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Artificial Neural Network-Based New Methodology for Modeling of Asphalt Mixtures and Comparison with IKE Method

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Abstract: Artificial Neural Networks (ANNs) are the most adopted approach in modeling of engineering problems. In this paper, we have developed ANN-based a novel modeling approach for asphalt mixtures. The Flow, Stability and MQ of the mixtures have been modeled and predicted by the introduced ANN-based approach. The legibility, comprehensibility, consistency, estimation performance, standard deviation etc. of the presented approach has been compared the literature. The experimental studies have shown that the proposed approach provides robustness, stability and a high accuracy ratio for estimation the Flow, Stability and MQ. While this paper has presented a novel approach to modeling the asphalt mixtures, it has also verified the results of literature. Thus, powerful, efficient and alternative approaches were presented to the literature for modeling the asphalt mixtures.

1. Introduction

The major properties to be incorporated in bituminous paving mixtures are stability, durability, flexibility and skid resistance (in the case of wearing surface). Traditional mix design methods are established to determine the optimum asphalt content that would perform satisfactorily, particularly with respect to stability and durability. There are many mix design methods used throughout the world e.g. Marshall mix design method, Hubbard-field mix design method, Hveem mix design method, Asphalt Institute Triaxial method of mix design, etc. Out of these only two are widely accepted, namely Marshall Mix design method and Hveem mix design method [1]. Marshall mixture design procedure (ASTM D 1559) is used for designing the asphalt concrete mixes in Turkey. Two properties are determined from the Marshall test [2]. These are:
(a) The maximum load the specimen will carry before failure, which is known as the Marshall stability.
(b) The amount of deformation of the specimen before failure occurred, which is known as the Marshall flow.

Stability of asphalt concrete determines the performance of the highway pavement. Low stability in asphalt concrete may lead to various types of distress in asphalt pavements. Cracking, especially fatigue cracking, due to repeated loading has been recognized as an important distress problem in asphalt concrete pavements. The stability of asphalt concrete pavements depends on the stiffness of the mix, bitumen content, softening point of bitumen, viscosity of asphalt cement, grading of aggregate, construction practice, traffic, and climate conditions [3].

Flow is the ability of an HMA pavement to adjust to gradual settlements and movements in the subgrade without cracking. The flow may be regarded as an opposite property to the stability, determining the reversible behavior of the wearing course under traffic loads and affecting plastic and elastic properties of the asphalt concrete [4, 5].

The ratio of the Marshall stability to Marshall flow is termed the Marshall Quotient (MQ) and is an indication of stiffness of the mix and the resistance against the deformation of the asphalt concrete. MQ

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values are calculated to evaluate the resistance of the deformation of the modified specimens. A higher value of MQ indicates a stiffer mixture and, hence, indicates that the mixture is likely more resistant [4–9].

The testing procedure in order to determine the Marshall stability, Marshall flow, and MQ is very time consuming and needs skilled workmanship. Due to this, if these values can be obtained for a standard mix by the help of another method as computer-aided data mining approaches, prepared specimens can be used for other mechanic test method.

Several alternative computer-aided data mining approaches have recently been developed. An instance is pattern recognition systems. These systems learn adaptively from experience and extract various discriminators. Artificial neural networks (ANNs) are one of the most widely used pattern recognition methods [10]. Detailed information about the applications of artificial neural networks in pavement engineering area can be found in the literature [11-18]. The relevant literature is summarized in detail [19]. It doesn't need for present the studies engaged in paper again and again.

Genetic programming (GP) is another alternative approach for the analysis of the rutting potential [20, 21]. GP may generally be defined as a supervised machine learning technique that searches a program space instead of a data space. Many researchers have employed GP and its variants to find out any complex relationships between the experimental data [22-25].

Recently, Aksoy et al. [26] introduced a novel approach for modeling stability test data. In the proposed model, the Intuitive k-Nearest Neighbor Estimator (IKE) based on genetic algorithm and k-nearest neighbor algorithm was used for understanding Marshall Parameters. The stability, flow and MQ values were interrogated with measured and predicted values. Using the genetic approach, the flow number, stability and MQ can accurately be estimated without carrying out sophisticated and time-consuming laboratory tests with any other testing equipment. Weighted features have a primary role in the value estimation of target parameters. Moreover, the proposed model successfully explores the effects of different features on the target parameters and predicts the real values of the parameters with a high accuracy rate. According to the experimental results, applying of IKE provides a high accuracy for the asphalt mixtures problem [26]. The IKE algorithm has been also applied to weight the parameters of synchronous motor and predict the excitation current of it. Please see the reference studies for detailed information about the IKE algorithm [26, 27].

Although the IKE model has been used in asphalt pavements area, it has not been compared the most frequently used model such as artificial neural networks (ANNs). The purpose of this study is to compare the performances of IKE and ANN for Marshall Test parameters and the MQ approach. Moreover, validity of IKE is researched on new samples prepared in laboratory at same parameters.

2. Materials and Method

2.1. Mixture design

Used aggregate combination was obtained from the Catak rock quarry in Trabzon province. Various engineering properties of coarse and fine aggregate were given in Table 1 and Table 2 and the gradation curve is shown in Figure 1. Asphalt cement with 50–70 penetration grades was used. Test results for bituminous binder supplied from Kirikkale oil refinery are given in Table 3. Design parameters were obtained with the ASTM D1559 Marshall method and optimum mixture parameters were presented in Table 4.

It was studied with 126 briquettes produced in the laboratory with the optimum asphalt cement content. 63 samples prepared with same parameters previously had been used IKE algorithm. Seven groups with nine samples had been created depending upon compaction energies. Seven samples had been used in the IKE for the training set and two samples had been used for the test set from each group [26].

Table 1. Properties of the used aggregate

Properties	Test Method	Value
L.A. Abrasion (%)	ASTM C-131	12.4
Flakiness (%)	BS 812 (Part 105)	14.3
Stripping resistance (%)	ASTM D-1664	30-35
Water absorption (%)	ASTM C-127	0.8
Soundness in $NaSO_4$ (%)	ASTM C-88	1.1
Polished stone value	BS 812 (Part 114)	0.60
Plasticity index for sandy aggregate	TS 1900	non-plastic

Table 2. Aggregate specific gravities (g/cm^3)

Grain-size fraction	Apparent specific gravity	Bulk specific gravity
Coarse aggregate	2.782	2.723
Fine Aggregate	2.800	2.703
Filler aggregate	2.885	-
Aggregate mixture	2.795	2.705

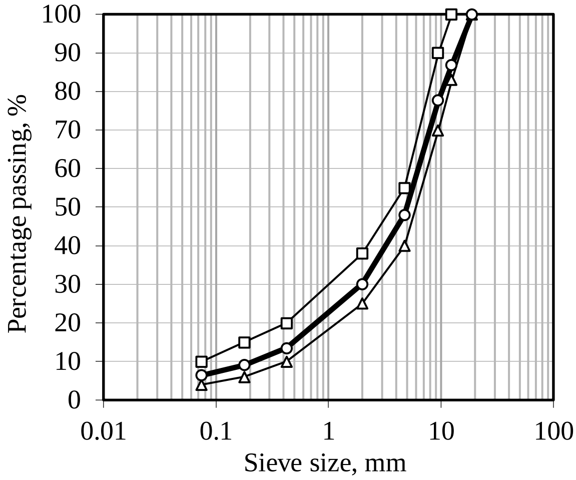


Figure 1. Aggregate distribution on gradation chart

In this research, 63 samples else produced with same parameters in addition to first paper. Also ANN was applied to samples apart from IKE. Same training set (49 samples) was used. Remained 77 Marshall briquettes were used for test set. Weights of IKE model were not changed and validity of model was investigated on new samples that are not introduced model before. Results of ANN which is the most used program in literature with results of IKE were compared. Properties of the samples used in the experimental stages are illustrated in Tables A1 and Table A2. Table A1 shows the training set sample properties while Table A2 gives test set properties.

