Modeling Marshall stability of steel fiber reinforced asphalt concrete by genetic expression programming

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ABSTRACT

This study presents the potential of Genetic Expression Programming (GEP) computing paradigm to forecast the Marshall Stability of steel fiber reinforced asphalt concrete and has various mix proportions has been developed. Experimental details were used to construct the model. The steel fiber content (0%, 0.25%, 0.50%, 0.75%, 1.0%, 1.5%, 2.0% and 2.5%), percentage of bitumen (5%, 5.5% and 6.0%) and unit weights (2,465-2,515 (gr/cm3)) was used as input variables and Marshall Stability (kg) values were used as output variables. The performance of models was comprehensively judged using several statistical verification tools. Results have shown that developed GEP model has a strong potential for predicting the Marshall Stability of asphalt concrete without performing any experimental studies.

INTRODUCTION

Flexible pavements are designed so as to have at least 20 years project life. The current research subjects include the studies focusing on increasing the performance and lifetime off-road pavements. It is aimed to increase the performance and lifetime of roads by using different additive materials [1].

The researchers that previously worked on this subject clearly indicated that the use of fiber inthe pavements and asphalt mixtures has a strengthening effect. Fibers can be used especially in the mixtures with continuous grading and in Stone Mastic Asphalt (SMA) mixtures in order to overcome the deterioration of asphalt during carriage and construction of the mixture, as well as in asphalt stabilization [2-4]. The use of fibers alters the visco-elasticity characteristics of the mixture [5]; enhances its dynamic modulus [6], enhances sensibility against humidity[7], enhances flow coherence, and provides resistance against the rutting [8-9]; as well as decreases the amount of reflective cracks in asphalt mixtures and pavement [10-12].

In recent decade, one of the most important and promising research field has been “Heuristicsfrom Nature”, an area utilizing some analogies with natural or social systems and using them to derive non-deterministic heuristic methods and to obtain very good results. Nowadays Artificial Intelligent methods have been extensively used in civil engineering applications [13-14].

The main purpose of this paper is to develop an Genetic Expression Programming (GEP) methodology for estimation of the Marshall Stability of steel fiber reinforced asphalt concrete.

EXPERIMENTAL PROCEDURE

Aggregates

Crushed limestone aggregates were used in asphalt mixtures. Aggregate material tests were carried out based on American Standards, in order to obtain the physical and mechanical characteristics of the materials to be used in the mixtures. Table 1 shows mixture ratios determined for hot mixtures. The physical and mechanical characteristics of the aggregates used in the mixtures are given in Table 2 [15].

Table 1 Mixture ratios determined for hot mixtures

	Sieve Diameters		
	25-4,75mm	4,75-0,075mm	Filler
Binder	40%	55%	5%

Table 2 Physical and Mechanical characteristics of Aggregates [15]

	Sieve Diameters				
	0-4,75 mm	4,75-9,5 mm	9,5-25 mm	StandartLimit	Standart
Water Absorption %	* (3,54)	1,63	0,81	Binder; % 2,5	ASTM C 127
Abrasion loss (%) (Los Angeles)	*	*	23,804	Binder; % 35	ASTM C 131
Fine Material %	* (14,51)	1,27	0,45	% 0,5	ASTM C 117
Organic Material	Clear	Clear	Clear	Clear	ASTM C 40
Freeze-Thaw %	*	*	6,69	Binder; % 12	ASTM C 88
Peeling Strength. %	*	More than %50	More than %50	Binder; % 50	HTS Part 403 App-A
Average Density (gr/cm^3)	2,576	2,642	2,677	-	ASTM C 127
Loose specific gravity (gr/cm^3)	1,61	1,40	1,41	-	ASTM C 29
Compact specific gravity(gr/cm^3)	1,91	1,62	1,64	-	ASTM C 29

*Tests not required according to the technical specifications prepared by Highways Commission (Karayolları Teknik Şartname - KTŞ)

Bitumen

AC 60/70 asphalt cement was used in asphalt mixtures as bitumen. The physical characteristics of this selected bitumen are given in Table 3.

