

Article

Utilizing Soft Computing Techniques to Estimate the Axial Permanent Deformation of Asphalt Concrete

Amjad H. Albayati ¹, Yazeed S. Jweihan ² and Mazen J. Al-Kheetan ^{2,*}¹ Department of Civil Engineering, University of Baghdad, Baghdad 10071, Iraq² Department of Civil and Environmental Engineering, College of Engineering, Mutah University, Karak 61710, Jordan

* Correspondence: mazen.al-kheetan@mutah.edu.jo

Abstract: Rutting is a crucial concern impacting asphalt concrete pavements' stability and long-term performance, negatively affecting vehicle drivers' comfort and safety. This research aims to evaluate the permanent deformation of pavement under different traffic and environmental conditions using an Artificial Neural Network (ANN) prediction model. The model was built based on the outcomes of an experimental uniaxial repeated loading test of 306 cylindrical specimens. Twelve independent variables representing the materials' properties, mix design parameters, loading settings, and environmental conditions were implemented in the model, resulting in a total of 3214 data points. The network accomplished high prediction accuracy with an R^2 of 0.93 and a mean squared error (MSE) of 0.0039. Results based on the sensitivity analysis and variable importance techniques showed that the percentage of aggregate passing the 4.75 mm sieve and the (rice) theoretical maximum specific gravity (Gmm) were the most significant factors in predicting axial permanent strain (ϵ_p). Furthermore, the connection weight method highlighted input variables' distinct positive and negative impacts on permanent deformation.

Keywords: rutting; asphalt concrete; machine learning; model; uniaxial load



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1. Introduction

Rutting is a permanent deformation that appears in pavement layers due to repeated loading from traffic and negatively affects its performance and strength and drivers' safety. This distress reduces the pavement's load-bearing capacity and lifespan, and consequently, the pavement would require extensive maintenance interventions that will place a substantial economic and operational burden on road agencies [1]. The development of rutting and its progression is a function of the mixture design, materials' properties, environmental factors, and traffic load levels [2,3]. Moreover, the intricate relationship between these factors has made it very difficult to predict the permanent deformation resulting from them accurately [4].

Different laboratory techniques have been used to determine and predict the development of rutting in asphalt mixtures. These include dynamic and static creep tests, wheel tracking tests (e.g., the Hamburg Wheel Tracking Test), shear tests, and repeated load axial tests [1,5]. Despite the importance and efficiency of these various methods in understanding the permanent deformation of pavement and the development of distresses, they are labor-intensive, time-consuming, and require expensive specific instruments. Also, many of the conventional tools used to predict permanent deformation are dominated by empirical models that are incapable of addressing the complex non-linear interaction between the composition of the mixture, traffic loading, and environmental conditions [6,7]. This deficit

indicates the urgency for developing new and efficient approaches for rutting prediction with high accuracy and confidence.

Recent developments in the field of artificial intelligence (AI) have introduced machine learning (ML) techniques as revolutionary tools that can be used to address challenging issues in pavement construction, maintenance, and distress prediction. In this regard, significant focus has been given to Artificial Neural Networks (ANNs) due to their exceptional ability to predict complex relationships and perform well with varying datasets [8]. Furthermore, ANNs do not have any explicit mathematical equation formulation as they are driven purely by the data, unlike the conventional empirical models that require a predetermined understanding of the problem at hand [9]. This mainly makes them useful for complicated problems such as permanent deformation resulting from the interaction between the used materials, loading, and environmental factors. Several efforts have been reported to implement the predictive capabilities of ANNs to estimate some essential concrete pavement performance indicators, including fatigue life and moisture susceptibility [10,11]. However, studies on using ANNs to predict permanent deformation parameters under relevant conditions are scant, creating a knowledge gap in the existing body of literature.

The incorporation of Artificial Neural Networks (ANN) in pavement engineering has various benefits, including the capacity to work with large and complex data sets, less reliance on extensive experimental testing, and the ability to provide predictions under a wide range of conditions [12–15]. These attributes will not only improve rutting predictions but also provide information that can be used to develop a reliable design of asphalt mixtures that can resist deformation.

Accordingly, this research proposes an effective ANN-based model that predicts the permanent deformation of asphalt concrete. The employed input variables are based on combining the primary mix design and material properties such as aggregate gradation, asphalt content, air voids, and other specific parameters, including the temperature and the applied load repetitions. Moreover, the ANN model has been accurately trained, validated, and tested for prediction purposes. Sensitivity analysis was also performed to establish the degree of variation in the parameters and define the most significant factors affecting rutting by means of axial permanent strain of asphalt concrete, which could be utilized to optimize asphalt mix designs and improve the future performance of asphalt pavement.

Both academia and practice may benefit significantly from the findings herein in this research. In the academic world, it contributes to the knowledge of permanent deformation of pavement and presents a new use of ANN-based modeling in asphalt concrete studies. In the hands of civil engineers and other practitioners, this work provides excellent resources for the better design, construction, and maintenance of flexible pavements, making them more durable, safe, and economical. This study is a crucial step towards improving the existing pursuit of sustainable and high-performing road networks by transcending the scope of traditional methods to more advanced predictive functions.

2. Permanent Deformation Influential Factors

Due to the combined impact of traffic loading, environmental conditions, and internal properties of asphalt mixtures, asphalt pavements tend to undergo permanent deformation, referred to as rutting [16]. Moreover, the magnitude and number of wheel passes and the change in ambient temperature are considered the main external factors influencing the rutting severity [17]. A high traffic volume induces significant shear stress within individual pavement layers and at the interfaces between layers, leading to plastic deformation that accumulates over time and manifests as surface ruts [1]. Higher temperatures also make pavements more susceptible to rutting since such temperatures reduce the viscosity of

bitumen, which increases the pavement's deformation and decreases its resistance to loading deformation [18].

On the other hand, internal factors mainly concerning the mixed design and material properties are equally important contributors to permanent deformation. The characteristics of the used aggregates, which include the particle size distribution, the shape of the particles, and the texture, are responsible for the degree of interlock and load transfer in the mixture [16]. Using angular and crushed aggregate leads to better internal friction and, therefore, greater interlocking, hence greater resistance of the mixture to shear deformation [17]. Bitumen percentage and air voids are also essential factors; high bitumen content or low air voids result in creating a mixture with low stiffness and low strength, thus making it more vulnerable to plastic deformation [1]. Inversely, low bitumen content or a higher percentage of air voids can reduce the cohesion of the mixture and increase the formation of premature cracking, which ultimately contributes to rutting [18]. Therefore, adequate compaction of the mixture during placement and using modifiers such as polymers can improve the ability of the mix to resist stress due to traffic and temperature [16]. For this reason, understanding the causes of rutting helps design asphalt mixtures that resist permanent deformation. Moreover, using predictive tools, such as machine learning models, offers additional opportunities to quantify the impact of these factors and refine design methodologies for modern traffic and environmental conditions.

