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Modeling Marshall Test Results of Hot Mix Asphalt Using Nonlinear Genetic Programming Techniques

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ABSTRACT: The Marshall test method is widely used for the design and control of hot mix asphalt (HMA). The Marshall and modified Marshall mix design methods are most widely used in Iran. Determining Marshall test results (Marshall stability, flow, and Marshall quotient (MQ)) are time-consuming. Therefore, using new and advanced methods to determine the results of Marshall testing is essential. In this study, the genetic programming method based on artificial intelligence was used for the prediction of Marshall test results. Input variables in the genetic programming models use the volumetric properties of standard Marshall specimens such as air voids, voids in mineral aggregate (VMA), and voids filled with asphalt (VFA). Also, multiple linear regression models were used as the base model to evaluate the models presented by the genetic programming method. The results indicated that the proposed methods are more efficient than the laboratory costly method and the performance of the genetic programming model is completely satisfactory in comparison to the base model and has been able to predict the results of Marshall testing based on the input parameters. The GP models have a higher coefficient of determination and fewer errors than MLR models. The presented models will also help further researchers willing to perform similar studies, without carrying out destructive tests.

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1- Introduction

Bruce Marshall developed the very basic fundamentals of the Marshall design. In 1948, the U.S. Corps of Engineers, improved and built up certain milestones to Marshall's test procedure. Since this time, Marshall design has been adopted by organizations and government departments worldwide with very minor modifications [1]. The Marshall method of mix design is for dense graded hot mix asphalt (HMA). It is the predominant mix design method for airport pavements. Currently, the Marshall and modified Marshall mix design method are most widely used in Iran, and in the Iran Ministry of Road and Transportation, Management and Planning Organization journal (code. No.234), the use of this method for mix design of asphalt mixtures is suggested [2]. Basically, two mechanical properties, stability and flow, are determined for the asphalt specimens from the standard Marshall test. The ratio of stability and flow is known as the Marshall quotient (MQ). MQ indicates the stiffness of asphalt mixtures and is directly related to their resistance to permanent deformation. [3].

Marshall mix design in the lab is a time-consuming and costly process. In addition, the two parameters of Marshall stability and flow are the output of the Marshall test, which are obtained physically. Other parameters such as air voids (V_a), voids filled with asphalt (VFA), voids in mineral aggregate (VMA), bulk and maximum unit weight of mixture can be calculated by further calculations. Therefore, if the two parameters of Marshall stability and flow are calculated using other methods, the researchers will obtain the other parameters with a series of mathematical calculations.

Besides, the construction and development of roads are one of the basics of economic and cultural development in countries. Hence according to the high costs of asphalt implementation and maintenance, the necessity of using new and advanced methods in the design and quality control of asphalt is becoming more and more evident. One of these modern methods is artificial intelligence algorithms. Artificial neural networks (ANN) are widely used to determine patterns between different parameters. Therefore, several studies have been performed to evaluate the performance of asphalt mixtures using ANN. In the study performed by Hassani and Heydari Panah [4], artificial neural networks were used to predict the Marshall stability of asphalt. For this purpose, the percentages of different sieve crossings, the percentage of fractured faces, and the percentage of bitumen were considered as network inputs, Marshall stability as network outputs. The results show that by increasing the number of hidden layer neurons to 8, the simulation power of the networks is maximized, and a further increase of the hidden layer neurons has no significant effect on the network simulation power. In the next step, by analyzing the sensitivity by a network with the highest simulation power, the trend of changes in Marshall stability toward the percentage of fractured faces of

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aggregate was modeled. The results show that the strength of the Marshall stability of asphalt increases with an increasing percentage of fractured faces of aggregate, which is in line with the general trend.

Also, Ozgan [5] investigated the effect of two factors, temperature (30, 40 and, 50 °C) and loading times (1.5, 3, 4.5, 6 hours) on the Marshall stability of field samples and used ANN to model them. Laboratory results show that the Marshall stability of asphalt samples at 30 °C after 1.5 and 6 hours of loading decreases 40.16% and 62.39%, respectively. These reduction values at 40 °C are 74.31% and 78.10%, and at 50 °C are 83.22% and 88.66%. Also, the experimental results and the ANN model have shown good correlation, so the ANN method can be used to model the Marshall stability of asphalt samples. Also in another study, the Marshall stability of polyethylene modified asphalt samples was simulated by ANN and least squares support vector machine (LS-SVM) methods. Laboratory results showed that the use of polyethylene improved the Marshall properties of asphalt samples such as stability, flow, and air void. The two simulation methods used in this study use polyethylene, bitumen, and aggregate contents as input parameters to predict three variables of Marshall stability, flow, and the percentage of air void. Of the two methods used, the ANN-based model has much higher accuracy than the LS-SVM model [6].

Despite the acceptable performance of ANN-based models, they have disadvantages. ANN models often do not provide a specific relation for calculating the output parameter in terms of input parameters. Therefore, they do not provide a realization of the nature of the relationship created between different input and output data. Genetic programming (GP) provided by Koza [7] is an alternative way to present a model for solving civil engineering problems. GP is a supervised machine-learning technique that searches for a program space instead of a data space. Therefore, many researchers have used GP to find out any complex relationships between experimental data in civil engineering [8-11].

In this research, GP has been used to represent the Marshall test results models in asphalt mixtures. Therefore, Marshall stability, flow, and MQ relations are represented based on air void, VMA, and VFA parameters. Also, multiple linear regression (MLR) models were used as the base model to evaluate the models presented by the GP method.