Table 3. The results of tests performed on asphalt cement (AC 50-70)

Properties	Test Method	Unit	Value
Specific gravity (25°C)	ASTM D-70	gr/cm³	1.027
Softening point (°C)	ASTM D36-76	°C	52
Flash point (Cleveland)	ASTM D-92	°C	210
Penetration (25°C)	ASTM D-5	0.1mm	65
Ductility (25°C)	ASTM D-113	cm	100+

Table 4. Marshall Design test results

Design parameters	Values	Board in Turkey	
		Min.	Max.
Bulk specific gravity, Gmb	2.438	-	-
Marshall stability, kg	1570	900	-
Air voids, Pa, %	4	3	5
Void filled with asphalt, Vf, %	71.5	75	85
Flow, F, 1/100 in.	3.3	2	4
Filler/bitumen	1.22	-	1.5
Asphalt cement, Wa	5.25		

2.2. The Intuitive k-nearest neighbor estimator (IKE method)

The IKE is an instance-based heuristic searching and prediction algorithm. It consists of genetic algorithm-based weight-tuning unit, similarity measurement unit and nearest-neighbor-based estimation unit. It heuristically explores the effectiveness and importance of input parameters/features on output parameters/target values of a problem. This process is called weighting. It is very useful for modeling the parameters of system and reveals the hidden states. Weighting of input parameters of a problem also improves the classification and prediction performance of nearest-neighbor-based algorithms. Flow chart of IKE algorithm was given in Figure 2.

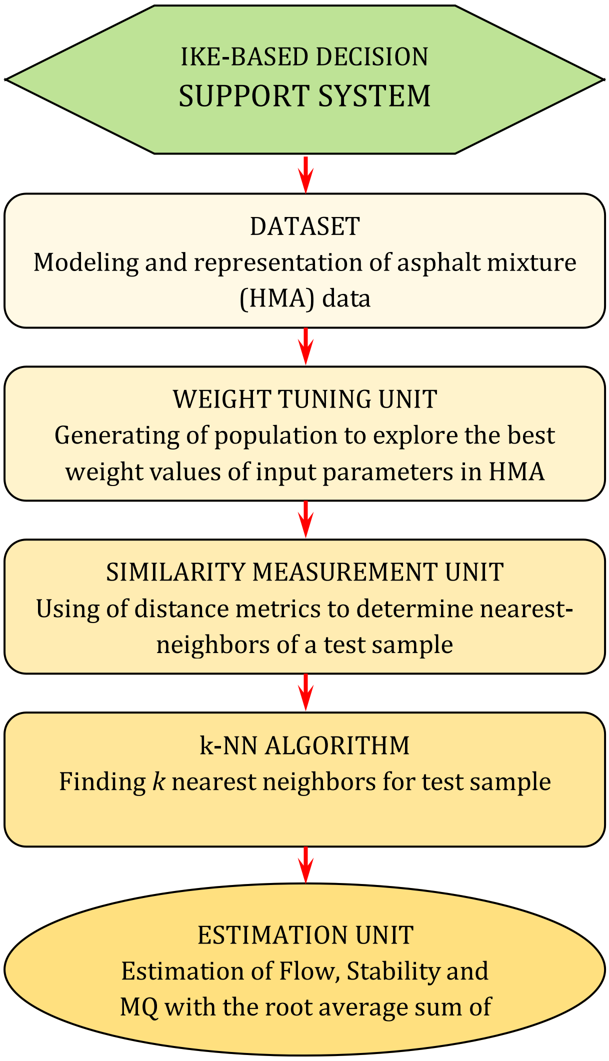


Figure 2. Steps for weighting the parameters of asphalt mixtures and predicting the flow, stability and MQ in IKE algorithm [26, 27]

- Dataset: In the IKE algorithm as is the case with most instance-based algorithms, a training and test dataset is prepared. The datasets are used to represent a sample space of observations belong to a problem, to model the relationships between the features and target values of the instances and to verify the training achievement of algorithm. In the previous study, we used 49 sample observations to create the training dataset and 14 sample observations to create the test dataset for asphalt mixture problem.

- Weight-tuning unit: It heuristically searches the optimal weight values of each input parameter or feature on the target parameter(s) of observation belong to a problem. The weighting of features changes the results of distance measurements among the observations. Depending on these changes the nearest neighbors of a test observation can be changed. Consequently, in the nearest neighbor-based approaches the decision of algorithms also changes. According to the literature [28-30], the usage of weighted features in the distance metrics improves the similarity measurements and the performance of nearest neighbor-based algorithms. The optimal weight values are explored by the heuristic methods. One of the popular heuristic searching methods is the GA. In the previous study, we used the GA-based weighting method and explored the best weight values of features for the "Flow", "Stability" and "MQ" in asphalt mixtures. Please see the reference study for detailed information about the weight-tuning method and the optimal weight values of features in asphalt mixtures [26].
- Similarity measurement unit: It is used to measure the distances among a test observation and training (sample) observations. It creates *n*-dimensional (*n* is the number of training observations) distance array. The array is used to determine the nearest neighbors of test observation in the k-NN algorithm.
- k-NN algorithm: It determines the nearest neighbors of test observation(s) depending on the distance measurements.
- Estimation unit: It estimates the values of Flow, Stability and MQ for test observation depending on the *k*-nearest neighbors of it. The *root average sum of squares* method was used to estimate the target values in the previous study. Please see the previous study for more information [26].

2.3. Artificial neural network model

Engineering community is always looking for higher accuracy, speed and reliability while evaluating any engineering process. Neural networks have emerged as successful computational tools for studying a majority of pavement engineering problems [12]. Increasingly, modern pattern recognition techniques such as neural network are being considered to develop models from data to their ability to learn and recognize trends in the data pattern [31].

