Determination of Optimum Bitumen Content and Marshall Stability Using Neural Networks for Asphaltic Concrete Mixtures

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Abstract: - Neural Networks technology provides several reliant analysis in many science and technology applications. In particular neural network is often applied to the development of statistical models for intrinsically non-linear systems, since neural networks behave better in complex conditions. In this research, applications of neural networks in determination of optimum bitumen content, Marshall Stability and Marshall Quotient of asphaltic concrete mixtures were investigated. To determine the properties of asphaltic concrete mixtures using neural networks, samples were collected from different regions in Mecca area during construction and tested at laboratories of Umm Al-Qura University for bitumen content, gradation of aggregate, Marshall Stability, Marshall Quotient determination. The conventional models for asphaltic concrete mixtures were developed on the basis of data collected. Part of the data set was used for validation. Suitability of using neural networks in developing a neural network model of the OBC, Marshall Stability and Marshall Quotient for asphaltic concrete mixtures was found; the models were developed and validated.

Keywords: - Neural networks, Optimum bitumen content, Marshall Stability, Marshall Quotient.

1 Introduction

Neural networks technique is widely used to solve variety of complex scientific and engineering problems. It is a computing system made up of simple interconnected elements, which are arranged to simulate neurons in biological systems of human beings. It is a non-linear mapping system, whose structure is loosely based on principle observed in the nervous system [1]. It has the capability of learning relationships between the inputs and outputs without any prior knowledge of relationships between them. Using the neural networks (NNs) technique, the computer learns to make intelligent decision using known input and output data and adjusts some internal parameters of the network through repetitive introduction of known examples.

In the present study, conventional models for optimum bitumen content, Marshall Stability and Marshall Quotient of asphaltic concrete mixtures were developed based on the experimental data.

2 Method

Loose mixtures (53 samples), which were used in this research, were collected from different regions in Mecca area during the construction of new roads and tested at asphalt laboratory of Umm Al-Qura University for bitumen content, gradation of aggregate determination. Compaction for 75 blows each side at 150^{o}c temperature was started. Density of compacted mix was calculated, voids, voids in mineral aggregate (VMA), and voids filled with bitumen (VFB). Finally Marshall Stability and Marshall Flow were measured. These mixtures were made using 60/70 pen. grade bitumen binder. The aggregate gradation of all bituminous mixtures lies within the upper and lower limits gradation of grade A wearing course for heavy traffic (Table 1) [2], as well as stability, flow, voids, VMA, VFB within Ministry of Transportation (M.O.T) specification (Tables 2) [2].

The data collected was divided into two parts: training data files, and test data files. Training data were used to train and also to verify the neural networks model's performance during training. Different test experiments were applied to measure the performance of the trained neural model. The predicted neural networks results are correlated with the actual data for Optimum Bitumen Content OBC, Stability, and Marshall Quitent MQ.

Table 1. M.O.T. specifications for Gradation of wearing course, class A.

Sieve Size Designation	M.O.T. specification limits (% Passing)
¾"	100
½"	80 - 95
3/8"	-
# 4	48 - 62
# 10	32 - 45
# 40	16 - 26
# 200	4 - 8

Table 2. M.O.T in Saudi Arabia design criteria (review form MRDWS 410D.c) for wearing course class A of heavy traffic.

Mix properties	Criteria
Compaction (No. of blows each end of specimen)	75
Marshall Stability, kg (min)	1000
Marshall Flow (mm)	2.0-3.5
Loss of Marshall Stability, % (Max.)	25
Voids in mix, %	4.0-7.0
Marshall mixing temperature, ºC	155-165
Marshall Compaction temperature, ºC	140-150
Voids in mineral aggregate, min	15
Voids filled with bitumen, %	65-75

2.1 Model induction from data

Recent advances in research in the area of model identification have revealed approaches for inducing models from data, based on learning systems. These approaches can determine the relationships between the input, and output variables from data presented to them, without resorting to describing these relationships explicitly in mathematical form. One such learning system, which is the subject of this study, is that of neural networks (NNs). The neural network is a system of processing units with simple multiplicative, additive and other functional elements that are connected into a network through a set of weight such that this network provides a relationship between the input and output data sets. The mode of functioning of the network is determined by the network's architecture, the magnitudes of the weights and the mode of operation of the processing elements.

