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# Presenting asphalt mixtures flow number prediction model using gyratory curves

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#### Abstract

Pavement permanent deformations due to lack of shear strength in mixture are a major reason of rutting. Any simple test to determine mixtures resistance to permanent deformation isn't distinguished in the 1st level of SUPERPAVE mix design method and prevalent methods for evaluating mixture rut resistance are expensive and time-consuming. Two aggregate types, gradations, asphalt cements and filler types were used in this research to present a prediction model for rutting based on flow number. A mathematical model to estimate flow number of dynamic creep test was developed using model parameters and gyratory compaction slope. The model is validated using Neural Network and Genetic Algorithm and makes it possible to evaluate mixtures shear strength while optimum asphalt content is being determined in laboratory. So not only there is no need to expensive test instruments of rutting or dynamic creep but a remarkable time saving in mix design procedure is achievable.

Keywords: Rutting, Gyratory, Dynamic creep, Flow number, Shear stress curve.

#### 1. Introduction

Increasing loading cycles on pavement leads to cumulative raise in permanent deformation and rutting as a surface depression in wheel path which can cause hydroplaning, reduce pavement drainage capacity, make moisture based deterioration growing rate faster, pavement thickness decreases in rutted zone and finally increase fatigue cracking in flexible pavements [1]. Mentioned parameters introduce rutting as an expensive flexible pavement deterioration mechanism [2]. Rutting could be recognized as a result of mixture volume decrease (pavement consolidation due to traffic (figure 1)), asphalt permanent deformation in constant volume (Plastic deformations due to normal shear stress in mixture (figure 2)) or a combination of them [3]. Another type of rutting is known which is due surface layer abrasion. Surface permanent deformation have the most share among various rutting causes, so considering it in mix design procedure seems essential [3,4].

Various laboratory methods are introduced to evaluate pavement permanent deformation which direct shear, repeated

The pressure of 300 kPa is applied to specimen in a cycle with 500ms loading and 1500 ms rest at 50°C in dynamic creep test. Drawing specimen cumulative permanent deformation curve versus loading cycles willproduce the illustrated curve of figure 3 with three main stages. It is proofed that the cycle in which territory phase is started (Fn) (Flow Number) is related to mixture rutting resistance directly [6,7].

This is a time-consuming test and UTM (Universal Testing Machine) which is used as the creep test instrument is expensive and needs skillful operator. So developing a method to distinguish asphalt mixture shear strength in a non-expensive and fast method is necessary.

#### 2. Problem Definition

#### 2.1. Research Target and Essence

Compaction as the most important issue on aggregates structure and positioning has considerable effect on mixtures rut and permanent deformation resistance [9]. It is proofed that aggregates rotary or transitive in asphalt mixture due to inadequate compaction will cause permanent deformation

shear at constant height, dynamic shear modulus test, creep and rutting test. Austria, France, Hungary, Romania and Switzerland use LCPC (Laboratoire Central des Ponts et Chaussées) and Finland, Sweden and Australia use Dynamic creep for rutting evaluation.

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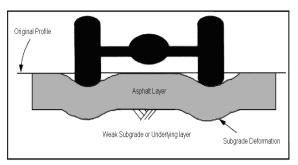


Fig. 1 Rutting due to bottom layers consolidation [5]

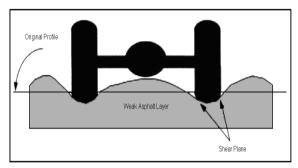


Fig. 2 Rutting due to lack of shear strength in asphalt mixture [5]

along shear planes [10]. On the other hand a weakness point of marshal method which is most applied method of compaction and mix design in Iran is compacting method which doesn't provide a fair simulation according to the researches [11]. Hence gyratory compaction machine (GCM) is used in SUPERPAVE mix design method after 40 years research on rotational compaction method by SHRP. This mix design method involves three levels which are divided by load and traffic. The first level is considered for traffic less than 10<sup>6</sup> ESALs (Equivalent Single Axle Loads) which composes of volumetric analysis and simple tests. Being simple and economical issues make this level interesting for engineers, but lack of performance tests is remarkable here. Simple methods for evaluating asphalt mixture workability should be developed to complete this level.

