

## Estimation of Specific Gravity with Penetration and Penetration Index Parameters by Artificial Neural Network

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### ABSTRACT

Specific Gravity of the bitumen changes according to the ambient temperature. Different specific gravity values can be calculated at different temperature. Estimating models like Artificial Neural Network – ANN could be very useful to obtain the specific gravity value uniform. Specific gravity values obtained from Long-Term Pavement Performance – LTPP were estimated with artificial neural networks. Penetration and Penetration Index of binder were used for estimating the specific gravity of the bitumen. As a result, ANN get 84% of R2 between obtained and estimated values.

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## 1. Introduction

Current practices for asphalt mix design and acceptance testing rely on volumetric properties. Vital to the calculation of mix volumetric properties are specific gravity measurements of the mixture and the aggregate in the mixture. Superpave mix design is getting popular day to day and more recognized by researchers. The volumetric analyses provide the basis for the Superpave mix design method. Specific gravity of the materials is essential to calculate the volume of the mixture.

Specific Gravity of the bitumen changes according to the ambient temperature. Different specific gravity values can be calculated at different temperature. Estimating models like Artificial Neural Network – ANN could be very useful to obtain the specific gravity value uniform.

Pavement researchers have been widely using ANNs in diverse subjects during the past decade. ANNs have been successfully used by researchers to predict/back-calculate pavement moduli by training the ANNs using deflection data from falling-weight deflectometers [1-3]. Tutumluer and Seyhan [4] estimated the horizontal and shear moduli by using confining and deviator stresses of triaxial test, deformation and aggregate properties. Lacroix et al. [5] used the resilient moduli data to predict the dynamic modulus master curve of asphalt mixtures. Some researchers predicted the fatigue life of pavements with ANN-based methods [6-7]. Tarefder et al. [8] used ANNs to predict permeability of asphalt mixtures by using mixture variables such as air voids, grain size, saturation and effective asphalt-to-dust ratio.

Several researchers also developed models to determine the severity and type of the cracks with the help of ANN [9-12].

In this study, Specific gravity values obtained from Long-Term Pavement Performance – LTPP [13] were estimated with artificial neural networks. Penetration and Penetration Index of binder were included to the model.

### 2. Materials and Method

Data used in this paper is obtained from Long-Term Pavement Performance – LTPP [13]. For modelling these, penetration, penetration index and specific gravity data are get from the program. It’s tried to obtain a relation between these parameters using ANN.

For predicting the specific gravity value of bitumen using ANN models, an appropriate selection of input parameters (neurons) is essential. There are two nodes in the input layer corresponding to two variables: penetration and penetration index of the bitumen. Model summary was seen in Table 1.

Table 1. ANN Model for specific gravity

Inputs	Number of Neuron	Number of Layers	Model	Output
Penetration Penetration Index	30-20-10	3	(2-30-20-10-1)	Specific Gravity

### 3. Research Findings

The relationship between obtained predicted values and measured values using the developed ANN model is shown in Figure 1. As it is illustrated in this figure, the predicted values are very close to experimental results, and this indicates a strong correlation between the input and output parameters of the ANN model. The R<sup>2</sup> values that are used to determine the significance of the ANN model.

From all parameters, 80% of parameters were selected as set of training randomly and the rest was selected as set of test (20%). Also the model was verified and tested. As seen from the Figure 1, training parameters were estimated as 100%, validation parameters were estimated as 98,6%, test parameters splitted by model were estimated as 98,5% and the all parameters were estimated as 92% of regression value by the model.