NN-based model was used to describe the spatial distribution of well flowing rates with horizontal variations. The variance provides an incomplete description of the variability, as there is no relationship between it and the distance between the observations. NN-based model offers an alternative approach with quantified spatial prediction with interdependence of flowing rates. To identify the spatial variation structure in the present study, the correlation among the existing wells producing from the highly fractured aquifer was based on the relationship between the root mean square error and the distance between well pairs.

A back-propagation NNs theory provides a general adaptive model for learning an arbitrary mapping from an input space to an output space. This mapping function is fulfilled by simulating a neural network topology, presenting it with a series of training samples, and applying the back-propagation learning rule. Through the learning rule, the network adapts and learns from the training set examples to respond correctly to its environment.

The NN model is composed of layers of simple information-processing neurons (nodes). The output of node j is given by

$$y_{\mathrm{i}} = f\left(\sum a_i w_{ji} + b_j\right)$$

Where a_i is the output of node i in the preceding layer, w_{ji} is the connection weight between nodes j and i, and b_j is the bias term of node j responsible for accommodating nonzero offsets in the data. The node's input-output transformation function, f, has the following form with an output value varies from 0 to 1:

$$f(x) = 1/\,(1 + \exp(-x))$$

In this application, a minimum three-layer feed-forward NN model was constructed. The network's output layer represented the free flowing rate of the target wells, and the input layer represented the flowing rates of other wells surrounding the target ones and their corresponding separation distances. During the network's learning process, a series of input patterns with their corresponding expected output values were presented to the network, and the connection weights between nodes of different layers were adjusted by back-propagation algorithm with the momentum term. The objective function used for optimization was the Root Mean Squared Error $(\mathrm{RMSE})_{\mathrm{NN}}$ which defined as:

$$(\mathrm{RMSE})_{\mathrm{NN}} = \left(\frac{1}{n}\sum_{s=1}^{n}\left[\sum_{k=4}^{m}(t_{sk} - y_{sk})^2\right]\right)^{0.5}$$

Where t_{sk} is the stability observations, y_{sk} is the predicted output, m is the number of output nodes, and n is the number of training set samples. To avoid the network's over fitting, a validation set obtained in a fashion similar to the training set was used to monitor the network's well-trained point. When the $(RMSE)_{ANN}$ error for the validation set reached a minimum value, the training process was stopped.

According to the generalized δ rule [3], the δ error term at output node k for training set sample s is expressed as:

$$\delta_{sk} = (t_{sk} - y_{sk})\, y_{sk}\, (1 - y_{sk})$$

While the δ error term at hidden node j for training set, sample s is expressed as:

$$\delta_{sj} = y_{sj}(1 - y_{sj})\left(\sum \delta_{sk} w_{kj}\right)$$

Where y_{sj} is output of hidden node j and w_{kj} is the connection weight between output node k and hidden node j. The basic of the latter equation is to propagate the δ error terms produced in the output layer backwards one layer through the network system. A similar procedure is recursively applied until the input layer is reached. Then these δ error terms are used to adjust the connection weights:

$$\Delta w_{ji}(q) = \eta\, \delta_{sj}\, y_{si} + \alpha\, \Delta w_{ji}(q-1)$$

where $\triangle w_{ji}$ is the change value in the connection weight between hidden node j and input node i, q and $(q-1)$ refer to the present and previous cycles of training set, respectively, η is the learning rate, and α is the momentum term, which is used to filter out high-frequency fluctuations of the network and to prevent to some extent the convergence process from getting trapped into the local minima. The output of input node i for training set sample s, y_{si} was directly set to the input signal of node i without any transformation in the present application. A similar equation is used to adjust the connection weight between output node k and hidden node j, and in this case, the δ error term at output node k, δ_{sk} is used.

