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Using Radial Basis Function Artificial Neural Network for Predicting Asphalt Content of Asphalt Paving Mixture

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ABSTRACT

The determination of the asphalt content of asphalt paving mixtures is a fundamentally important test for many authorities and researchers in highways field . This study seek to examined the application and use of radial basis function artificial neural network with Gaussian activation function by MATLAB software for predicting the asphalt content of the hot mix asphalt paving mixtures using their properties of Marshall test. The architecture of the study developed network consist of five input nodes representing five properties of Marshall test, with six hidden nods, while the output consist of one output node representing the asphalt content percent.

The study results have show that the radial basis function network can be applied as a recommended and appropriate computational tool to accurately and quickly determine the asphalt content of asphalt mixtures as alternative to using traditional techniques.

استخدام شبكة دالة الأساس الشعاعي العصبية الاصطناعية للتنبؤ بالمحتوى الإسفلتي لمزيج التبليط الإسفلتي

الملخص

يعد إيجاد محتوى الإسفلت في مزجات التبليط الإسفلتي فحص أساسي مهم لدى الكثير من المؤسسات والباحثين في مجال الطرق. تحاول هذه الدراسة أختبار إمكانية تطبيق واستخدام الشبكة العصبية الاصطناعية من نوع دالة الأساس الشعاعي مع دالة التنشيط كاوس باستخدام برمجيات MATLAB للتنبؤ بمحتوى الإسفلت في مزجات التبليط الإسفلتي الساخن اعتمادا على خواص فحص مارشال. معمارية الشبكة المطورة لهذه الدراسة تتكون من خمسة عقد إدخال تمثل خواص فحص مارشال، مع ستة عقد في الطبقة المخفية، بينما طبقة الإخراج تتكون من عقدة واحدة تمثل نسبة المحتوى الإسفلتي.

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وقد أظهرت نتائج الدراسة أن شبكة دالة الأساس الشعاعي يمكن استخدامها كوسيلة حسابية مقترحة ومناسبة لإيجاد محتوى الإسفلت في المزجات الإسفلتية بدقة وسرعة وكبديل لاستخدام التقنيات التقليدية.

1. Introduction

Asphalt binders are an essential component of asphalt concrete, they are the cement that holds the aggregate together. Binder content is one of the most important characteristics of asphalt concrete. Use of the proper amount of binder is essential to good performance in hot mix asphalt (HAM) paving mixtures. HMA is a mixture of asphalt cement and aggregate. Too little binder will result in a dry stiff mix that is difficult to place and compact and will be prone to fatigue cracking and other durability problems. Too much binder will be uneconomical, since asphalt binder is, by far, the most expensive component of the mixture and will make the mixture prone to rutting and shoving [Transportation Research Board, 2011].

The Marshall method is the first systematic and widely used method of HMA mix design in Iraq. The Marshall properties of the mixtures to be determined should be good indicators of performance of the mixtures in service, so that these properties can be used to determine the acceptability of the mixtures and to select the optimum mix design to be used [Tia,2005].

Artificial Neural Networks (ANN) have been successfully used for tasks involving pattern recognition, function approximation, optimization, forecasting, data retrieval, and automatic control, to name just a few [Haykin, 1999]. In recent years many researchers have applied the use of ANN in an effort to improve evaluation and prediction of corrective measures [Thomas, 2001].

The Radial Basis Function (RBF) neural network is a kind of feed-forward neural network with the input layer, hidden layer and output layer, which has the global approximation [Li, 2012]. RBF networks provide an excellent solution to many pattern recognition and classification problems [Yaol and Han, 2012]; also these networks have been successfully applied for nonlinear function approximation and data classification in wide range areas[Pekcan, Tutumluer, and Thompson, 2008].

2. Problem and objective of Research

In recent years there has been a growing interest in using performance testing and performance prediction models in HMA mixture design and acceptance. Laboratory investigation is the primary tool used by pavement engineers and researchers to understand mixture behavior and resolve the real world pavement problems [Taha, (2011]. Traditionally, asphalt content has been measured in the laboratory by extraction from the paving mixture with hazardous solvents. A new method for prediction of asphalt content of a given HMA mixture should be made to dispense with the need for these harmful solvents.