Asphalt mixtures with various aggregates, asphalt cements, gradation and filler were prepared and a model to predict flow number and consequently rutting resistance were developed after determining OAC for each group and performing dynamic creep test. As a result of this study mixture rutting

potential is predictable in a short time with low cost in laboratory simultaneously with preparing them.

#### 2.2. Literature Review

Lack of a test in 1st level of SUPERPAVE mix design to predict rutting of asphalt mixtures lead a lot of researches focus on this issue in FHWA (Federal Highway Administration), NCHRP (National Cooperative Highway Research Program) and FAA (Federal Aviation Administration) [12]. Other studies in this field using GCM output information will be stated in the following part.

# 2.2.1. Studies on Compaction Slope of SGC (Superpave Gyratory Compactor)

The idea of using SGC compaction slope was developed for the first time in 2000 [13]. Later studies stated that compaction slope is only an aggregates internal friction property [14]. But according to Mohr-Coulomb formula, shear stress ( $\tau$ ) is a function of cohesion (C) and internal friction angle ( $\Phi$ ). Although other studies proofed SGC compaction slope effect on rutting, but this parameter can't be used singly to predict asphalt shear strength performance.

$$\tau = C + \sigma_{n} \times tan(\phi) \tag{1}$$

# 2.2.2. Studies Considered a Part of Compaction Slope Curve

Researches define various indexes for asphalt rutting resistance with studying volumetric mass versus curve. TDI (Terminal Densification Index) which is assumed as compaction curve integral from 4% to 2% voids was one of them. DEI (Densification Energy Index) was defined as 8% to 4% voids in mentioned curve and CEI (Compaction Energy Index) as compaction start to 8% voids integral (Figure 4). Studies showed models based on these indexes were affected by aggregates positioning in molds greatly and wide tests showed this models aren't reliable. [15,16].gyration

# 2.2.3. Studies on Shear Parameters in Compaction

Gyratory shear strength, gyration number corresponding to maximum shear and gyratory shear slope were defined using gyratory shear curve. Researches performed in Florida and Michigan Universities although there is a relation between APA (Asphalt Pavement Analyzer) rut depth and these parameters but presented models didn't show good relation and aren't applicable [17].

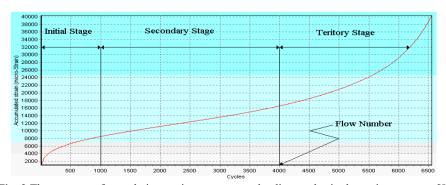


Fig. 3 Three stages of cumulative strain curve versus loading cycles in dynamic creep test [8]

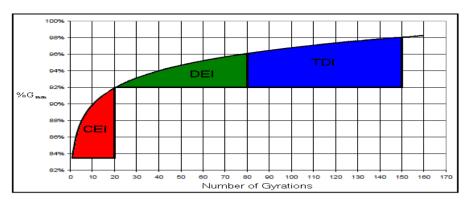


Fig. 3 Energy indices in density variations vs. gyratory gyration number curve [18]

#### 2.3. Research Assumptions

Although asphalt rutting is derived from cumulative deformation of base and subbase layers consolidation, abrasion and permanent deformation in asphalt layer but the main reason of rutting is asphalt permanent deformation [4]. This parameter was studied in this research under  $50^{\circ}$ C temperature. To consider design requirements asphalt mixtures were prepared using OAC ( $\pm 0.5\%$ ). Materials were similar from shape and aggregate texture issues and all specimens were prepared in a constant situation.

# 3. Methodology

#### 3.1. Materials Selection and Tests

RudehenAsbcheran mine (east of Tehran) and Rivand mine (Sabzevar) were used for limestone 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. Asphalt cement was supplied from Pasargad Oil Company in tow types of AC60-70 and AC85-100. Penetration, SayboltForol Viscosity, Softening Point, Ignition Point, Specific Gravity, Weight Loss and Ductility performed for both types and results passed Code234 (Iranian Pavement Code) requirements [19]