3 Results and Discussion

One of the main issues encountered in NN is determination of the structure of the neural network in the number of hidden layers and the number of hidden neurons in each hidden layer. In most reported applications, the number of hidden layers and the number of hidden neurons are determined based on experience. Very often several arbitrary architectures are tried, and one giving the best performance is selected.

The optimum bitumen content of asphaltic concrete mixture (OBC) and Marshall stability are greatly influenced by several parameters: (i) Aggregate (type- size- shape- roughness- angularity – texture – gradation - absorption), (ii) Filler (type – shape – size - quantity), and (iii) bitumen (type – penetration - viscosity). Consequently developing models for OBC, Marshall Stability and Marshall Quitent of asphaltic concrete mixture requires an extensive understanding of the relation between these parameters and the properties of the resulting matrix. But in this research most of these factors were fixed, because the materials were used from the city of Mecca and the properties of these materials and gradations, job mix formula, mixture design were based on the specifications of Ministry of transportation in Saudi Arabia (MOT).

The input data for neural networks model has been chosen as percentage of course aggregate which is basalt type (igneous rock), percentage of fine aggregate (natural sand), and percentage of filler (ordinary Portland cement type 1) and the output is the percentage of optimum bitumen content (OBC), Marshall stability and Marshall Quitent.

The work presented here is based on a neural network model of three layer multi-layer perceptron architecture. The successful applied neural network model is of 3-15-3 multi-layer perceptron MLP, as shown in Fig.1: where three inputs in the input layer, fifteen hidden nodes (units), and three nodes in its output layer. The OBC, Marshall Stability and Marshall Quotient are the three predictions of the NN-based model.

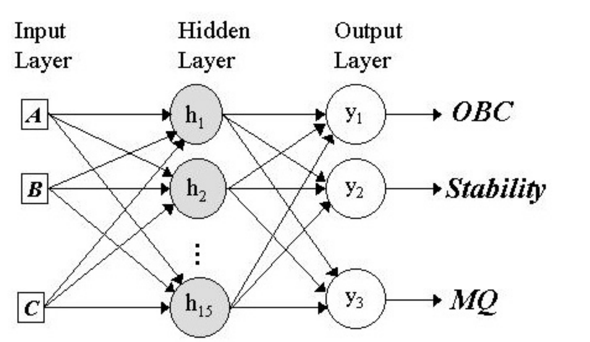

Fig.1. Structure of the neural network: 3-15-3 multi-layer perceptron.

The successful NN parameters for learning rate, momentum are found as 0.5, 0.9, respectively; Table 4. Different NNs parameters were experimented using sigmoid function transfer function and 3 to 25 hidden nodes; Table 3. According to the network run statistics, the smallest NN-RMS error reached is 0.0005. Table 3 shows the characteristics of the feed-forward NN model trials, while Table 4 shows the characteristics of the most successful NN model.

Table 3. Characteristics of NN testing model trials. OBC, stability, and MQ for 13 tested data.

Hidden Nodes	η	α	NN RMS Error	Correlations OBC	Stability	MQ
4	0.7	0.8	0.003	0.478	0.300	0.112
6	0.7	0.8	0.003	0.585	0.559	0.311
9	0.7	0.8	0.003	0.587	0.562	0.380
10	0.7	0.8	0.003	0.605	0.508	0.564
13	0.7	0.8	0.003	0.586	0.439	0.508
14	0.7	0.8	0.003	0.530	0.377	0.255
15	0.7	0.8	0.003	0.633	0.548	0.602
15	**0.5**	**0.9**	0.001	0.758	0.905	0.892
20	0.7	0.8	0.003	0.574	0.498	0.329
25	0.7	0.8	0.003	0.575	0.521	0.343

Table 4. Summary of the successful NN model structure of OBC,stability, and MQ.

