Developing a Forecasting Model for Asphalt Rutting Potential Using Gyratory Compactor Parameters

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ABSTRACT: Rutting is one of the most important deteriorations in flexible pavements which a significant amount of maintenance and rehabilitation funds are consumed for repairing it annually. On the other hand lack of a simple test to determine specimen resistance to permanent deformation as the main reason for asphalt rutting is sensible in Superpave first level mix design which owes considerable advantages in comparison with the marshall method. Prevalent methods of evaluating rutting potential of asphalt mixtures are usually expensive and time consuming. Mentioned parameters illustrates the necessity of developing a simple method, not only having fine precision but also be able to predict specimens rutting performance in the short term in laboratory. In this research two types of aggregates (silica and calcareous base), two types of gradation, two types of bitumen, two types of filler and three bitumen contents were used to prepare specimens. After modeling gyratory shear stress, the model and gyratory compaction slope parameters were used to develop two mathematical models to estimate specimen wheel Track apparatus rut depth. These models were validated using ANN and GA and make it possible to evaluate rutting potential while preparing specimens in laboratory to determine optimum bitumen content. Hence not only expensive instruments for rutting test aren't necessary but a considerable reduction in mix design procedure time is gained.

[*Hassan Ziari, Hassan Divandari , Hamid Behbahani and Mamoud Ameri*. **Developing a Forecasting Model for Asphalt Rutting Potential Using Gyratory Compactor Parameters.** *Life Sci J* 2012;9(4);4140-4149]. (ISSN: 1097-8135). http://www.lifesciencesite.com. 616

Keywords: Rutting, Gyratory Compaction Machine, Wheel Track Apparatus, Shear Stress Curve

1. Introduction

A rut is a surface depression in the wheel path due to cumulative permanent deformations which can lead to pavement drainage capacity reduction, hydroplaning, raise in deterioration rate due to moisture and increase in fatigue cracking of flexible pavements as a result of thickness reduction in rutted location [1]. Rutting could be a result of mixture volume reduction (pavement consolidation due to traffic (figure 1)), asphalt permanent deformation in a constant volume (plastic deformations as a result of shear stresses in asphalt mixtures (figure 2)) or a combination of these reasons [2]. Among different layers exposed to rutting, asphalt layer owes high share, hence noticing permanent deformations of asphalt mixtures because of low shear stress is an important issue in presenting the appropriate mix design procedure [3].

Different researches used various methods to evaluate asphalt mixtures rutting potential. Dynamic creep test is used widely in Finland, Sweden and Australia while LCPC wheel trucker is used more in Austria, France, Hungary, Romania and Switzerland. Hamburg Wheel Tracking Device and Georgia Loaded Wheel Tester are used for rutting performance evaluation in many countries in the world. Wheel Trucker applies wheel cyclic load to the specimen and the rut depth is recorded after 8000 cycles in a specific temperature. It is proofed that rut depth is related to specimen shear strength inversely. Although it is a simple test, but it is time consuming and the instrument used for loading is expensive. So developing a method to determine asphalt mixture shear strength in less time with cheaper equipments seems necessary.

2. Problem Definition

2.1. Research Targets

Asphalt mixtures low quality plays an important role in mixture rutting. Aggregates rotational or transitive movement in asphalt mixture due to insufficient compaction leads to permanent deformation occurrence along shear plates [4]. So compaction as the most effective parameter in aggregates structure and positioning in mixture has an important effect on mixture resistance to permanent deformation and rutting [5]. According to previous researches, a disadvantage of Marshall method is compacting procedure which doesn't simulate real condition fine [6]. Gyratory Compacting Machine, the result of 40 years researches in rotational compacting system were used by SHRP[1] in SUPERPAVE[2] mix design procedure. This design method has three levels which are categorized based on traffic and load. First SUPERPAVE level (AASHTO MP2, PP28) is for traffic with less than 1000000 ESAL[3] including volumetric analysis and simple tests [7]. This level which is noteworthy level for engineers because of being simple and economical consideration doesn't include asphalt performance tests. To complete first level design in these method simple tests should be used to evaluate asphalt mixture workability such as rutting resistance [8].

In this paper it is tried to develop predicting models of rutting performance by preparing specimens with a wide range of aggregate types and gradations, bitumen types and contents and filler types and testing them by wheel trucker, so the mixture rutting performance can be predicted during mixture preparation before production without consuming considerable time and cost.

2.2. Literature Review

Lack of a test with mentioned properties to predict asphalt mixtures rutting strength in 1st level caused validated research centers such as NCHRP[4] and FHWA[5] and FAA[6] to start a spread

[1] Strategic Highway Research Program
[2] SUPerior PERforming asphalt PAVEment
[3] Equivalent Single Axle Load
[4] National Cooperative Highway Research Program
[5] Federal Highway Administration
[6] Federal Aviation Administration

researches in this field [9-11]. Other studies with this target and using SGC output data will be mentioned in this section:

2.2.1. Studies on Compaction Slope in SGC[7]

The first idea of using compaction slope was developed for the first time in 2000 [12]. Later studies showed compaction slope is an index of aggregates internal friction [13]. So this parameter can't be used singly to predict asphalt shear strength performance.

2.2.2. Studies Considered a Specific Part of Compaction Slope

Researches define various indexes for asphalt rutting resistance with studying volumetric mass against gyration curve. One of these parameters was TDI[8] which is assumed as compaction curve integral from 4% to 2% voids. DEI[9] was defined as 8% to 4% voids in mentioned curve and CEI[10] as compaction start to 8% voids integral. Models based on these indexes were affected by aggregates positioning in molds greatly and wide tests showed this models aren't reliable [14-15].

2.2.3. Studies on Shear Parameters During Compaction

Gyratory Maximum shear strength, gyration corresponding with maximum shear and gyratory shear slope were defined using gyratory shear stress curve. Studies in Florida and Michigan University showed although there is a relation between these parameter with APA[11] rut depth, but developed models have no convenience correlation coefficient and aren't applicable in practically [16].

