International Journal of
Intelligent Systems and Applications in Engineering

ISSN:2147-6799 www.ijisae.org Original Research Paper

Comparison of Artificial Neural Networks and Response Surface Methodology in Stone Mastic Asphalt Using Waste Granite Filler

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Accepted : 27/10/2017 Published: 30/12/2017

Abstract: This study examined the modeling performance of Artificial Neural Networks (ANN) and Response Surface Methodology (RSM) using experimental data of mechanical and volumetric properties of stone mastic asphalt (SMA) samples. These samples were produced with Marshall Design method using different ratios of granite sludge filler (11-12%) and limestone filler (10%). The impact of percentage of bitumen, mineral filler rates and unit volume weights of samples were used as input parameters and Marshall Stability (MS) values were used as output parameter. Mechanical immersion tests were performed to examine moisture susceptibility on SMA samples that have different filler rates (10-11-12%). In order to examine the reliability of the obtained models error and regression analysis results were shown comparing model responses with the experimental results.

Keywords: *Marshall stability, Stone mastic asphalt, Response Surface, Neural network, Waste granite.*

1. Introduction

SMA was developed in Germany during the mid-1960s and has advantageous of high resistance to rutting, improving low temperature performance, resisting studied tire wear [1].

Focusing environment and economy is required in terms of sustainability in the concept of asphalt road production due to the increase of demand and limited aggregate and binder supply. Recycling and use of waste materials had become a priority goal for these focusing aims.

Granite sludge is obtained resulting from the purification of water that has been used to clean granite during cutting and polishing, consisting primarily of quartz. This material is a waste of factories in stone production industry. So the sludge, waste material, can be used as the filler in bituminous hot mixtures [2].

In order to optimize the parameters of any process, it is necessary to construct relationships between the response and each interested process parameter. RSM and the ANN are well-known methods serving this purpose. ANN and response surface methodology are usable modelling methods and there are many studies to estimate inter-values of experimental results. Performance comparison of both method is becoming popular during the last decade.

A numerous studies has been done using both methods such as surface roughness prediction [3], estimation of environmentally benign catalyst parameters [4], a modelling approach for the evaluation of heavy metal adsorption process in terms of parameter sensitivity and optimization [5], predictive modelling of dye extraction process dyes from natural sources [6], improvement of an drug extraction process from a plant leaves [7], developing of prediction models for lead removal from industrial sludge leachate using red mud [8].

This study aimed modelling performance comparison for MS prediction using RSM and ANN methods. In this study, mineral filler which was dried, milled and sieved using a No. 200 obtained from the granite sludge was used in stone mastic asphalt (SMA). Marshall Method was performed in order to obtain optimum bitumen ratios of the mix which has 10%, 11% and 12% filler ratios. Filler and bitumen rates are used as inputs while MS is output. Three layer feedforward network and three data division as training, validation and test are used for ANN method. In addition to two independent factors a categorical factor which separates the low and high filler rates are used for second order with interaction RSM. According to the error analysis results and graphical comparison ANN is quite successful for modelling despite using segmented data as training, validation and test.

2. Experimental details

2.1. Marshall stability-flow test

Stability is important properties of SMA because of the dynamic loads from vehicles, long term static loads, stress caused by vehicle speeding and stopping, and shear effects or aggregate loss [2], [9]. Stability is the resistance to deformation of the SMA pavement under heavy traffic. If pavement has low stability, higher deformation is expected [9]. After aggregate testing, the optimum bitumen ratio was determined for each sample (10%, 11%, and 12%) using the Marshall Design method. SMA samples were prepared in compliance with the technical specifications required by Highway General Directorate [10].

SMA mixture samples were produced using 5.0%, 5.5%, 6%, 6.5%, 7%, and 7.5% bitumen contents, and three specimens were prepared for each level of bitumen content. For all of the specimens, Marshall Stability-Flow tests were performed and the results were given Table 4 according to percentage of bitumen content-stability.