Artificial neural networks (ANNs) are proposed on the research about modern neurobiology and human information processing by cognitive science, and they can achieve a variety of complex information processing functions by simulation of the neurons in the network structure and characteristics. ANN has the capability of establishing a functional relationship between two data spaces during a learning process and reproduce/generalize these data during a recall process. In other words, in one of their basic applications and after successful training, they can provide the correlating mathematical relationship between multi-dimensional input/output data sets [32].

Their inherited abilities such as nonlinear learning and noise tolerance make them particularly useful in situations where the problem is likely to change. ANN are especially useful at solving problems that cannot be clearly represented with a procedure, i.e. expressed as a series of steps, such as recognizing patterns, classification, series prediction and data mining [33].

The development of artificial neural network (ANN) models significantly depends on the experimental results. In the present work, blows, sample height (mm), density (g/cm^3), void (%), VMA (%), and VFA (%) were considered as the prime processing variables. The proposed ANN model was designed by software developed using the MATLAB Neural Network Toolbox. The data were obtained from previous study [26] and new samples were produced in laboratory. Among these data, 49 samples were selected for ANN training process, while the remaining 77 samples were used to verify the generalization capability of ANN. The data sets used in the prediction model are shown in Tables A1 and A2.

The ANN models, which have different network structures and parameters were constituted, and ANNs training processes were performed with MATLAB package software to determine weight and bias values and to minimize the mean square error. In order to determine the performance of networks, the models were tested using a set of data (namely test data) containing input–output pairs which were not utilized for training processes. Thus the most sensitive (appropriate) ANN result was targeted.

The obtained predicted values as a result of the testing process were compared with the real (measured) values. The model providing the best prediction values with respect to the root mean-square error (RMSE) ratio, calculated with Eq. 1, and the mean absolute percentage error (MAPE) ratio, calculated with Eq.2, was chosen as the prediction model.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - td_i)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad \text{Eq. 1}$$

$$\mathrm{MAPE} = \frac{1}{N}\left(\sum_{i=1}^{N}\left[\left|\frac{t_i - td_i}{t_i}\right|\right]\right) \times 100 \ldots\ldots\ldots\ldots\ldots \quad \text{Eq. 2}$$

In Eqs. 1 and 2, t_i is the actual output values, td_i is the neural network predicted values, and N is the number of objects. In Tables A1 and A2, the values calculated by utilizing this prediction model for the training and test data, real values, and predicted values are indicated.

Figures 3 and 4 show the ANN models containing 1 input layer, 2 hidden layers and 1 output layer. The selected ANN model represents the prediction model that produced the closest values to the measured values for the flow and stability. The blows, sample height (mm), density (g/cm^3), void (%), VMA (%), and VFA (%) were used as the input variables, while the flow and stability values were used as the output variables in the ANN models. The processing element numbers (neurons) of the two hidden layers were chosen as 4 and 3 for the flow model in Figure 3, and 4 and 4 for the stability model in Figure 4 respectively.

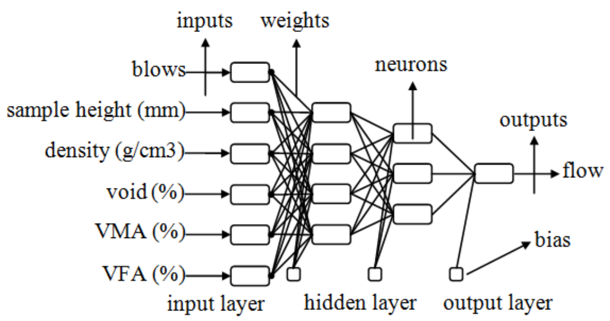


Figure 3. The ANN architecture selected as the prediction model for the flow

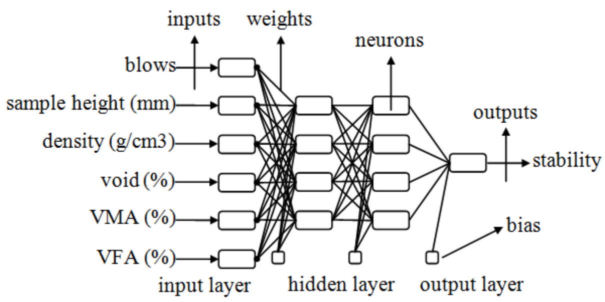


Figure 4. The ANN architecture selected as the prediction model for the stability

A feed forward and back propagation multilayer ANN was used for solving problems, and the network training and testing was carried out using the MATLAB software package. In this study, the hyperbolic tangent sigmoid function (tansig) and the linear transfer function (purelin) were used as the activation transfer functions, the levenber gmarquardt algorithm (trainlm) was used as the training algorithm, the gradient descent with a momentum back propagation algorithm (traingdm) was used as the learning rule, and the mean square error (MSE) was used as the performance function.
The mean square error (MSE) was calculated using Eq. 3.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(t_i - td_i)^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Eq. 3}$$

Where, t_i is the actual output (targeted values), td_i is the neural network output (predicted values), and N is the total number of training patterns.

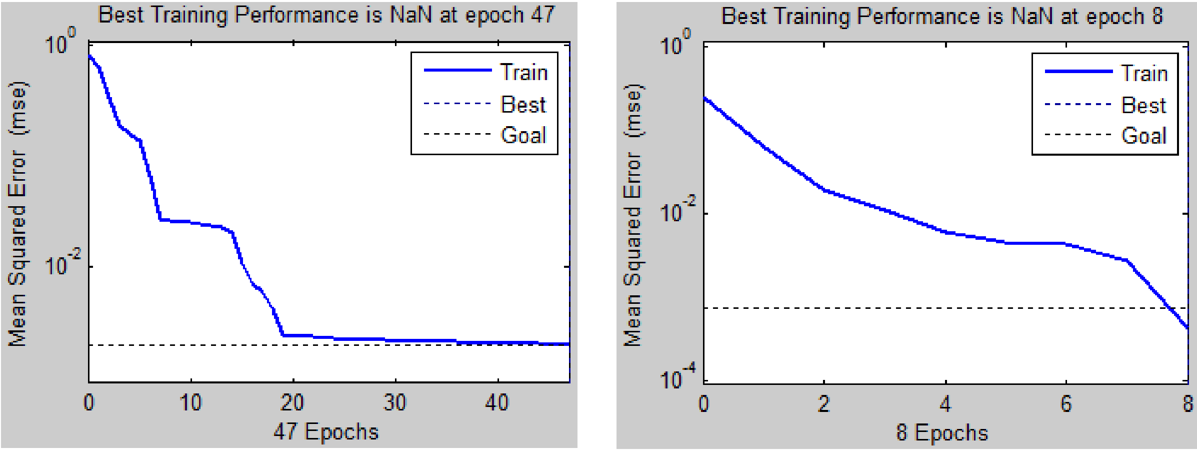
To ensure an equal contribution of each parameter in the model, the training and test datasets were normalized (-1, 1 range) due to the use of the hyperbolic tangent sigmoid function in the model and network, which allowed the data to be translated into the original value, with a reverse normalizing process for the interpretation of the results. The normalization (scaling) operations were carried out using Eq. 4.

$$X_{norm} = 2 \times \frac{X - X_{min}}{X_{max} - X_{min}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Eq. 4}$$

In this equation, X_{norm} is the normalized value of a variable X (real value of the variable), and X_{max} and X_{min} are the maximum and minimum values of X, respectively.