#### 3.2. Optimum Asphalt cement Content

#### 3.2.1. Gradation

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

# 3.2.2. OAC Determination and Specimen Naming

According to various types of aggregates, gradation, filler and asphalt cement, 288 specimens were prepared for OAC using marshal method and finally 16 optimum asphalt contents were determined as table 2. Combination of two letters and two numbers was used for specimen naming. Left to right, first

Table 1 Aggregates gra	dation for Binder and	Topka layers [4	1]
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Sieve Specification			Number 4	Continuous G	radation	Number 5	Continuous G	radation
	Sieve		Passed Range	Passed	Remained	Passed Range	Passed	Remained
mm	Number	Inches	Weight (%)	Ave. Weight (%)	Weight (%)	Weight (%)	Ave. Weight (%)	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	34/5
0.15	100	-	-	-	-	-	-	-
0.075	200	-	2-10	6	7	2-10	6	9

Table 2 Determined OAC 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

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 asphalt cement type (6 for AC60-70 and 8 for AC85-100).

### 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  $N_{\rm ini}$ ,  $N_{\rm des}$  and  $N_{\rm max}$  respectively according to table 3 for ESALs equal to 106.

#### 3.3.2. Determining Number of Specimens for Research

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

#### 3.1. Gyratory Parameters

#### 3.4.1. Gyratory Shear Stress Modeling Parameters

Shear stress versus gyration number is one of the SGC output curves. 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 model after testing all models:

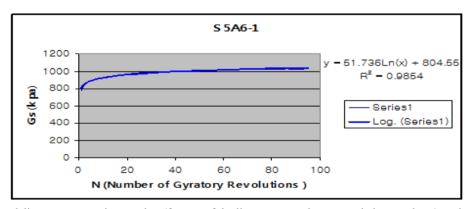
$$G_{\mathcal{S}} = K_1 Ln(N) + K_2 \tag{2}$$

In which Gs is gyratory shear stress in a specific gyration of N while  $K_1$  and  $K_2$  are gyratory shear stress semi-log curve slope and y-intercept respectively.

In other words graphs such as figure 5 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 95.14% of models have more than 75% correlation coefficient.

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

FOLES					Maximun	ı Design T	emperatur	e Average				
ESALS 10 <sup>6</sup>	< 39 °C				39-40 °C			41-42 °C			43-44 °C	
10	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



**Fig. 5** Shear stress modeling versus gyration number (for one of the limestone specimens, gradation number 4, rock powder as the filler and 60-70 asphalt cement)

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

Correlation Coefficalent (R							
R <sup>2</sup> Range	100-95	95-90	90-85	85-80	80-75	<75	
Number of Specimens	84	29	9	10	5	7	144
Percent	58.33	20.14	6.25	6.94	3.48	4.86	100

#### 3.4.2. Compaction Slope Parameter

Specimen height is the other parameter measured by gyratory per cycle. Since specimen height is distinguished in each cycle, compaction slope can be determined using eq. 3 considering constant specimen weight and specimen cross section. Studies showed compaction slope is related to aggregates internal friction directly, so it can affect shear strength of mixture [20].

$$K = \frac{(\%G_{\text{mm,Ndes}} - \%G_{\text{mm,Nin}})}{\left[\log(N_{\text{des}}) - \log(N_{\text{in}})\right]} * 100$$
(3)

In which:

$$\%G_{mm,Ndes} = \frac{G_{mb}}{G_{mm}} \tag{4}$$

$$\%G_{mm,Nini} = \%G_{mm,Ndes} * \frac{h_{des}}{h_{mi}}$$

$$(5)$$

- $\%G_{mm,Ndes}$  and  $\%G_{mm,Nini}$ : Asphalt mixture maximum specific gravity percent at 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- $S_m$ ), Voids in mineral aggregates (VMA), height and density variations were determined for each specimens which only K,  $K_I$  and  $S_m$  introduced as effective parameters in sensitivity analysis. (table 5)

#### 3.5. Creep Test

Three creep tests were performed for each combination at 50°C, under 300 kpa pressure with 500 ms loading and 1500 ms rest using UTM-5 and flow number of each combination were determined [21]. The results could be seen in table 6.