2.3. Research Assumptions

Asphalt rutting is cumulative deformation due to base and subbase layers consolidation, abrasion and permanent deformation in asphalt layer. The main reason of rutting is asphalt permanent deformation [17]. This parameter was studied in this research under 50°C temperature. Various materials, gradation, bitumen and filler were used in this study to increase applicability of research results.

3. Methodology

3.1. Materials Selection and Related Tests

Rudehen Asbcheran mine (east of Tehran) and Rivand mine (Sabzevar) were used for limestone aggregates and silica aggregates source respectively. Minimum Percentage of Fracture, Maximum Abrasion, Maximum Water Absorption, Minimum Adhesion in Bitumen-Aggregate System, Minimum Sand Equivalent and Minimum Sulfate Soundness Value tests results were in the standard range. Saveh mine rock powder and Qom limestone powder passed from 0.075mm sieve were used as two filler types in specimen preparation procedure. PI and Hydrometry test results located in standard range either. Bitumen was supplied from Pasargad Oil Company in tow types of 60-70 and 85-100. Penetration, Saybolt Forol Viscosity, Softening Point, Ignition Point, Specific Gravity, Weight Loss and Ductility performed for both types and results passed Code234 (Iranian Pavement Code [18]) requirements.

3.2. Optimum Bitumen Content Determination

3.2.1. Gradation

Middle range of number 4 and 5 continuous gradations were used according to table 1 [18].

3.2.2. OBC Determination and Specimen Naming

Since various types of gradation, filler, bitumen and aggregates, 288 specimens were prepared for OBC using marshal method and finally 16 bitumen contents were determined as table 2. Combination of two letters and two numbers was used for specimen naming. From left to right, first character shows aggregate type (S for silica base aggregate and A for limestone base aggregate), second character is a number shows gradation number (4 for gradation number 4 and 5 for gradation number 5), third character is the filler type (P for rock powder and A for limestone powder) and the forth character is the bitumen type (6 for 60-70 bitumen and 8 for 85-100 bitumen).

3.3. Preparing Specimens for Tests

3.3.1. Choosing Gyration Number

Gyratory Compaction Machine was used for compacting specimens. 8, 95 and 150 gyrations were chosen for N_{ini}, N_{des} and N_{max} respectively according to table 3 for ESAL equal to 10^6.

3.3.2. Determining Number of Specimens for Research

To perform rutting test, due to various parameters, 144 specimens were prepared totally with OBC, 0.5% less and 0.5% more bitumen content with SGC. To validate test results 3 specimens were made for each similar condition.

3.4. Gyratory Parameters

3.4.1. Shear Stress Modeling Parameters

Shear stress versus gyration number is one of the output curves of gyratory compactor. To gain more parameters from gyratory output curves and since it is proofed shear stress is related to rutting inversely, gyratory shear stress were modeled versus gyration number as independent parameter. Following logarithmic model seemed to be the best models after testing all models:

$G_S = K1\ Ln(N) + K_2$ (1)

In which Gs is gyratory shear stress in a defined N.

Graphs such as figure 3 were drawn for all 144 specimens and the result of modeling is shown in table 4. As it is clear in this table more than 96.5% of models have more than 75% correlation coefficient.

Maximum shear (S_m) is the other variable which can be determined by the presented model except K_1 and K_2.

3.4.2. Compaction Slope Parameter

One of the parameters measured by gyratory in each cycle is specimen height. Since specimen height is distinguish in each cycle and constant specimen weight and specimen cross section, compaction slope can be determined using eq. (2). Studies showed compaction slope is related to aggregates internal friction directly [19]. So it can be effective in mixtures shear strength:

$$K \quad \frac{\%G_{des} \quad \%G_{ini}}{\log(N_{des}) \quad \log(N_{ini})} * 100$$

(2)

in which:

$$\%G_{mm,Ndes} \quad \frac{G_{mb}}{G_{mm}} \qquad (3)$$

$$\%G_{mm,Nini} \quad \%G_{mm,Ndes} * \frac{h_{des}}{h_{ini}}$$

$\%G_{(mm),Ndes}$ and $\%G_{(mm),Nini}$: Asphalt mixture maximum specific gravity in initial gyration and design gyration respectively,

h_{ini} and h_{des}: Specimen height in N_{ini} and N_{des} during compaction respectively,

G_{mb} and G_{mm}: Bulk and maximum specific gravity respectively.

3.4.3. Other Parameters

Other parameters like air voids in initial and design gyration (Va_{ini} and Va_{des}), gyration number in which maximum shear stress is given ($N\text{-}S_m$), Voids in mineral aggregates (VMA), height and density variations were determined for each specimens which only K, K_2 and S_m introduced as effective parameters in sensitivity analysis.

3.5. Rutting Test

Rutting test was performed for each specimen in 50°C, under 700kpa pressure and 60 loads per second as loading rate and the

[7] Superpave Gyratory Compactor
[8] Terminal Densification Index
[9] Densification Energy Index
[10] Compaction Energy Index
[11] Asphalt Pavement Analyzer

rut depth after 8000 cycles were recorded. The results could be seen in table 5.

4. Presenting Laboratory Model

4.1. Developing a Model using SPSS 19

Predicting a variable behavior using other variables behaviors is the target of regression. It means to recognize the relation between effective parameters (x) and affected parameters (y) and to ensure a meaningful correlation between variables and finally to estimate a variable using another one. Correlation Coefficient (R^2) is a parameter which illustrates a relation between model results and actual results. Two assumptions are considered in regression as H_0 and H_1:

H_0: R=0 and H_1: R≠0 (5)

H_0 assumption should be rejected using sig F change coefficient. Whatever this coefficient is less, R^2 meaningfulness is more and so the model is more validated. This coefficient should be less than 0.05 since reliability is considered as 95% in this model. Statistical analysis results of 144 data series in SPSS 19 is listed in table 6 and two models were gained as following:

4.1.1. Model Number 1

According to tables 7 and 8, eq. (6) is the output model:

$WT = 0/009\ K_2 - 0/285\ K$ (6)

In which:

WT: Rut depth of Wheel Trucker, mm

K: Gyratory Compaction Slope from eq. (2)

K2: Gyratory Shear Stress Curve Y-Intersect from eq. (1)

As it is obvious from tables 7 and 8, R^2 is 0.921 for this model which is meaningful in 95% reliability level.

