# Prediction of Marshall Parameters of Modified Bituminous Mixtures Using Artificial Intelligence Techniques

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## ABSTRACT

This study presents the application of artificial neural networks (ANN) and least square support vector machine (LS-SVM) for prediction of Marshall parameters obtained from Marshall tests for waste polyethylene (PE) modified bituminous mixtures. Waste polyethylene in the form of fibres processed from utilized milk packets has been used to modify the bituminous mixes in order to improve their engineering properties. Marshall tests were carried out on mix specimens with variations in polyethylene and bitumen contents. It has been observed that the addition of waste polyethylene results in the improvement of Marshall characteristics such as stability, flow value and air voids, used to evaluate a bituminous mix. The proposed neural network (NN) model uses the quantities of ingredients used for preparation of Marshall specimens such as polyethylene, bitumen and aggregate in order to predict the Marshall stability, flow value and air voids obtained from the tests. Out of two techniques used, the NN based model is found to be compact, reliable and predictable when compared with LS-SVM model. A sensitivity analysis has been performed to identify the importance of the parameters considered.

**Key Words:** Marshall stability, flow value, air voids, waste polyethylene, ANN, LS-SVM

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## 1. INTRODUCTION

Bituminous mixtures mainly comprise of aggregates, both coarse and fine, mineral filler, and bitumen, heated separately, mixed together appropriately and compacted as per the prescribed procedure to result in strong and durable paving mix that can resist the heavy wheel loads from the traffic. The Marshall tests are simple and low cost tests used characterization of bituminous mixes. The parameters used such as Marshall stability and flow value resulting from Marshall tests on bituminous mixtures relate to some extent on the performance of highway bituminous pavement. As per Brown et al. (2001), the Marshall test was being widely used with the basic purpose of measuring the strength of an asphalt mixture that had been compacted to a standard laboratory compactive effort. This test is also used as part of the Marshall mix design procedure for optimizing the design asphalt content, and in the quality control of asphalt mixtures. Two properties are basically determined: the maximum load the specimen will carry before failure (known as the Marshall stability) and the amount of deformation of the specimen before failure occurs (known as Marshall flow) [4]. Cooper and Pell (1974) observed that the stability of asphalt concrete pavements depends on the stiffness of the mix, bitumen content, softening point of bitumen, viscosity of bitumen, grading of aggregate, construction practice, traffic, and climate conditions [5]. The air voids also contribute to some extent on these two properties in respect of mixes with same composition and characteristics. The parameters such as Marshall stability value, flow value and air voids of the bituminous mixtures quantify to certain extent the distresses of the bituminous mixes in the field. These parameters in respect of the bituminous mixtures are found to be enhanced by various ways and one such way is use of polymers. Kalantar et al. (2012) made a review of use of virgin and waste polymers in improving the engineering properties of bituminous mixes. Low density polyethylene when modified with bitumen has been found to enhance the Marshall properties of bituminous mixes [9]. As reported by Panda and Mazumdar (2002), Low-density polyethylene (LDPE) has been used by many to modify asphalt cement and to improve the properties of bituminous mixes (hot-mix asphalt). In their investigation, reclaimed polyethylene (PE) obtained from LDPE carry bags, was used to modify asphalt cement. The basic properties of modified binder and mixes containing such binders were studied and compared with those of asphalt cement [17]. However, in this present study the bituminous mixture has been modified with the addition of waste polyethylene in the form commercially available milk packets processed in the form of fibres, to result in improvement of the engineering properties of bituminous mixtures in addition to partly solving the management problem of solid waste of the surrounding environment. The variations in the Marshall parameters considered in this study such as Marshall stability value, flow value and air voids of modified and un-modified bituminous mixture for different aggregate gradings, bitumen contents and waste polyethylene concentrations in mixes were studied. The Marshall tests for bituminous mixture are quite time consuming process, which requires human effort. Hence the present study intends towards the modeling of the stability value, flow value and air voids of modified bituminous mixture to identify their relationships with bituminous mixture ingredients such as percentage of aggregates, percentage of fillers, percentage of bitumen, and percentage of waste polyethylene, all in terms of weight of the mixture.

An approach towards the viscoelastic modeling of asphalt concrete in compression in combination with a Schapery-type viscoelastic continuum damage model was studied by Gibson (2006) [7]. Modelling of Marshall stability of asphalt concrete using fuzzy-logic and artificial neural network has been studied in terms of relationship with volume of voids, unit volume weight for saturated surfaces, unit volume weight for dry air, temperature and exposure time [14–16]. An artificial neural network approach has been used to predict the optimum bitumen content, Marshall stability and Marshall quotient of asphaltic concrete mixtures quickly without conducting costly and time consuming experimental tests [1].

In this study two soft-computing techniques have been mainly applied for prediction of the Marshall parameters of modified bituminous mix prepared with addition of waste polyethylene in fibre forms. Other techniques like ANFIS, Genetic Programming, Regression splines etc. can be used for increasing the accuracy of the models.

## 2. OBJECTIVES OF STUDY

The present study adopts ANN and LS-SVM for prediction of Marshall stability value (SV), flow value (FV) and air voids (AV) of bituminous mixture. This paper aims at the following objectives.