2- Materials

2.1. Aggregate

Three types of aggregate with different characteristics have been used in this study to investigate the influence of aggregate type on Marshall test results. Thus, specific gravity, Los Angeles abrasion, the percent of flat and elongated particles, and durability tests have been conducted on three types of aggregate, and the results have been proposed in Table 1.The aggregates used in asphalt mixtures should have a definite gradation. In this research, o investigate the effect of gradation type on Marshall test results, three types of gradation were used that their specifications were presented in Fig.1. Also, the gradations used in this study are for dense-graded asphalt mixtures.

2.2. Bitumen

In the present study, bitumen with 60-70 and 85-100 penetration grades, which are two common types of bitumen in the investigated country, have been used. Also, in this study, to control the characteristics of two types of bitumen and to compare them with the existing standards, conventional tests such as penetration grade, ductility, softening point, and flash point have been done, and the results shown in Table 2.

3- Experimental

3.1. Mix design

In the current study, Marshall mix design based on ASTM D6927-15 standard is used to determine the optimum bitumen [12]. Hence, asphalt samples were made with 1200 g aggregate and different amounts of bitumen. According to the type of gradation a based on previous studies, the following amounts of bitumen used to prepare samples:

Gradation type 1: 4, 4.5, 5, 5.5, and 6%,

Gradation type 2: 4.5, 5, 5.5, 6, and 6.5%,

Gradation type 3: 5, 5.5, 6, 6.5, and 7%.

To simulate heavy traffic, each side of the cylindrical sample was hit 75 times. To achieve mix and compaction temperatures, the temperature-viscosity graphs were used. The mix temperature for mixtures containing bitumen with 60-70 penetration grade was determined as 168-173 °C, and its compaction temperature was determined as 150-155 °C. Also, these temperatures for mixtures containing bitumen with 85-100 penetration grade were determined 155-160 °C and 137-142 °C, respectively.

The stability of the mix is defined as a maximum load carried by a compacted specimen at a standard test temperature of 60^{0}C. The flow is measured as the deformation in units of 0.25 mm between no-load and maximum load carried by the specimen during the stability test. A useful factor in the assessment of mix quality is the stability to flow ratio (MQ). Besides, the bulk specific gravity and maximum specific gravity are calculated according to ASTM D2726 and ASTM D2041 standards for all asphalt samples, respectively. In the following, based on the properties of the materials, mixtures, and values obtained from the above experiments, the other volumetric properties of the asphalt mixtures were determined using the following equations:

$$V_a = \left(\frac{G_{mm} - G_{mb}}{G_{mm}} \right) \times 100 \tag{1}$$

$$V_a = \left(\frac{G_{mm} - G_{mb}}{G_{mm}} \right) \times 100 \tag{2}$$

$$VFA = \frac{100\left(VMA - V_a\right)}{VMA} \tag{3}$$

Table 1. The physical characteristics of used aggregates in this study

Test	Standard	Type 1	Type 2	Type 3	Specification limit
Specific gravity (coarse agg.)	ASTM C 127				
Bulk		2.47	2.52	2.56	-----
Saturated surface dry (SSD)		2.50	2.53	2.59	-----
Apparent		2.51	2.56	2.60	-----
Specific gravity (fine agg.)	ASTM C 128				
Bulk		2.40	2.47	2.51	-----
Saturated surface dry (SSD)		2.43	2.48	2.53	-----
Apparent		2.44	2.50	2.55	-----
Specific gravity (filler)	ASTM D854	2.38	2.42	2.50	-----
Los Angeles abrasion (%)	ASTM C 131	28	20	14	Max 30
Maximum water absorption (%)	ACTM C 127	2.5	1.4	0.7	Max 2.8
Flat and elongated particles (%)	ASTM D 4791	13	10	4	Max 15
Fractured faces (two-fractured face) (%)	ASTM D 5821	80	88	92	Traffic level
Soundness in $NaSO_4$ (%)	ASTM C 88	11	9	3	Max 12

Table 2 .The characteristics of two types of bitumen using in this study

Tests	Standards	Two types of bitumen	
		60-70	85-100
Penetration (100 g, 5 s, 25 ºC), 0.1 mm	ASTM D5-73	65	91
Ductility (25 ºC, 5 cm/min), cm	ASTM D113-79	114	>150
Softening point, ºC	ASTM D36-76	57	52
Flash point, ºC	ASTM D92-78	264	243
Viscosity at 135 ºC, mPas	ASTM D2171-07	0.274	0.221

where VMA is void in mineral aggregate (%), G_{mb} is the bulk specific gravity of asphalt sample, P_b is the amount of bitumen as a percentage of the total weight of the mixture, G_{sb} is the bulk specific gravity of aggregates, G_{mm} is the maximum specific gravity of asphalt mixture, V_a is the air void in dense asphalt mixture (%), and VFA is voids filled with asphalt as a percentage of VMA.