3. Materials and Testing

The properties of the materials used in this work, including asphalt binder, aggregates, and fillers, were determined by employing suitable ASTM standard experiments, and the results were checked with the specifications of the Iraqi State Corporation for Roads and Bridges [19].

3.1. Asphalt Cement (AC)

To evaluate the effect of asphalt cement consistency on the permanent deformation behavior of asphalt concrete mixtures, three types of asphalt cement were used in the experimental work: AC 40–50, AC 60–70, and AC 85–100. All were sourced from the Dora Refinery, located southwest of Baghdad. Table 1 illustrates the properties of the used asphalt cement.

Table 1. Asphalt cement characterization.

Properties	ASTM Standard	Units	Asphalt Type			Specification Limit (ASTM D 946)		
			40/50	60/70	85/100			
Before the Thin Film Oven Test								
Penetration	D5	1/10 ^{mm}	46	66	89	40-50	60-70	85-100
Specific Gravity	D70	----	1.031	1.024	1.018	----	----	----
Flash Point	D92	°C	322	296	291	>232	>232	>232
Softening Point	D36	°C	49	42	38	----	----	----
Ductility	D113	cm	>100	>100	>100	>100	>100	>100
Rotational Viscosity	D4402	Pa. Sec	0.71	0.496	0.350	----	----	----
Solubility in Trichloroethylene	D2042	%	99.3	99.3	99.4	>99	>99	>99
After Thin Film Oven Test, D1754								
Retained Penetration	D5	%	62	65	71	>55	>52	>47
Ductility	D113	cm	60	80	>100	----	>50	>75

3.2. Aggregate

Crushed quartz sourced from the Amanat Baghdad asphalt concrete mix plant in Taji, north of Baghdad, was used to prepare the asphalt mixtures in this work. The coarse and fine aggregates were sieved and blended in appropriate proportions to meet the gradation requirements for surface, binder, and base courses, following ASTM D 3515. Five different gradations were evaluated: three for the surface course with varying aggregate fractions passing the 12.5 mm and 4.75 mm sieves, identified as WCG 1, WCG 2, and WCG 3, with WCG 3 having a higher proportion of coarse aggregate (retained on the 4.75 mm sieve) compared to the other two types of surface course mixes; one for the binder course (BiCG); and one for the base course (BaCG). The gradation of the used aggregate is shown in Figure 1. Moreover, the physical properties of the aggregate are presented in Table 2 and compared with the SCRB recommendations [19].

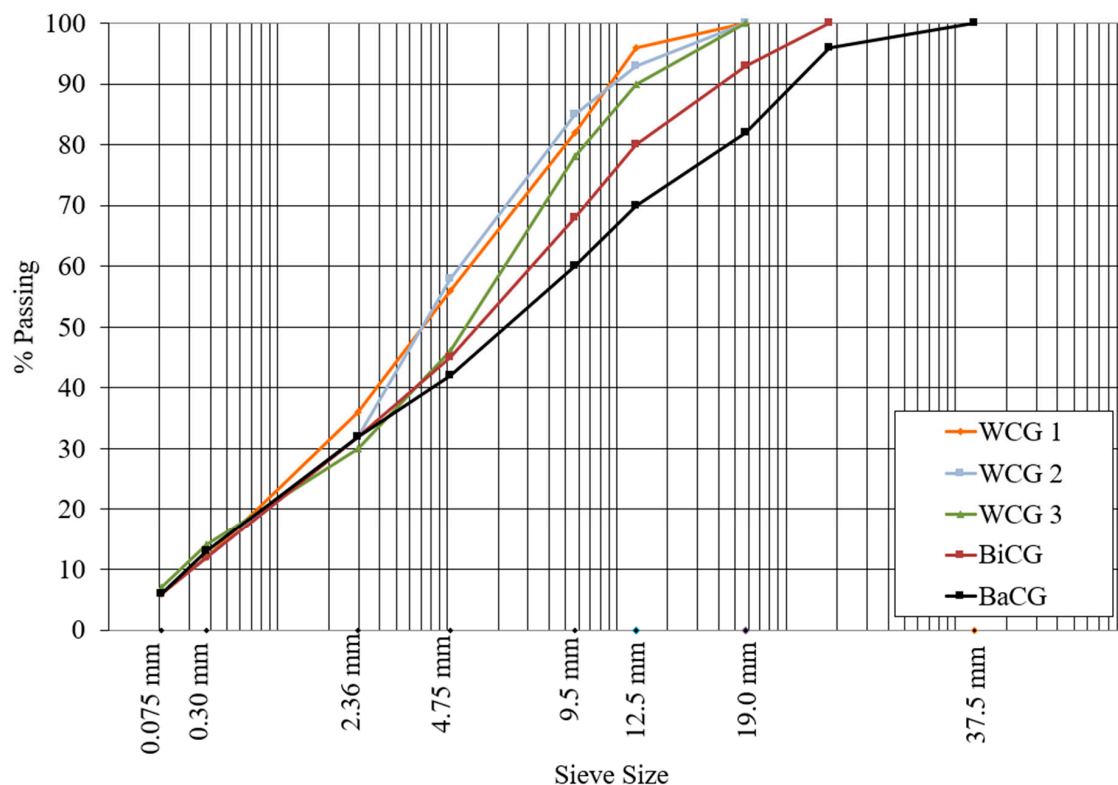


Figure 1. The gradation of aggregates used in asphalt concrete mixtures.

Table 2. Physical properties of the used aggregates.

Tested Properties	Results	ASTM Standard	SCRB Requirements
Fine aggregates			
Apparent specific gravity	2.695	C-127	-
Bulk specific gravity	2.661	C-127	-
Sand equivalent (%)	52	D-2419	45 minimum
Water absorption (%)	0.901	C-127	-
Coarse aggregates			
Apparent specific gravity	2.691	C-127	-
Bulk specific gravity	2.631	C-127	-
Los Angeles abrasion (%)	19.3	C-127	30 maximum
Fractured pieces (%)	94	C-88	95 minimum
Water absorption (%)	0.458	C-127	-
Soundness loss by sodium sulfate solution (%)	3.9	C-131	10 maximum

3.3. Mineral Filler

Limestone dust (passing 0.075 mm sieve) that was sourced from the Amanat Baghdad asphalt concrete mix plant south of Baghdad was used in this study as a filler. Table 3 illustrates the physical properties of the used limestone filler.