4.1.2. Model Number 2

According to tables 9 and 10, eq. (7) is determined:

$WT = -0/376\ K + 0/008\ S_m$ (7)

In which:

WT: Rut depth of wheel Trucker, mm

K: Gyratory Compaction Slope from eq. (2)

S_m: Maximum Shear Stress in Gyratory Curve

As it is obvious from tables 9 and 10, R_2 is 0.92 for this model which is meaningful in 95% reliability level.

4.2. Validating the models using ANN

ANN[12] is a simulation of brain nerve and has learning, generalization, and decision making power like human's brain. In designing the network, after defining a dynamic system mechanism, the model is trained and system mechanism is saved in model memory, so this memory is used to estimate new cases. Neural networks have been used in various aspects of pavement engineering such as estimating asphalt dynamic and elasticity modulus [20-21], bitumen properties effect on asphalt features [22] and Mixture Compaction Quality Control [23].

A neural network is composed from several processors which are called neurons or nodes. Each neuron is connected to other neurons with oriented lines having specific weight. Weight shows the amount of information used by network to solve the problem. Neurons are organized in groups called layers. Generally there are two layers to connect network with out of it as input layer (to get input data) and output layer to transfer answers out of network. Other layers between these two layers are called hidden layers. Network input and output layer number depends on dependent and independent variables of the desired relation respectively. Both models in this paper have two independent variables and one dependent variable, so the network in both of them has two input neurons and one output neuron (figure 4).

Figure 5 shows input (I) and output (O) and a hidden neuron structure. B and w parameters could be set up and f function type is selected by designer so the neuron output is desired. Determining b and w for total network is called network training. Network output is compared with actual observations and error is calculated in training process. Coefficients are modified based on this error. Whatever root mean square error (RMSE) is closer to zero, error is less, so the model is better.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}}$$

(8)

R^2 is the statistical index to validate output accuracy which whatever closer to 1, more precise the model is.

$$R^2 = \left(\frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}\right)^2$$

MATLAB 2008 software was use for coding the network. About 67% of data were used for training the network after normalizing by eq. (10) and remained data were used for validation.

$X_n = (x - x_{min}) / (x_{max} - x_{min}) \quad 0 \le X_n \le 1$ (10)

4.2.1. Neural Network results for model number 1 ($WT=0.009K_2-0.285K$)

Considering two neurons in input layer and one in output and using 5, 10, 15 and 20 neurons in median layers, results were obtained as table 11 and figure 6. R^2 were determined as 0.8578 in best structure in validation phase as it is stated in table.

4.2.2. Neural Network results for model number 2 ($WT=-0.376K+0.008S_m$)

Neurons and layers number were assumed as the network for model number 1 and the results are illustrated in table 12 and figure 7. R^2 was determined as 0.8846 in best structure in validation phase as it is clear in table.

4.3. Validating models Using GA

Genetic Algorithm (GA) is a method of optimizing and validating data which using a natural inception performs based on evolution principle (Survival of the fittest). GA applies survival fittest rule on a set of solutions to obtain better answers. Better estimations of solutions are calculated using a selection process proportional to answer costs in each generation and reproduction selected answers with functions imitated from natural genetic. Hence the new generation is more compatible with problem condition after this process. Independent variables should be determined such that less variation existed between actual answer and estimated answer of dependent variable of that model in each step of evolution (figure 8). MATLAB 2008 software was used for coding and Excel 2007 for comparing the results in this study.

3.4.1. GA results for model number 1 ($WT=0.009K_2-0.285K$)

As it is illustrated in figure 9, 0.965 is obtained as determination coefficient for this model.

3.4.2. GA results for model number 2 ($WT=-0.376K+0.008S_m$)

As it is illustrated in figure 10, 0.8575 is obtained as determination coefficient.

5. Conclusion

One of the most important consequences of this study is shear stress modeling versus gyration number. It was proofed that logarithmic model results in the best trend. This curve has two main parts. The first part can be named as compaction phase, which has an intense slope. Shear stress variation in this part is more than condensation part. Voids variation of first part is more that the second one too. Two models for predicting rut depth were presented using Y-Intercept of this relation, compaction slope and maximum shear stress. Compaction slope coefficient is negative in both of the models. In other words specimens with more compaction slope are more resisted to rutting which is due to more internal friction and structural establishment of them. Maximum

[12] Artificial Neural Network

shear stress positive coefficient and shear stress curve intercept of these models states that asphalt mixtures with more shear stress in compaction phase are exposed to rutting more. Simply means more shear stress in condensation phase in comparison with compaction phase shows more shear strength of the mixture.

6. Acknowledgement

Writers are thankful of Technical and Soil Mechanic Laboratory Co and IUST Asphalt and Bitumen Research Center personnel helping researchers during the study.

