kN}/F_{mm}}{VMA_{\%}} \tag{9}$$

In the Figure 9, the results of the flow numbers predicted by the MARS and MEP models have been presented. As can be seen, the MEP coefficient of determination (R^2 = 0.91) is less than the MARS model (R^2=0.966), which indicates a higher accuracy of the MARS model for predicting the flow number.

6.2. Gene expression programming (GEP)

Gandomi et al. (2011) developed six different models based on the gene expression programming and then selected the best one as follows:

$$\begin{aligned} Log(F_n) &= 0.362 + (16 + Va_{\%})/VMA_{\%} \\ &+ Log(0.602 + 7/Va_{\%}) + \\ &VMA_{\%}/(VMA_{\%} - M_{Kn}/F_{mm}) + \\ &C_{\%}/S_{\%}\times VMA_{\%}/5\times(M_{Kn}/F_{mm} - 9) \end{aligned} \tag{10}$$

The input parameters of this model were the percentage of air voids (Va%), percentage of coarse aggregates (C%), percentage of fine aggregates (S%), voids in mineral aggregate (VMA%), Marshall stability (M_{kn}) and Marshall flow (F_{mm}). The effect of the percentage of the filler was not considered in this model. The MARS and GEP model were compared in the Figure 10. As can be seen in this figure, the accuracy of the GEP model is much lower than the MARS model, so that the coefficient of determination of the GEP and MARS were 0.789 and 0.966, respectively.

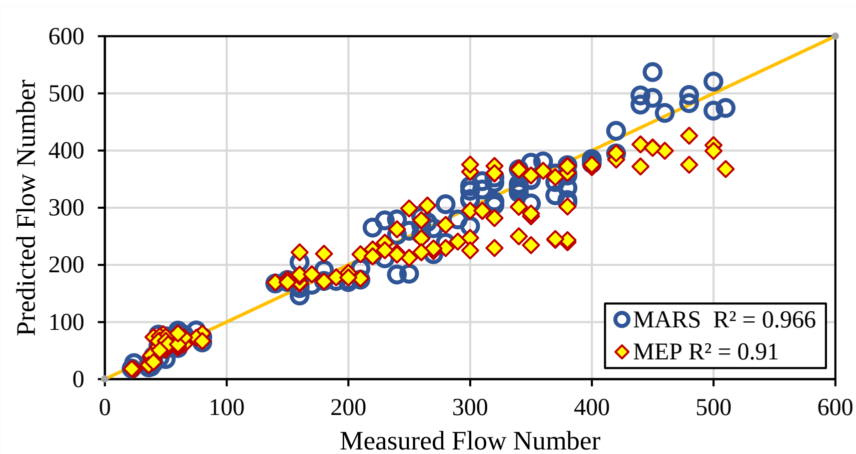

Figure 9. Comparison of the MARS and MEP for predicting the flow number of asphalt mixtures.

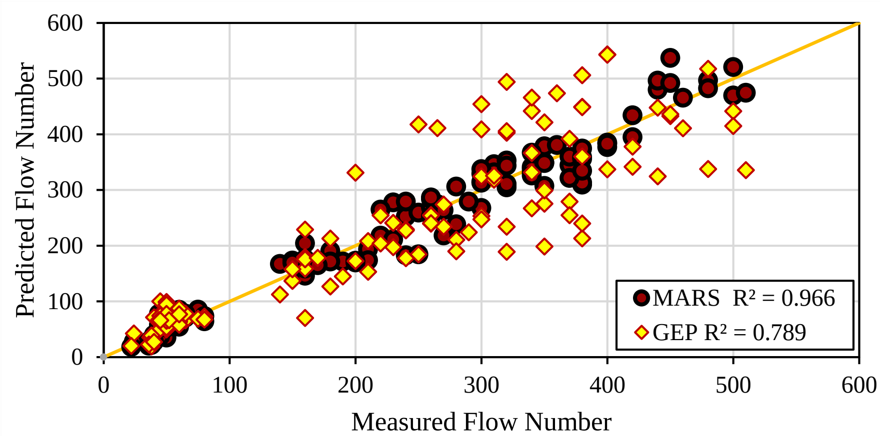

Figure 10. Comparison of the MARS and GEP for predicting the flow number of asphalt mixtures.