- Evaluation of the performance of HMA mixture by addition of waste polyethylene.
- Examination of capability of ANN and LS-SVM for prediction of Marshall parameters of bituminous mixture.
- Comparative study between ANN and LS-SVM models.
- Development of model equation for prediction of SV, FV and AV.
- Determination of the importance of parameters in the prediction.

## 3. EXPERIMENTAL INVESTIGATIONS

### 3.1. Material Properties

This section deals with preparing the database needed for development of the models. A total of 270 unmodified and modified bituminous mixture samples were prepared in the laboratory. The standard VG 30 grade bitumen was used in this study. The physical properties of bitumen are given in Table 1. In order to get different variations of aggregate gradation, the samples were prepared for three different grades of aggregate as Stone matrix asphalt (SMA), bituminous concrete (BC), and dense bitumen macadam (DBM) as per Ministry of road transport and highway of India (MORTH) specification [11] taking a number of 90 bituminous mixture samples for each aggregate grading. Physical properties of the aggregates used in sample preparation are summarized in Table 2 and Table 3. Waste polyethylene in this study has been used in the form of fibres and was obtained from the collection of used locally available milk packets. The milk packets found to be made of low density polyethylene have been cleaned, dried and processed to form fibres of approximate dimension of 50 mm × 5 mm. The physical properties of waste polyethylene are enlisted in Table 4.

**Table 1. Physical properties of VG30 bitumen used in paving mixture preparation**

| Property | Test result |
|---|---|
| Penetration Value (dmm) at 25°C | 67.7 |
| Softening point (°C) | 48.5 |
| Specific gravity | 1.03 |
| Ductility (mm) | >1000 |
| Viscosity at 60°C (Poise) | 2462 |
| Viscosity at 135°C (cSt) | 365 |

**Table 2. Specific gravity of aggregates**

| Type | Specific gravity |
|---|---|
| Coarse aggregates | 2.75 |
| Fine (Stone) aggregates | 2.6 |
| Mineral Filler (Stone dust) | 2.7 |

**Table 3. Physical properties of coarse aggregates**

| Property | Test result |
|---|---|
| Aggregate Impact Value (%) | 14.3 |
| Aggregate Crushing Value (%) | 13 |
| Los Angels Abrasion Value (%) | 18 |
| Flakiness Index (%) | 18.8 |
| Elongation Index (%) | 21.5 |
| Water Absorption (%) | 0.1 |

**Table 4. Physical properties of waste polyethylene used in bituminous mixture samples**

| Property | Test result |
|---|---|
| Specific gravity | 0.905 |
| Softening point ($^0$C) | 54.22 |
| Young modulus (MPa) | 109.75 |
| Tensile Stress at peak (Pa) | 14.59 |

## 3.2. Preparation of Samples

The bituminous mix samples were prepared in the laboratory according to the Marshall procedure (ASTM D 6927, 1997) [2]. Waste polyethylene in form of fibres ranging from 0.5 to 2.5% at an increment of 0.5% by weight of total mix was used for preparation of Marshall samples. The Marshall stability, flow value and air voids have good potential for evaluation of bituminous mixes. Thus, the Marshall test was chosen in this study as an appropriate laboratory method for evaluation of the modified mixes.

### 3.3. Tests of Bituminous Mixture Samples

Prior to the testing stage, both the modified and unmodified samples were kept in the water bath maintained at 60°C temperature for at least 30 minutes in order to have uniform temperature distributions. The specimens were subjected to failure at a constant loading rate of 51 mm/min. The resistance to loading and deformations at the failure point are expressed in terms of stability value and flow value of the specimen respectively. After conducting the Marshall test, the stability, flow value and percentage of the air voids of the samples were evaluated for each aggregate gradation and waste polyethylene concentration. At the end of the tests, the optimum bitumen content for both modified and unmodified bituminous mixture samples were determined for different cases of aggregate gradation and waste polyethylene content considered.

## 4. DETAILS OF ANN AND LS-SVM

### 4.1. Artificial Neural Network

A multi-layer perceptron network consists of parallel layers of artificial units (neurons) associated by connections: a set of input neurons, one or more hidden layers and the output layer. Each connection transmits a signal to a neuron in the next layer through a feed-forward algorithm. Each signal is multiplied by the connection weight and a sigmoid activation function is applied to the sum of the weighted signals and the bias through this transition process [10]. The calculation performed by a typical neural network to find the output vector is given below:

$$P = f_n\left[ b_0 + \sum_{k=1}^{h} \left\{ w_k\, f_n\left( b_{hk} + \sum_{i=1}^{m} w_{ik} X_i \right) \right\} \right] \tag{1}$$

where $P$ = predicted value, $f_n$ = transfer function, $h$ = no. of neurons in the hidden layer, $X_i$ = value of inputs, $m$ = no of input variables, $w_{ik}$ = connection weight between ith layer of input and kth neuron of hidden layer, $w_k$ = connection weight between kth neuron of hidden layer and single output neuron, $b_{hk}$ = bias at the kth neuron of hidden layer and $b_0$ = bias at the output layer. The output layer presents the solution to the problem.