The prediction of asphalt content of a given HMA mixture is based on several variables and properties of the mixture according to the design method and specifications. In Marshall design method, the correlation of the asphalt content percent with each of the Marshall properties of HMA mixtures { Marshall stability, Marshall flow, percent of air voids, percent of voids in the mineral aggregate (VMA), and density} is non-linear. ANNs are useful tools in place of conventional physical models for analyzing complex relationships involving multiple variables, and for correlating nonlinear relationships between the inputs and outputs variables . These attributes make the study problem a suitable for analysis based on ANN.

The main objective of this research is to explore the possibility of application and using of RBF neural network as a predictive tool for asphalt content percent in HMA mixture using software of MATLAB and its neural network toolbox according to the properties of Marshall test. The study seek to develop an architecture for RBF neural network that can discover a pattern in the relationship among the Marshall properties and it can then predict the percent of the asphalt content of a given HMA paving mixture.

3. Pavement Applications of ANNs

Over the past few years, ANN models have been successfully used in many civil engineering applications [Waszczyszyn, 2011]. The results indicated that these models are more effective than the traditional models and can easily be implemented in a spreadsheet, thus making it easy to apply[Zhang and Zhang, 2004]. ANNs are particularly amenable to modeling the complex behavior of these applications and have generally demonstrated superior predictive performance when compared with traditional methods.

These models have been widely applied to various relevant civil engineering areas such as structural engineering [Nazarko, and Ziemiański, 2011], geotechnical engineering [Jaksa, Maier, and Shahin, 2008]. Recently, there has been an increased interest in ANNs for use in many fields of pavement engineering applications as well as other fields of transportation engineering [Taha, (2011].

There are many studies of using ANN in pavement distress [Choi, Adams, and Bahia, 2004], pavement structural modeling [Venayagamoorthy, and Allopi, 2007], pavement performance, analysis and design [Ozgan, 2011], pavement rehabilitation and maintenance [Gopalakrishnan,2010], pavement materials and properties [Singh, D., Zaman, and Commuri, 2013], and pavement management [Saghafi, Hassani, Noori, and Bustos, 2009].

4. Radial Basis Function Networks

The radial basis function (RBF) network comprises one of the most used network models. RBF networks can be used to solve a common set of problems[Miller, 2011]. The built-in commands provided by the package and the associated options are very similar. Problems where these networks are useful include; function approximation, classification, and modeling of dynamic systems and time series. The idea of RBF Networks derives from the theory of function approximation[Tsai, and Chuang, 2004].

The structure of RBF networks typically have three layers: an input layer, a hidden layer with a non-linear RBF activation function and a linear output layer[Guoqiang, Zhongzhi, and Zongyi, 2010]. The input can be modeled as a vector of real numbers ($x \in R^n$). The output of the network is then a scalar function of the input vector, $\varphi: R^n \rightarrow R$ [Qingjiang, 2012] , and is given by:

$$\varphi(x) = \sum_{i=1}^{N} a_i \, \rho (\| x - c_i \|) \qquad \ldots\ldots\ldots\ldots\ldots\ldots 1$$

Where N is the number of neurons (nodes) in the hidden layer, $\mathbf{c}_i$ is the center vector for neuron i, and a_i is the weight of neuron i in the linear output neuron. Functions that depend only on the distance from a center vector are radially symmetric about that vector, hence the name radial basis function. In the basic form all inputs are connected to each hidden neuron [Dachapak et al., 2004]. The norm is typically taken to be the Euclidean distance (although the Mahalanobis distance appears to perform better in general) and the radial basis function is commonly taken to be Gaussian:

$$\rho (\| x - c_i \|) = exp\,[- \beta_i (\| x - c_i \|)^2] \quad \ldots\ldots\ldots\ldots\ldots 2$$

The Gaussian basis functions are local to the center vector in the sense that:

$$\lim_{\|x\| \to \infty} \rho(\| x - c_i \|) = 0 \qquad \text{……..…..… 3}$$

i.e. changing parameters of one neuron has only a small effect for input values that are far away from the center of that neuron. Given certain mild conditions on the shape of the activation function, RBF networks are universal approximators on a compact subset of R^2. This means that an RBF network with enough hidden neurons can approximate any continuous function with arbitrary precision. The parameters a_i, c_i, and β_i are determined in a manner that optimizes the fit between φ and the data [Wen, Wang, and Wang, 2012].