4- Modeling

4.1. MLR method

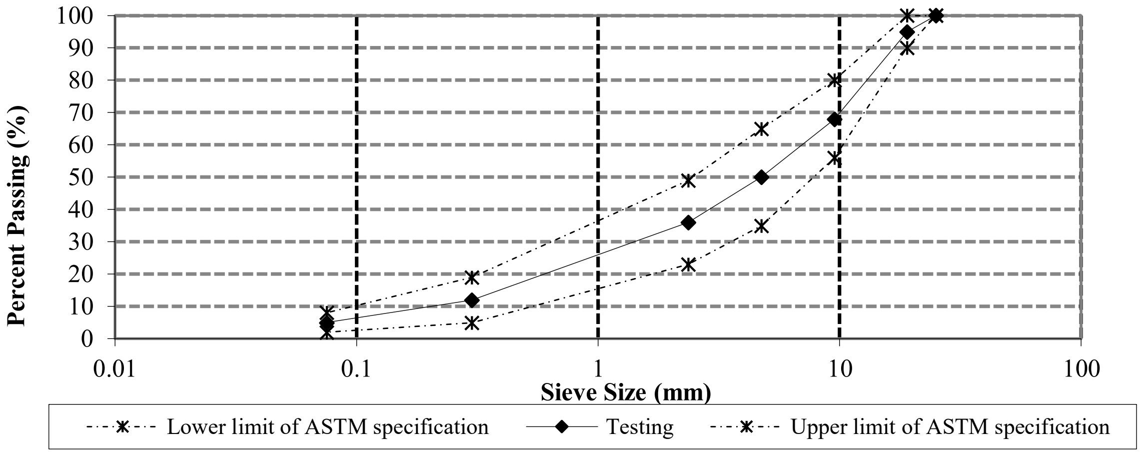
One of the most common methods in multivariable analysis is MLR. Based on regression analysis, a linear relation between a response or dependent variable is made with one or more explanatory or independent variables. The linear relation between independent variables x_1, x_2, … x_n and the dependent variable Y is described in the MLR model as follows [13]:

$$Y = a_0 + a_1 x_1 + a_2 x_2 + \ldots + a_n x_n + e \quad (4)$$

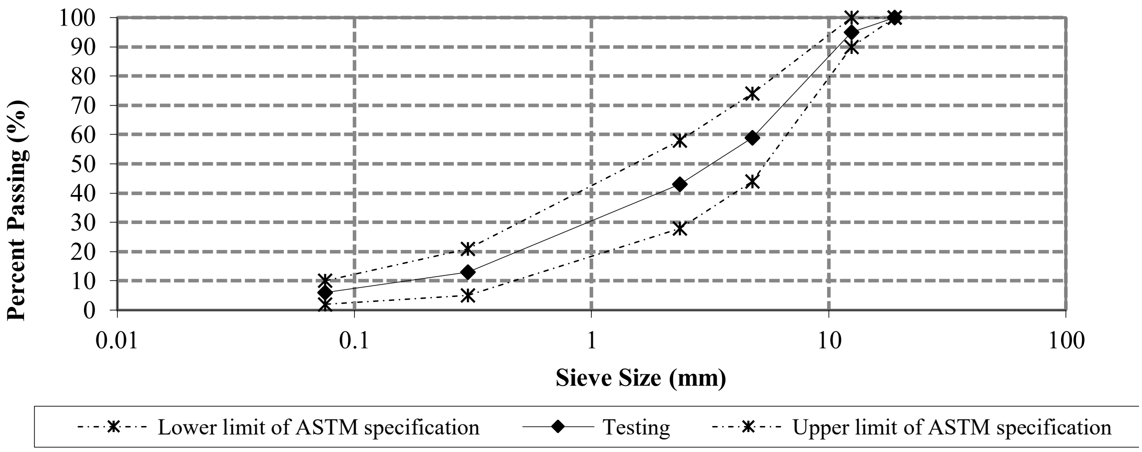
where is the width from source, the parameters a_1, a_2, …, and a_n are regression coefficients, and e is the fit error rate.

4.2. GP method

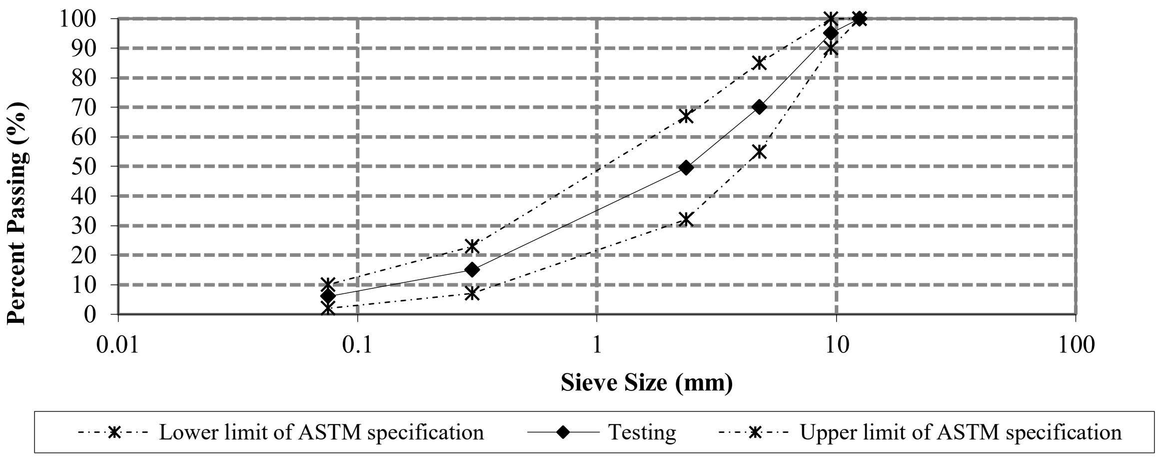
In 1992, Koza introduced the GP method as an extension of the genetic algorithm approach. GP is a new technique for computer program generation derived from the biological evolution model. According to this method, tree structure computer programs with dynamically changeable sizes and shapes are evolved for problem-solving. The breeding of tree populations is based on the Darwinian principle of genetic operations and natural selection [7]. In a GP population, each individual is a program including primitives composed terminals and functions in a hierarchical tree structure. Terminals are commonly in the form of variables or constants. A function can be programming, logical operators, standard arithmetic, mathematical, or any problem-specific function in the domain. The GP process begins with an initial population of programs that are commonly produced randomly. Each individual within this population is then appraised by a predefined problem-specific fitness function. The fitness value demonstrates the corresponding individual capability for problem-solving in a determined environment. After creating an initial population, various parents are chosen



a: Type 1



b: Type 2



c: Type 3

Fig. 1. The three types of gradation used in this study [2]