The first stage of the neural network methodology performs calculations on known input signals to determine the network's connection weights to determine the closest final output to the known target value. These calculations are the training stage. The network's designer usually selects the activation functions and the learning stage generally determines the weights and biases assigned to the network's connections. The most common learning method is the back propagation algorithm where the weights and biases update in the direction of the negative gradient of the average error between the network output and the target output:

$$w_{k+1} = w_k - \alpha_k e_k \tag{2}$$

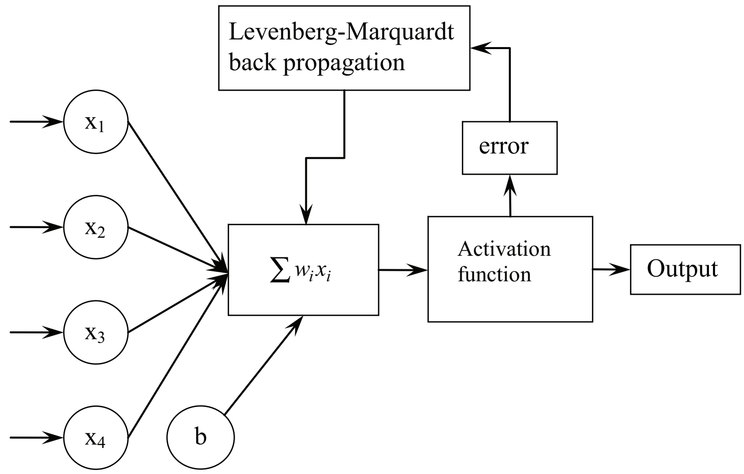


Figure 1. Architecture of single neuron back-propagation neural network

Here, $w_k$ is a vector of current weights and biases, $e_k$ is the current gradient and αk is the rate of learning. The network's weights and biases only update after the entire training set is presented to the network. The process of single neuron back propagation neural network is given in Figure 1.

The basic methodology of the artificial neural network generally includes a network testing stage with the training process. A new data set, unexposed to the network during the training stage, is presented to the trained network and the outputs are compared with the target values. The average error indicates the trained network's performance. The trained network can simply predict the output for a new set of input data using Eqn. (1).

This study used a three-layer feed-forward back propagation neural network. The initial weights and biases connecting neurons of the input layer, hidden layer and output layer are usually assigned randomly. The network was trained by a training function that updates weight and bias values according to the Levenberg–Marquardt adaptive optimization method.

The different trials have been made using linear, sigmoidal (log-sigmoid and tan-sigmoid) activation functions. The selection of number of hidden layers and hidden neurons is a very difficult task as it requires a number of trials. Boger and Guterman [3] suggested about the selection of the number of hidden neurons for the development of models by avoiding over-fitting.

## 4.2. Least Square Support Vector Machine (LS-SVM)

SVM algorithm was proposed by Vapnik and Vapnik [20] and LS-SVM is a nonlinear regression method that builds a nonlinear model in the feature space where the inputs have been transformed by means of a nonlinear mapping function ϕ. This is converted to the dual space and the use of a positive definite kernel, without explicitly computing the mapping ϕ. The model is an alternate formulation of SVM regression proposed by

Suykens and Vandewalle [19]. Let's consider a given training set of N data points $\{x_k, y_k\}_{k=1}^{N}$ with input data $x_k \in R^N$ and output $y_k \in r$ where $R^N$ the N-dimensional vector space and r is the one-dimensional vector space.

In feature space LS-SVM models take the form Eqn. (3).

$$y(x) = w^T \varphi(x) + b \tag{3}$$

where the non-linear mapping $\varphi(.)$ maps the input data into a higher dimensional feature space by the Kernel function K; $w \in R^n$; $b \in r$; $w = n$ adjustable weight vector; $b$ = the scalar threshold.

In LS-SVM the following optimization problem is formulated for function estimation:

$$\text{Minimize: } \frac{1}{2} w^T w + \gamma \frac{1}{2} \sum_{k=1}^{N} e_k^2 \tag{4}$$

Subject to: $y(x) = w^T \varphi(x_k) + b + e_k, \quad k = 1, 2, \ldots\ldots\ldots, N$

where $e_k$ = error variable and $\gamma$ = regularization parameter.

The following equation for prediction has been obtained by solving the above optimization.

$$y(x) = \sum_{\mathrm{k}=1}^{\mathrm{N}} \alpha_k K(x_k, x) + \mathrm{b} \tag{5}$$

$$\text{where } K(x_k, x) = \exp\left[-\frac{\|x_k - x\|^2}{\sigma^2}\right], \ \mathrm{k} = 1, 2, \ldots\ldots\ldots\ldots\ldots \mathrm{N}$$

$\sigma$ is the width of radial basis function and $\alpha_k$ is the Lagrange multiplier.

In LS-SVM regression algorithm, the regularization parameter $\gamma$ and RBF kernel parameter $\sigma^2$ have to be tuned in order to achieve an accurate solution. An integrated parameter optimization approach via simplex i.e. multidimensional unconstrained non-linear optimization and 10 fold cross-validation is used to minimize generalization error [12]. The optimum values of parameters [$\gamma$, $\sigma^2$] and bias values have been used for the models developed herein. LS-SVMlab [18] has been used for SVM model in matlab.

## 5. MODEL DEVELOPMENT

The data consists of 90 laboratory experimental observations. The database contains information about percentage of coarse aggregate (CA), fine aggregate (FA), filler material (F), waste polyethylene content (P) and bitumen content (B) to predict stability value (SV), flow value (FV) and air voids (AV).