5. Network Architecture

(ANN) is a network consisting of several nodes, known as neuron. The connection between these neurons carries weights, which defines the relationship between input and output data. One of the most important issues in the development of an ANN model is its architecture, i.e. the determination of the input and output variables, and number of neurons (nodes) in the hidden layer. The architecture of the ANN model has significant effect on the success of the developed model [Haykin, 1999]. The number of neurons (nodes) in the middle (hidden) layers can be varied depending on the complexity of the problem and size of the input formation. The MATLAB Neural Network Toolbox is used to construct and train the networks. The implementation of this network is readily available in popular software MATLAB and its neural network toolbox. MATLAB is a high-performance language for technical computing, it integrates computation, visualization, and programming in an easy-to-use environment, where problems and solutions are expressed in familiar mathematical rotation [Demuth, H, and Beale, 2003].The typical RBF network used in this study is sketch in Figure 1. The selected network for this study has one input layer with five input nodes, and one output layer with one output node . The input layer will have five nodes corresponding to the Marshall Properties of HMA mixtures: Marshall stability, Marshall flow, percent of air voids, percent of voids in the mineral aggregate, and density G_{mb} . All these properties must meet the requirements of the General Specification for Roads and Bridges in Iraq for binder course [Republic of Iraq , Ministry of Housing and Construction, 2003]. The hidden layer will have five nodes and the node threshold (bias node), six nodes in total. While the output layer will have one node corresponding to the predictive percent of asphalt content, as quality control parameter of HMA mixtures.

6. Mixture Design Method

Due to its simplicity, the Marshall method of HMA design is adopted for use in this study. This method involves selecting the aggregates and asphalt to be used, testing the asphalt mixtures at various different