It was decided that the 0.001 targeted MSE values would be sufficient for the training of the artificial neural networks. When MSE of ANN training process reached 0.001, the training was terminated and change of flow and stability were modeled with obtained network parameters.

The amounts of error variation depending on iteration of the selected artificial neural networks are shown in Fig. 5, for flow (Fig. 5a), stability (Fig. 5b). The number of epochs after which the training models were stopped is 47 and 8.



(a) Flow (b) Stability

Figure 5. A plot of error variation depending on iteration of the ANN

3. Results and Evaluation

One of the most important properties of IKE model is that effect of input parameters on the target parameters can be determined. Modeling of data can be performed with classical system via this correspondence. From the point of repeatability of research, all details included used data were given clearly. Thus, opportunity of comparison with other models is created to researchers. Weighting effects of input parameters on the target for flow, stability and MQ are presented in Table 5.

It was seen that the compaction energy was the most effectual parameter on Marshall Quotient from Table 5. The other input parameters (sample height, density, air void, VMA, and VFA) were more effectual on stability values than MQ and flow. Air void level was found direct relation with flow according to IKE.

77 samples were used in both IKE and ANN model as test set. Real test results and predicted values form models were presented in Figure 6 - Figure 8. Both measured and predicted stability, flow and MQ values were observed in compatible with each others.

Table 5. Effects of input parameters on the target parameters for flow, stability and MQ [26]

	Degree of correspondence	Compaction energy	Sample height	Density	Air Void	VMA	VFA
Flow	1.53008	0.36826	0.04971	0.24003	0.64961	0.42475	0.00162
Stability	0.01542	0.54533	0.81421	0.98152	0.5802	0.90526	0.85213
Marshall quotient	0.00969	0.81859	0.57302	0.80202	0.45871	0.34327	0.19848

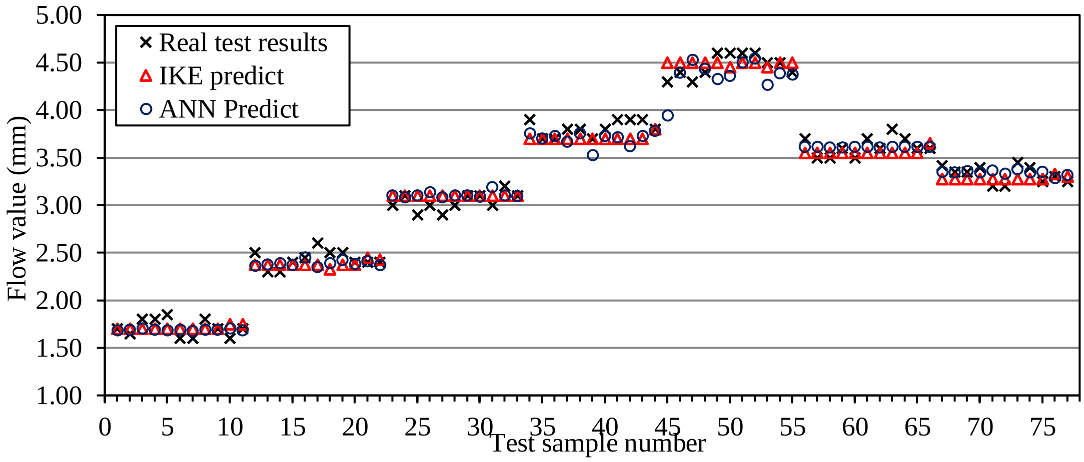


Figure 6. Comparison of predicted values of IKE and ANN with real flow values

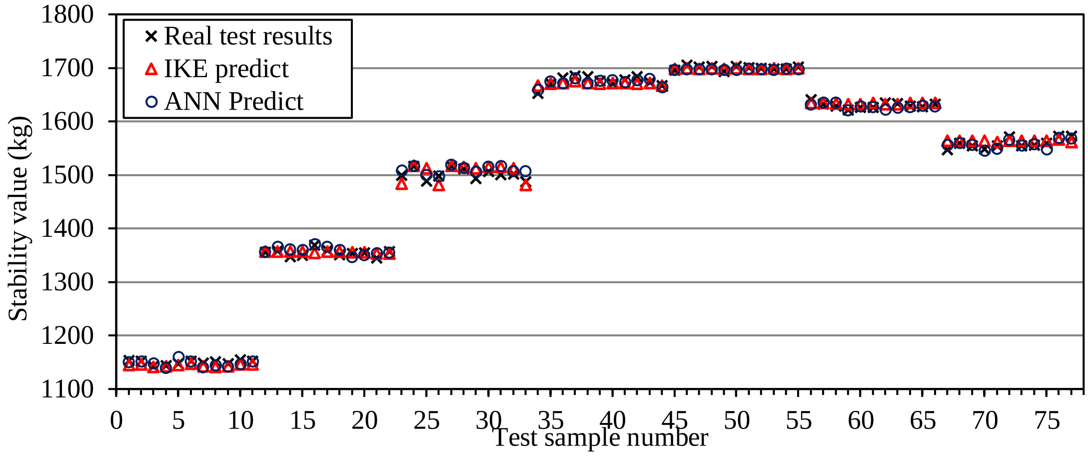


Figure 7. Comparison of predicted values of IKE and ANN with real stability values

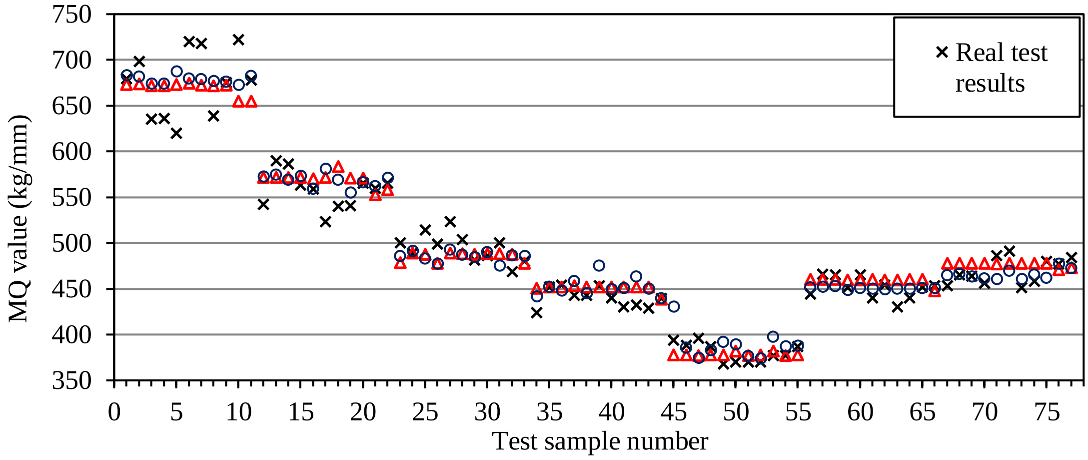


Figure 8. Comparison of predicted values of IKE and ANN with real MQ values

The coefficient of determination (R^2), the root mean squared error (RMSE), and mean absolute % error (MAPE) were calculated on the back of flow, stability, and MQ values were predicted. R^2 was used to provide a measure of the goodness of fit of the model. RMSE, a frequently-used measure of the differences between values predicted by a model and the values actually observed from the test. And MAPE was used to determine the error rate between real and predicted flow, stability and MQ values. MAPE and RMSE were calculated with Eq. 1, Eq. 2 and related data was shown in Table 6.