The data set obtained from 90 experimental results employed to determine the stability value, flow value and air voids. Some of the experimental results have been presented in Table 5. The datasets have been randomly divided into two groups namely training and testing. This study uses 63 (70%) data out of 90 as a training dataset and 27 (30%) for testing dataset which is used to assess the performance of the models.

**Table 5. Some experimental data considered in present study**

| Coarse aggregate (%) | Fine aggregate (%) | Filler (%) | Polyethylene (%) | Bitumen (%) | Air voids (%) | Stability value (kN) | Flow value (mm) |
|---|---|---|---|---|---|---|---|
| 63.69 | 23.16 | 9.65 | 0 | 3.5 | 4.68 | 9.23 | 2.45 |
| 36.48 | 52.8 | 6.72 | 0.5 | 3.5 | 5.88 | 11.876 | 2.6 |
| 30.56 | 60.165 | 4.775 | 1 | 3.5 | 8.02 | 13.63 | 2.3 |
| 62.7 | 22.8 | 9.5 | 1.5 | 3.5 | 3.57 | 11.879 | 2.85 |
| 35.91 | 51.975 | 6.615 | 2 | 3.5 | 4.65 | 12.124 | 2.7 |
| 62.04 | 22.56 | 9.4 | 2.5 | 3.5 | 1.91 | 12.043 | 2.92 |
| 30.72 | 60.48 | 4.8 | 0 | 4 | 6.03 | 10.932 | 2.8 |
| 63.03 | 22.92 | 9.55 | 0.5 | 4 | 3.77 | 13.065 | 2.85 |
| 30.4 | 59.85 | 4.75 | 1 | 4 | 5.2 | 14.592 | 2.6 |
| 35.91 | 51.975 | 6.615 | 1.5 | 4 | 3.03 | 17.587 | 2.45 |
| 62.04 | 22.36 | 9.6 | 2 | 4 | 3.84 | 14.965 | 2.97 |
| 29.92 | 58.905 | 4.675 | 2.5 | 4 | 6.78 | 15.67 | 3 |
| 36.29 | 52.525 | 6.685 | 0 | 4.5 | 1.53 | 10.875 | 3.9 |
| 62.7 | 22.8 | 9.5 | 0.5 | 4.5 | 2.87 | 12.526 | 2.95 |
| 30.24 | 59.535 | 4.725 | 1 | 4.5 | 5.8 | 12.537 | 2.9 |
| 35.72 | 51.7 | 6.58 | 1.5 | 4.5 | 1.95 | 15.017 | 3.25 |
| 61.71 | 22.44 | 9.35 | 2 | 4.5 | 2.85 | 14.089 | 3.1 |
| 29.76 | 58.59 | 4.65 | 2.5 | 4.5 | 5.1 | 12.832 | 3.32 |
| 62.7 | 22.8 | 9.5 | 0 | 5 | 2.77 | 10.005 | 3.01 |
| 30.24 | 59.535 | 4.725 | 0.5 | 5 | 5.45 | 11.43 | 3.23 |
| 35.72 | 51.7 | 6.58 | 1 | 5 | 1.35 | 14.56 | 3.48 |
| 61.71 | 22.44 | 9.35 | 1.5 | 5 | 2.2 | 12.872 | 3.2 |
| 29.76 | 58.59 | 4.65 | 2 | 5 | 5.55 | 12.95 | 2.95 |
| 35.15 | 50.875 | 6.475 | 2.5 | 5 | 3.36 | 14.95 | 3.7 |
| 62.37 | 22.68 | 9.45 | 0 | 5.5 | 2.02 | 9.76 | 3.13 |
| 30.08 | 59.22 | 4.7 | 0.5 | 5.5 | 4.85 | 11.23 | 3.43 |
| 35.53 | 51.425 | 6.545 | 1 | 5.5 | 3.67 | 14.95 | 3.63 |
| 61.38 | 22.32 | 9.3 | 1.5 | 5.5 | 2.32 | 10.443 | 3.43 |
| 29.6 | 58.275 | 4.625 | 2 | 5.5 | 5.17 | 12.78 | 3.23 |
| 34.96 | 50.6 | 6.44 | 2.5 | 5.5 | 3.02 | 12.65 | 3.85 |

The mean, median, standard deviation, minimum and maximum of the data set are shown in Table 6. The successful application of a method depends upon the identification of suitable input parameters. The selection of the input parameters is based on the correlation coefficient (R) with output. This is shown in Table 7. The more the absolute value of correlation coefficient close to value 1, the stronger will be the linear correlation. While closer to 0 will be very poor correlation between the tested variables. From Table 7, it is observed that CA, FA, F and B are the important input

**Table 6. Summary of statistical value of parameters**

| | CA (%) | FA (%) | F (%) | P (%) | B (%) | Air voids (%) | Stability value (kN) | Flow value (mm) |
|---|---|---|---|---|---|---|---|---|
| Mean | 42.727 | 44.609 | 6.914 | 1.250 | 4.500 | 3.916 | 12.796 | 3.093 |
| Median | 35.815 | 51.838 | 6.598 | 1.250 | 4.500 | 3.660 | 12.770 | 3.105 |
| Standard Deviation | 14.054 | 15.954 | 1.952 | 0.859 | 0.711 | 1.709 | 2.054 | 0.436 |
| Minimum | 29.440 | 22.080 | 4.600 | 0.000 | 3.500 | 1.190 | 9.120 | 2.000 |
| Maximum | 63.690 | 60.795 | 9.650 | 2.500 | 5.500 | 8.020 | 17.587 | 3.980 |