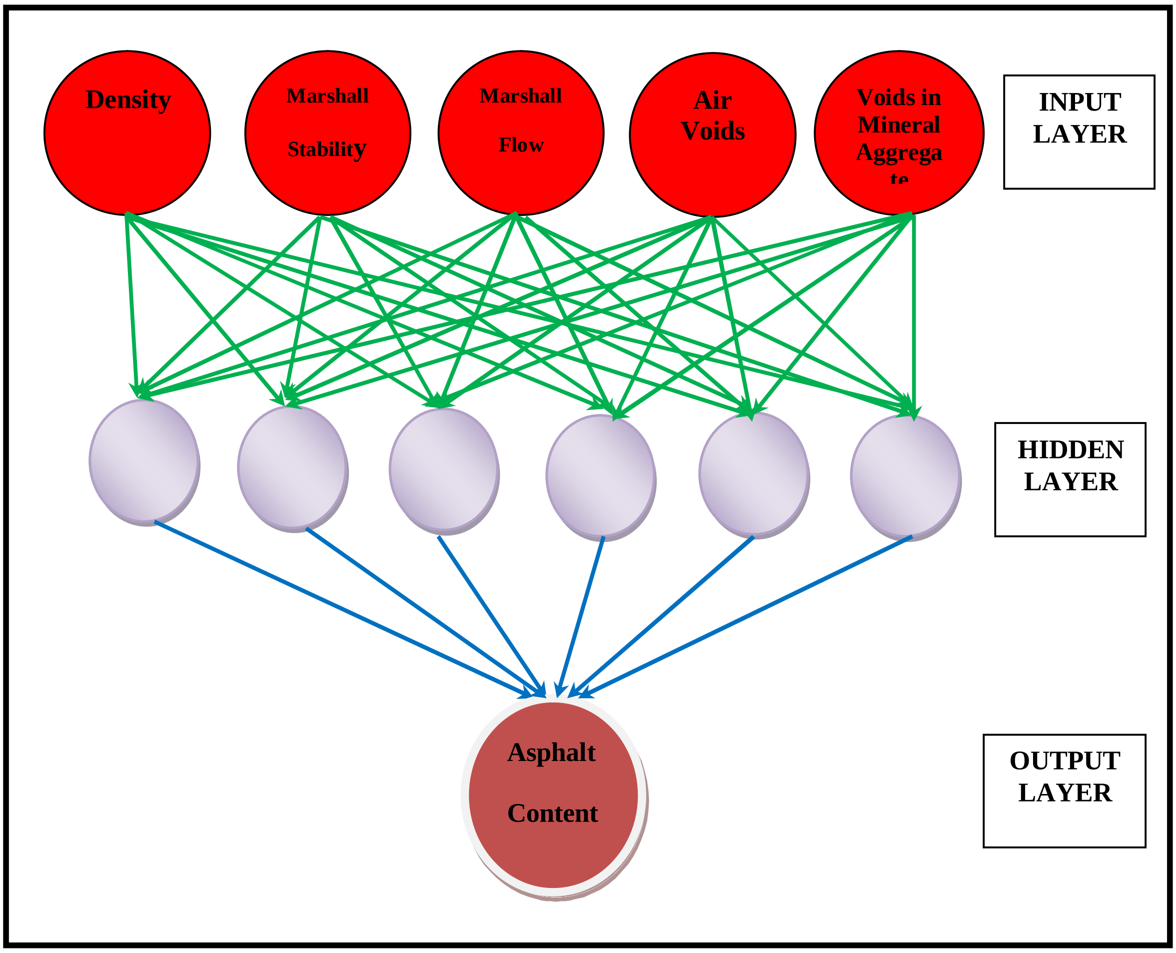

Figure 1: Structure of Radial Basis Function Network

proportions of ingredients, and selecting the optimum mix design which give the best anticipated performance in service [Tia, 2005]. The tests to be run on the Marshall specimens include:

1. Marshall test, which measures the Marshall stability and Marshall flow, in accordance with ASTM-D1559 [American Society for Testing and Materials, 2004]
2. Two different measures of densities in accordance with ASTM-D2726 [American Society for Testing and Materials,2004] are taken; bulk specific gravity(G_{mb}). These densities are used to calculate the volumetric parameters, air voids and voids in the mineral aggregate(V.M.A.).

7. Study Data

To develop the RBF Network for this study, sufficient set of mix proportions with corresponding Marshall Properties. Since sufficient data for mix design is not available, HMA mixture design data corresponding Marshall Properties has been generated experimentally with the statistical analysis for the training and testing of the study network.

The study data are generated from 10 mixtures based on laboratory mix design using Marshall method for developing the plant job mix formula curried out in Highway Laboratory at University of Mosul. For each mixture, the correlation of the asphalt content percent with each of the Marshall properties of HMA mixtures is derived using the statistical analysis. Using curve fitting method and from the plots of the Marshall properties versus asphalt content percent, the equation which representing the best relationship between each of these properties and asphalt content is determined, corresponding to the statistical values of coefficient of determination (R^2), standard error of estimate (S.E.), and t-statistics. For example, Table (1) presents the best relationships between the Marshall properties and the asphalt content percent for study mixture No.3.

Then, by using these equations, the generated data of each properties are calculated for different percents of asphalt content within the acceptance limits of the Iraqi specifications for the binder course. Sample of these calculations of generated data for study mixture No.3 is shown in Table (2).

Finally, the available HMA data of 400 records are used in this study. These data are divided into two sets:

1. Training set: used to determine the network weights, where 300 records are used to develop the network.
2. Testing set: used to verify the effectiveness of the stop criterion and to overcome network over-fitting , then to estimate the network

performance. Remaining 100 records are used as input for testing the trained network.