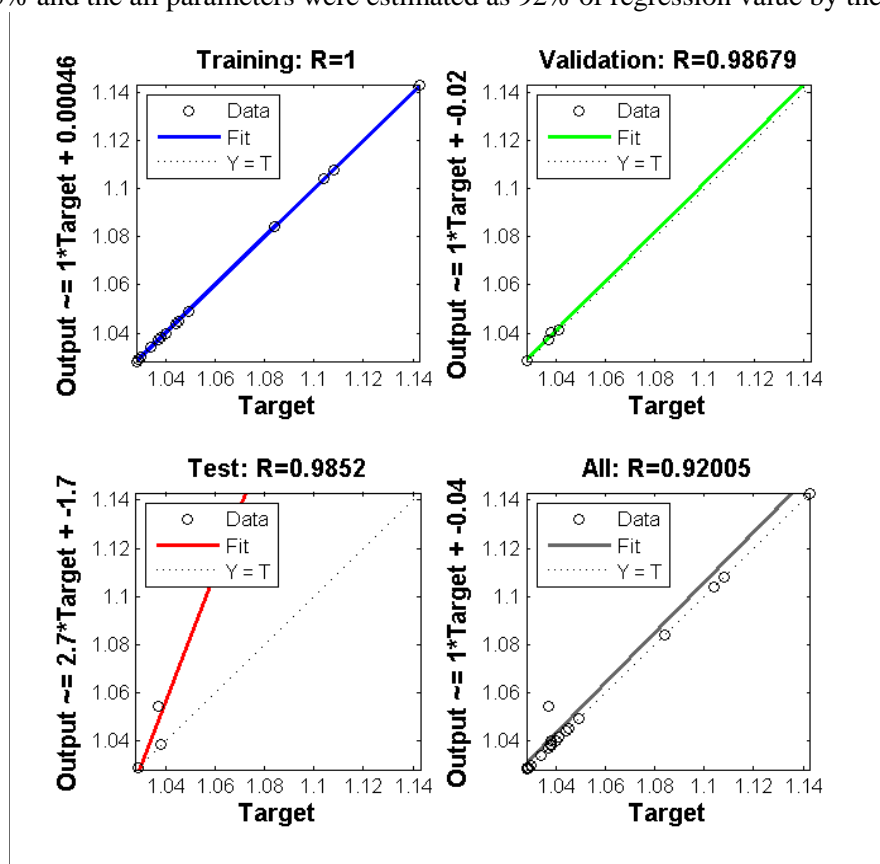


Figure 1. Relationship between the actual and predicted values by ANN for training data, validation data, testing data, and all data.

Input parameters of test parameters were given to the model after the model was trained successfully and output parameters were predicted. Obtained estimation results were compared to the real test results (Figure 2). Model predicted the test parameters successfully with  $R^2$  value of 84%.

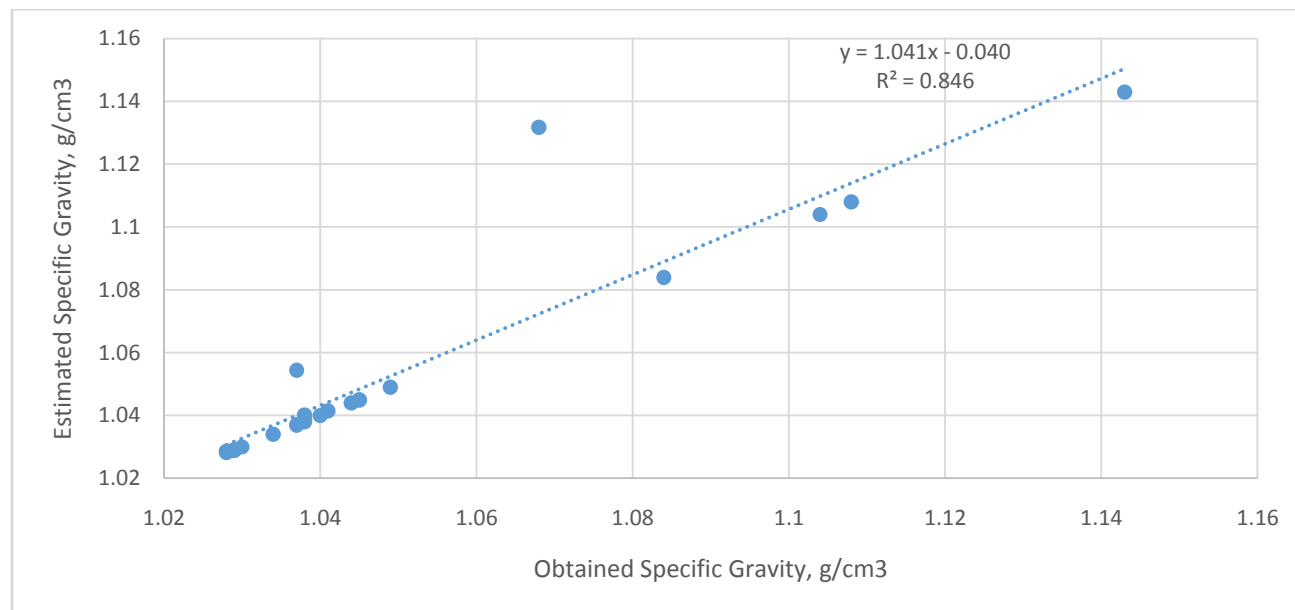


Figure 2.  $R^2$  graph for test parameters of model

#### 4. Results

In this study, an ANN method was developed to model the specific gravity of the bitumen for varying penetration and penetration index values of the bitumen. The ANN model predicted the test parameters successfully with regression value of 98%. The result indicates that the proposed model can be applied in estimating specific gravity of bitumen. The model is further applied to evaluate the effect of different values of penetration and penetration index on specific gravity.

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