**Table 7. Cross correlation between inputs and outputs**

| | CA (%) | FA (%) | F (%) | P (%) | B (%) | Air voids (%) | Stability value (kN) | Flow value (mm) |
|---|---|---|---|---|---|---|---|---|
| CA (%) | 1.00 | | | | | | | |
| FA (%) | –1.00 | 1.00 | | | | | | |
| F (%) | 0.97 | –0.97 | 1.00 | | | | | |
| P (%) | –0.03 | –0.03 | –0.03 | 1.00 | | | | |
| B (%) | –0.02 | –0.02 | –0.03 | 0.00 | 1.00 | | | |
| Air voids (%) | –0.48 | 0.52 | –0.60 | –0.08 | –0.40 | 1.00 | | |
| Stability value (KN) | –0.26 | 0.24 | –0.22 | 0.46 | –0.15 | –0.02 | 1.00 | |
| Flow value (mm) | –0.01 | –0.04 | 0.07 | 0.10 | 0.75 | –0.62 | –0.14 | 1.00 |

parameters for air voids. Almost all parameters are affecting the stability value and B, P are affecting flow value. Other two models are performed by considering mix of fine aggregate and filler material and another by excluding the filler material.

## 6. PERFORMANCE EVALUATION CRITERIA

The present study uses various statistical error measure criterions like over-fitting ratio, R, MAPE and RMSE to compare developed model performances. A good model should have; R value (expresses degree of similarity between predicted and actual values) close to 1 and low MAPE and RMSE values (indicate high confidence in model-predicted values).

Root mean-squared error (RMSE) is used to compute the square error of the prediction compared to actual values as well as the square root of the summation value. Thus the RMSE is expressed using the following equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_p - y)^2} \tag{6}$$

Mean absolute percentage error (MAPE) is a measure of closeness of predictions to actual values. The mean absolute error is given by

$$MAPE = \frac{1}{n}\sum\left|\frac{y_p - y}{y}\right| \times 100 \tag{7}$$

The Coefficient of correlation (R) value is a measure of linear relationship between the predictions and the actual values. The R value is calculated using the following formula:

$$R = \frac{n(\Sigma y \cdot y_p) - (\Sigma y)(\Sigma y_p)}{\sqrt{[n\Sigma y^2 - (\Sigma y)^2][n\Sigma y_p^2 - (\Sigma y_p)^2]}} \tag{8}$$

where $y$ and $y_p$ are the actual and the predicted values; $n$ is the number of observation.

The over-fitting ratio determines that the model is over-fitted or under-fitted. When its value is closer to 1, then the model can be said to be a better model as compared to the other models. It can be calculated using the following formula:

$$Over\ fitting\ ratio = \frac{RMSE\ in\ testing}{RMSE\ in\ training}$$

## 7. MODEL ARCHITECTURES

### 7.1. Artificial Neural Network

The performance of ANN is generally based on parameters architecture and setting. One of the most difficult tasks in studying ANN is finding an appropriate architecture. This task is performed via trial and error process and the number of hidden neurons and transfer functions are being identified. Appropriate designation of initial amounts of weights and biases is very effective on the performance of network and the time of calculation. But there is not a reasonable law and process to identify suitable architecture. Only method which is very time consuming is trial and error. When this stage has been finished, software utilizes test part data to study on the network performance. At the end, using entire data simulation software performs modeling operation. Software gives user the model parameter values with optimal value of the weight and bias as the output. Stopping criteria is employed as 2000 for training on all networks. A learning rate of 0.07 and momentum of 0.1 were fixed for selected network after training and model selection was completed for training set. Details of Neural Network architecture for modeling of Marshall parameters presented in sections 8.1 through 8.3.

### 7.2. LS-SVM

The data are normalized between 0 and 1. Some common kernels functions used such as polynomial, radial basis function, Gaussian function, sigmoid etc. for non-linear cases. This study uses radial basis function as a kernel function. For the LS-SVM model, a trial-and-error approach has been used to determine the design values of $\gamma$, $b$ and $\sigma^2$. An integrated parameter optimization approach via simplex and 10 fold cross-validation is used [12].

## 8. RESULTS

The main aim of the present study is to predict the stability value, flow value and air voids of bituminous mix specimen obtained from a series of experimental results. From the results of the different models for prediction presented in Tables 8 through 10, it is observed that the accuracy of prediction in LS-SVM and ANN are very close to each other. The performance of NN model gives better predictability as compared to LS-SVM model when compared in terms of closeness of over-fitting ratio towards 1. Model 1 predicts stability value and model 3 predicts air voids and flow value very precisely in ANN.