Table 3. Physical properties of the limestone filler.

Property	Test Results
Passing sieve No.200 (0.075 mm)	96
Specific gravity	2.787

3.4. Specimen Preparation

Two types of cylindrical specimens were prepared for this study, both with a diameter of 101.6 mm (4 inches) but with different heights. For the Marshall mix design, the specimen height was 63 mm (2.5 inches), whereas for permanent deformation evaluation, the height was 203.2 mm (8 inches). Aggregates received from the mixing plant were separated into fractions based on their retention on specific sieves (37.5, 25.0, 19.0, 12.5, 9.5, 4.75, 2.36, 0.3, and 0.075 mm). The aggregates retained in the pan were discarded and replaced with an equivalent amount of limestone dust as a mineral filler. To meet the gradation requirements shown in Figure 1, 1150 g of aggregate was weighed for the Marshall specimens, while 3800 g was weighed for the permanent deformation specimens. Both were then heated to 150 °C and placed in a mixing bowl. The asphalt cement was separately heated to 140–145 °C, corresponding to a viscosity of 170 ± 20 cSt, and then added to the preheated aggregates in the mixing bowl. The materials were thoroughly mixed on a hot plate for two minutes to ensure uniform coating. The mixture was then placed back in an oven at 140 °C for 10 min to maintain a uniform compaction temperature. Meanwhile, the compaction molds were preheated to 100 °C. A 4-inch paper disk was placed at the base of each mold, and the mold's interior edges were lubricated to facilitate specimen extraction. Half of the heated mixture was poured into the mold using a funnel. To ensure a homogeneous blend, the mixture was vigorously spaded with a heated spatula 15 times around the perimeter and 10 times over the interior before compaction, following ASTM D1559. The same procedure was repeated for the remaining portion of the mixture.

For the Marshall specimens, compaction was performed using 75 blows per side of a Marshall hammer, as per ASTM D1559. In contrast, the double plunger method was employed for the permanent deformation specimens, in which a 65,000 lb (29,491 kg) load was applied to each end of the specimen for one minute using a hydraulic compression machine. Finally, the compacted specimens were cooled overnight on a smooth, flat surface at room temperature before being extracted and stored for testing.

3.5. Uniaxial Repeated Loading Test

A pneumatic repeated load system (PRLS) was used to determine the permanent deformation resulting from repeated uniaxial loading. During the test, specimens were subjected to repetitive compressive stress, and the resulting axial permanent deformation was measured over a range of loading cycles. The compressive load was applied as a rectangular wave at a consistent frequency of 60 cycles per minute, using two different loading patterns: one with a 0.1 s load duration followed by a 0.9 s rest period, and the other with a 0.4 s load duration followed by a 0.6 s rest period. Six levels of compressive stress (44.82 kPa (6.5 psi), 68.95 kPa (10 psi), 89.63 kPa (13 psi), 137.89 kPa (20 psi), 186.15 kPa (27 psi), and 206.84 kPa (30 psi)) were applied, and the experiments were conducted at seven

distinct temperatures (20, 25, 40, 55, 60, 65, and 70 °C). Then, the permanent strain (ϵ_p) was estimated by employing the following equation:

$$\epsilon_p = \frac{p_d \times 10^6}{h} \quad (1)$$

where ϵ_p is the axial permanent microstrain, p_d is the axial permanent deformation, and h is the specimen height.

3.6. Mix Design

The Marshall mix design method was utilized to achieve the objectives of this study, especially to determine the Optimum Asphalt Content (OAC) for the various asphalt mixtures. The OAC was calculated as the average asphalt content corresponding to three critical parameters: 4% air voids (AV%), maximum stability, and maximum unit weight. Additionally, the remaining properties were checked against their specified ranges at the OAC, as outlined by the Marshall method guidelines.

For the surface course mixes with different gradations, the Marshall plots, shown in Figure 2, depict the relationships between asphalt content and Marshall properties, including stability, flow, unit weight, air voids (AV%), voids in mineral aggregate (VMA%), and voids filled with asphalt (VFA%). The OAC obtained for WCG 1 and WCG 2 was 4.6% by weight of the total mix. For WCG 3, the calculated OAC was slightly lower at 4.53%; however, it was rounded to 4.6% for practical purposes. Similarly, the Marshall plots for the binder course (BiCG) and base course (BaCG) mixes are presented in Figure 3. The OAC values determined were 4.2% for BiCG and 3.9% for BaCG by weight of the total blend. These OAC values ensure optimal performance of the asphalt mixtures while meeting the specified Marshall property requirements.

3.7. Factors Influencing Permanent Deformation

An extensive experimental program was undertaken to comprehensively evaluate the factors influencing permanent deformation in asphalt mixtures. A total of 306 cylindrical specimens were prepared and tested under repeated uniaxial compression loading. Three replicates were produced for each test sample, and the average results were calculated. The study aimed to analyze the impact of various parameters on the permanent strain behavior of asphalt mixtures. These parameters were categorized into 12 predictor variables, representing environmental conditions, traffic loading, and mixture properties. The predictor variables included testing temperature, loading conditions (traffic repetitions, stress level, and load duration), mixture properties (asphalt viscosity and content, aggregate gradation using aggregate percent passing $\frac{1}{2}$ " (PP1/2) and 4.75 mm sieves (PPNo.4)), and mix volumetric properties. The experimental phase resulted in the collection of 3214 data points. The experimental design incorporated a comprehensive range of factors and levels to capture the variability in asphalt mixture performance under different conditions. Table 4 summarizes the predictor variables and their respective levels.