6.3. Multiple Least Squares Regression (MLSR)

The MLSR model has been widely used for its simplicity. Gandomi et al. used the MLSR method to predict the flow number of asphalt mixtures [Gandomi et al. 2011]. In this study, two equations developed by Gandomi et al. have been used. These equations are as follows:

$$\log(F_n) = -0.4893 \times C_{\%}/S_{\%} - 0.0019 \times V_{a\%} - 0.1490 \times VMA_{\%} - 0.0639 \times M_{(KN)}/F_{mm} + 5.7881 \quad (11)$$

In the equation 11, the ratio of coarse to fine aggregates, air voids, voids in mineral aggregate and the ratio of Marshall stability to flow were considered as the input parameters, while in the equation 12, the ratio of the coarse to fine aggregates, voids in mineral aggregate and the ratio of Marshall stability to flow were considered as the input variables.

$$\log(F_n) = -0.4886 \times C_{\%}/S_{\%} - 0.1492 \times VMA_{\%} - 0.0642 \times M_{(KN)}/F_{mm} + 5.7818 \quad (12)$$

The MARS model and the two proposed equations of MLSR were compared in the Figure 11. As can be seen, the accuracy of equation 11 with R^2 equal to 0.791 is very close to the accuracy of the equation 12 with R^2 equal to 0.790. It can also be seen that the accuracy of these two models are much lower than the MARS model.

6.4. Support Vector Machine (SVM)

In this section, the proposed model was compared with the model developed by Yan et al. based on the SVM method [Yan et al. 2014]. They developed various models based on different kernel functions, and then three models (SVM I, SVM II and SVM III) were selected as the best ones based on the RBF kernel function (Yan et al., 2014).

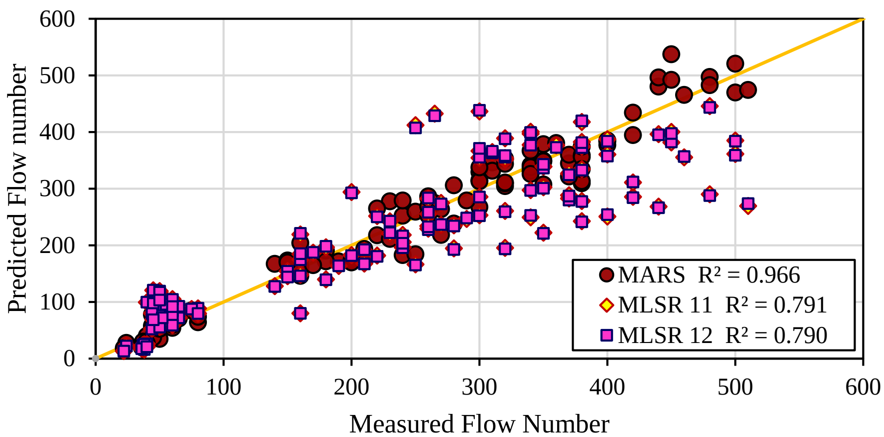

Figure 11. Comparison of the MARS and MLSR for predicting the flow number of asphalt mixtures.

In the SVM I model, four parameters including the coarse to fine ratio, air voids, voids in mineral aggregate and the Marshall stability to flow ratio, in the SVM II, the coarse to fine ratio, voids in mineral aggregate and the Marshall stability to flow ratio, and in the SVM III, two parameters, including the coarse to fine ratio and the voids in mineral aggregate were considered as the inputs [Yan et al. 2014]. The general form of the equation used in the SVM is complex and consists of several kernel functions that were not mentioned in the Yan et al. study. For this reason, the required data of models were extracted from the graphs. The ability of the MARS compared to the three SVM models was shown for the test and training sets in the Figures 12 and 13, respectively. As can be seen from the figures, the coefficient of determination (R^2) for the training and test set of the SVM I model was approximately equal to 0.93. Also, the R^2 for the training set of the SVM II and SVM III is 0.87 and 0.83, and for the test set, this value is equal to 0.91 and 0.90, respectively. As previously mentioned, the R^2 of the MARS method for the training and test set is 0.970 and 0.961, respectively, which indicates the higher accuracy compared to the SVM-based models.

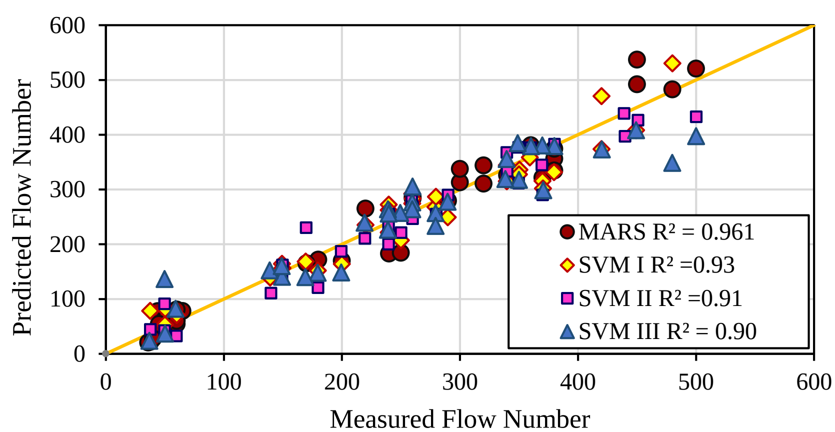

Figure 12. Comparison of the MARS and SVM models for the test data.