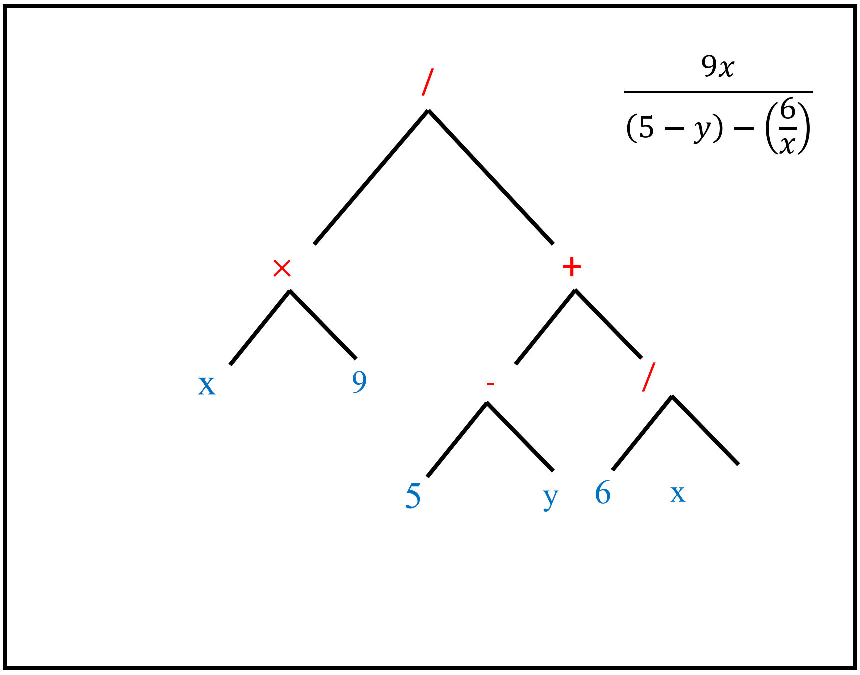


Fig. 2. A sample of a tree structure in GP [7]

from the population-based on fitness measures. In the next step, genetic operators such as mutation and crossover are used on the parents to produce new offspring and to form a new generation, which is usually fitter than the prior one. This trend continues up to the stop criteria are satisfied. A tree structure for the GP model is presented in Fig2. In order to achieve models to predict Marshall test results, GP parameters were configured as listed in Table 3.

4.3. Performance Measures

To compare and evaluate model functions, statistical parameters including root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) were used. These parameters are defined as follows.

$$R^2 = \left[\frac{\sum_{i=1}^{n}\left(h_i - \overline{h_i}\right)\left(t_i - \overline{t_i}\right)}{\sqrt{\sum_{i=1}^{n}\left(h_i - \overline{h_i}\right)^2 \sum_{i=1}^{n}\left(t_i - \overline{t_i}\right)^2}} \right]^2 \tag{5}$$

$$RMSE = \left[\sum_{i=1}^{n}\left(h_i - t_i\right)^2 / n \right]^{0.5} \tag{6}$$

$$MAE = \sum_{i=1}^{n}\left|h_i - t_i\right| / n \tag{7}$$

where h_i and t_i are the experimental and calculated output values for the i[th] output, respectively; $\overline{h_i}$ and $\overline{t_i}$ are average of the experimental and calculated outputs; and n is number of sample.

5- Result and discussion

5.1. Experimental results

The results of the Marshall mix design for all the asphalt samples used in this study are presented in Table 4. As can be seen, asphalt mixtures containing type 3 aggregates have the highest Marshall stability and the lowest flow compared to the other two types of aggregates. Because type 3 aggregates compared to the other two types have the best physical characteristics that their results are presented in Table 1. The aggregates properties in terms of shape, angularity, and texture are among influential parameters on Marshall test results. The fracture faces and rough surfaces of aggregates increased the friction and interlocking among them that can lead to resistance of asphalt mixtures against deformation.

Also, the amounts of fine and coarse aggregate in asphalt mixture and the nominal maximum size of aggregate significantly affect Marshall test results. Asphalt mixtures containing coarser aggregates are more resistant to deformation at high temperatures due to their higher internal friction and interlocking. Therefore, as it can be seen, the asphalt mixtures made with coarser gradation, have more MQ and consequently lower rutting potential.

Bitumen is used as an adhesive to keep aggregates next to each other in the asphalt mixture. The Marshall test results of

Table 3. Initial configuration of GP-based model

Parameter	Value	Parameter	Value
Function set	(+,-,*,/)	Terminal set	(x_1,…,x_3,r_1,…,r_3)
Population size	5000	Number of generations	1000
Max initial depth	6	Max depth	25

asphalt mix depend significantly on their bitumen properties. With the increase of bitumen stiffness, the stiffness of asphalt mixtures and consequently their resistance against deformation will be increased. As can be seen, mixtures containing bitumen 60-70, which has more viscosity compared to bitumen 85-100, have a higher Marshall stability and less flow. Furthermore, the results of this study have shown that asphalt mixtures with similar gradation and aggregate type, higher amounts of bitumen decrease the air void and increase the MQ and rutting potential.