Table 3 Basic Physical Characteristics of Bitumen [15]

Characteristics of Bitumen	
Test Name	Average Values
Penetration (25 ºC)	60-70
Flash Point	180ºC
Fire Point	230 ºC
Softening Point	45,5°C
Ductility (5 cm/minute)	>100 cm
Specific Gravity	1,034 gr/cm^3

Steel Fiber

In this study, Dramix RC-80/60-BN fiber was used. The characteristics of the mentioned steel fiber are given Table 4 and a photograph of these fibers is available in Figure 1.The characteristics of Dramix RC-80/60-BN Steel Fiber: In the denomination of Dramix steel fibers, R and C define the hook and the admixture features of fiber, respectively, while 80defines the performance class and 60 defines the length of fiber in mm. B stands for Bright. N stands for Low Carbon [15].

Table 4 Properties of steel fiber

Length	Max. Diameter	Slenderness Ratio	Specific Gravity	Modulus of Elasticity (MPa)	Tensile Strength (MPa)	The Number of Fiber (kg)
60 mm ± %5	0.75 mm ± %5	80	7480	200000	1035	4600

Asphalt mixtures were prepared in accordance with the technical specifications required by Highway General Directorate of Turkey [16]. The upper and lower limits required for the mixture grading of aggregate are shown in Figure 2.

Figure 1 Steel Fibers

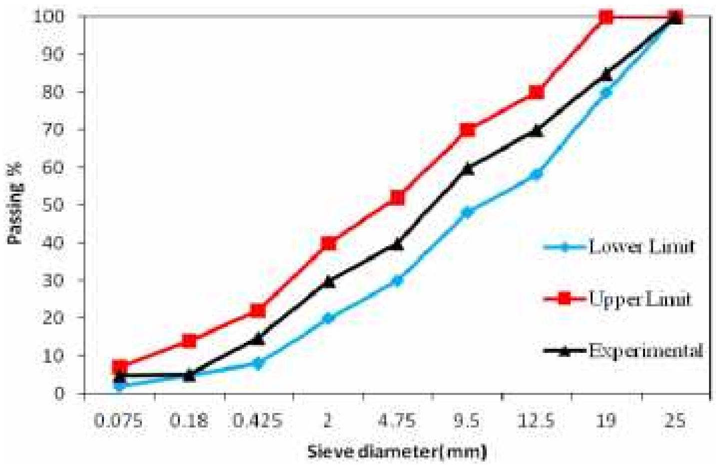

Figure 2 Gradation curve of the aggregates used in mixture

A series of tests were carried out to determine the optimum bitumen content. Asphalt mixture samples were produced using as 4.5%, 5.0%, 5.5%, and 6.0% bitumen contents. Optimum bitumen content obtained as 5.5%.

Based on the obtained optimum bitumen content value, steel fibers were added in different ratio in weights (0% - 0.25% - 0.50% - 0.75% - 1.0% - 1.5% - 2.0% - 2.5%) as three samples for each fiber rate. Maximum Marshall Stability value was obtained for 5.5% bitumen content and 0.75% fiber addition [15].

GENETIC ALGORITHMS

The fundamental unit of information is in living systems in the gene. In general, a gene is defined as a portion of a chromosome that determines or affects a single character or phenotype (visible property), for example, eye color. It comprises a segment of deoxyribonucleic acid (DNA), commonly packaged into structures called chromosomes. This genetic information is capable of producing a functional product which is most a protein19.

Genetic Algorithm (GA) is inspired by the mechanism of natural selection where stronger individuals are likely the winners in a competing environment. Here, GA uses a direct analogy of such natural evolution. Through the genetic evolution method, an optimal solution can be found and represented by the final winner of the genetic game [17].

GA presumes that the potential of ant problem is an individual and can be represented by set of parameters. These parameters are regarded as the genes of a chromosome and can be structured by a string of values in binary form. A positive value, generally known as a fitness value, is used to reflect the degree o “goodness” of chromosome for the problem which would be highly related with its objective value[17].

Pragmatic researchers see evolution’s remarkable power as something to be emulated rather than envied. Natural selection eliminates one of the greatest hurdles in software design: specifying in advance all the features of a problem and the actions a program should take the deal with them. By harnessing the mechanism of evolution, researchers may able to “breed” programs that solve problems even when no person can fully understand their structure. Indeed, these so-called genetic algorithms have already demonstrated the ability to make breakthroughs in the design of such complex systems as jet engines[18].

Genetic algorithms make it possible to explore a far greater range of potential solutions to a problem than do conventional programs. Furthermore, as researchers probe the natural selection of programs under controlled and well-understood conditions, the practical results they achieve may yield some insight into the details of how life and intelligence evolved in natural world[18].