3. For validating the study network, new data of 30 records are used, these data are collected from Extraction experiments. Extraction experiments are conducted according to ASTM D2172 [American Society for Testing and Materials, 2004]by using the centrifuge extractor to determine the asphalt quantity for all of the HMA samples.

8. Results and Discussion

When researchers discuss a set of test results, the two most important characteristics of the data are the central tendency and variability[1]. All real data sets exhibit variability, that is, the test results are not all exactly the same but vary within a certain range. The overall value of a data set is usually measured by calculating the mean value, often called the average. Variability in a set of numbers is usually measured by calculating the standard deviation. Table (3) shows the descriptive statistics for the study data.

The selected RBF network is trained for several epoch with respect to the mean squared error (MSE). The number of epochs against the MSE for the predicted values of the output parameter is shown in the Figure (2). The MSE decreased, training converged, as the number of epochs were increased as shown in this figure. With 1000 epochs and more , the MSE decreased slightly. Figure (3) describes the predicted values (outputs) versus the actual values (targets) of percent of asphalt content for both training and testing phases.

The smaller spread of the result points would mean that predicted values of the output parameter are closer to the actual values and hence errors are small and vice-versa. These insignificant levels of MSE and high values of coefficient of determination (R^2) are a good indication to degree of the applicability and acceptability of the network performance.

10. Conclusions and Recommendations

ANNs are increasingly becoming an engineering tool for deriving data-driven predictive models. The developed ANN can easily be implemented in a spreadsheet module for practical applications. In this work, radial basis function neural network is treated as an analysis tool, just like statistical regression method. Study results indicate that radial basis function neural network predicts the asphalt content percent of the hot mix asphalt paving mixtures with reasonable accuracy.

Also, this network has been shown to be a feasible predictive method that can reduce the time consumed and can provide environmental and health benefits, and cost saving when compared with traditional laboratory methods. This network can be used as an appropriated and effective tool for laboratories conducting quality control test and performing independent assurance, verification and acceptance testing because it is easy to understand, and can be easily implemented as a software simulation.

Many researches and works should be applied the use of different types of ANN in an effort to improve evaluation and prediction of corrective measures in pavement engineering. Also, more efforts will be required to investigate various quality control processes of measure the acceptance of HMA paving mixtures.

Table 1: The Correlation Equations Between the Marshall Properties and the Asphalt Content Percent for Study HMA Mixture No.3.

Equation	R^2	S.E.
Density = $1.48 + 0.33X - 0.03X^2$ (3.78) (4.43)	0.81	0.103
Marshall Stability = $345 - 103.4X + 109.1X^2 - 13.6X^3$ (4.69) (1.07) (2.24)	0.95	10.33
Marshall Flow = $2.5 – 0.84X + 0.177X^2$ (1.65) (4.99)	0.96	0.27
Air Voids = $102.7\ X^{-2.2}$ (5.01)	0.991	0.055
V.M.A. = $31.5 – 7.3X + 0.78X^2$ (3.88) (2.00)	0.94	0.69

Notes:

- X : Asphalt content percent.
- R^2: Coefficient of determination.
- S.E.: Standard error of estimate.
- (t-statistics in parentheses).

Table 2: Sample of the Calculation Results of the Generated Data of Marshall Properties for Study HMA Mixture No.3.

Asphalt Content %	Density g/cm^3	Marshall Stability Kg	Marshall Flow mm	Air Voids %	V.M.A. %
4.0	2.32	806.6	2.02	4.864503	14.78
4.05	2.32443	812.2931	2.05045	4.733358	14.72895

4.1	2.3287	817.7054	2.0818	4.607294	14.6818
4.15	2.33283	822.8269	2.11405	4.486055	14.63855
4.2	2.3368	827.6472	2.1472	4.369402	14.5992
4.25	2.34063	832.1563	2.18125	4.257109	14.56375
4.3	2.3443	836.3438	2.2162	4.148966	14.5322
4.35	2.34783	840.1997	2.25205	4.044772	14.50455
4.4	2.3512	843.7136	2.2888	3.944342	14.4808
4.45	2.35443	846.8755	2.32645	3.847498	14.46095
4.5	2.3575	849.675	2.365	3.754075	14.445

Table 3: Descriptive Statistics for all Properties of the HMA Samples.