Table 6. Comparison parameters for IKE and ANN models

	IKE			ANN		
	Flow	Stability	MQ	Flow	Stability	MQ
MAPE	3.078	0.427	3.234	3.014	0.361	3.086
RMSE	0.113	7.993	21.53	0.122	6.7871	21.07
R^2	0.983	0.998	0.944	0.981	0.999	0.947

From the Table 6, it can be inferred that IKE and ANN approaches can be applied to Marshall test parameters. MAPE value of ANN model for specimens are 3.014, 0.361, and 3.086 for flow, stability and MQ respectively. These values lower than IKE ones. R^2 values are considerable close. These values indicate that the ANN is slightly effective to predict the flow, stability and MQ.

Comparison of error rate distribution of two models was illustrated in Figure 9 – Figure 11. According to the figures, it can be say that in generally, predict ability of two methods for this problem is similar. Thus, from sample to sample increasing or decreasing of error amount is similar. Although error ratio increases to 9% for flow, it is not to exceed 1.6% for stability. Detailed list was prepared and given in Table A2.

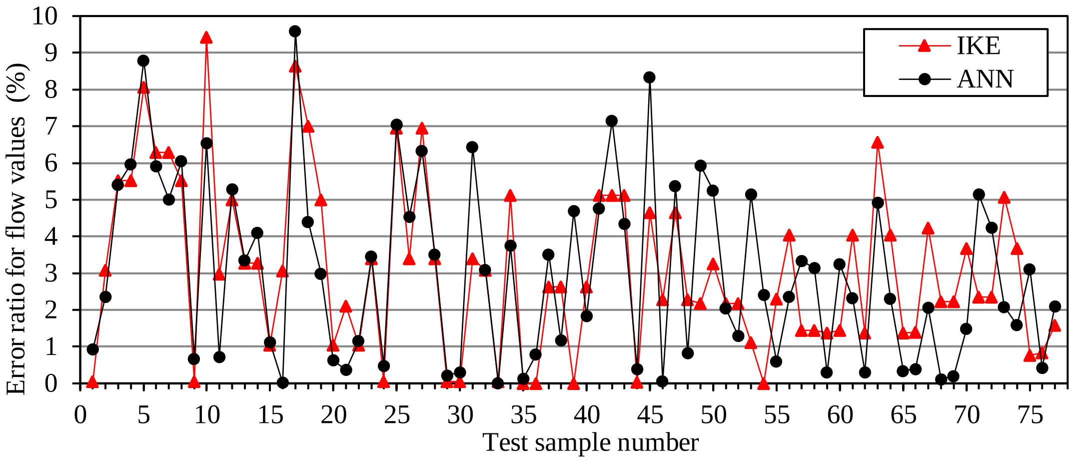


Figure 9. Distribution of error rates obtained from IKE and ANN for flow

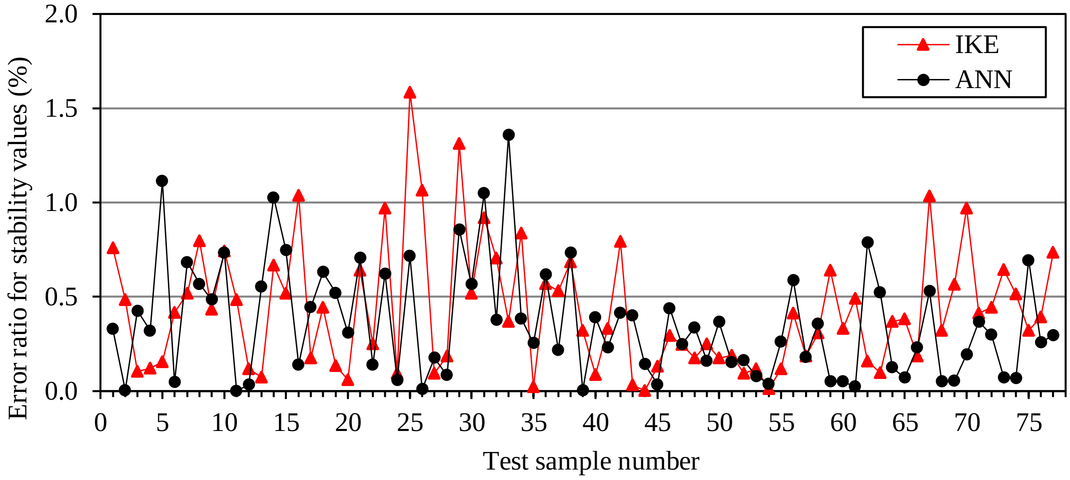


Figure 10. Distribution of error rates obtained from IKE and ANN for stability

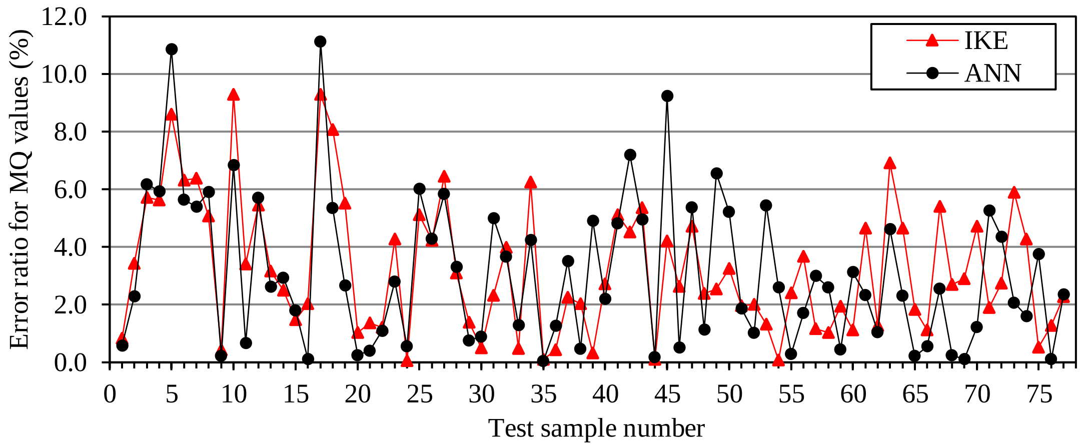


Figure 11. Distribution of error rates obtained from IKE and ANN for MQ

The IKE was applied to Marshall Test parameters. 49 samples were used for training set and 12 samples were used for test set. Blows, sample height, density, void, VMA, and VFA were selected as input parameters and flow stability, and MQ were selected as target parameters. The IKE predicted the real values of the parameters with a high accuracy rate. MAPE values were determined as 1.849, 0.361, and 1.568 for flow, stability, and MQ respectively. Also high level of R^2 was calculated between predicted and real test results [26]. In this study, test set samples increased to 77 samples. The same algorithm and degree of correspondence were used. Test results showed that new MAPE values changed as 3.078, 0.427, and 3.234.It was understand that although new data set was not introduced to algorithm, observed error ratios for flow, stability, and MQ are at acceptable levels.