# 4. Presenting Experimental Model

#### 4.1. Developing a Model using SPSS19

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

Table 5 Analysis of variance (SPSS 19 Output)

		A	NOVA			
	Model	Sum of Squares	df	Mean Square	F	Sig.
	Regression	5.809E8	2	2.904E8	436.047	.000
1	Residual	87258037.990	131	666091.893		
	Total	6.682E8	133			

results. Two assumptions are considered in regression as  $H_0$  and  $H_1$ :

$$\begin{cases} H_0: & R=0 \\ H_1: & R \neq 0 \end{cases}$$
 (6)

The aim is to reject  $H_0$  assumption which sig F change coefficient is used for validation. 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 7 and the model was gained as following:

According to tables 8 and 9, final model was presented as equation 7:

$$F_n = 743.562 K - 94.115 K_1 \tag{7}$$

In which:

 $F_n$  = Flow number from dynamic creep test

K =Gyratory Compaction Slope from Eq3

 $K_1$  = Gyratory Shear Stress Curve Slope (Eq2)

As it can be understood from table 7, R for this model is 0.932 which is meaningful in 95% reliability level.

#### 4.2. Validating the model using ANN

ANN (Artificial Neural Network) 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 [22,23], asphalt cement properties effect on asphalt features [24] and Mixture Compaction Quality Control [25].

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. The model in this paper has two independent variables and one dependent variable, so the network has two input neurons and one output neuron (figure 6).

Figure 7 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.