2.2. Mechanical marshall immersion test

In order to investigate the variations in the properties of SMA mixtures under the effect of moisture, mechanical immersion tests were performed. A test was carried out on each of the stone mastic asphalt mixture specimens with different filler contents (10%, 11%, 12%). Stone mastic asphalt mixture specimens which had the

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optimum bitumen content were produced and cured in a water bath at 60 ^{0}C for 48 h. After the cure, a MS test was performed on the specimens. According to the test results, the stability loss is lower in the 11% filler additive specimens than in the others (Fig. 1).

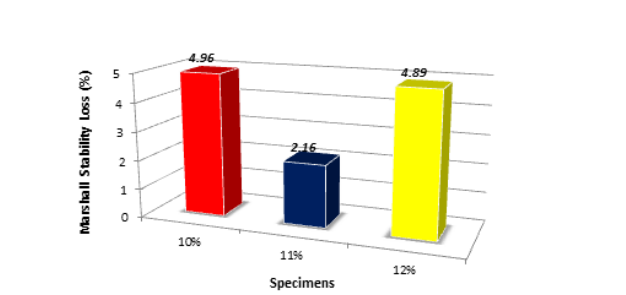

Figure 1. Loss of percent Marshall Stability.

2.3. Modified Lottman Test

In this study, Modified Lottman test was conducted on 9 samples preparing 10%, 11% and 12% filler rates and Tensile Strength Ratio (TSR) values were determined. The Modified Lottman test was obtained according to AASTHO T 283. Three specimens were prepared for each filler rates. After the compaction of the specimens with 50 blows, specimens left for 24 h to cool down. After 24 h, all the specimens cured in an oven at 40 ^{0}C for 72 h. Then all the specimens were taken out and left to cool down to room temperature. When the specimens get 25 ^{0}C then one of each filler addition rate was loaded till failure. The results were recorded as unconditioned (dry) strengths. The rest of the specimens were put into water bath at 25 ^{0}C for 24 h. After 24 h in water bath, the specimens were taken out at vacuum saturated till the saturation level was between 55% and 80%. The saturated specimens were subjected in a freezing cabinet at minus 18 ^{0}C for 16 h and then were put into water bath at 60 ^{0}C for 24 h. After all, the specimens get out from 60 ^{0}C water bath and were put in a water bath at 25 ^{0}C for two hours. Finally, the specimens were loaded till failure and the results were recorded as conditioned (wet) strengths. The ratio of the conditioned samples strength value to unconditioned samples strength value was called Tensile Strength Ratio (TSR). TSR value is calculated as Eq. (1). In Table 1, the wet and dry strength values were shown.

$$TSR = \frac{conditioned\left(wet\right)}{uncontidioned\left(dry\right)} \qquad (1)$$

Table 1. Modified Lottman Test Results

Filler Rates	*Dry (KN)*	*Wet (KN)*
10%	10.2	9.8
11%	10.5	10.0
12%	8.7	8.2

3. RSM based predicted model

RSM is a collection of mathematical and statistically based technique useful for the modeling and analysis of problems with several process variables. It also has important applications in the design, development, and formulation of new products, as well as in the improvement of existing product designs [11].

The most extensive applications of RSM are in the situation where several input variables (independent variable) are potentially influencing some performance measure or quality characteristic of the product or process (response). Since the form of the relationship between the response and the independent variable is unknown, the first step in RSM is to find the suitable approximation for the true functional relationship between response (y) and the set of independent variables (x). Usually a low-order polynomial in some relatively small region of the independent variable space provides a suitable approximation of the true form of the response function. In many cases, either a first-order or a second-order model is sufficient [12].