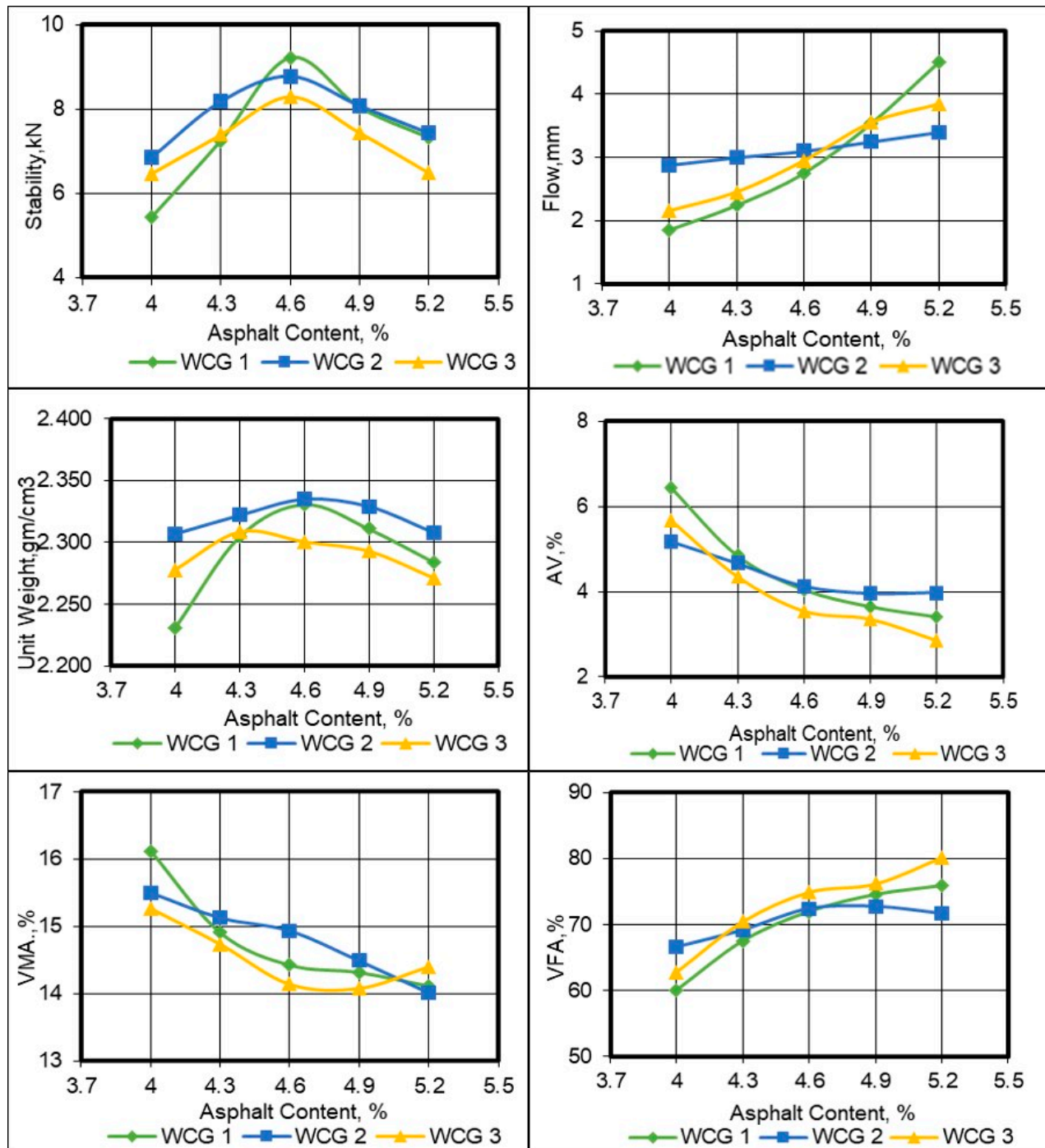


Figure 2. Marshall properties for surface course mixes.

Table 4. Predictors variables and their levels.

Factor	Levels	Description
Asphalt content	3	OAC and OAC $\pm 0.6\%$
Asphalt viscosity	3	40/50, 60/70 and 85/100
Aggregate gradation	5	WCG 1, WCG 2, WCG 3, BiCG and BaCG
Temperature	7	20, 25, 40, 55, 60, 65 and 70 °C
Stress level	6	44.82 (6.5 psi), 68.95 (10 psi), 89.63 (13 psi), 137.89 (20 psi), 186.15 (27 psi), and 206.84 kPa (30 psi)
Volumetric properties	Variables	AV, VMA, Gmm, Gmb, Gsb

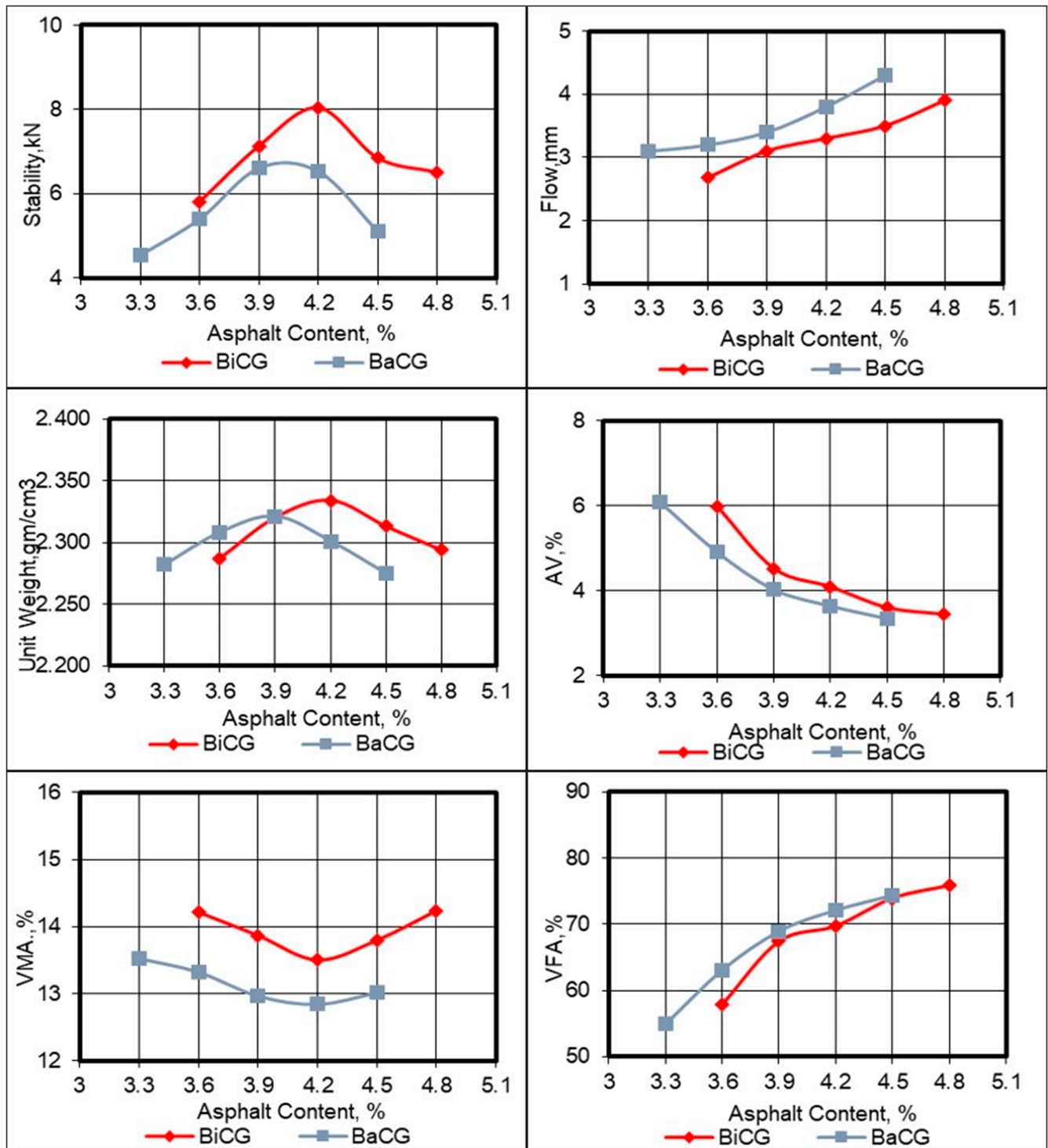


Figure 3. Marshall properties for binder and base course mixes.