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8. Tables

Table 1. Aggregates gradation for Binder and Topka layers [18]

Sieve Specification			Number 4 Continuous Gradation			Number 5 Continuous Gradation		
mm	Sieve Number	Inches	Passed Range (Weight %)	Passed (Average weight %)	Remained (Weight %)	Passed Range (Weight %)	Passed (Average weight %)	Remained (Weight %)
19	-	3/4	100	100	0	-	-	-
12.5	-	1/2	90-100	95	5	100	100	0
9.5	-	3/8	-	-	-	90-100	95	5
4.75	4	-	44-74	59	36	55-85	70	25
2.36	8	-	28-58	43	16	32-67	49.5	20.5
1.18	16	-	-	-	-	-	-	-
0.6	30	-	-	-	-	-	-	-
0.3	50	-	5-21	13	30	7-23	15	35.4
0.15	100	-	-	-	-	-	-	-
0.075	200	-	2-10	6	7	2-10	6	9

Table 2. Determined OBC for 16 various asphalt mixture combination

Limestone Specimen Specification	A4P6	A4P8	A5P6	A5P8	A4A6	A4A8	A5A6	A5A8
OBC	5.81	5.70	5.92	5.80	6.16	5.90	6.24	6.00
Silica Specimen Specification	S4P6	S4P8	S5P6	S5P8	S4A6	S4A8	S5A6	S5A8
OBC	5.05	4.96	5.24	5.02	5.40	5.15	5.45	5.25

Table 3. N_{ini}, N_{des} and N_{max} in SGC

ESAL 10^6	Maximum Design Temperature Average											
	< 39 ºC			39-40 ºC			41-42 ºC			43-44 ºC		
	N-initial	N-design	N-max	N-initial	N-design	N-max	N-initial	N-design	N-max	N-initial	N-design	N-max
< 0.3	7	68	104	7	74	114	7	78	121	7	82	127
0.3-1	7	76	117	7	83	129	7	88	138	8	93	146
1-3	7	86	134	8	95	150	8	100	158	8	105	167
3-10	8	96	152	8	106	169	8	113	181	9	119	192
10-30	8	109	174	9	121	195	9	128	208	9	135	220
30-100	9	126	204	9	139	228	9	146	240	10	153	253
>100	9	143	235	10	158	262	10	165	275	10	172	288

Table 4. Determining Correlation Coefficient of presented model for all gyratory shear stress curves (144 specimens)

Correlation Coefficient (R^2)							Total
R^2 Range	100-95	95-90	90-85	85-80	80-75	<75	
Number of Specimens	79	34	10	11	5	5	144
Percent	54.86	23.61	6.94	7.64	3.47	3.47	100