Data Sets*		Network parameters	
I_1	% of course aggregate	Hidden Nodes	**15**
I_2	% of fine aggregate	Learning rate	**0.5**
I_3	% of filler	Momentum rate	**0.9**
O_1	% optimum bitumen content OBC	Maximum iterations	241,831
O_2	Stability	Converged error	0.0005
O_3	Marshall Quitent		

* I = Input layer O = output layer

Figures 2,3 show the comparison of predicted and experimental values for OBC. Similarly, Figures 4,5 and Figures 6,7 show the comparisons between the predicted and the actual experimented values of Stability and Marshall Quotient, respectively. Trained data are verified in Figures 2,4,6 whereas tested data are verified in Figures 3,5,7. From these figures it can be noticed that the prediction can be seen as fairly close to the corresponding actual values for optimum bitumen content, Marshall stability and Marshall Quotient. The successful NN model, Table 4, demonstrates the highest correlation coefficients of 0.970, 0.969, and 0.862 for OBC, Marshall stability, and MQ, respectively.

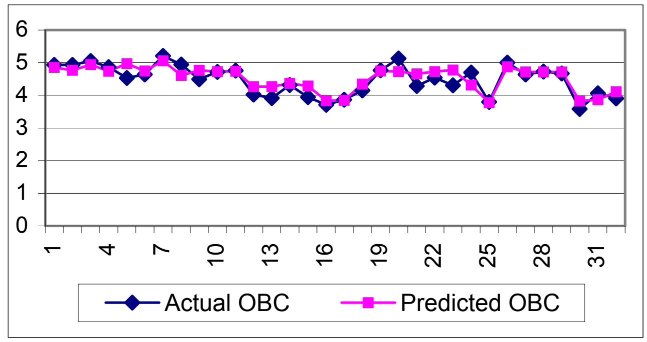

Fig.2. Comparison of actual and predicted values of optimum bitumen content *OBC* for trained data.

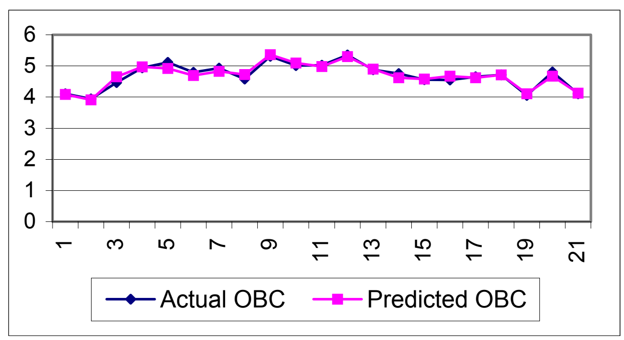

Fig.3. Comparison of actual and predicted values of *OBC* for tested data.

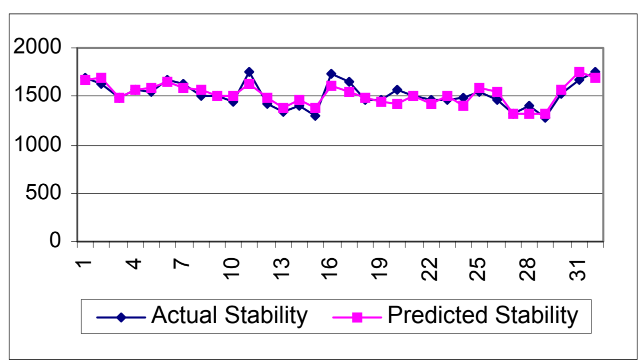

Fig.4. Comparison of actual and predicted values of *stability* for trained data.

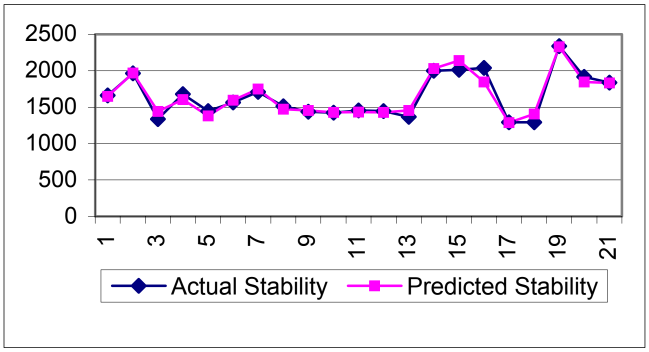

Fig.5. Comparison of actual and predicted values of *stability* for tested data.