Property	N	Min.	Max.	Average	Std. Dev.	Std. Error
Asphalt content %	420	4	6	5.10	0.275	0.026
Marshall stability Kg	420	715	1255	925	42.58	9.014
Marshall flow mm	420	2.09	4.00	3.16	0.183	0.028
Density g/cm^3	420	2.205	2.393	2.325	0.033	0.005
Air voids %	420	3.00	4.95	2.93	0.510	0.077
V.M.A. %	420	14.11	16.35	15.37	0.881	0.106

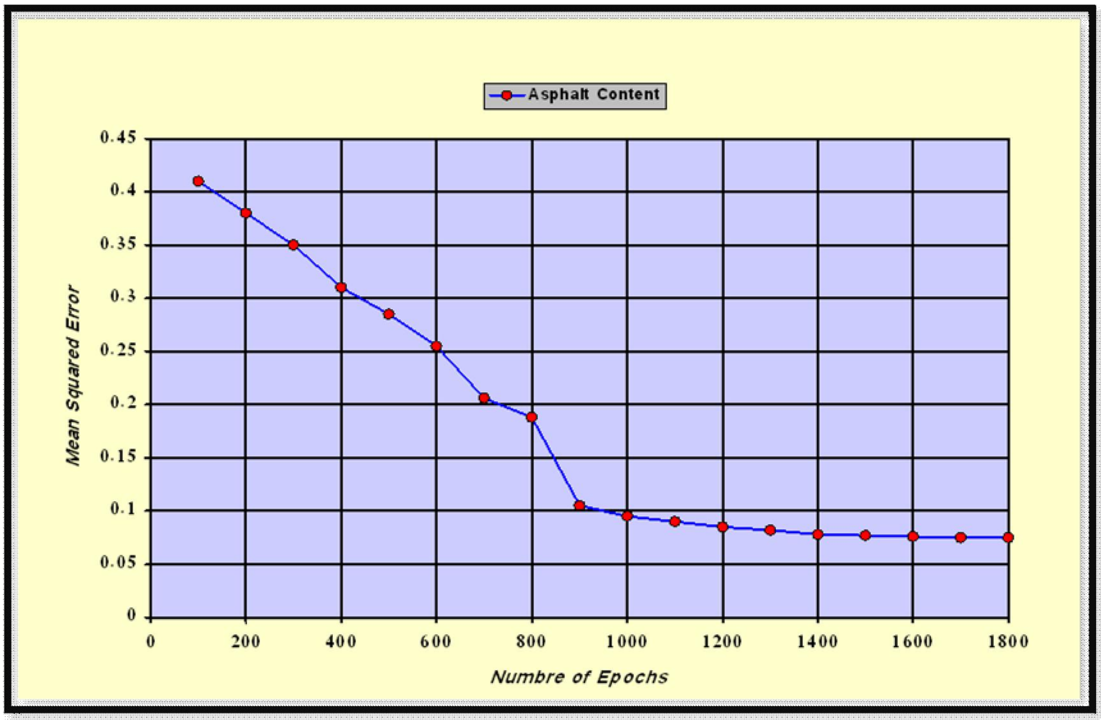

Figure 2: Mean Squared Error for the Output Parameter at Different Numbers Epochs of the Study RBF Network.