Applications of IKE to asphalt pavement tasks are quite new. In this research, genetic algorithm was applied to Marshall test parameters. It is understand that a practical solution is possible with the IKE method for understanding Marshall test parameters and in some measure, in context with the permanent deformation with the MQ method or flow comment.

Neural networks (NNs) were applied for the prediction of Marshall test results for polypropylene (PP) modified asphalt mixtures. Marshall stability and flow tests were carried out on specimens fabricated with different type of PP fibers and also waste PP at optimum bitumen content. The proposed NN model uses the physical properties of standard Marshall specimens such as PP type, PP percentage, bitumen percentage, specimen height, unit weight, voids in mineral aggregate, voids filled with asphalt and air voids in order to predict the Marshall stability, flow and Marshall Quotient values obtained at the end of mechanical tests. The proposed neural network models for stability, flow and Marshall Quotient have shown good agreement with experimental results (R^2=0.97, R^2= 0.81, R^2= 0.87). The proposed neural network model and formulation of the available stability, flow and Marshall Quotient of asphalt samples is quite accurate, fast and practical for use by other researchers studying in this field [2]. In this study, used NN model gives high accuracy results. It was obtained averagely 96.986%, 99.639%, and 96.914% accuracy results for flow, stability and MQ. Marshal test parameters predicted by IKE and ANN were compared with real test results. ANN gives slightly more accuracy results than IKE. The reader must not forget that the obtained results at the end of this study are valid only for this problem.

4. Conclusions

An intuitive k-NN estimator has been used for modeling the features and outputs of asphalt mixtures. Relationships between features and target parameters of the problem have been chosen same as previous study [26]. Dataset of asphalt mixture has been extended and larger test set has been prepared and tested with the algorithm. Validity of IKE on new data has been researched. Also, ANN model has been established and the performance of IKE and ANN models has been compared. Below considerations can be drawn from this investigation.

The results generally show small differences between the predicted and measured flow, stability, and MQ values of the mixtures. ANN model reveals slightly lower MAPE values than IKE. Error ratios (MAPE) of ANN are 3.014, 0.361, and 3.086 for flow, stability and MQ. IKE gives slightly high values (3.078, 0.427, and 3.234). Generally, high R^2 value and low RMSE value achieved from both model. As a result, the developed ANN models have a slightly better prediction rate than the IKE model since the ANN model have a higher R^2 value and lower RMSE and MAPE values in comparison with the IKE model.

Although new data set consist of 77 samples (it was not introduced to model previously) was tested with IKE, error ratio (MAPE) increased to 3.078, 0.427, and 3.234 from 1.849, 0.361, and 1.568 for flow, stability and MQ. The values are in acceptable level of correctness. It is concluded that validity of Intuitive k-NN estimator continues on new data too.

Both IKE and ANN model can estimate accurately the flow number, stability and MQ without carrying out sophisticated and time-consuming laboratory tests with any other testing equipment. Using the methods can provide convenience to the laboratory working. Samples prepared for determined the flow and stability values can be used for other test method.

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APPENDIX

Please see Table A1 and Table A2.

Table A1. Properties of the training set samples

Sample ID	Blows	Sample Height (mm)	Density (gr/cm^3)	Void (%)	VMA (%)	VFA (%)	Flow (mm)	Stability (kg)	MQ (kg/mm)
1	45	61.60	2.362	7.221	17.611	58.996	1.70	1154	679
2	45	62.80	2.360	7.320	17.698	58.643	1.65	1140	691
3	45	62.30	2.369	6.939	17.360	60.030	1.70	1148	675
4	45	63.20	2.357	7.443	17.808	58.205	1.65	1131	685
5	45	62.00	2.353	7.589	17.938	57.692	1.75	1152	658
6	45	62.40	2.362	7.242	17.630	58.919	1.60	1149	718
7	45	63.10	2.365	7.117	17.518	59.376	1.80	1141	634
8	50	63.90	2.372	6.840	17.273	60.398	2.45	1361	556
9	50	63.50	2.379	6.552	17.017	61.497	2.50	1350	540
10	50	63.90	2.372	6.833	17.266	60.426	2.40	1346	561
11	50	64.10	2.368	6.996	17.411	59.818	2.40	1349	562
12	50	63.00	2.372	6.828	17.262	60.443	2.30	1362	592
13	50	62.60	2.366	7.068	17.475	59.553	2.35	1361	579
14	50	62.00	2.370	6.914	17.338	60.123	2.40	1355	565
15	55	63.03	2.382	6.444	16.921	61.916	3.00	1514	505
16	55	63.97	2.386	6.291	16.785	62.522	3.10	1507	486
17	55	62.27	2.388	6.203	16.707	62.870	3.10	1522	491
18	55	61.53	2.375	6.702	17.150	60.920	3.00	1522	507
19	55	61.77	2.384	6.372	16.857	62.199	3.20	1518	474
20	55	62.07	2.378	6.599	17.058	61.316	3.20	1511	472
21	55	63.00	2.387	6.255	16.753	62.665	3.30	1509	457
22	60	63.37	2.390	6.136	16.647	63.141	3.80	1655	436
23	60	62.53	2.383	6.403	16.885	62.077	3.70	1689	456
24	60	63.03	2.386	6.277	16.772	62.578	3.90	1673	429
25	60	63.57	2.395	5.926	16.461	64.000	3.80	1662	437
26	60	63.37	2.384	6.358	16.844	62.255	3.70	1663	449
27	60	62.63	2.388	6.202	16.706	62.874	3.70	1682	455
28	60	62.47	2.394	5.965	16.496	63.838	3.60	1681	467
29	65	64.67	2.402	5.664	16.228	65.098	4.40	1702	387
30	65	62.17	2.390	6.124	16.636	63.191	4.50	1704	379
31	65	61.67	2.398	5.814	16.361	64.464	4.60	1700	370
32	65	62.60	2.404	5.582	16.155	65.447	4.30	1703	396
33	65	61.47	2.401	5.695	16.256	64.965	4.40	1706	388
34	65	62.27	2.393	6.016	16.541	63.630	4.50	1689	375
35	65	61.93	2.394	5.970	16.500	63.820	4.50	1693	376
36	70	63.50	2.413	5.221	15.835	67.027	3.50	1630	466
37	70	63.03	2.417	5.061	15.693	67.747	3.70	1631	441
38	70	63.03	2.406	5.501	16.083	65.797	3.60	1636	454
39	70	63.23	2.410	5.349	15.949	66.459	3.70	1633	441
40	70	63.07	2.403	5.623	16.191	65.274	3.50	1626	465
41	70	62.87	2.412	5.272	15.880	66.801	3.70	1639	443
42	70	62.23	2.409	5.378	15.974	66.334	3.60	1637	455
43	75	62.97	2.443	4.037	14.784	72.690	3.30	1558	472
44	75	62.27	2.455	3.565	14.364	75.182	3.40	1566	461
45	75	62.13	2.449	3.814	14.585	73.851	3.45	1563	453
46	75	61.93	2.457	3.497	14.304	75.552	3.20	1572	491
47	75	61.90	2.449	3.814	14.586	73.848	3.20	1560	488
48	75	62.47	2.454	3.609	14.403	74.945	3.30	1557	472
49	75	62.70	2.460	3.383	14.202	76.182	3.30	1546	468