4. Model Development

Artificial Neural Network (ANN) is a machine-learning tool that is widely employed due to its superior ability and high accuracy in developing robust prediction models and solving complex numerical problems. Its arithmetic consists typically of feed-forward networks of multi-layers of input, hidden, and output layers. The input layer consists of many neurons representing selected independent variables for the model. The hidden layer includes a set number of neurons assigned by the trial-and-error process, which controls the model's accuracy. A single neuron representing a response variable typically exists in

the output layer of the model. The ANN model is also generated with calibrated weights connecting each hidden neuron, input variable, and output neuron. Other constant values, known as bias, are also developed in the model, which is associated with each neuron in the hidden layer as well as the output neuron.

In this study, the ANN model is developed to investigate the effect of various asphalt mixes' characteristics on the axial permanent strain (ϵ_p) measurements. The model utilized twelve testing and mixture parameters as input variables for predicting the permanent strain. The testing measures include the number of applied cyclic stress (n), testing temperature (Temp.), and normal stress value (Stress) applied on testing specimens. The other variables include asphalt contents (AC), asphalt viscosity (Vis), percentage of aggregate passing $\frac{1}{2}$ " sieve (PP1/2) and 4.75 mm sieve (PPNo.4), air void contents (AV), percentage of voids in mineral aggregate (VMA), theoretical maximum specific gravity of asphalt mixes (Gmm), bulk specific gravity of asphalt mixes (Gmb), and bulk specific gravity of combined aggregate (Gsb). Figure 4 demonstrates the framework of the developed model.

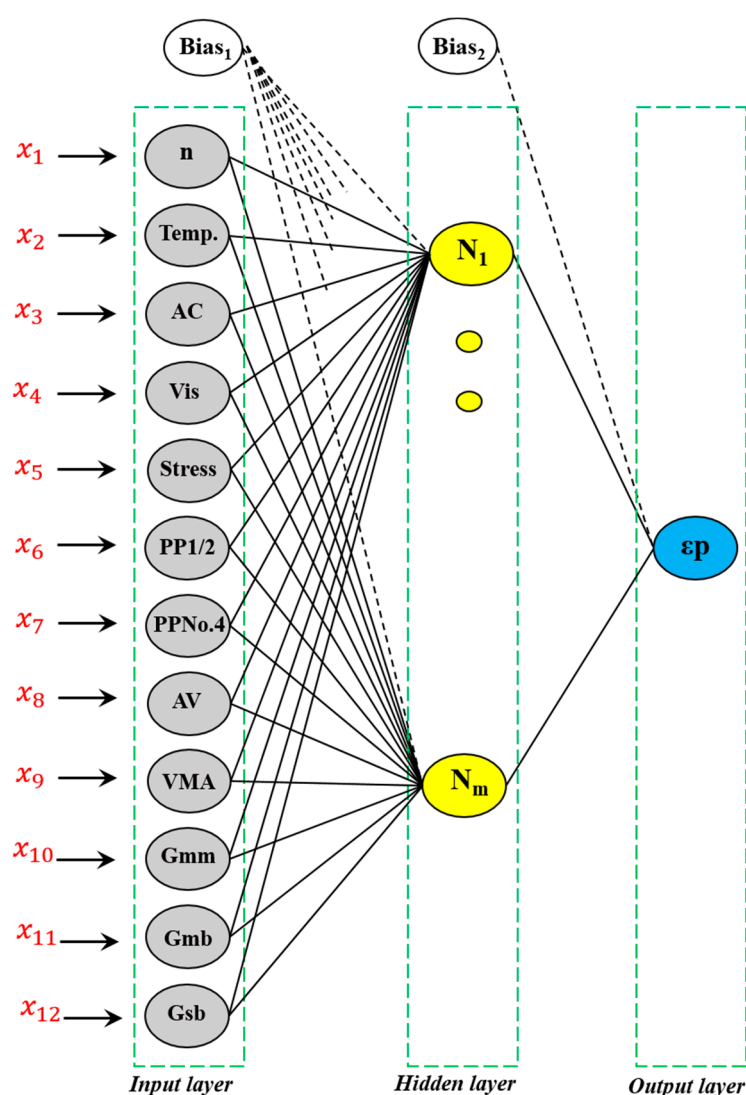


Figure 4. Schematic diagram of the ANN model.

The ANN tool in Matlab R2022b was used in this study to develop the model. The Levenberg–Marquardt training algorithm is used for the ANN as it is fast, converged, and suitable for a data set of intermediate size [20,21]. To facilitate the model and improve its accuracy, performance, and generalization, the inputs and output data were initially nor-

malized to the scale of $(-1, +1)$ using Equation (2) [22]. It is worth noting that (Equation (3)) can be used to de-normalize the data sets.

$$X^{norm} = \frac{(Y_{max} - Y_{min})(X^{act} - X_{min})}{(X_{max} - X_{min})} + Y_{min} \quad (2)$$

$$X^{act} = \frac{(X_{max} - X_{min})(X^{norm} - Y_{min})}{(Y_{max} - Y_{min})} + X_{min} \quad (3)$$

where

X^{norm} : The normalized values of inputs and output data set.

X^{act} : The original values of inputs and output data set.

X_{min} , X_{max} : Each data set's minimum and maximum values (see Table 5).

Y_{min} , Y_{max} : Minimum and maximum values of normalizing data, defaulting to -1 and $+1$, respectively.

Table 5. Ranges of the used data sets.