Second-order RSM model with interaction term (Eq. 2) is used in this study.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i<j} \sum \beta_i x_i x_j + \sum_{i=1}^{k} \beta_i x_i^2 + \in \qquad (2)$$

where β is a RSM coefficient of each term, k is a number of independent variables, and ∈ is a residual error. The second-order model is widely used in RSM for several reasons. First, the second-order model is very flexible; it can take on a wide variety of functional forms. Second, an estimation of the coefficient (β) can be done easily by the method of least squares. Furthermore, there is considerable practical experience indicating that the second order works well in solving real response surface problem [13].

In this study, MS value was selected as responses while filler and bitumen rates were independent variables. Values of the two factors in experimental data includes 3 and 6 levels, respectively. In order to use all six levels in modelling, values of second factor are coded as in two groups using a categorical factor "C".

Table 2. Factors with levels used in RSM.

Variables	*Factor Codes*	*Factor Levels*		
		-1	*0*	*1*
Filler rate %	A	10	11	12
Bitumen rate % for group 1	B	5	5.5	6
Bitumen rate % for group 2	B	6.5	7	7.5
Group number	C	Two groups are showed by 1 or 2		

Table 3. Experimental results and coded values according to response surface array with two continuous and 1 categorical factors.

Run	*Coded values of factors*			*Real values of Factors*		*MS*
	A	*B*	*C*	*Filler(%)*	*Bitumen(%)*	*("kN")*
1	1	0	1	12	5,5	9,8
2	-1	1	2	10	7,5	9,0
3	1	-1	2	12	6,5	8,8
4	-1	-1	2	10	6,5	9,2
5	0	1	2	11	7,5	7,7
6	0	0	1	11	5,5	9,8
7	0	0	1	11	5,5	9,8
8	0	-1	1	11	5,0	10,1
9	0	0	2	11	7,0	8,8
10	0	-1	2	11	6,5	9,3
11	0	0	1	11	5,5	9,8
12	-1	-1	1	10	5,0	11,5
13	1	1	1	12	6,0	9,4
14	0	1	1	11	6,0	9,6
15	1	-1	1	12	5,0	8,7
16	-1	0	2	10	7,0	8,7
17	-1	1	1	10	6,0	10,0
18	0	0	2	11	7,0	8,8
19	0	0	2	11	7,0	8,8
20	0	0	1	11	5,5	9,8
21	0	0	2	11	7,0	8,8
22	1	1	2	12	7,5	7,8
23	-1	0	1	10	5,5	11,4
24	1	0	2	12	7,0	8,0
25	0	0	2	11	7,0	8,8
26	0	0	1	11	5,5	9,8

This methodology is applied with face centered central composite array using α=1. Results of RSM model formulations of these two groups are given in (Eq. 3 and Eq. 4).

$$MS1 = 997{,}9 - 82{,}2A - 20{,}6B + 17{,}5A^2 - 13{,}6B^2 + 16{,}4AB \quad (3)$$

$$MS2 = 867{,}4 - 34{,}9A - 46{,}8B + 17{,}5A^2 - 13{,}6B^2 + 16{,}4AB \quad (4)$$

Levels of factors and their codes used for RSM modelling and array of the RSM method are tabulated in Tables 2 and 3.
However total data includes 18 samples, here the number has been increased to 26 using repetitive runs due to nature of the used RSM array structure. Based on the experimental result in Table 3, the second order RSM models for responses of both groups were formulated using the estimated regression coefficients. Equation 3 and 4 represents the RSM model for MS.

4. ANN based model

ANN model is composed of an input layer, some hidden layers and an output layer. To develop the model, there must be three stages [14]. Firstly, data of input and output variables which are supposed to be good relation is chosen as vectors. Secondly, the network is trained to predict an output based on input data using a training algorithm. In addition to training data validation data can be used to overcome overtraining problem [15]. Determining of optimal number of hidden layer and the number of neurons in layer/layers are important structural problems. Finally, the network is tested using test data which is not used for training stage. In order to evaluate network performance, ANN output for test input data are compared with experimentally obtained data if exist. If the results are not satisfactory network is re-trained. If the test results are good enough training parameters is saved. At the end of the testing stage, error calculations of different measures are used to show the effectiveness of the well trained network.
The network structure used in this study has two hidden layers which have 9 and 5 neurons. Thus the number of neurons in eachlayers are 18-9-5-1. Two inputs are filler and bitumen ratio values as percentage. MS value is used as output variable. Aim of the network is to predict MS value using data of input variables. To solve this problem; the network is trained by using Matlab codes. Percentages of data for training, validation and test stages are 70%, 10% and 20% by using “divider and function”, respectively. Levenberg Marquardt (LM) method is chosen as training algorithm due to its good performance. Training was interrupted by reaching the value of minimum gradient.