5.2. Predictions Models

In this study, 270 asphalt samples were made and examined. Since three samples have been made for each compound of asphalt mixtures and experimental conditions (the type of bitumen and aggregate, gradation) 90 samples were used to represent models. Next, data randomly divided into two groups of training and testing to analyze data and represent a model. So, 80% and 20% of data were used in this study for training (representation) and testing model, respectively. It is essential to mention that all input and output data have been normalized between 0 and 1 by equation (8) before any analysis of data.

Normalized value= [(Actual)_value-(minimum)_(Actual value)]/((maximum)_(Actual value)-(minimum)_(Actual value)) (8)

5.2.1. Models offered based on MLR method

In this section, the traditional Marshall test results models, obtained through linear regression analysis, were presented. These models used air void, VMA, and VFA as input variables which are shown in equations 9 to 11.

$$\overline{S} = 1.369 - 0.751\overline{V_a} + 0.496\overline{VMA} - 1.513\overline{VFA} \tag{9}$$

$$\overline{F} = 0.412 - 0.454\overline{V_a} - 0.127\overline{VMA} + 0.568\overline{VFA} \tag{10}$$

$$\overline{MQ} = 1.776 - 1.029\overline{V_a} + 0.597\overline{VMA} - 2.166\overline{VFA} \tag{11}$$

where $\overline{S}$. is Marshall stability normalized b 0 and 1 (kg), $\overline{F}$. is flow normalized between 0 and 1 (0.25 mm), $\overline{MQ}$. is Marshall quotient normalized between 0 and 1 (kg/mm) $\overline{V_a}$ is air void between normalized 0 and 1 (%), $\overline{VMA}$ are voids in mineral aggregate normalized between 0 and 1 (%), $\overline{VFA}$ is voids filled with asphalt normalized between 0 and 1 (%).

Fig.3 depicts the results of calculated Marshall test results versus experimental amounts. As it is observed, experimental and calculated results have a relatively poor fit. Therefore, calculate Marshall test results in asphalt mixtures may not be true based on this model.

A coefficient of determination is a statistic parameter to measure the degree of a linear relationship between two variables, which each of them has been measured by their units. In this study, based on the quantitative content of data, the Pearson coefficient of determination has been used. Pearson coefficient of determination is defined in a way that only accepts amounts between -1 and +1, which +1 means perfect positive correlation and -1 means perfect negative correlation. In other words, the larger absolute value of this coefficient confirms that a stronger linear relationship between two parameters exists. Results of the correlation between data used in this study are represented in Table 5. The results show that the two parameters of air void and VFA compared with VMA have a greater impact on the Marshall test results.

5.2.2. Models based on the GP method

In the following, the Marshall test results models based on GP are presented:

$$\overline{S} = \overline{V_a} \times \overline{VMA}\left(\overline{VMA} - \overline{V_a}\right) + \overline{V_a} + \overline{VMA}^2 - 0.75\overline{VMA} + \left[\frac{\overline{VFA}}{9} - \frac{\overline{VMA} \times \overline{VFA}}{4}\right] \times 8\left(\overline{VFA} - \overline{VMA}\right) \tag{12}$$

$$\overline{F} = \frac{0.857\overline{VFA}}{1 + \overline{VMA} + \overline{VFA}^2} + \frac{\overline{VFA} - 0.333\overline{V_a}}{\dfrac{\overline{VMA}}{\overline{V_a}} + \dfrac{5}{\overline{VFA}}} \tag{13}$$

$$\overline{MQ} = \frac{\overline{V_a}\left(6 - \overline{VMA}\right) + 2\overline{VMA}^3}{\left(8 + \overline{VFA}\right) \times \dfrac{5 - \overline{V_a}}{5}} \tag{14}$$