Table 6 Gyratory compactor and creep test results for 144 specimens

	Limestone	Differen						Silica					
	Specimen	ce	Fn	К	K <sub>1</sub>		aximum Shear	Specimen	F <sub>n</sub>	К	<b>K</b> <sub>1</sub>	K <sub>2</sub>	Maximum Shear
	Specificati on	with OAC					(Sm)	Specificati on					(Sm)
1	A4P6		1225	10.560	61.387	787.630	1049	1	S4P6	320	8.281	54.606	803.12
2	A4P6	-0.5	2000	8.620	44.936	647.320	839	2	S4P6	620	7.909	54.593	835.41
3 1	A4P6 A4P6		1300 5100	10.747 8.034	64.181 40.065	774.380 676.750	1046 893	3 1	S4P6 S4P6	2704 664	6.906 8.632	38.522 60.530	911.16 825.94
2	A4P6 A4P6	0.0	5250	10.161	28.635	845.770	977	2	S4P6	1872	7.676	37.358	923.89
3	A4P6	0.0	5000	10.713	40.814	839.350	1026	3	S4P6	788	8.718	56.609	835.55
1	A4P6		7375	8.869	47.824	815.980	1062	1	S4P6	684	8.945	58.899	843.50
2	A4P6	0.5	6900	7.743	44.735	658.330	870	2	S4P6	756	7.423	46.943	874.27
3	A4P6		6500	10.061	44.325	838.820	1047	3	S4P6	860	8.332	47.344	853.31
1	A4P8 A4P8	-0.5	1475	11.216	69.459	742.240	1049	1 2	S4P8 S4P8	490 640	7.453	48.512	856.06
3	A4P8	-0.5	1250 1550	11.363 11.127	69.312 65.995	738.510 769.230	1058 1074	3	S4P8	544	7.955 8.098	51.713 53.093	838.22 836.63
1	A4P8		3850	10.573	54.222	821.510	1052	1	S4P8	1036	8.280	49.258	843.15
2	A4P8	0.0	3300	10.897	49.539	816.900	1032	2	S4P8	1584	7.850	43.737	876.39
3	A4P8		5500	10.604	50.411	829.960	1047	3	S4P8	2480	7.798	40.790	884.45
1	A4P8		2550	10.805	59.273	783.790	1052	1	S4P8	2664	7.816	33.519	900.33
2	A4P8	0.5	4750	11.105	58.485	810.780	1058	2	S4P8	2400	7.989	34.831	912.03
3 1	A4P8 A5P6		4875 3200	10.805 10.468	59.273 25.534	783.790 781.18	1052 909	1	S4P8 S5P6	2160 424	8.220 7.927	44.317 48.384	867.48 843.71
2	A5P6	-0.5	2900	10.723	39.783	690.46	864	2	S5P6	668	7.469	49.990	851.30
3	A5P6		3500	10.835	48.797	651.37	861	3	S5P6	764	7.517	48.195	852.17
1	A5P6		4125	10.710	42.101	698.30	876	1	S5P6	744	7.883	47.150	861.43
2	A5P6	0.0	1625	10.584	43.333	698.03	887	2	S5P6	888	7.605	47.644	857.71
3	A5P6		5750	10.166	48.614	704.55	942	3	S5P6	900	7.380	46.585	858.58
1	A5P6 A5P6	0.5	3250 3560	10.819 9.016	45.744 47.100	661.46 564.90	869 776	1 2	S5P6 S5P6	2440 1824	7.473 7.134	37.069 32.490	895.56 906.45
3	A5P6	0.5	3875	9.906	48.275	639.55	891	3	S5P6	3488	7.038	31.084	911.38
1	A5P8		2550	10.217	38.543	663.54	825	1	S5P8	672	7.445	57.682	835.79
2	A5P8	-0.5	2375	9.161	59.753	756.67	1016	2	S5P8	396	7.265	53.960	859.17
3	A5P8		4750	8.083	23.693	723.37	830	3	S5P8	512	7.656	56.813	842.73
1	A5P8		5625	7.171	24.845	711.25	836	1	S5P8	1020	7.460	51.417	853.31
2	A5P8 A5P8	0.0	4125 3125	9.798 10.155	54.522 32.938	773.04 681.47	1008 825	2	S5P8 S5P8	1608 1616	7.652 7.844	46.923 50.780	872.31 868.75
1	A5P8		1425	10.422	36.944	667.57	824	1	S5P8	2232	7.201	36.618	905.04
2	A5P8	0.5	4875	5.335	38.374	795.48	819	2	S5P8	6112	7.177	38.223	903.16
3	A5P8		5125	6.232	35.887	764.24	822	3	S5P8	4400	7.520	44.138	895.43
1	A4A6		444	6.119	39.965	778.64	959	1	S4A6	564	8.026	50.107	827.97
2	A4A6	-0.5	538	6.282	44.871	787.96	984	2	S4A6	326	7.435	46.117	832.25
3 1	A4A6 A4A6		238 450	5.855 6.419	44.249 46.253	773.68 780.63	971 987	3 1	S4A6 S4A6	426 888	7.723 8.312	50.088 54.104	811.04 809.26
2	A4A6	0.0	235	6.137	48.104	783.91	998	2	S4A6	544	7.693	46.870	830.14
3	A4A6		538	6.188	43.421	784.84	975	3	S4A6	1392	7.938	44.122	849.20
1	A4A6		906	6.716	44.815	776.91	983	1	S4A6	1408	8.073	46.509	847.04
2	A4A6	0.5	714	6.673	45.196	788.27	992	2	S4A6	1312	7.832	39.271	859.24
3	A4A6		1816	6.419	42.104	799.94	992	3 1	S4A6	3000	7.905	38.328	865.18
1	A4A8 A4A8	-0.5	1176 1372	9.123 8.877	51.139 49.526	772.79 794.28	998 1005	2	S4A8 S4A8	324 356	6.868 6.971	44.123 50.617	829.01 804.45
3	A4A8	0.5	1824	8.614	53.073	794.55	1029	3	S4A8	688	7.483	56.506	803.21
1	A4A8		1680	9.744	52.217	803.84	1026	1	S4A8	486	7.695	52.007	807.22
2	A4A8	0.0	2144	9.742	48.769	807.65	1013	2	S4A8	3616	7.386	31.991	862.23
3	A4A8		812	10.258	58.466	769.10	1023	3	S4A8	344	7.767	44.967	818.20
1	A4A8 A4A8	0.5	2440 2448	10.225 6.204	46.158 44.110	801.24 799.73	993 992	1 2	S4A8 S4A8	900 948	8.264 8.313	45.079 36.983	856.14 846.30
3	A4A8 A4A8	0.5	2448 840	6.204	44.110	799.73	992	3	S4A8 S4A8	732	8.313	44.112	833.02
1	A5A6		1524	8.543	53.748	770.26	1008	1	S5A6	296	6.739	51.736	804.55
2	A5A6	-0.5	2024	8.157	55.907	785.50	1029	2	S5A6	324	6.780	52.890	801.58
3	A5A6		1424	8.900	58.416	780.06	1037	3	S5A6	350	6.532	52.481	814.92
1	A5A6		1416	9.648	58.161	775.22	1029	1	S5A6	440	7.541	46.088	828.54
2	A5A6	0.0	2480	9.622	53.063	802.01	1028	2	S5A6	600	7.364	44.679	833.53 812.41
3 1	A5A6 A5A6		3928 4024	9.256 8.632	45.210 40.233	872.15 832.11	1065 1017	3 1	S5A6 S5A6	560 728	7.895 8.487	52.836 48.941	812.41
2	A5A6	0.5	2544	9.064	41.651	830.60	1017	2	S5A6	824	7.312	46.536	830.80
3	A5A6		3376	8.979	47.587	813.47	1013	3	S5A6	1076	7.557	42.811	846.27
1	A5A8		2640	8.427	50.076	789.29	1007	1	S5A8	314	6.701	46.173	810.62
2	A5A8	-0.5	1888	8.665	55.004	789.63	1029	2	S5A8	380	6.786	51.148	789.57
3	A5A8		2744	8.038	53.134	798.62	1029	3	S5A8	378	7.298	50.725	793.20
1	A5A8	0 0	1640	9.026	46.620	821.98	1016	1	S5A8	728	8.685	55.412	791.73 819.08
2	A5A8 A5A8	0.0	2312 3392	8.931 8.909	48.718 52.352	814.79 802.56	1022 1031	2	S5A8 S5A8	724 740	7.788 8.096	48.103 51.413	819.08
1	A5A8		2776	9.547	38.051	824.58	983	1	S5A8	2128	8.447	51.536	814.41
2	A5A8	0.5	2344	9.217	34.710	835.80	984	2	S5A8	1264	8.699	53.506	812.96
3	A5A8		3344	9.325	40.075	819.42	986	3	S5A8	1144	9.188	54.484	793.68