Inputs/Output	X_{min}	X_{max}	Y_{min}	Y_{max}
n	0	10,000	-1	1
Temp.	20	70	-1	1
AC	3.4	5.6	-1	1
Vis	0.35	0.71	-1	1
Stress	6.5	30	-1	1
PP1/2	68	96	-1	1
PPNo.4	43	58	-1	1
AV	1.87	10.49	-1	1
VMA	9.36	20.54	-1	1
Gmm	2.37	2.52	-1	1
Gmb	2.22	2.47	-1	1
Gsb	2.53	2.64	-1	1
ϵp	0.05	103,000	-1	1

5. Results and Analysis

In this study, a total of 3214 data points were utilized and randomly divided into 70% training, 15% validation, and 15% testing data sets by the software. The weights and bias values in the network are trained and determined using the training data set. The network generalization performance is assessed through a cross-validation process using the validation data. The accuracy of the developed model is evaluated through the testing data set. Several iterations have been conducted using a trial-and-error approach to allocate the ideal number of hidden neurons in the network. The model was sequentially examined with three, five, seven, and nine hidden neurons. The results of each iteration were statistically evaluated using coefficient of determination values R^2 and mean square errors of MSE, as results in Table 6.

Table 6. Statistical performance of trial neurons in the network.

Neurons	Training		Validation		Test		All Data	
	R^2	MSE	R^2	MSE	R^2	MSE	R^2	MSE
3	0.86564	0.0069	0.71538	0.0087	0.87049	0.0057	0.87265	0.0078
5	0.89643	0.0058	0.91623	0.0049	0.89246	0.0051	0.89814	0.0052
7	0.93412	0.0038	0.92064	0.0043	0.90592	0.0041	0.9305	0.0039
9	0.92602	0.0038	0.89284	0.0067	0.93586	0.0042	0.9213	0.0041

The results indicate that the accuracy of models improves by increasing the number of neurons in the hidden layer. However, the best performance of the model was achieved when seven neurons were used in the network, where the R^2 and MSE values were converged and consistent across the data groups. Therefore, a network model with seven neurons was adopted in this study for predicting the (ϵ_p) values. Figure 5 shows a plot of all the predicted versus experimental (ϵ_p) data points. Figure 6 shows the high degree of convergence for the measured MSE of this model's training, validation, and test datasets, where the best performance is achieved at epoch 79. The weights and bias results of the proposed model were extracted from the software and summarized in Table 7. In this table, the notation $w_1(i,j)$ represents the connection weights between the hidden layer (i) neurons and inputs (j), whereas $w_2(i)$ represents the connection weights between the neurons in the hidden layer (i) and the output. As illustrated in Figure 4, each neuron in the hidden layer (i) has a bias value of $B_1(i)$, whereas the output has a bias value (B_2) equal to -0.7068 .

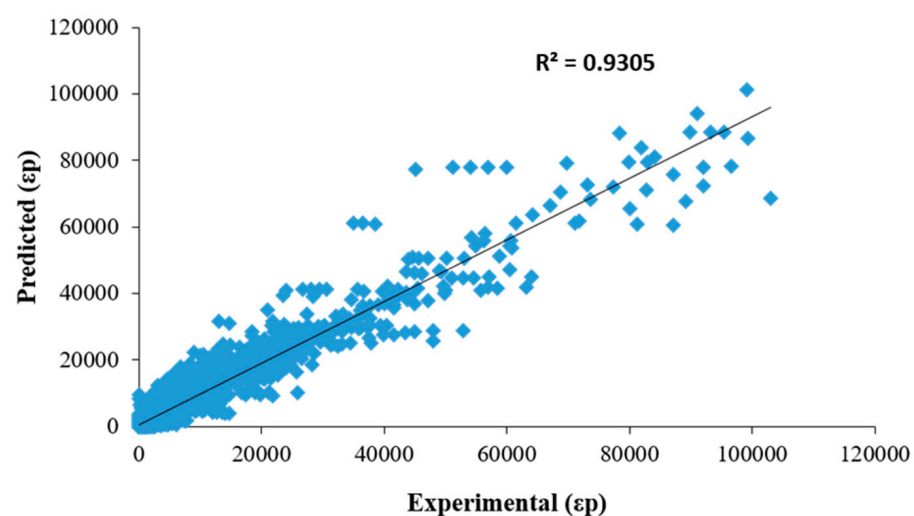


Figure 5. Predicted versus experimental (ϵ_p) values.

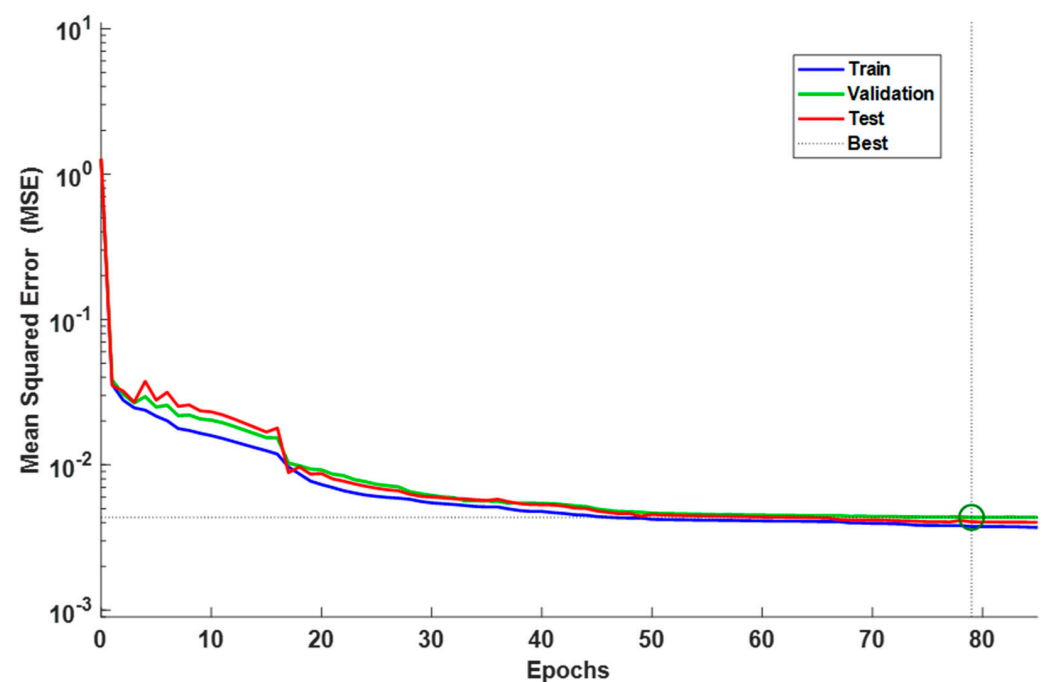


Figure 6. Network training process with seven neurons.

Table 7. Connection weights and bias values of the proposed model.