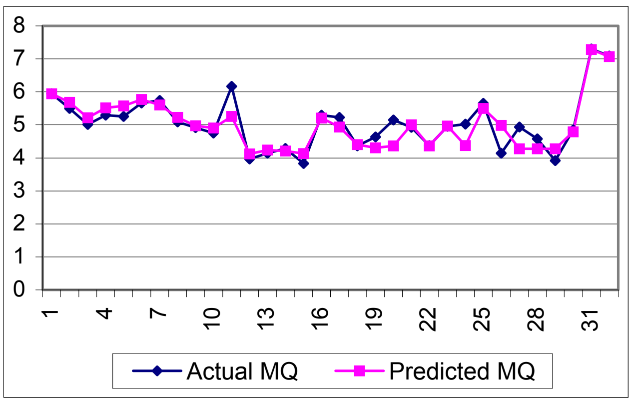

Fig.6. Comparison of actual and predicted values of *MQ* for trained data.

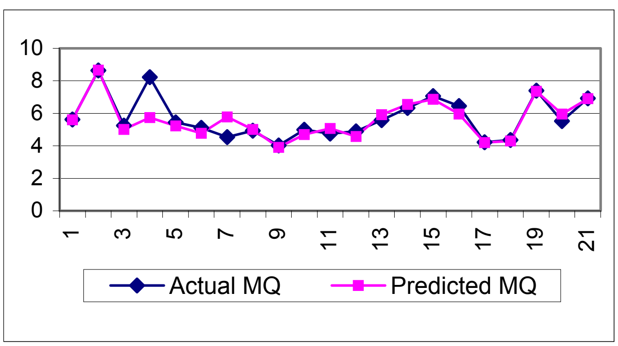

Fig.7. Comparison of actual and predicted values of *MQ* for 21 tested data.

4 Conclusions

Using the back-propagation learning rule for the data set, the developed neural networks model for the optimum bitumen content (OBC_{NN}), Marshall stability and Marshall Quotient of asphaltic concrete mixtures was found and a model was developed and validated. However OBC_{NN}, Marshall stability and Marshall Quotient model used more data input, it produced better performance with considerably less expense and effort to decide a priori on the class of input-output relationships.

The OBC_{NN}, Marshall Stability and Marshall Quotient model prediction was fairly close to the corresponding actual values. The successful NN mode demonstrates the highest correlation coefficients of 0.970, 0.969, and 0.862 for OBC, Marshall stability, and MQ, respectively.

The results indicated that the OBC_{NN}, Marshall Stability and Marshall Quotient model could predict the optimum bitumen content of asphaltic concrete mixtures with adequate accuracy required for practical design purpose. Transportation and highway engineers can use this model to predict the optimum bitumen content, Marshall Stability and Marshall Quotient of asphaltic concrete mixtures without conducting costly and time consuming experimental tests.

References

[1] Charalambous, C., "Conjugate gradient algorithm for efficient training of artificial neural networks", IEEE Proceedings, 139(3), 301-310, 1992.

[2] Ministry of Transportation (M.O.T), " Bituminous Mix Design Form MRDWS 410D.c, Circular No. 2401/2403, Riyadh, Kingdom of Saudi Arabia, 1998.

[3] Maren, A., C. Harston, and R. Pap, "Handbook of Neural Computing Applications. Academic", San Diego, California, 488 pp., 1990.

[4] Kenue, S.K., "Efficient activation functions for the back-propagation neural network", SPIE Vol. 1680 Intelligent Robots and Computer Vision X, 450-459, 1991.

[5] Smith, M., "Neural Networks for Statistical Modelling", Van Nostrand Reinhold, New York, 1993.

[6] Alawi, M.H. and Elbisy, M., "Prediction of Optimum Bitumen Content with Neural Networks for Asphaltic Concrete Mixtures", The Third International Conference for Advanced Trends in Engineering, Minia University, Minia, Egypt, 3-5 April 2005.