Table 5. Gyratory compactor and rutting test results for 144 specimen

Limestone Specimen Number		Bitumen Percent (Pb)	Difference With OBC	Rut Depth (mm)	K	K1	k2	Maximum shear (Sm)	Limestone Specimen Number		Bitumen Percent (Pb)	Difference With OBC	Rut Depth (mm)	K	K1	k2	Maximum shear (Sm)
1	A4P6			3.19	10.644	75.684	740.68	1065	1	S4P6			8.71	8.314	55.653	828.82	1074
2	A4P6	5.3	-0.5	4.63	10.984	63.005	775.03	1065	2	S4P6	4.6	-0.5	7.35	7.595	56.488	843.56	1086
3	A4P6			2.84	10.400	45.680	810.94	1019	3	S4P6			8.20	8.416	56.842	816.65	1067
1	A4P6			2.82	11.168	65.583	785.62	1083	1	S4P6			5.59	8.432	52.113	858.15	1085
2	A4P6	5.8	0.0	4.34	10.693	67.488	773.39	1065	2	S4P6	5.1	0.0	7.91	8.837	56.950	845.34	1088
3	A4P6			3.85	10.964	53.719	787.96	1026	3	S4P6			6.06	7.860	53.417	861.33	1094
1	A4P6			5.78	11.122	63.118	770.88	1038	1	S4P6			3.80	7.771	45.727	889.35	1086
2	A4P6	6.3	0.5	3.49	10.304	67.758	736.96	1074	2	S4P6	5.6	0.5	6.47	8.347	54.959	841.50	1076
3	A4P6			7.05	7.944	50.292	806.88	1068	3	S4P6			9.55	7.483	37.180	917.44	1077
1	A4P8			2.69	11.668	66.131	788.85	1099	1	S4P8			7.11	7.824	54.572	846.07	1076
2	A4P8	5.2	-0.5	2.91	10.896	43.520	832.17	1016	2	S4P8	4.5	-0.5	3.71	7.740	50.098	843.66	1053
3	A4P8			3.55	11.166	58.347	805.52	1052	3	S4P8			3.97	7.978	55.757	831.18	1073
1	A4P8			3.18	10.687	62.514	768.71	1044	1	S4P8			5.97	7.705	46.592	859.18	1055
2	A4P8	5.7	0.0	2.65	10.866	49.968	829.30	1037	2	S4P8	5.0	0.0	4.34	7.950	46.117	851.23	1043
3	A4P8			4.07	10.846	49.920	820.97	1041	3	S4P8			6.35	8.167	49.670	859.26	1068
1	A4P8			3.46	10.732	62.964	753.15	1043	1	S4P8			11.57	9.609	50.594	926.20	1141
2	A4P8	6.2	0.5	3.97	9.834	38.115	844.82	1019	2	S4P8	5.5	0.5	5.84	8.454	45.644	873.38	1071
3	A4P8			6.53	9.637	24.287	724.04	845	3	S4P8			5.64	8.116	44.116	882.81	1073
1	A5P6			1.38	10.064	35.803	686.45	845	1	S5P6			7.17	7.535	51.705	848.93	1070
2	A5P6	5.4	-0.5	1.38	9.938	41.004	699.90	873	2	S5P6	4.7	-0.5	5.44	7.650	55.055	854.55	1089
3	A5P6			3.45	10.273	50.201	666.07	876	3	S5P6			4.47	7.615	50.070	842.45	1052
1	A5P6			1.93	10.710	45.989	702.50	908	1	S5P6			6.09	7.408	45.921	885.91	1083
2	A5P6	5.9	0.0	0.92	10.522	47.167	711.08	930	2	S5P6	5.2	0.0	5.11	7.176	39.374	894.97	1061
3	A5P6			5.70	7.093	19.041	707.10	813	3	S5P6			3.43	7.502	42.900	876.46	1055
1	A5P6			3.09	9.848	42.946	664.93	869	1	S5P6			6.99	6.826	25.900	921.59	1046
2	A5P6	6.4	0.5	0.92	9.977	42.742	665.33	863	2	S5P6	5.7	0.5	8.38	7.237	33.478	927.13	1073
3	A5P6			6.94	6.157	18.223	744.45	831	3	S5P6			7.26	7.195	32.190	925.66	1070
1	A5P8			2.53	10.018	32.200	686.87	827	1	S5P8			6.31	7.561	56.582	832.66	1080
2	A5P8	5.3	-0.5	1.45	8.240	28.287	725.44	863	2	S5P8	4.5	-0.5	5.73	8.233	57.658	824.05	1076
3	A5P8			2.72	8.646	38.997	688.40	860	3	S5P8			3.62	7.533	55.142	833.91	1079
1	A5P8			2.95	7.623	22.200	725.51	836	1	S5P8			3.99	7.751	55.123	849.76	1094
2	A5P8	5.8	0.0	3.58	7.167	23.188	733.71	837	2	S5P8	5.0	0.0	3.92	7.348	49.202	878.74	1089
3	A5P8			4.22	6.604	24.064	708.59	818	3	S5P8			6.62	7.385	48.443	882.77	1088
1	A5P8			9.14	6.077	19.468	734.99	827	1	S5P8			7.25	7.343	40.508	909.04	1080
2	A5P8	6.3	0.5	6.72	9.969	48.067	632.33	866	2	S5P8	5.5	0.5	5.47	7.109	37.800	913.79	1074
3	A5P8			13.27	6.842	55.394	621.48	900	3	S5P8			7.58	7.396	45.272	889.75	1085
1	A4A6			5.09	6.278	45.333	788.59	990	1	S4A6			8.75	7.278	44.642	838.27	1034
2	A4A6	5.7	-0.5	5.08	6.361	47.952	791.61	1007	2	S4A6	4.9	-0.5	6.62	7.348	49.778	812.62	1031
3	A4A6			8.34	6.227	45.878	785.93	989	3	S4A6			3.96	8.920	54.293	792.75	1025
1	A4A6			4.59	6.311	45.086	793.47	995	1	S4A6			2.96	7.842	50.787	828.35	1049
2	A4A6	6.2	0.0	4.58	6.476	45.550	797.19	1001	2	S4A6	5.4	0.0	2.29	7.972	46.869	838.26	1041
3	A4A6			8.07	6.519	46.688	775.64	987	3	S4A6			0.45	7.825	47.945	832.71	1040
1	A4A6			7.87	6.839	46.198	791.65	993	1	S4A6			3.15	9.377	51.503	809.15	1025
2	A4A6	6.7	0.5	6.06	6.379	43.376	803.55	995	2	S4A6	5.9	0.5	3.68	7.987	43.781	839.74	1028
3	A4A6			3.85	6.581	46.846	785.41	992	3	S4A6			2.40	8.249	46.984	827.45	1029
1	A4A8			6.60	8.878	54.751	802.55	1041	1	S4A8			5.24	7.262	50.224	799.32	1020
2	A4A8	5.4	-0.5	10.79	8.998	49.545	805.27	1016	2	S4A8	4.7	-0.5	4.50	6.715	47.873	821.86	1031
3	A4A8			11.40	9.767	59.956	764.72	1029	3	S4A8			2.71	6.669	42.862	830.72	1016
1	A4A8			6.33	10.230	52.048	789.95	1008	1	S4A8			5.54	8.100	50.815	820.90	1040
2	A4A8	5.9	0.0	6.40	6.252	44.600	781.24	980	2	S4A8	5.2	0.0	5.12	8.138	51.271	800.58	1022
3	A4A8			4.47	9.826	49.696	794.99	1007	3	S4A8			2.51	7.687	50.807	817.65	1037
1	A4A8			10.61	6.404	49.918	785.22	1010	1	S4A8			4.51	8.145	44.199	831.48	1019
2	A4A8	6.4	0.5	5.96	9.608	42.519	814.84	992	2	S4A8	5.7	0.5	7.45	8.412	53.902	791.64	1031
3	A4A8			3.74	6.443	45.230	800.04	998	3	S4A8			2.08	8.566	47.613	824.49	1026
1	A5A6			5.88	9.162	58.800	786.82	1046	1	S5A6			3.43	7.181	52.829	830.95	1068
2	A5A6	5.7	-0.5	5.85	7.767	49.741	817.90	1037	2	S5A6	5.0	-0.5	4.17	6.371	48.049	837.75	1052
3	A5A6			4.70	8.636	53.797	795.13	1031	3	S5A6			1.88	6.558	49.410	841.82	1061
1	A5A6			5.85	8.514	47.230	829.10	1029	1	S5A6			3.38	7.511	51.732	824.75	1052
2	A5A6	6.2	0.0	4.75	8.818	45.953	819.07	1010	2	S5A6	5.5	0.0	3.83	7.106	48.058	830.22	1046
3	A5A6			5.88	8.459	41.592	841.39	1016	3	S5A6			3.14	7.578	49.802	840.59	1058
1	A5A6			6.63	8.486	45.060	813.30	1016	1	S5A6			3.50	8.144	44.640	831.34	1020
2	A5A6	6.7	0.5	8.87	8.303	38.636	849.80	1025	2	S5A6	6.0	0.5	4.15	7.789	48.327	825.28	1037
3	A5A6			7.88	8.642	46.524	812.35	1020	3	S5A6			2.76	7.727	43.582	839.48	1026
1	A5A8			6.44	8.127	57.619	793.34	1049	1	S5A8			5.35	7.087	49.989	795.55	1017
2	A5A8	5.5	-0.5	5.86	8.377	56.843	803.52	1052	2	S5A8	4.8	-0.5	6.01	7.263	45.765	829.78	1032
3	A5A8			7.48	8.658	55.392	801.11	1038	3	S5A8			5.70	7.111	48.880	818.43	1035
1	A5A8			5.83	8.893	44.277	822.64	1007	1	S5A8			3.05	7.976	56.738	815.88	1068
2	A5A8	6.0	0.0	6.30	9.154	47.371	825.33	1026	2	S5A8	5.3	0.0	4.36	8.579	54.157	815.37	1052
3	A5A8			4.77	9.313	55.743	781.31	1025	3	S5A8			2.42	7.850	47.826	827.37	1040
1	A5A8			10.12	8.752	28.280	867.92	995	1	S5A8			3.68	9.010	55.236	797.11	1034
2	A5A8	6.5	0.5	7.94	8.830	32.669	854.94	999	2	S5A8	5.8	0.5	4.22	8.661	52.333	811.74	1038
3	A5A8			6.36	9.200	35.573	840.55	995	3	S5A8			3.03	8.845	52.256	808.50	1032