Table A2. Test set samples and Marshall test parameters

	Blows	Sample Height (mm)	Density (g/cm³)	Void (%)	VMA (%)	VFA (%)	Test results			IKE predicted			ANN predicted		
							Flow	Stability	MQ	Flow	Stability	MQ	Flow	Stability	MQ
1	45	62.23	2.359	7.347	17.722	58.546	1.70	1154	679	1.70074	1145.232029	673.375	1.68422	1150.201767	682.929
2	45	62.00	2.364	7.140	17.539	59.290	1.65	1152	698	1.70074	1146.411968	674.068	1.68892	1151.942453	682.058
3	45	63.47	2.368	6.992	17.407	59.834	1.80	1143	635	1.70074	1141.818462	671.368	1.70253	1147.861729	674.208
4	45	63.23	2.354	7.538	17.892	57.870	1.80	1144	636	1.70074	1142.62391	671.841	1.69248	1140.338472	673.766
5	45	61.83	2.353	7.582	17.931	57.717	1.85	1147	620	1.70074	1145.232029	673.375	1.68734	1159.769031	687.336
6	45	62.03	2.363	7.204	17.596	59.057	1.60	1152	720	1.70074	1147.214191	674.540	1.69473	1151.458601	679.435
7	45	63.67	2.361	7.250	17.637	58.891	1.60	1149	718	1.70074	1143.027471	672.078	1.68014	1141.153198	679.200
8	45	63.30	2.365	7.114	17.515	59.387	1.80	1151	639	1.70074	1141.818462	671.368	1.69119	1144.456667	676.717
9	45	63.60	2.363	7.191	17.584	59.106	1.70	1148	675	1.70074	1143.027471	672.078	1.68879	1142.426738	676.478
10	45	63.00	2.367	7.038	17.448	59.665	1.60	1155	722	1.75071	1146.411968	654.825	1.70470	1146.537333	672.574
11	45	62.00	2.364	7.137	17.536	59.300	1.70	1152	678	1.75071	1146.411968	654.825	1.68771	1151.974571	682.567
12	50	62.90	2.368	6.988	17.404	59.849	2.50	1356	542	2.37513	1357.609075	571.593	2.36768	1356.451311	572.902
13	50	61.83	2.371	6.878	17.306	60.258	2.30	1358	590	2.37513	1357.013412	571.342	2.37695	1365.526500	574.487
14	50	62.47	2.373	6.797	17.234	60.563	2.30	1348	586	2.37513	1357.013412	571.342	2.39441	1361.845347	568.760
15	50	62.57	2.371	6.875	17.303	60.270	2.40	1350	563	2.37513	1357.013412	571.342	2.37302	1360.104828	573.154
16	50	61.47	2.377	6.637	17.092	61.170	2.45	1369	559	2.37513	1354.814083	570.416	2.44961	1370.921713	559.649
17	50	61.73	2.369	6.949	17.369	59.994	2.60	1360	523	2.37513	1357.609075	571.593	2.35050	1366.035740	581.168
18	50	62.83	2.373	6.799	17.236	60.552	2.50	1351	540	2.32513	1357.013412	583.628	2.38993	1359.526284	568.855
19	50	64.00	2.364	7.162	17.558	59.210	2.50	1354	541	2.37513	1355.817318	570.839	2.42525	1346.944067	555.383
20	50	63.83	2.368	6.990	17.406	59.841	2.40	1355	565	2.37513	1355.817318	570.839	2.38496	1350.826211	566.394
21	50	64.03	2.377	6.633	17.088	61.187	2.40	1345	560	2.45051	1353.616046	552.381	2.40890	1354.487216	562.285
22	50	63.63	2.373	6.790	17.228	60.589	2.40	1357	565	2.42513	1353.616046	558.163	2.37231	1355.084212	571.210
23	55	63.43	2.372	6.826	17.260	60.451	3.00	1499	500	3.10161	1484.44562	478.604	3.10355	1508.324169	485.999
24	55	62.37	2.376	6.679	17.130	61.008	3.10	1516	489	3.10161	1517.406274	489.231	3.08504	1516.908194	491.699
25	55	64.17	2.379	6.559	17.023	61.470	2.90	1489	514	3.10161	1512.60907	487.685	3.10421	1499.660673	483.105
26	55	64.57	2.370	6.916	17.340	60.116	3.00	1498	499	3.10161	1482.069567	477.838	3.13594	1497.846147	477.638
27	55	62.10	2.374	6.759	17.200	60.706	2.90	1516	523	3.10161	1517.406274	489.231	3.08360	1518.682887	492.503
28	55	62.77	2.382	6.438	16.915	61.942	3.00	1512	504	3.10161	1514.807314	488.393	3.10533	1513.277939	487.316
29	55	63.67	2.374	6.754	17.196	60.722	3.10	1493	481	3.10161	1512.60907	487.685	3.10675	1505.785068	484.682
30	55	62.53	2.377	6.646	17.100	61.136	3.10	1507	486	3.10161	1514.807314	488.393	3.09086	1515.529176	490.326
31	55	62.37	2.385	6.324	16.814	62.390	3.00	1501	500	3.10161	1514.807314	488.393	3.19320	1516.752035	474.995
32	55	63.37	2.379	6.569	17.032	61.432	3.20	1502	469	3.10161	1512.60907	487.685	3.10100	1507.665149	486.187
33	55	63.57	2.372	6.818	17.253	60.481	3.10	1487	480	3.10161	1481.523945	477.662	3.10038	1507.206704	486.136
34	60	63.83	2.397	5.852	16.395	64.308	3.90	1653	424	3.70000	1666.825006	450.493	3.75398	1659.364169	442.028
35	60	62.53	2.393	6.005	16.531	63.674	3.70	1671	452	3.70000	1670.633592	451.523	3.70453	1675.244638	452.216
36	60	62.97	2.389	6.170	16.677	63.004	3.70	1682	454	3.70000	1672.445395	452.012	3.72898	1671.622272	448.279
37	60	61.87	2.390	6.132	16.644	63.156	3.80	1685	443	3.70000	1676.040572	452.984	3.66648	1681.322032	458.565
38	60	63.03	2.386	6.294	16.787	62.509	3.80	1684	443	3.70000	1672.445395	452.012	3.75562	1671.630487	445.101
39	60	62.37	2.397	5.850	16.393	64.314	3.70	1676	453	3.70000	1670.633592	451.523	3.52642	1675.908970	475.244
40	60	62.47	2.384	6.356	16.843	62.262	3.80	1671	440	3.70000	1672.445395	452.012	3.73019	1677.528654	449.716
41	60	62.73	2.389	6.164	16.672	63.028	3.90	1678	430	3.70000	1672.445395	452.012	3.71396	1674.130296	450.767
42	60	62.27	2.396	5.892	16.431	64.139	3.90	1684	432	3.70000	1670.633592	451.523	3.62129	1677.009200	463.097
43	60	62.23	2.382	6.437	16.915	61.943	3.90	1673	429	3.70000	1672.445395	452.012	3.73071	1679.701890	450.237
44	60	63.67	2.387	6.243	16.743	62.710	3.80	1667	439	3.80132	1667.026754	438.539	3.78540	1664.628074	439.749
45	65	62.37	2.406	5.502	16.084	65.792	4.30	1696	394	4.50000	1698.211706	377.380	3.94155	1696.600988	430.440
46	65	64.27	2.400	5.736	16.292	64.792	4.40	1705	388	4.50000	1700.01000	377.780	4.39769	1697.500344	385.998
47	65	62.47	2.397	5.851	16.394	64.310	4.30	1702	396	4.50000	1697.81006	377.291	4.53128	1697.798574	374.684
48	65	63.87	2.403	5.608	16.178	65.339	4.40	1703	387	4.50000	1700.01000	377.780	4.43621	1697.253903	382.591
49	65	62.27	2.403	5.608	16.178	65.337	4.60	1694	368	4.50000	1698.211706	377.380	4.32704	1696.728083	392.122
50	65	64.57	2.406	5.491	16.074	65.843	4.60	1703	370	4.45028	1700.01000	382.001	4.35881	1696.763771	389.272
51	65	62.43	2.394	5.979	16.508	63.779	4.60	1701	370	4.50000	1697.81006	377.291	4.50610	1698.415985	376.915
52	65	61.87	2.399	5.780	16.331	64.607	4.60	1700	370	4.50000	1698.412317	377.425	4.54046	1697.221599	373.799
53	65	64.67	2.408	5.422	16.013	66.141	4.50	1698	377	4.45028	1700.01000	382.001	4.26808	1696.646800	397.520
54	65	63.27	2.392	6.043	16.564	63.521	4.50	1698	377	4.50000	1697.81006	377.291	4.39163	1698.663642	386.796
55	65	64.37	2.399	5.775	16.326	64.630	4.40	1702	387	4.50111	1700.01000	377.687	4.37344	1697.537200	388.147