Table 4. Marshall test results

Test No.	Type of aggregate	Type of bitumen	Type of grading	Amount of bitumen	Air void (%)	VMA (%)	VFA (%)	Marshall stability (kg)	Flow (0.25 mm)	MQ (kg/mm)
1	1	60-70	1	4	5.72	14.22	59.74	949	9.21	412.16
2				4.5	5.25	14.39	63.49	1002	9.65	415.34
3				5	4.62	14.80	68.79	1061	10.34	410.44
4				5.5	4.34	15.52	72.06	976	11.18	349.19
5				6	3.92	16.12	75.67	904	12.01	301.08
6	2	60-70	1	4	6.20	14.29	56.62	1161	8.39	553.52
7				4.5	5.48	13.86	60.48	1224	9.04	541.59
8				5	5.16	14.13	63.52	1292	9.93	520.44
9				5.5	4.58	14.17	67.68	1201	10.79	445.23
10				6	4.35	14.52	70.03	1109	11.65	380.77
11	3	60-70	1	4	6.96	14.87	53.23	1408	7.32	769.40
12				4.5	5.93	14.34	58.65	1483	7.65	775.42
13				5	5.21	14.27	63.46	1591	8.24	772.33
14				5.5	4.79	14.46	66.88	1532	9.06	676.38
15				6	4.45	14.72	69.77	1476	10.12	583.40
16	1	60-70	2	4.5	5.64	15.12	62.69	903	9.42	383.44
17				5	5.09	15.14	66.36	981	9.83	399.19
18				5.5	4.59	15.66	70.67	927	10.65	348.17
19				6	4.23	16.30	74.06	842	11.34	297.00
20				6.5	3.91	16.98	76.96	733	12.18	240.72
21	2	60-70	2	4.5	5.83	15.06	61.27	1111	8.55	519.77
22				5	5.16	15.01	65.63	1169	9.31	502.26
23				5.5	4.89	15.76	69.00	1218	10.06	484.29
24				6	4.44	16.36	72.83	1147	10.95	419.00
25				6.5	4.18	17.10	75.57	1083	11.82	366.50
26	3	60-70	2	4.5	6.68	15.56	57.10	1391	7.75	717.94
27				5	5.84	15.70	62.83	1425	8.19	695.97
28				5.5	4.95	15.92	68.89	1498	9.14	655.58
29				6	4.58	16.59	72.41	1532	10.32	593.80
30				6.5	4.25	17.29	75.44	1467	11.17	525.34
31	1	60-70	3	5	5.32	15.45	65.55	902	9.63	374.66
32				5.5	4.70	15.66	70.01	981	10.05	390.45
33				6	3.93	15.95	75.33	907	10.89	333.15
34				6.5	3.44	16.47	79.13	829	11.66	284.39
35				7	2.99	17.03	82.45	714	12.37	230.88
36	2	60-70	3	5	5.74	15.83	63.72	1086	9.09	477.89
37				5.5	5.04	15.93	68.37	1145	9.54	480.08
38				6	4.36	16.32	73.26	1209	10.22	473.19
39				6.5	3.86	16.86	77.09	1143	11.03	414.51
40				7	3.34	17.38	80.78	1057	11.95	353.81
41	3	60-70	3	5	6.53	16.48	60.38	1344	8.16	658.82
42				5.5	5.60	16.47	65.98	1396	8.95	623.91
43				6	4.68	16.65	71.89	1472	9.74	604.52
44				6.5	4.01	17.06	76.49	1519	10.63	571.59
45				7	3.56	17.65	79.85	1481	11.59	511.13

where parameters are introduced in the previous section. Calculated Marshall test results using the above model for training and testing data versus experimental amounts are shown in Fig. 4. The results of the above model have better fitness than the laboratory values compared to the results of the MLR model.

Table 5.(Continued.)

Test No.	Type of aggregate	Type of bitumen	Type of grading	Amount of bitumen	Air void (%)	VMA (%)	VFA (%)	Marshall stability (kg)	Flow (0.25 mm)	MQ (kg/mm)
46				4	5.93	14.30	58.50	732	9.57	305.96
47				4.5	4.97	14.47	65.64	791	10.49	301.62
48	1	85-100	1	5	4.30	14.88	71.13	844	11.31	298.50
49				5.5	3.97	15.60	74.53	785	12.09	259.72
50				6	3.61	16.28	77.82	702	12.87	218.18
51				4	5.89	14.40	59.12	966	8.47	456.20
52				4.5	5.23	13.98	62.62	1010	9.19	439.61
53	2	85-100	1	5	4.82	14.21	66.07	1069	10.31	414.74
54				5.5	4.25	14.29	70.27	1003	10.98	365.39
55				6	4.02	14.67	72.59	949	11.74	323.34
56				4	6.42	14.95	57.06	1212	7.64	634.55
57				4.5	5.67	14.46	60.76	1282	7.93	646.66
58	3	85-100	1	5	4.91	14.38	65.84	1319	8.42	626.60
59				5.5	4.45	14.57	69.48	1391	9.26	600.86
60				6	4.07	14.84	72.57	1279	10.44	490.04
61				4.5	5.44	15.20	64.21	702	9.79	286.82
62				5	4.77	15.22	68.64	747	10.81	276.41
63	1	85-100	2	5.5	4.28	15.78	72.89	811	11.55	280.87
64				6	3.83	16.38	76.62	766	12.35	248.10
65				6.5	3.52	17.09	79.42	699	13.43	208.19
66				4.5	5.64	15.14	62.76	903	8.69	415.65
67				5	4.82	15.08	68.02	988	9.54	414.26
68	2	85-100	2	5.5	4.51	15.84	71.51	1015	10.64	381.58
69				6	4.07	16.47	75.27	939	11.27	333.27
70				6.5	3.77	17.21	78.10	867	12.08	287.09
71				4.5	6.17	15.64	60.53	1193	7.83	609.45
72				5	5.54	15.81	64.97	1251	8.25	606.55
73	3	85-100	2	5.5	4.61	16.03	71.23	1297	9.32	556.65
74				6	4.20	16.70	74.87	1318	10.45	504.50
75				6.5	3.91	17.48	77.61	1245	11.51	432.67
76				5	4.87	15.53	68.66	719	10.11	284.47
77				5.5	4.34	15.74	72.44	775	11.24	275.80
78	1	85-100	3	6	3.62	16.10	77.50	789	12.08	261.26
79				6.5	3.13	16.67	81.20	723	13.43	215.34
80				7	2.60	17.19	84.87	657	14.18	185.33
81				5	5.34	15.91	66.42	873	9.26	377.11
82				5.5	4.71	16.05	70.65	911	10.18	357.96
83	2	85-100	3	6	3.97	16.41	75.80	968	11.05	350.41
84				6.5	3.41	16.93	79.87	902	11.93	302.43
85				7	2.85	17.45	83.70	834	12.69	262.88
86				5	6.10	16.56	63.16	1089	8.32	523.56
87				5.5	5.23	16.54	68.42	1146	9.04	507.08
88	3	85-100	3	6	4.30	16.76	74.34	1193	10.11	472.01
89				6.5	3.59	17.17	79.08	1191	10.87	438.27
90				7	3.10	17.76	82.56	1107	11.63	380.74