Table 6. Parameters statistical analysis in SPSS 19 results

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
WT	144	12.82	0.45	13.27	5.1768	2.32230	5.393
k	144	5.59	6.08	11.67	8.3197	1.34949	1.821
k1	144	57.46	18.22	75.68	47.6105	9.78674	95.780
k2	144	305.65	621.48	927.13	809.1351	58.07185	3372.339
Sm	144	328.00	813.00	1141.00	1018.2569	69.97280	4896.192

Table 7. Model Number 1 statistical specification summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics
					Sig. F Change
1	0.921	0.848	0.845	2.22973	0.000

Table 8. Model Number 1 independent parameters coefficients

Model		Un standardized Coefficients		Standardized Coefficients	T	Sig.	0.95 % Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	k	-0.285	0.114	-0.423	-2.493	0.014	-0.511	-0.059
	k2	0.009	0.001	1.332	7.846	0.000	0.007	0.012

Table 9. Model Number 2 statistical specification summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics
					Sig. F Change
2	0.920	.847	0.845	2.23541	0.847

Table 10. Model Number 2 independent parameters coefficients

Model		Un standardized Coefficients		Standardized Coefficients	t	Sig.	0.95% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
2	k	-0.376	0.127	-0.559	-2.967	0.004	-0.626	-0.125
	S_m	0.008	0.001	1.465	7.780	0.000	0.006	0.010

Table 11. Neural Network Run Output for Model Number 1 (for 5, 10, 15 and 20 neurons in a hidden layer)

Neural Network Structure	Training Phase		Validation Phase
	R^2	RMSE	R^2
2-5-1	0.6403	0.0192	0.5411
2-10-1	0.7942	0.0120	0.7509
2-15-1	0.8491	0.0091	0.8438
2-20-1	08698	0.0085	0.8578

Table 12. Neural Network Run Output for Model Number 2 (for 5, 10, 15 and 20 neurons in a hidden layer)

Neural Network Structure	Training Phase		Validation Phase
	R^2	RMSE	R^2
2-5-1	0.6282	0.0197	0.4578
2-10-1	0.7892	0.0171	0.5985
2-15-1	0.8595	0.0112	0.7809
2-20-1	0.8900	0.0085	0.8846

9. Figures

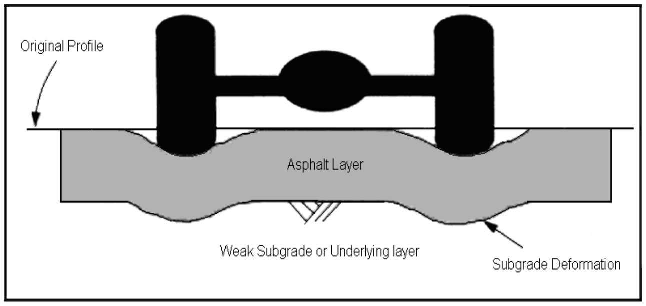


Fig 1. Rutting due to underneath layer deformation

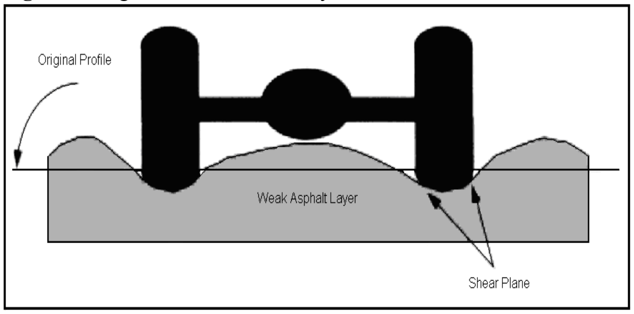


Fig 2. Rutting in asphalt layer due to lack of shear strength

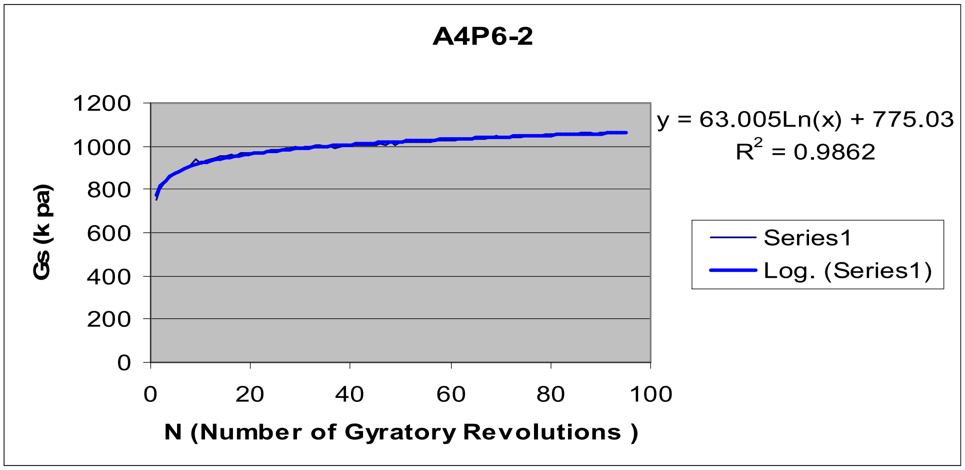


Figure 3. Shear stress modeling versus gyration number (for one of the limestone specimens, gradation number 4, rock powder as the filler and 60-70 bitumen)