Table A2. Test set samples and Marshall test parameters (continue)

	Blows	Sample Height (mm)	Density (g/cm³)	Void (%)	VMA (%)	VFA (%)	Test results			IKE predicted			ANN predicted		
							Flow	Stability	MQ	Flow	Stability	MQ	Flow	Stability	MQ
56	70	62.97	2.401	5.689	16.251	64.991	3.70	1641	444	3.55035	1634.206291	460.294	3.61279	1631.348581	451.548
57	70	62.57	2.411	5.303	15.908	66.662	3.50	1632	466	3.55035	1635.003058	460.519	3.61678	1634.950178	452.045
58	70	62.77	2.416	5.114	15.740	67.507	3.50	1629	465	3.55035	1634.003672	460.237	3.60991	1634.834791	452.874
59	70	64.17	2.402	5.652	16.218	65.148	3.60	1622	451	3.55035	1632.404974	459.787	3.61073	1621.175882	448.989
60	70	63.57	2.407	5.453	16.041	66.006	3.50	1627	465	3.55035	1632.404974	459.787	3.61355	1627.827165	450.478
61	70	63.70	2.410	5.340	15.940	66.502	3.70	1627	440	3.55035	1635.003058	460.519	3.61422	1627.382138	450.272
62	70	64.10	2.403	5.620	16.189	65.285	3.60	1635	454	3.55035	1632.404974	459.787	3.61107	1622.129755	449.211
63	70	63.87	2.408	5.421	16.012	66.146	3.80	1634	430	3.55035	1632.404974	459.787	3.61314	1625.450527	449.872
64	70	63.80	2.412	5.264	15.873	66.838	3.70	1629	440	3.55035	1635.003058	460.519	3.61441	1626.968012	450.134
65	70	63.30	2.402	5.657	16.222	65.126	3.60	1628	452	3.55035	1634.206291	460.294	3.61234	1629.157203	450.998
66	70	63.57	2.409	5.385	15.980	66.303	3.60	1632	453	3.65034	1635.003058	447.904	3.61418	1628.240202	450.514
67	75	63.07	2.441	4.116	14.853	72.291	3.42	1548	453	3.27510	1564.008824	477.546	3.34963	1556.205236	464.590
68	75	62.73	2.447	3.896	14.658	73.420	3.35	1559	465	3.27510	1564.008824	477.546	3.34607	1559.791106	466.156
69	75	62.97	2.453	3.643	14.434	74.759	3.35	1555	464	3.27510	1563.807725	477.485	3.35680	1555.831145	463.487
70	75	63.87	2.449	3.817	14.588	73.833	3.40	1549	456	3.27510	1564.008824	477.546	3.34919	1545.968704	461.595
71	75	63.47	2.456	3.530	14.333	75.372	3.20	1555	486	3.27510	1561.42403	476.757	3.36456	1549.288423	460.473
72	75	62.27	2.442	4.084	14.825	72.450	3.20	1571	491	3.27510	1564.008824	477.546	3.33552	1566.306423	469.583
73	75	63.17	2.438	4.242	14.965	71.657	3.45	1554	451	3.27510	1564.008824	477.546	3.37818	1555.139169	460.348
74	75	62.97	2.444	4.014	14.763	72.812	3.40	1556	458	3.27510	1564.008824	477.546	3.34600	1557.078149	465.354
75	75	63.67	2.449	3.801	14.573	73.921	3.25	1559	480	3.27510	1564.008824	477.546	3.35078	1548.180176	462.036
76	75	61.97	2.451	3.741	14.520	74.238	3.30	1573	477	3.32735	1566.808093	470.888	3.28592	1568.954143	477.478
77	75	62.07	2.446	3.928	14.690	73.250	3.25	1573	484	3.30151	1561.42403	472.942	3.31843	1568.344156	472.616