Neuron	$w_1(i,j)$												$w_2(i)$	$B_1(i)$
	n	Temp.	AC	Vis	Stress	PP1/2	PPNo.4	AV	VMA	Gmm	Gmb	Gsb		
1	−0.063	1.362	0.621	−0.309	0.565	0.909	−1.395	2.534	0.386	−1.548	1.810	0.197	0.254	−1.010
2	−0.906	2.615	19.854	−0.181	0.857	13.522	−2.743	−1.906	−2.915	40.903	−2.121	−22.235	1.693	1.566
3	−5.384	−20.487	6.720	0.558	1.189	5.493	−7.919	6.953	−14.087	3.908	−5.020	7.584	−0.070	5.314
4	−3.833	1.581	0.697	−0.240	0.665	1.198	−0.801	2.522	0.375	−0.828	2.461	−0.307	−0.340	−4.321
5	−24.829	3.567	12.649	−1.086	0.969	10.043	−4.558	9.975	−10.829	15.669	5.539	−12.805	−1.392	−23.011
6	0.874	−1.256	1.529	−0.138	1.005	−2.901	−7.176	2.326	−7.482	−0.716	−2.387	3.080	−12.994	4.115
7	0.819	−0.175	0.666	−0.141	0.956	−0.243	−4.461	0.367	−2.055	0.767	−0.417	−1.619	12.988	3.497

While the ANN model is developed in this study to evaluate the influence of various parameters on the axial permanent strain (ϵ_p) measurements, the model sensitivity is further validated by analyzing the relative importance (contribution) and the impact of each input in the model. The relative importance generally quantifies the contribution of each input variable in the prediction of the output in the network. Input variables with higher values matter much in the model's accuracy. On the other hand, the impact analysis indicates how changes in a particular input affect the output by identifying whether increasing an input will increase or decrease the output.

Garson algorithm method [23] is used to compute the relative importance of the input variables, as shown in the results in Figure 7. In this method, Equation (4) was used to calculate the contribution of each input variable using the absolute values of the connection weights $w_1(i,j)$ and $w_2(i)$, resulting in Table 7.

$$I_j = \frac{\sum_{m=1}^{m=Nh} \left(\frac{w_{jm}^{ih}}{\sum_{k=1}^{k=Ni} w_{km}^{ih}} w_{mn}^{ho} \right)}{\sum_{k=1}^{k=Ni} \left[\sum_{m=1}^{m=Nh} \left(\frac{w_{km}^{ih}}{\sum_{k=1}^{k=Ni} w_{km}^{ih}} w_{mn}^{ho} \right) \right]} \quad (4)$$

where

I_j : relative importance (contribution) of j th input variables

k : input neurons

m : hidden neurons

n : output neuron

i : input layer

h : hidden layer

o : output layer

Ni : number of neurons in the input layer

Nh : number of neurons in the hidden layer

w : connection weights

The results indicate that the percentage of aggregate passing the 4.75 mm sieve (PPNo.4) and theoretical maximum specific gravity (Gmm) were the most influential variables, contributing 13% and 11.8%, respectively. These findings align with those of [24], who reported that aggregate gradation significantly impacts the rutting potential of asphalt mixtures due to its role in load distribution and shear resistance. The importance of Gmm is also consistent with previous research, which has shown that asphalt mixtures with higher Gmm values tend to have improved stability and resistance to permanent deformation [25]. In contrast, asphalt viscosity (Vis) and normal stress levels (Stress) were found to have the lowest contributions, with values of 1.1% and 3.3%, respectively. While these factors influence the mix behavior, their relatively lower impact can be attributed to their interaction with other variables, such as temperature and binder content, which have a more pronounced effect on deformation characteristics. This observation is consistent with the findings of [25], who reported that stress levels alone do not fully dictate rutting

behavior, as other parameters, including binder stiffness and mix volumetrics, play a more dominant role.

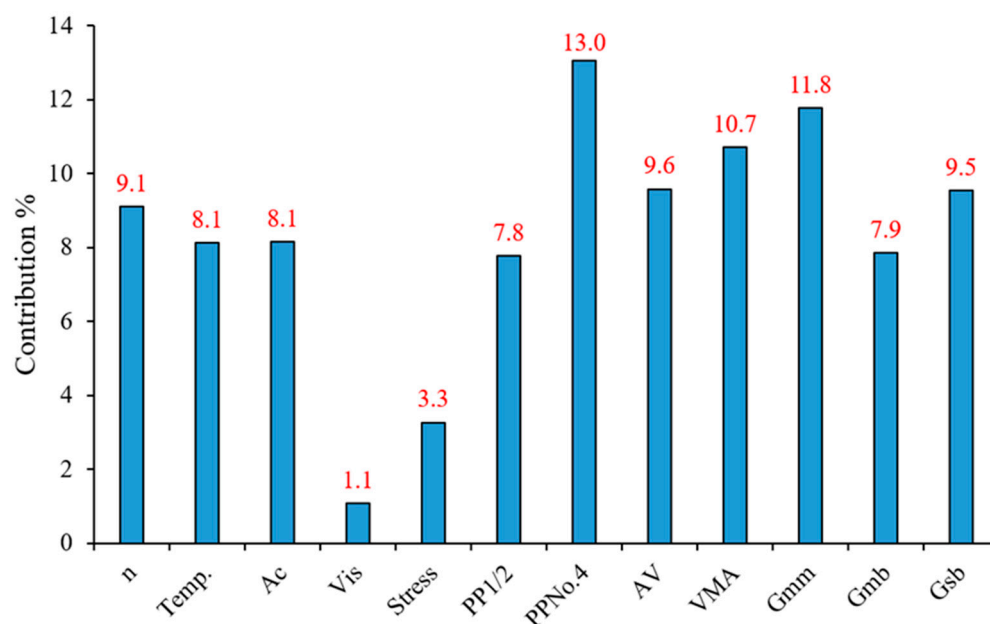


Figure 7. Contribution of input variables in the model.