Table 7 Parameters statistical analysis in SPSS 19 results

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
Flow Number	144	7140	235	7375	1954.76	1604.082	2573077.54
K	144	6.03	5.34	11.36	8.3890	1.37017	1.877
$\mathbf{k}_1$	144	77.83	-8.37	69.46	46.7772	9.99775	99.955

Table 8 Model statistical specification summary (SPSS 19 output)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics Sig. F Change
1	0.932	0.869	0.867	816.145	.000

Table 9 Model independent variable coefficient (SPSS 19 output)

#### Coefficients

	Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.	۰/۹۰% Confiden	ice Interval for B
		В	Std. Error	Beta	_		Lower Bound	Upper Bound
1	k	743.562	39.843	2.816	18.662	0.000	664.743	822.382
2	$\mathbf{k}_1$	-94.115	6.993	-2.031	-13.459	0.000	-107.948	-80.282

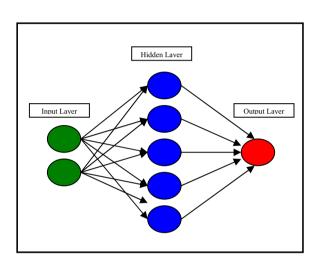


Fig. 6 ANN layers

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.

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n} (x_i - y_i)^r}{n}}$$
(8)

 $R^2$  is the statistical index to validate output accuracy which

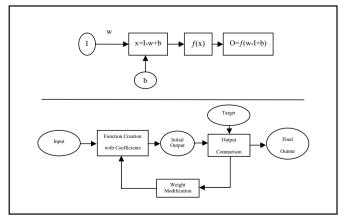


Fig. 7 Neural network architecture

whatever closer to 1, more precise the model is.

$$R^{2} = \left(\frac{(x_{i} - \overline{x})(y_{i} - \overline{y})}{\sqrt{(x_{i} - \overline{x})^{T}(y_{i} - \overline{y})^{T}}}\right)^{2}$$
(9)

MATLAB 2008 software was use for coding the network. About 67% of data were used for training the network after normalizing by equation 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 presented model

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 10 and figure 8.  $R^2$  were determined as 0.9122 in best structure in validation phase as it is stated in table.