Basic Steps of Genetic Algorithms

Given a way or a method of encoding solution of a problem into the form of chromosomes and given an evaluation function that returns a measurement of the cost value of any chromosome in the context of the problem, a GA consist of the following steps (See Figure 3) [19].

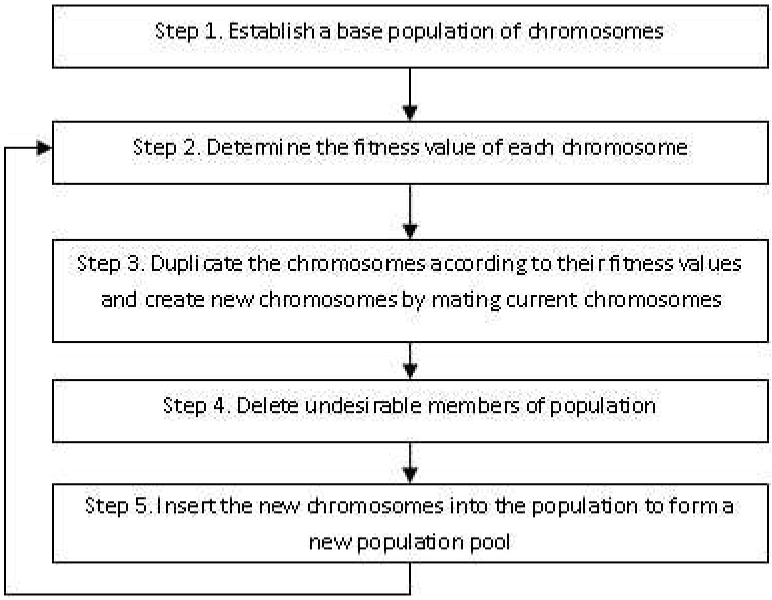

Figure 3 Basic Steps of Genetic Algorithm [20]

Step 1 : Initialize a population of chromosomes.
Step 2 : Evaluate each chromosome in the population.
Step 3 : Create new chromosomes by mating current chromosomes; apply mutation and recombination as the parent chromosomes mate.
Step 4 : Delete members of population to make room for new chromosomes.
Step 5 : Evaluate the new chromosomes and insert them into the population.
Step 6 :If stopping criterion is satisfied, then stop and return the best chromosome; otherwise, go to step 3.

Genetic Expression Programming (GEP)

The phenotype of GEP individuals consists of the same kind of ramified structures used in genetic programming. However, these complex entities are encoded in simpler, linear structures of fixed length – the chromosomes. Thus, there are two main players in GEP: the chromosomes and the ramified structures or expression trees (ETs), the latter being the expression of the genetic information encoded in the former. Figure 4 shows an example of ETs.

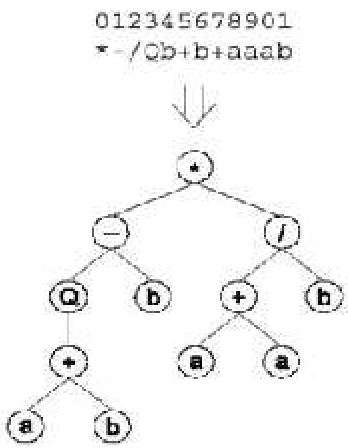

Figure 4an example of ETs

As in nature, the process of information decoding is called translation. And this translation implies obviously a kind of code and a set of rules. The genetic code is very simple: a one-to-one relationship between the symbols of the chromosome and the functions or terminals they represent. The rules are also very simple: they determine the spatial organization of the functions and terminals in the ETs and the type of interaction between sub-ETs in multi-genic systems. In GEP there are therefore two languages: the language of the genes and the language of ETs. However, thanks to the simple rules that determine the structure of ETs and their interactions, it is possible to infer immediately the phenotype given the sequence of a gene, and vice versa. This bilingual and unequivocal system is called Karva language. Figure 5 shows an example of Karvalanguage [21].