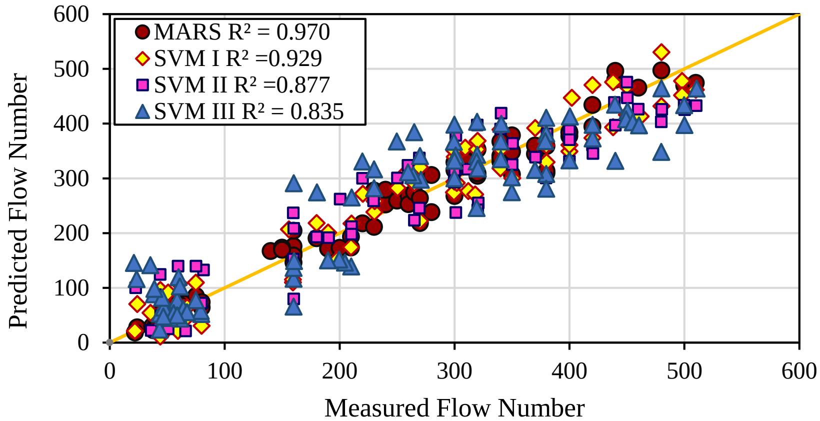

Figure 13. Comparison of the MARS and SVM models for the training data.

Figure 14 shows the Root Mean Square Error (RMSE) of different methods based on the training and test sets. As can be seen, the proposed model (MARS) has less error than the others. Therefore, the proposed model is more reliable to predict the flow number and rutting potential of asphalt mixtures.

7. Conclusion

In this paper, a Multivariate Adaptive Regression Spline model was developed to predict the flow number of asphalt mixtures based on the Marshall mix design parameters. To this end, a dataset consisting of 118 records of the flow number for different asphalt mixtures was employed. The inputs of the developed model were considered as the percentage of coarse and fine aggregates, air void, voids in mineral aggregate, Marshall stability and the Marshall flow, and the output was considered as the asphalt mixture flow number. The coefficient of determination for the MARS model was more than 0.96. The parametric analysis of the developed model indicates that the results of model is in accordance with the actual behavior of the asphalt mixtures. Also, the results confirms the superior accuracy of the proposed model in comparison with the other models. Therefore, the developed model can be used to predict the flow number without the need for any advanced laboratory tests and only based on the Marshall mix design parameters. It should be noted that the developed model is valid only in the range of gradation, bitumen contents, bitumen type, and testing conditions used in this study.

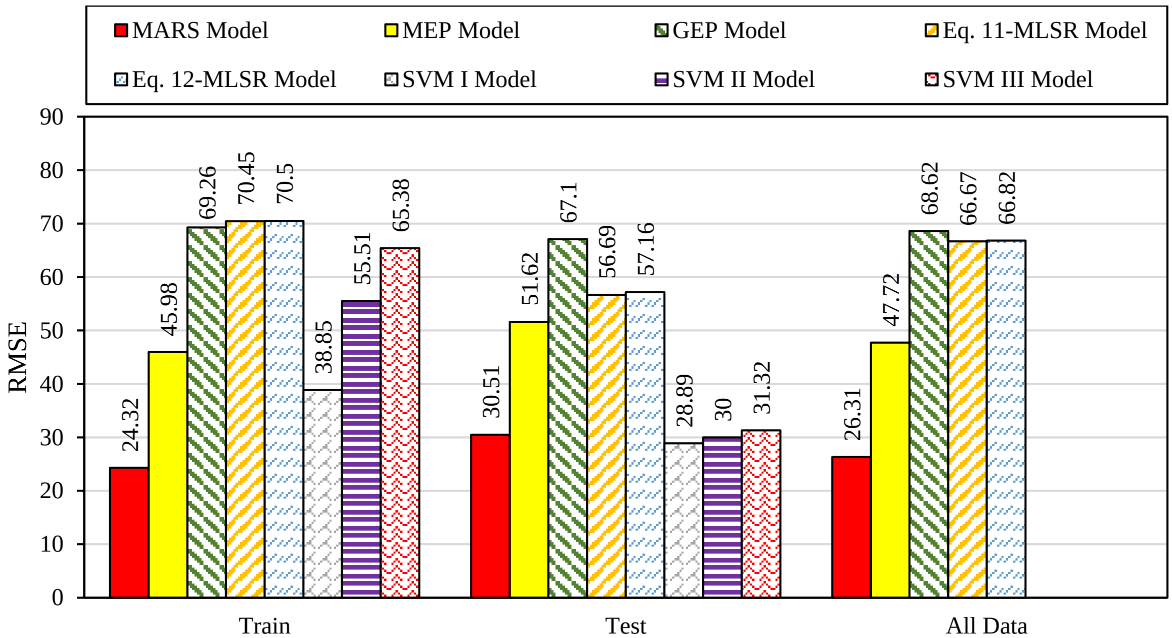

Figure 14. Comparison of the RMSE for different models.

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