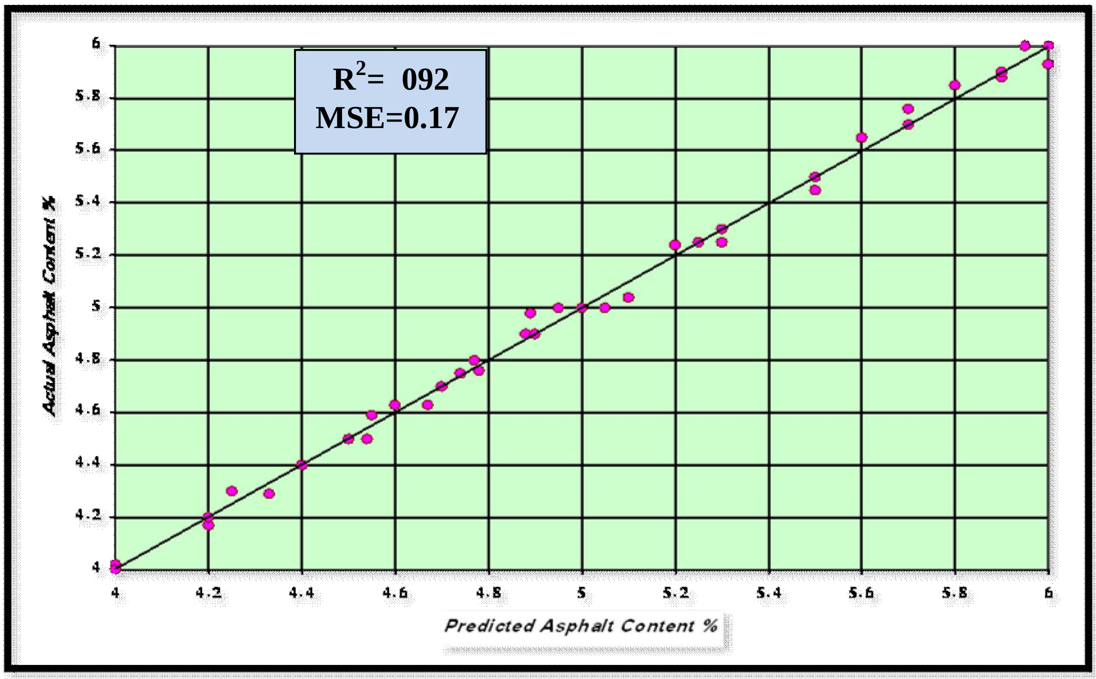

Figure 3: Actual Versus Study RBF Network Predicted Asphalt Content Percents.

10. References

1. American Society for Testing and Materials, ASTM, (2004), "Annual Book of ASTM Standards", PA, U.S.A.
2. Choi, J. H., Adams, T. M., and Bahia, H. V., (2004), " Pavement Roughness Modeling Using Back-Propagation Neural Networks",Computer Aided Civil and Infrastructure Engineering, Vol. 19, Issue 4, pp. 295-303 .
3. Dachapak C., et al.,(2004),"Orthogonal Least Squares for Radial Basis Function Network in Kernel Hilbert Space", IFAC Workshop, Japan, pp. 847-852.
4. Demuth, H, and Beale, M., (2003), "Neural Network Toolbox User's Guide", Math-Works, Inc., New York, U.S.A.
5. Gopalakrishnan, K., (2010)," Effect of Training algorithms on Neural Networks Aided Pavement Diagnosis", International Journal of Engineering, Science and Technology, Vol. 2, No. 2, pp. 83-92.
6. Guoqiang, C., Zhongzhi, T., and Zongyi, X., (2010)," Modelling of Electrohydraulic System using RBF Neural Networks and Genetic Algorithm", Journal of Convergence Information Technology, Vol.38, pp. 29 - 35.

7. Haykin, S.,(1999), "Neural Networks: A Comprehensive Foundation " , Second Edition, Prentice Hall Publication, Englewood Cliff, NJ., U.S.A.

8. Jaksa, M. B. , Maier, H. R., and Shahin, M.A., (2008)," Future Challenges for Artificial Neural Network Modelling in Geotechnical Engineering", The 12th International Conference of International Association for Computer Methods and Advances in Geomechanics, India, pp. 1710-1719.

9. Li, Q.,(2012),"Tuberculosis Prediction Method Based on PSO-RBF Neural Network" Journal of Computational Information Systems, Vol. 8, No. 24, pp.10250–10243 .

10. Miller, B., (2011)," Application of Neural Networks for Structure Updating", Journal of Computer Assisted Mech. Eng. Sci., Vol. 18, No. 3, pp. 191–203.