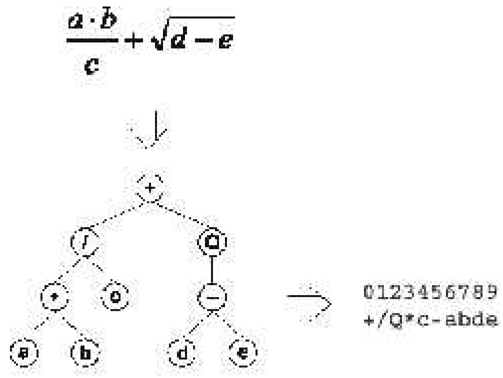

Figure 5an example of Karva language

DEVELOPED GEP MODEL

In this section of the paper, the developed model for the Marshall stability is given.In this study developed GEP model is mainly aimed to generate the mathematical functions for the prediction of the Marshall stability of reinforced asphalt concrete containing steel fiber. In GEP model three input parameters were preferred such as percentage of bitumen(%), percentage of steel fiber and unit weight (gr/cm^3) and output was the Marshall stability (kg) of asphalt concrete. So this mathematical function was generated in the form of y = f(bitumen (%),steel fiber (%)and unit weight (gr/cm^3) for prediction of Marshall Stability. Table 5 presents the model parameters used for GEP model. The relationship between the input parameters and Marshall Stability has been transformed into the Visual Basic program code based on the GEP model yielding the best result as follows:

GEP MODEL

The following variables in the program code stand for the values assigned to them as follows Marshall Stability (MS), POB= Bitumen, SF= Steel Fiber, UW= Unit weight.The mathematical formula of the Visual Basic program code obtained as a result of the evolutionary programming has been written as follows using abbreviation of parameters (Eq. (1)):

Marshal Stability = (10 ^ ((IIf(Int((POB- UW)) <= UW, Int((POB- UW)) , UW) * Cos((UW* UW))))) + (10 ^ (IIf(UW>Exp(Sin(((SF* SF) + IIf(UW= SF, UW, SF)))) , UW, Exp(Sin(((SF* SF) + IIf(UW= SF, UW, SF))))))) + (10 ^ ((IIf((10 ^ (1 / (UW))) < UW, (10 ^ (1 / (UW))) , UW) * Cos((UW* UW)))))

Table 5 GEP parameters of the models developed.

Population size	50
Generation	977
Number of the genes	3
Length of the gene head	8
Linking function	+
Function set	+, -, *, /,√, exp, sin, cos, arctan
Mutation rate	0,044
One-point recombination rate	0,3
Two-point recombination rate	0,3
Inversion rate	0,1
Transposition rate	0,1

PREDICTION RESULTS AND DISCUSSIONS

In order to learn the performance of the developed model is, several statistical verification criteria were used such as coefficient of determination (R^2) Eq. (2), root mean squared error (RMSE) Eq. (3) and Standard Error of the Estimate (SEE) Eq. (4).

$$R^2 = 1 - \left\{\left[\sum_{i=1}^{n}\left(Y_{i(observed)} - Y_{i(model)}\right)^2\right] / \left[\sum_{i=1}^{n}\left(Y_{i(observed)} - Y_{i(mean)}\right)^2\right]\right\} \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Y_{i(observed)} - Y_{i(predicted)}\right)^2} \quad (3)$$

$$SEE = \sum_{i=1}^{n}\left(Y_{i(observed)} - Y_{i(model)}\right)^2 \quad (4)$$

Where;

n= Total number of data
$Y_{i(observed)}$= Measured (experimental)
$Y_{i(model)}$= Developed model result

Table 6 represent calculated R^2, RMSE, SSE and SEE values for training and test groups of developed GEP model.

Table 6 Performance statistics of the model

		GEP model
Training set	R-square	0.842
	RMSE	47.32
	SEE	6.94e+004
Test set	R-square	0.9219
	RMSE	44.35
	SEE	1.18e+004

Marshall Stability (MS)values estimated from model were graphically compared with the experimental results in Figures 6 and 7 it clearly appears that the results from the GEP are in good agreement with the experimental results.