#### 4.3. Validating model Using GA

Genetic Algorithm (GA) is a method of optimizing and validating models 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. Independent variables are determined in each phase of evolution so that less difference is achieved between real value of dependent variable and estimated value (Figure 9). MATLAB 2008 software was used for coding and Excel 2007 for comparing the results in this study.

# 4.3.1. GA results for presented model

As it is illustrated in figure 10, 0.835 is obtained as determination coefficient for this model.

**Table 10** Neural network run output (for 5, 10, 15 and 20 neurons in a hidden layer)

Neural Network	Trainiı	ng Phase	Validation Phase
Structure	$\mathbb{R}^2$	RMSE	$R^2$
2-5-1	0.8231	0.0162	0.7061
2-10-1	0.8117	0.0120	0.7861
2-15-1	0.8927	0.0102	0.8366
2-20-1	0.9270	0.00705	0.9122

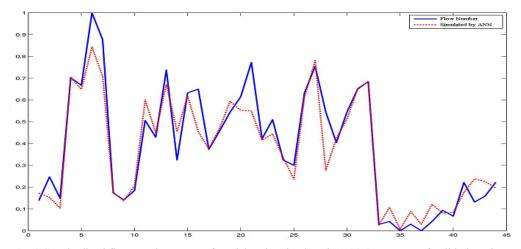


Fig. 8 Standardized flow number curve of model and real values in 1-20-2 structure of validating phase

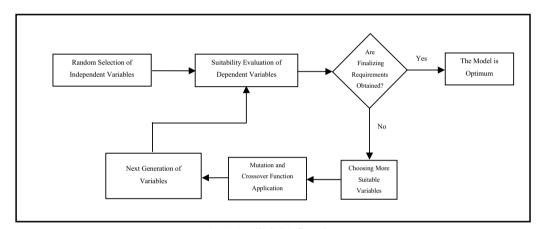


Fig. 9 Applied GA flowchart

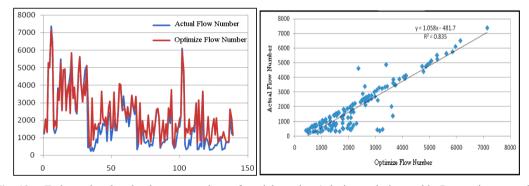


Fig. 10 a. Estimated and real values comparison of model number 1 during evolution and b. Regression on real and estimated values of model

# 5. Discussion and Conclusion

One of the most important consequences of this study is GSM shear stress modeling versus gyration number. It was proofed that logarithmic model results in the best trend. This curve has two main phases. The first phase can be named as compaction phase, has an intense slope. Shear stress variation in this phase is more than condensation phase, as the second phase of the curve. Voids variation of first phase is more than

that of the second one too. Using the GSM compaction slope and equation slope the model for predicting flow number was developed. It should be noted the model is developed in 50°C and with OAC. Other conclusions are as following:

• In compaction phase, particle movement in various directions will case asphalt compaction initially. But in second phase aggregates rotation and slippage lead to volume reduction and specimen density increase. So mixture voids is more in compaction slope in compare with condensation phase

considerably.

- Average compaction slope for specimens prepared with gradation #4 is more than #5 prepared specimens. Compaction slope is an index of aggregates internal friction. So #4 gradation which has more coarse aggregates has more compaction slope than #5 gradation.
- Shear stress variation in compaction phase is more than condensation phase. The reason will be for materials more impacts and a resistance to mixture volume change in this phase.
- Compaction slope coefficient is positive in the developed model. So specimens with higher compaction slope have more flow number and are resisted to rutting more. This is due to high resistance because of more internal friction and structural form. This is in accordance with other consequences about compaction slope.
- Shear stress curve negative coefficient in this model states asphalt mixtures with higher shear stress gradient in compaction phase are resisted to rutting more. In other words the more the shear stress in the compaction slope in compare with condensation phase is, the less the shear strength of mixture is.
- Using developed model, flow number can be estimated simultaneously during specimen preparation for determining OAC and evaluate rutting index before preparation, so a considerable save will be held in time and costs.

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