11. Nazarko, P., and Ziemiański,L., (2011), " Application of Artificial Neural Networks in the Damage Identification of Structural Elements", Journal of Computer Assisted Mech. Eng. Sci., Vol. 18, No. 3, pp. 175–189.

12. Ozgan, E., (2011), " Artificial Neural Network Based Modelling of the Marshall Stability of Asphalt Concrete", Journal of Expert Systems with Applications, Vol. 38, pp. 6025–6030

13. Qingjiang LI, (2012),"Tuberculosis Prediction Method Based on PSO-RBF Neural Network", Journal of Computational Information Systems, 8: 24 , pp.10243–10250, China.

14. Pekcan, O., Tutumluer, E. and Thompson, M. R., (2008), "Nondestructive Pavement Evaluation Using ILLI-PAVE Based Artificial Neural Network Models ", Civil Engineering Studies, Illinois Center for Transportation, Research Report FHWA- ICT-08-022.

15. Republic of Iraq , Ministry of Housing and Construction, (2003)," General Specification for Roads and Bridges ", Revised Edition 2003, Department of Planning and Studies, Iraq.

16. Saghafi, B., Hassani,A., Noori,R., and Bustos, M., (2009),"Artificial Neural Networks and Regression Analysis for Predicting Faulting in Jointed Concrete Pavements Considering Base Condition", International Journal of Pavement Research and Technology, Vol. 2, No.1, pp. 20-25.

17. Singh, D., Zaman, M., and Commuri, S., (2013), "Artificial Neural Network Modeling for Dynamic Modulus of Hot Mix Asphalt Using Aggregate Shape Properties", Journal of Materials in Civil Engineering, Vol. 25, No. 1, pp. 54–62.

18. Taha, M. Y., (2011), " Evaluation of acceptance of the Hot Mix Asphalt Paving Mixture Using Backpropagation Artificial Neural Network " , Al-Rafidain Engineering Journal, Vol.19, No.2, pp. 40-54.
19. Thomas, B.,(2001),"Use of Artificial Neural Networks for Predicting Skid Resistance of Hot Mix Asphalt Concrete Pavements",Ph.D. Thesis, Texas Technology University, Texas, USA.
20. Tia, M., (2005), " Fundamental and Practice of Asphalt Mixture Design Procedures to Assure Adequate Performance ", Paper for presentation, 13th Conference on Pavement Engineering, Taiwan.
21. Transportation Research Board, (2011), " A Manual for Design of Hot Mix Asphalt with Commentary", National Cooperative Highway Research Program, NCHRP Report 673, Washington D.C., U.S.A.
22. Tsai, C. H., an Chuang, H. T.,(2004),“ Dead-Zone Compensation Based on Constrained RBF Neural Network”, Journal of the Franklin Institute, Journal of Vol.341, No.4, pp.361-374.
23. Venayagamoorthy, V. and Allopi, D., (2007), " Use of Neural Networks in the Prediction of Bearing Capacity of Pavement Structures ", Proceedings of the 26th Southern African Transport Conference, Pretoria, South Africa.
24. Waszczyszyn, Z., (2011), " Artificial Neural Networks in Civil Engineering: Another Five Years of Research in Poland", Institute of Fundamental Technological Research, Polish Academy of Sciences, Computer Assisted Mechanics and Eng. Sciences,Vol. 18, pp.131–146.
25. Wen, X. L., Wang, H., T., and Wang, H., (2012)," Prediction Model of Flow Bboiling Heat Transfer for R407C Inside Horizontal Smooth Tubes Based on RBF Neural Network", Procedia Engineering, Vol. 31, pp. 233 – 239.
26. Yaol, J., and Han, H., (2012)," RBF Neural Network Evaluation Model for MDO Design of Ship", International Conference on Computer Technology and Science, Vol. 47, pp. 309-312, Singapore.
27. Zhang, A., and Zhang, L., (2004), “RBF Neural Networks for The Prediction of Building Interference Effects”, Journal of Computers & Structures, Vol. 82, No.27, pp.2333-2339, China.