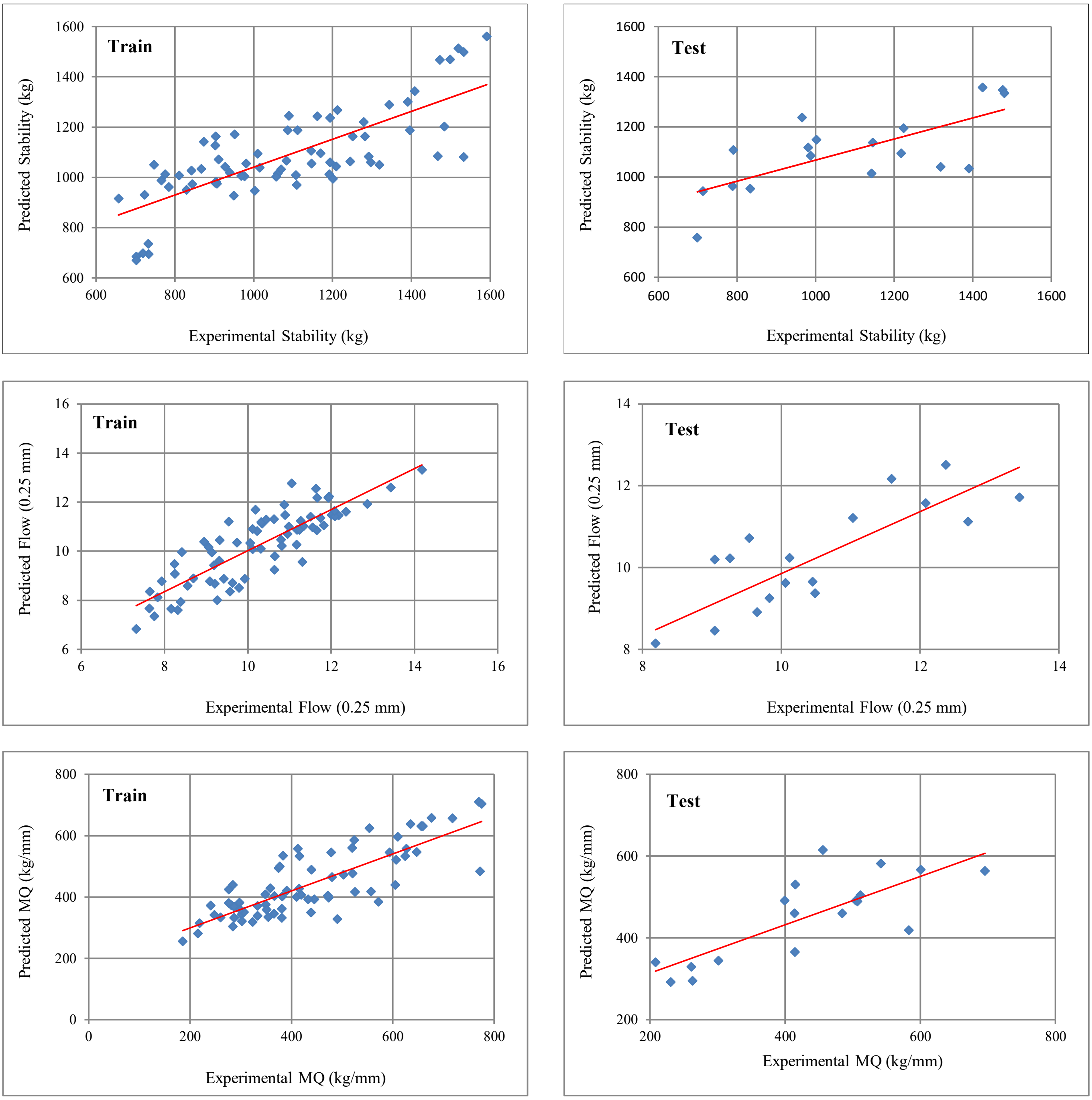


Fig. 3. Experimental versus predicted Marshall test results using MLR models

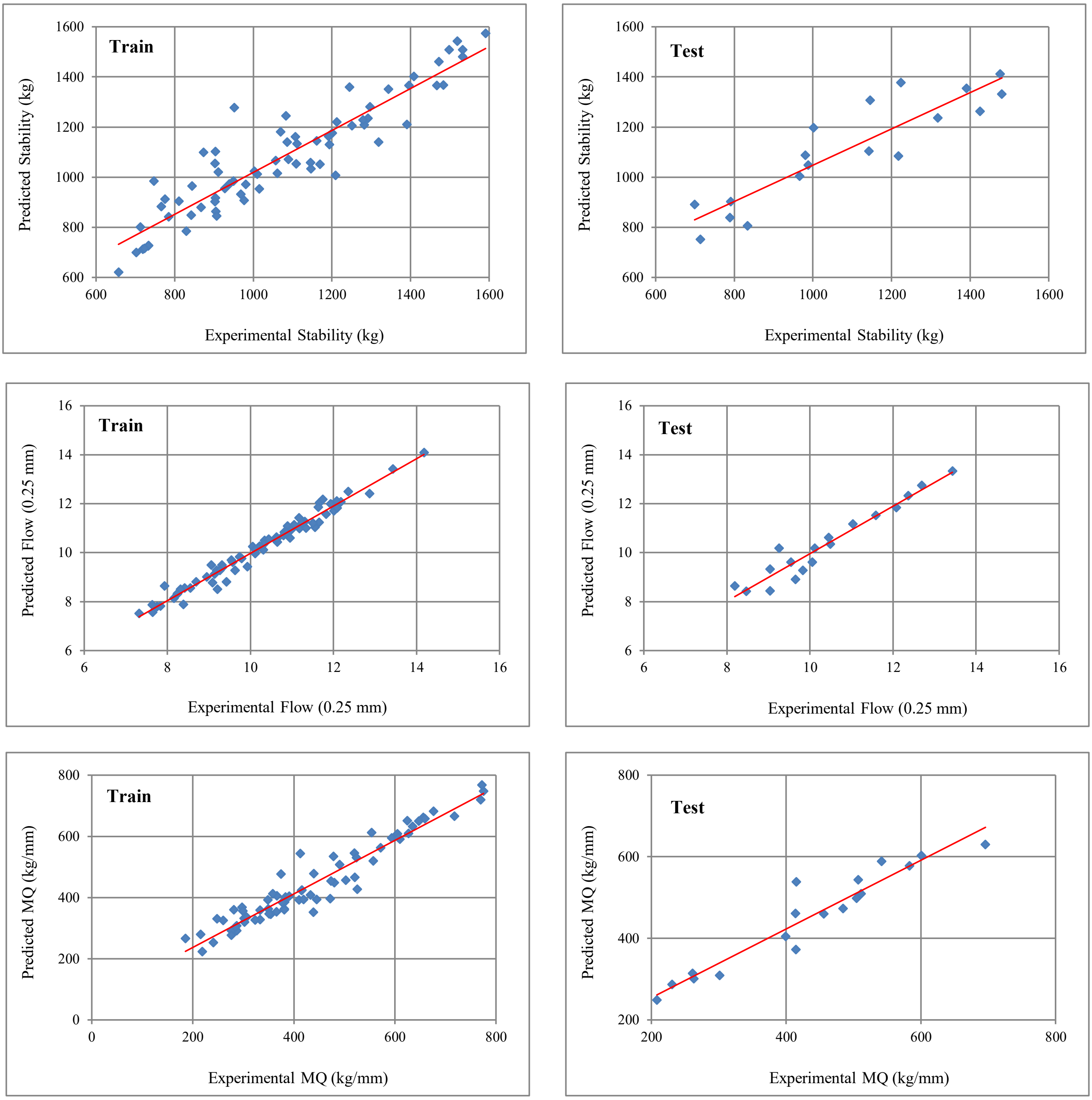


Fig. 4. Experimental versus predicted Marshall test results using GP models

Table 5 Correlation coefficient between independent and dependent variables

Independent parameters	Dependent parameters		
	Marshall stability	Flow	MQ
Air void	**-0.554**	**-0.916**	**-0.646**
VMA	0.198	-0.438	+0.391
VFA	-0.416	**0.893**	**-0.608**

Table 6. Comparison of performance of MLR and GP models

Marshall test results	Model type		Model performance		
			R^2	RMSE	MAE
Marshall stability	MLR	Train	0.583	131.54	109.10
		Test	0.509	158.35	125.58
	GP	Train	0.854	57.60	47.28
		Test	0.817	73.71	65.79
Flow	MLR	Train	0.720	0.631	0.562
		Test	0.687	0.818	0.696
	GP	Train	0.972	0.195	0.071
		Test	0.931	0.252	0.180
MQ	MLR	Train	0.662	86.30	68.70
		Test	0.620	95.20	77.09
	GP	Train	0.923	22.37	8.21
		Test	0.910	41.04	17.09

5.2.3. Comparison of prediction models

In this study to compare the performance of models, the R^2, MAE, and RMSE parameters have been used whose amounts for GP and MLR models are shown in Table 6. According to logical hypothesis [14, 15], if a model contains minimum errors (characterized in this study by RMSE and MAE parameters) and the coefficient of determination approaches to values more than 0.8, it would be an appropriate model to predict experimental observations with high accuracy. Results of Table 6 demonstrate that the GP model has a higher coefficient of determination and fewer errors than the MLR model.

6. Conclusion

In this study, GP has been used to represent the Marshall test results models in asphalt mixtures. Therefore, Marshall stability, flow, and MQ relations are represented based on air void, VMA, and VFA parameters. Also, MLR models were used as the base model to evaluate the models presented by the GP method. The most essential results out of this study are as follows:

- Asphalt mixtures containing type 3 and type 2 aggregates, assuming the other parameters are constant, have the best and the worst performance, respectively.
- Asphalt mixtures containing coarser aggregates are more resistant to deformation at high temperatures due to their higher internal friction and interlocking.
- GP model, in comparison with the MLR model, has been able to calculate Marshall test results more accurately. To investigate the performance of models, R^2, MAE, and RMSE parameters have been used that the GP model has the highest R^2 and the least errors.
- The GP model is relatively short and simple. Since the above model is the result of a relatively wide range of materials, characteristics, and conditions, it can be used for pavement design.
- Among independent parameters used to predict Marshall test results, the air void and VFA have the most effect.

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