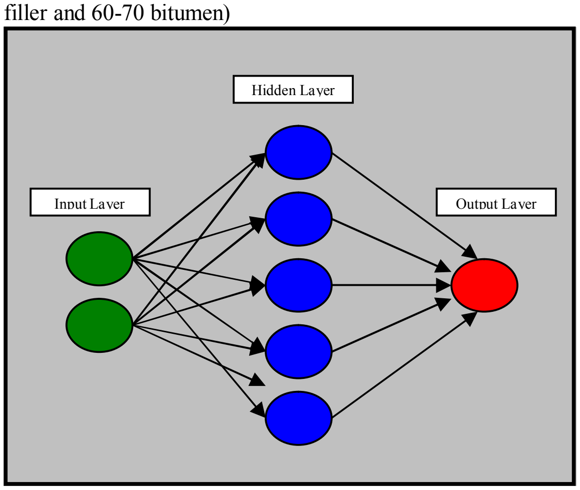
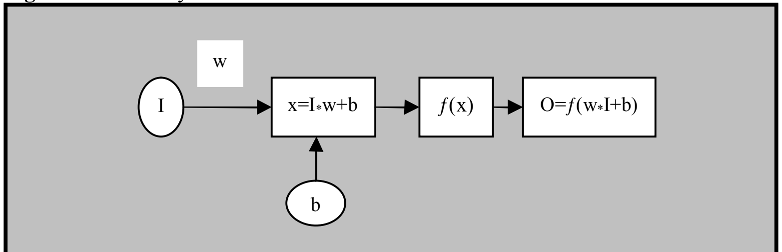


Figure 4. ANN Layers



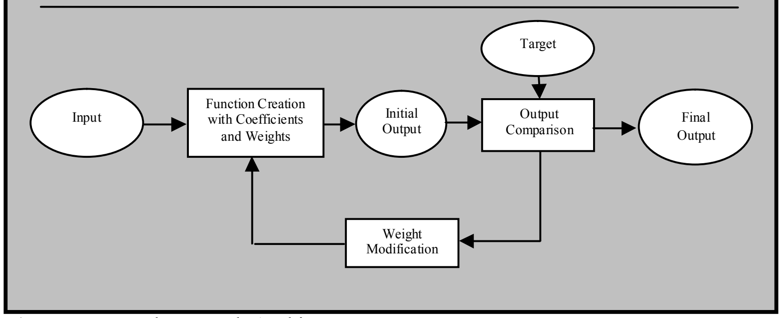


Figure 5. Neural Network Architecture

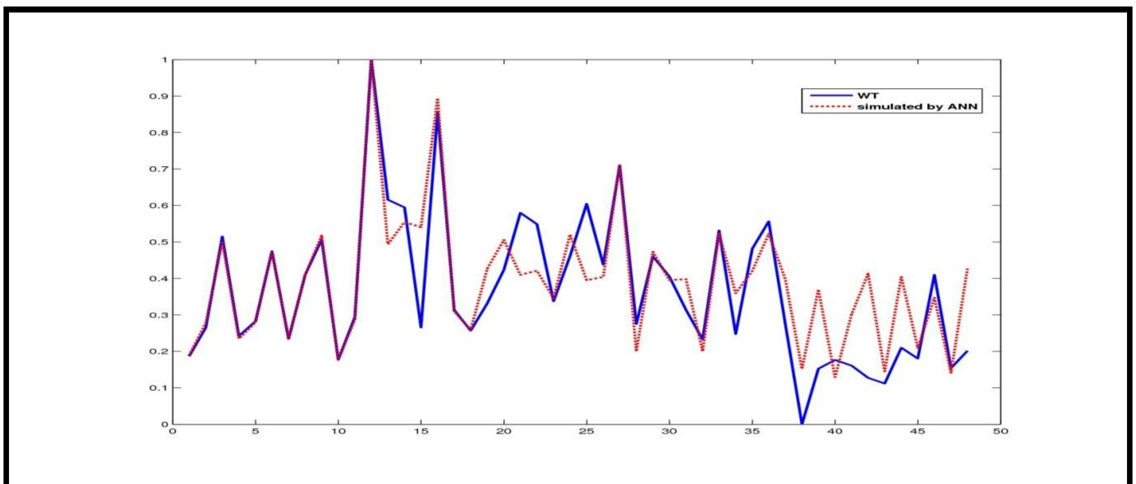


Figure 6. 1-20-2 structure curve in validation phase of model number 1 (best structure with R^2=0.8578)

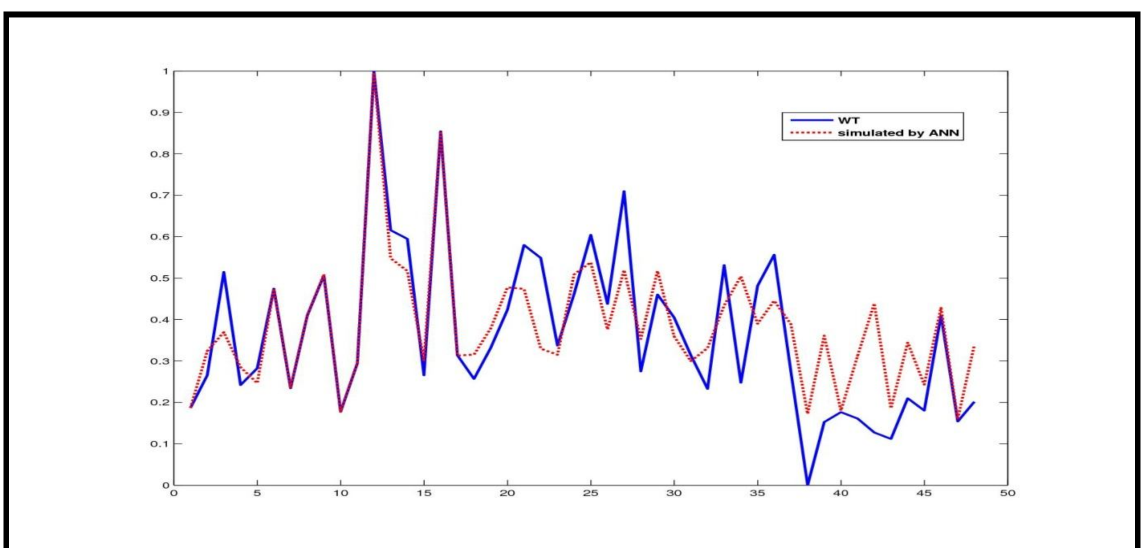


Figure 7. 1-20-2 structure curve in validation phase of model number 2 (best structure with R^2=0.8846)