**Table 8. Results of different models for prediction of stability value**

| Model | Model inputs | | | RMSE | MAPE | Correlation coefficient (R) | Over-fitting ratio |
|---|---|---|---|---|---|---|---|
| Model 1 | CA, FA, F P, B | ANN | Training | 0.73 | 4.07 | 0.936 | 0.96 |
| | | | Testing | 0.7 | 4.45 | 0.93 | |
| | | SVM | Training | 0.88 | 4.74 | 0.91 | 0.93 |
| | | | Testing | 0.82 | 5.3 | 0.89 | |
| Model 2 | CA, (FA+F), P, B | ANN | Training | 0.9 | 5.6 | 0.89 | 1.02 |
| | | | Testing | 0.92 | 5.6 | 0.92 | |
| | | SVM | Training | 0.75 | 4.41 | 0.94 | 1.15 |
| | | | Testing | 0.86 | 5.37 | 0.9 | |
| Model 3 | CA, FA, P, B | ANN | Training | 0.98 | 5.4 | 0.88 | 0.99 |
| | | | Testing | 0.97 | 5.77 | 0.89 | |
| | | SVM | Training | 0.86 | 4.64 | 0.91 | 0.97 |
| | | | Testing | 0.83 | 5.05 | 0.9 | |

**Table 9. Results of different models for prediction of flow value**

| Model | Model inputs | | | RMSE | MAPE | Correlation coefficient (R) | Over-fitting ratio |
|---|---|---|---|---|---|---|---|
| Model 1 | CA, FA, F P, B | ANN | Training | 0.13 | 3.2 | 0.96 | 0.77 |
| | | | Testing | 0.1 | 2.3 | 0.97 | |
| | | SVM | Training | 0.11 | 2.4 | 0.97 | 1.18 |
| | | | Testing | 0.13 | 3.14 | 0.95 | |
| Model 2 | CA, (FA+F), P, B | ANN | Training | 0.12 | 2.5 | 0.96 | 0.83 |
| | | | Testing | 0.1 | 2.64 | 0.97 | |
| | | SVM | Training | 0.11 | 2.45 | 0.965 | 1.18 |
| | | | Testing | 0.13 | 3.06 | 0.96 | |
| Model 3 | CA, FA, P, B | ANN | Training | 0.12 | 3.14 | 0.96 | 1.08 |
| | | | Testing | 0.13 | 3.38 | 0.96 | |
| | | SVM | Training | 0.11 | 2.48 | 0.97 | 1.18 |
| | | | Testing | 0.13 | 3.14 | 0.95 | |

**Table 10. Results of different models for prediction of air void**

| Model | Model inputs | | | RMSE | MAPE | Correlation coefficient (R) | Over-fitting ratio |
|---|---|---|---|---|---|---|---|
| Model 1 | CA, FA, F P, B | ANN | Training | 0.43 | 10.31 | 0.965 | 0.88 |
| | | | Testing | 0.38 | 8.25 | 0.98 | |
| | | SVM | Training | 0.46 | 10.28 | 0.967 | 0.96 |
| | | | Testing | 0.44 | 9.9 | 0.954 | |
| Model 2 | CA, (FA+F), P, B | ANN | Training | 0.46 | 10.25 | 0.96 | 0.93 |
| | | | Testing | 0.43 | 9.52 | 0.97 | |
| | | SVM | Training | 0.56 | 12.9 | 0.95 | 0.89 |
| | | | Testing | 0.5 | 14.43 | 0.96 | |
| Model 3 | CA, FA, P, B | ANN | Training | 0.42 | 9.11 | 0.96 | 1.05 |
| | | | Testing | 0.44 | 9.23 | 0.97 | |
| | | SVM | Training | 0.54 | 13.9 | 0.95 | 1.06 |
| | | | Testing | 0.57 | 10 | 0.945 | |

## 8.1. Prediction of Stability Value

The optimal NN architecture for stability value was found to be 5-5-1 (5 hidden neurons). Hyperbolic tangent sigmoid and linear transfer functions were used for hidden layer and output layer respectively. There is a good correlation exists in training and testing (R = 0.936 and R = 0.93). A comparison of observed and predicted stability values for the training and testing data is shown in Figure 2. The developed model equation for the prediction of stability value is given below:

$$A_1 = 5.082\,CA + 0.223\,FA - 30.97\,F + 18.29\,P - 5.96\,B + 3.542$$
$$A_2 = 0.089\,CA + 0.25\,FA + 0.94\,F - 0.705\,P - 4.34\,B + 3.74$$
$$A_3 = 0.018\,CA + 0.03\,FA + 0.058\,F - 0.75\,P + 0.045\,B - 4.735$$
$$A_4 = 11.504\,CA - 10.2\,FA + 6.854\,F + 10.366\,P + 49.95\,B - 1.265$$
$$A_5 = 0.621\,CA + 0.684\,FA + 1.1\,F + 0.86\,P - 18.785\,B - 0.286$$

$$SV = -125.13 - 1.47\tanh(A_1) + 1.423\tanh(A_2) - 139.42\tanh(A_3) - 1.54\tanh(A_4) - 1.22\tanh(A_5) \tag{9}$$

## 8.2. Prediction of Flow Value

The optimal NN architecture for flow value was found to be 4-4-1 (4 hidden neurons). Log-sigmoid and linear transfer functions were used for hidden layer and output layer respectively. The correlation coefficient R is found to be 0.96 and 0.96 in training and testing respectively for the prediction of flow value. The observed and predicted flow values are visualized in Figure 3. The developed model equation for the prediction of flow value is given below:

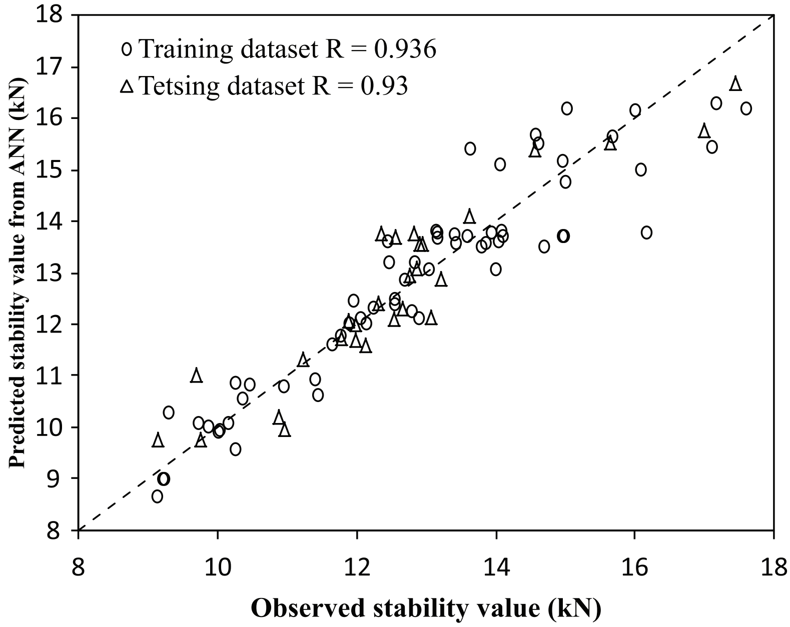


Figure 2. Predicted versus observed stability value in training and testing

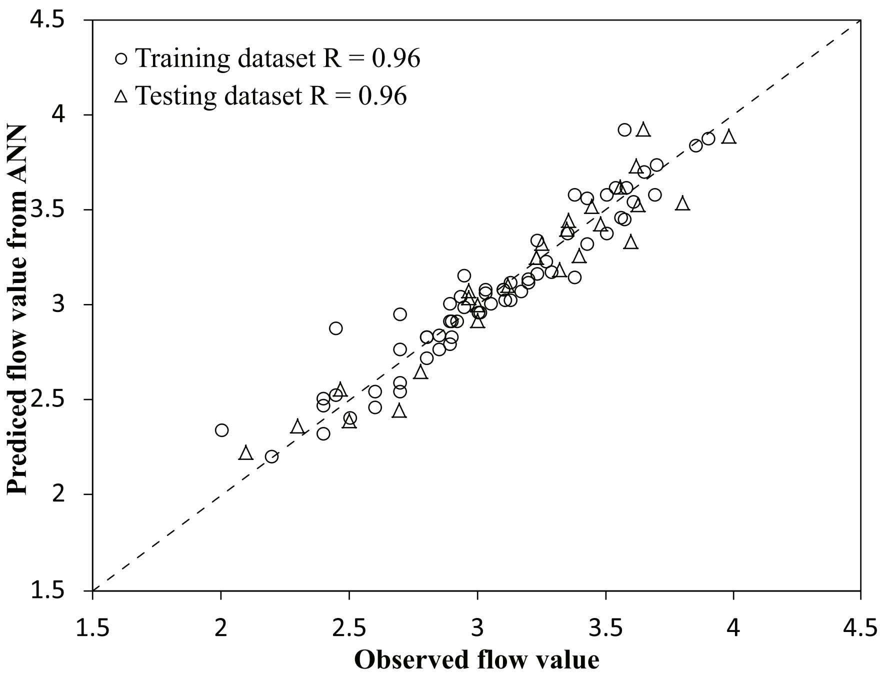


Figure 3. Predicted versus observed flow value (mm) in training and testing

$$A_1 = 0.757CA + 0.482FA + 1.664P + 1.122B - 57.47$$
$$A_2 = 0.635CA + 0.39FA + 1.524P + 1.0156B - 47.76$$
$$A_3 = -0.318CA + 0.13FA + 0.962P + 5.56B - 15.7$$
$$A_4 = -39.83CA - 46.84FA + 186.04P + 858.51B + 57.62$$
$$FV = \frac{-145.28}{1+e^{-A_1}} + \frac{149.8}{1+e^{-A_2}} + \frac{1.13}{1+e^{-A_3}} + \frac{0.2626}{1+e^{-A_4}} - 1.665 \quad (10)$$

### 8.3. Prediction of Air Voids

The optimal NN architecture for air voids was found to be 4-4-1 (4 hidden neurons). Hyperbolic tangent sigmoid and linear transfer functions were used for hidden layer and output layer respectively. There exists a strong correlation in training and testing (R = 0.97 and R = 0.96) for the prediction of air voids. The observed and predicted air voids are visualized in Figure 4. The developed model equation for the prediction of air voids is given below:

$$A_1 = -0.11CA - 0.08FA - 0.16P - 0.574B + 9.542$$
$$A_2 = -0.01CA - 0.144FA - 0.318P - 1.42B + 15.05$$
$$A_3 = -0.569CA + 0.94FA + 9.95P - 2.4364B - 2.51$$
$$A_4 = -3.5CA + 4.833FA + 9.57P - 31.51B - 8.03$$
$$AV = 28.83 + 26.1\tanh(A_1) - 3.38\tanh(A_2) - 2.77\tanh(A_3) + 0.5\tanh(A_4) \quad (11)$$