The impact of the input variables in predicting the (ϵ_p) values is analyzed using the connection weight method by Olden and Jackson [26]. The connection weight approach of input variables was calculated using Equation (5). The notation (I_x) represents the impact of input neuron (x), the (w_{xy}) is the input to hidden connection weights, and the (w_{yz}) is the hidden to output connection weights.

$$I_x = \sum_{y=1}^m (w_{xy} \cdot w_{yz}) \quad (5)$$

Figure 8 shows the computed impact of all input variables in the model. It is demonstrated that only the normal stress, AV, and G_{sb} variables negatively impact the permanent strain (ϵ_p) value. Within the investigated data, the marginal negative impact of normal stress can be attributed to its interaction with other variables, such as temperature and binder content, which have a more pronounced effect on deformation characteristics. This observation aligns with the findings of [25], who reported that stress levels alone do not fully dictate rutting behavior, as other parameters, including binder stiffness and mix volumetric, play a more dominant role. Reducing the air void contents (AV) in asphalt mixes also makes the asphalt more susceptible to rutting due to the induced plastic deformation, where the mix becomes fully compacted and the ability of aggregates to interlock is reduced [27]. The negative impact of the G_{sb} on the permanent strain (ϵ_p) of asphalt refers to the fact that un-dense aggregates would generally have low G_{sb} that are prone to rutting as they are porous or soft, leading to a weak structure of early breaking down under heavy traffic loads [25,28]. In contrast, all the other variables (n, Temp., Ac, Vis, PP1/2, PPNo.4, VMA, Gmm, and Gmb) showed a positive impact on the (ϵ_p) value. These results prove that the developed ANN model reflects the presence and importance of each input variable in predicting the (ϵ_p) value. Practically, the results would help optimize asphalt mix designs and improve the future performance of asphalt pavement in terms of permanent deformation.

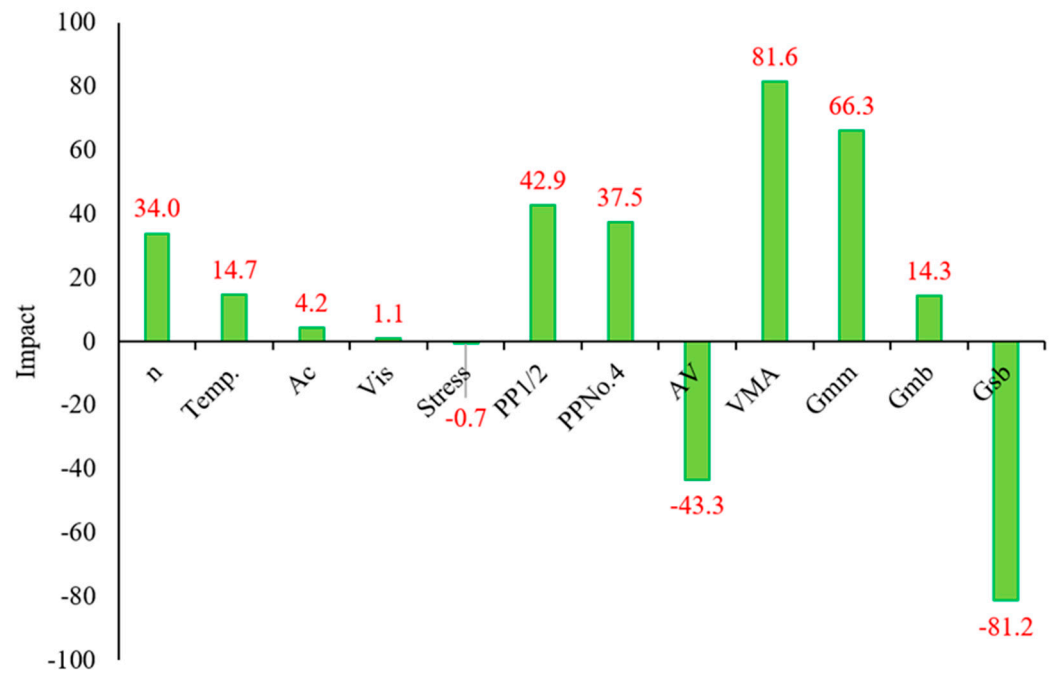


Figure 8. Impact of input variables in the model.

6. Conclusions

This study aimed to utilize the ANN prediction tool to evaluate the influence of various mixing characteristics and testing conditions on the axial permanent strain (ϵ_p) of asphalt mixes by developing a robust model and conducting sensitivity analysis. To measure the mixes' axial permanent deformation, a pneumatic repeated load system (PRLS) was used to test 306 laboratory-produced asphalt concrete specimens of different asphalt cement types and aggregate gradations (ϵ_p). Twelve input variables were utilized to develop the model. They include the number of applied cyclic normal stress (n), testing temperature (Temp.), applied normal stress (Stress), asphalt contents (AC), asphalt viscosity (Vis), percentage of aggregate passing $\frac{1}{2}$ " sieve (PP1/2) and 4.75 mm sieve (PPNo.4), air void contents (AV), percentage of voids in mineral aggregate (VMA), theoretical maximum specific gravity of asphalt mixes (Gmm), bulk specific gravity of asphalt mixes (Gmb), and bulk specific gravity of combined aggregate (Gsb). Some findings and insights from the study are summarized as follows:

1. The ANN model accurately predicted axial permanent strain (ϵ_p) in asphalt mixtures, achieving an R^2 value of 0.9305 and an MSE of 0.0039.
2. Seven hidden neurons were included in the optimal ANN model, resulting in reliable and consistent outcomes, making the model effective in predicting permanent deformation under various conditions.
3. Based on the sensitivity analysis, aggregate passing the 4.75 mm (PPNo.4) sieve and Gmm were the most influential factors in predicting rutting, with 13% and 11.8% contribution rates, respectively.
4. Permanent deformation increased with an increase in the number of applied loads and high testing temperatures, demonstrating the importance of designing asphalt mixtures based on temperature and load resistance.
5. Input impact analysis showed that the normal stress levels, air voids (AV), and aggregate bulk specific gravity (Gsb) had an adverse impact on permanent deformation, while factors like temperature, asphalt content (AC), and gradation (PP1/2, PPNo.4) contributed positively to ϵ_p values.

7. Limitations and Future Research

The results of this research are limited to the material sources and types used in this study, which may affect the generalizability of the findings to other asphalt mixtures with different compositions. Additionally, the stress application method during testing follows a uniaxial repeated load approach without accounting for the triaxial state of stress typically experienced in field conditions. This testing method primarily simulates loading conditions under the center of a wheel load at the level of the neutral axis, where the stress is predominantly compressive. While this provides valuable insights into the permanent deformation behavior of asphalt mixtures, it does not fully capture the shear stresses and confinement effects present in actual pavement structures.

Future studies should consider incorporating triaxial testing and field validation in order to enhance the applicability of the findings to real-world pavement performance. The results of this study provide guidance for optimizing asphalt mixture design, improving construction procedures, and enhancing the long-term performance of pavements by targeting key factors contributing to permanent deformation. However, future research should explore additional influencing factors such as layer thickness, aging effects, and modifiers. Moreover, applying alternative machine learning algorithms in successive and comparative studies should be investigated to improve prediction accuracy and model robustness.

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