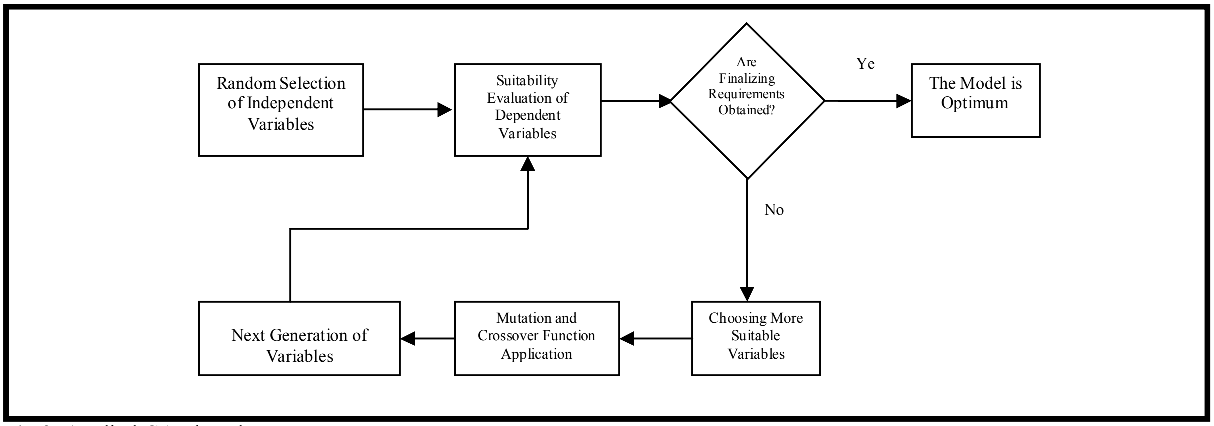


Fig 8. Applied GA Flowchart

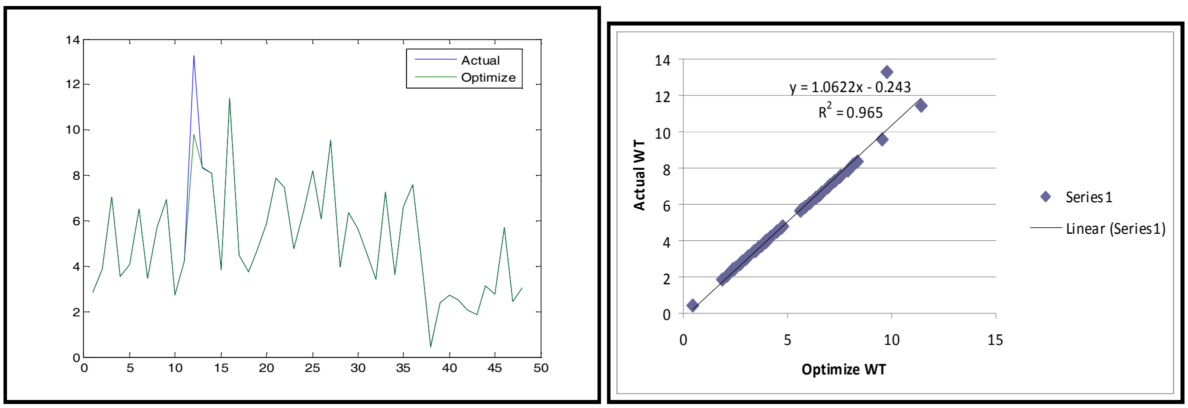


Fig 9. a) Regression on actual and estimated values of model number 1, b) Comparison between actual and estimated values of model number 1 during evolution

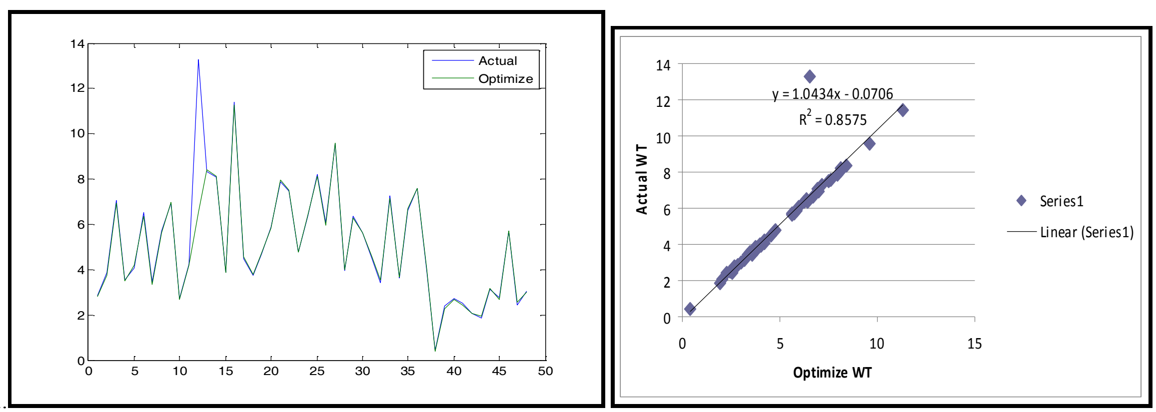


Fig 10. a) Regression on actual and estimated values of model number 2, b) Comparison between actual and estimated values of model number 2 during evolution