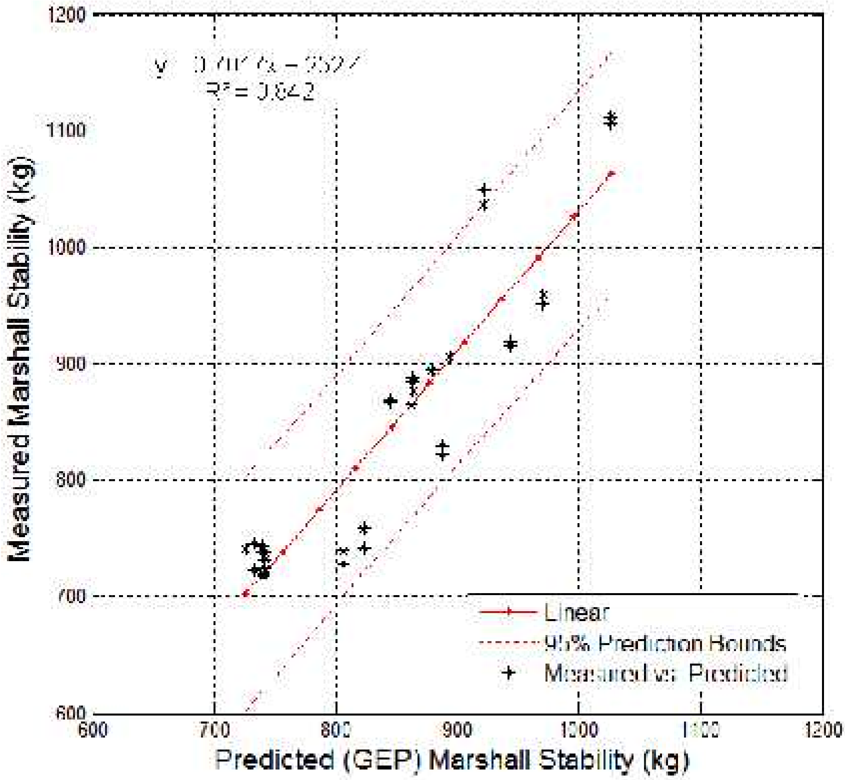

Figure 6 Comparison of experimental results with predicted Marshall Stability values from GEP Model (training set)

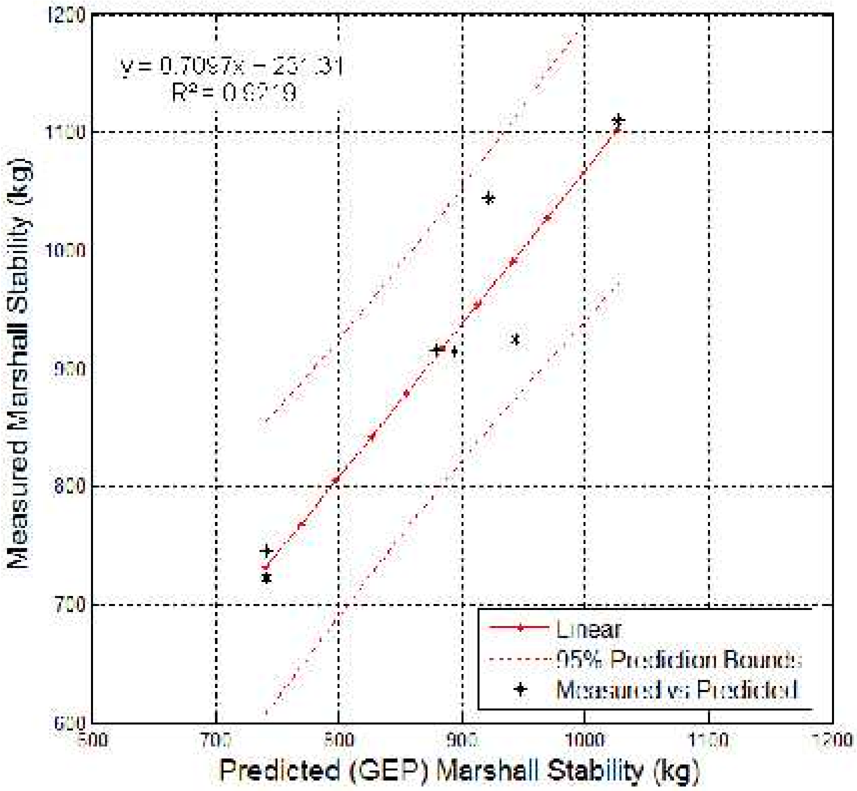

Figure7 Comparison of experimental results with predicted Marshall Stability values from GEP Model (testing set)

CONCLUSIONS

In this work, GEP modeling approach was studied and its prediction capability for Marshall Stability was illustrated. For training set, 33 samples were randomly selected and the residual data (8 samples) were selected as test set. After finding the best closely GEP model with experimental, the results of GEP model were compared with the experimental results. The coefficient of determination (R^2), Root mean square error (RMSE) and Standard Error of estimation (SEE) were used as comparison criteria.

When predicted and measured values compared in the training set, RMSE and R^2 were found as 47.32 and 0.842 respectively. These values were found as 44.35 and 0.9219 in the test stage respectively. As a result, it can be concluded that GEP is a useful method for this kind of engineering applications.

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