5. Comparison of the RSM and ANN models

The MS predictive models developed by RSM and ANN were compared on the basis of their prediction accuracy. Figure 2 shows regression results of RSM and ANN. According to this, the ANN model probably could predict MS with a better performance owing to their greater flexibility and capability to model nonlinear relationships. Here, the dashed line is the perfect fit line where outputs and targets are equal to each other. The circles are the data points and colored line represents the best fit between outputs and targets. Here it is important to note that circles gather across the dashed line, so our outputs are not far from their targets. According to these results we can say that used MLP structure of ANN using three inputs is very well to predict MS values.
Figure 3 shows a comparison results of RSM and ANN prediction performances with experimental results for MS Although each model has similar trackingability ANN model is closer to the real values. Therefore, in the case of datasets with a limited number of observations in which regression models fail to capturereliably, advanced soft computing approaches like ANN may be preferred.

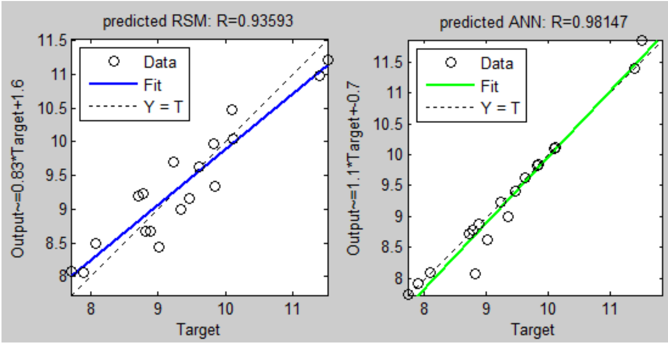

Figure 2. Regression results of RSM and ANN models.

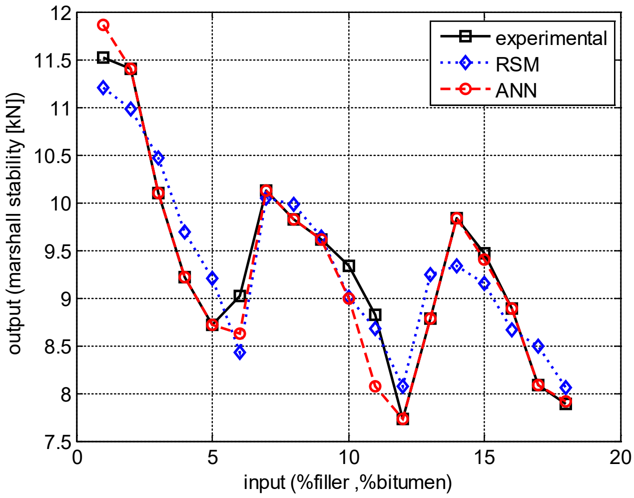

Figure 3. Comparison of the RSM and ANN models response with experimental results.

When compared with the experimental data consist of 18 samples predicted results with their percentage errors were summarized in Table 4. experimental results of each samples was obtained by taking average values of three repetition.