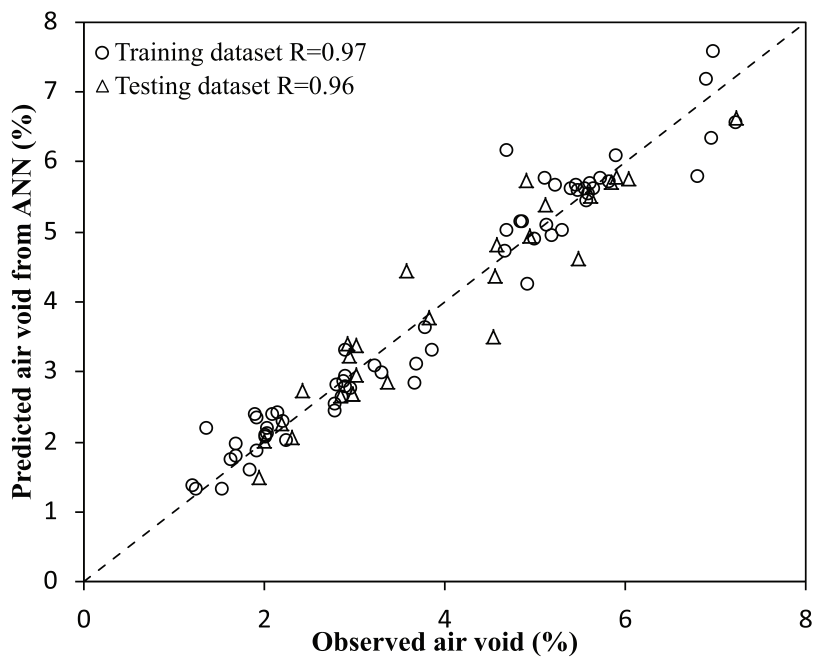


Figure 4. Predicted versus observed air voids in training and testing

**Table 11 Relative importance of different inputs as per Garson's algorithm and connection weight approach.**

| Output | Parameters | Garson's algorithm | | Connection weight approach | |
|---|---|---|---|---|---|
| (1) | (2) | Relative importance (%) (3) | Ranking of inputs as per relative importance (4) | Si values as per connection weight approach (5) | Ranking of inputs as per relative importance (6) |
| Stability Value (kN) | *CA* | 6 | 4 | –0.31 | 4 |
| | *FA* | 3.97 | 5 | –0.33 | 3 |
| | *F* | 19.54 | 3 | 2 | 2 |
| | *P* | 44.3 | 1 | 0.16 | 5 |
| | *B* | 26.16 | 2 | 3.46 | 1 |
| Flow Value (mm) | *CA* | 11.17 | 3 | -25.64 | 3 |
| | *FA* | 7.23 | 4 | -23.57 | 4 |
| | *P* | 28.58 | 2 | 36.41 | 2 |
| | *B* | 53 | 1 | 220.88 | 1 |
| Air Voids (%) | *CA* | 5.9 | 4 | -3.03 | 3 |
| | *FA* | 8.22 | 3 | -1.78 | 4 |
| | *P* | 31.24 | 2 | -25.8 | 1 |
| | *B* | 54.63 | 1 | -19.28 | 2 |

## 9. SENSITIVITY ANALYSIS

Sensitivity analysis is performed for selection of important input variables. Different approaches have been suggested to select the important input variables. Garson's algorithm [6] have been used, in which the input hidden and hidden output weights of trained NN model are partitioned and the absolute values of the weights are taken to select the important input variables, and the details with example have been presented by Goh (1994) [8]. It does not provide information on the effect of input variables in terms of direct or inverse relation to the output. A connection weight approach [13] is based on the Neural Interpretation Diagram (NID), in which the actual values of input hidden and hidden output weights are taken. It sums the products across all the hidden neurons, which is defined as Si. The relative inputs are corresponding to absolute Si values, where the most important input corresponds to highest Si value.

The relative importance of the input parameters as per Garson's algorithm and connection weight approach is presented in Table 11. The P and B are found to be the most important input parameter for all models. In case of the determination of stability value is affected by F, P & B mostly and air voids and flow value, P and B affects the output with higher relative importance.

## 10. CONCLUSIONS

The overall improvement of Marshall parameters used for evaluation of paving mixes modified with waste polyethylene deserves attention. The AI approach is very important in the sense that for a specific type of bituminous mixture and for predetermined testing conditions, the stability, flow and air voids values obtained at the end of Marshall test can be estimated without carrying out the destructive tests which are time consuming and cumbersome. Moreover, the paving mixes modified with waste polyethylene provides a significant development in the performance of flexible pavements. These findings will have important practical implications in the design of high performing flexible pavements.

This study presents an efficient approach for the prediction of Marshall parameters such as stability, flow value and air voids obtained from Marshall tests utilizing NN and LS-SVM. The proposed neural network models have shown good agreement with experimental results as corresponding correlation coefficients were found to be 0.936, 0.96 and 0.97 respectively. The proposed NN model is valid for the ranges of the experimental database used for the modeling. To obtain the main effects of each variable on stability, flow and air voids, sensitivity analysis has been performed. As a result, the proposed neural network model and formulation for waste polyethylene modified bituminous mix samples is quite accurate and hence practically applicable in the field.

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