Table 4. Input and output data for modelling and Predictive model errors

No	*Filler %*	*Bitumen %*	*MS [kN] (Real)*	*Predicted MS (RSM)*	*Error% (RSM)*	*Predicted MS (ANN)*	*Error% (ANN)*
1	10	5	11,5	11,2	2,6	11,8	2,9
2	10	5,5	11,4	10,9	3,7	11,4	9,6E-08
3	10	6	10,0	10,4	3,6	10,0	1,5E-07
4	10	6,5	9,2	9,6	5,1	9,2	3,3E-07
5	10	7	8,7	9,1	5,5	8,7	2,6E-07
6	10	7,5	9,0	8,4	6,5	8,6	4,4
7	11	5	10,1	10,0	0,6	10,1	2,2E-08
8	11	5,5	9,8	9,9	1,5	9,8	1,8E-07
9	11	6	9,6	9,6	0,2	9,6	4,5E-07
10	11	6,5	9,3	9,0	3,5	8,9	3,6
11	11	7	8,8	8,6	1,6	8,0	8,4
12	11	7,5	7,7	8,0	4,4	7,7	1,2E-07
13	12	5	8,7	9,2	5,1	8,7	6,1E-07
14	12	5,5	9,8	9,3	5,1	9,8	3,0E-07
15	12	6	9,4	9,1	3,3	9,3	0,7
16	12	6,5	8,8	8,6	2,4	8,8	1,4E-07
17	12	7	8,0	8,5	5,1	8,0	5,8E-08
18	12	7,5	7,8	8,0	2,1	7,9	0,2

It is shown that percentage of prediction errors of ANN model have different values. Although errors values of training samples are almost zero, error values for validation and test samples are below 5% except one excessive.
It is shown from the bar grafics that ANN has excessive errors for

sample sexcept training (Figure 4). RSM model has errorvaluesaround0.5kNandbelowfor MS values around 10kN.

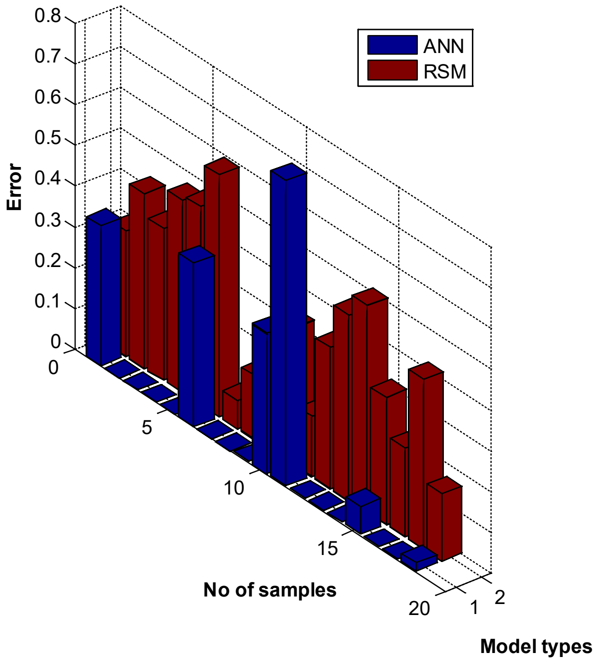

Figure 4. Demonstration of each sample absolute errors as bar graphics.

6. Conclusion

Present study established a comparative investigation of the modelling approaches by response surface methodology and artificial neural networks for MS prediction in the SMA using different ratio of waste granite filler. Error analysis and plot comparison of the results were held in order to understand correlation of the measured and estimated MS values for two modelling studies.

The two modelling application was applied with the experimental data obtained via Marshall Stability-Flow tests. Employed database for the development of the RSM and ANN based models consist of two factors with three and six levels. A categorical factor was used to use all levels of the second factor for the RSM based model. That leads the model consists of two parts and considered as a drawback.

The ANN structure was tuned for the best results with three hidden layers included neuron numbers as 18, 9, and 5. In the nature of the ANN, the database can be evaluated in three parts divided as training, evaluation and testing. In this study, the numbers of samples used for these parts are 12, 2 and 4 respectively. ANN modelling results seem like very good for training but residual errors variates between 0.72-8.48 % for the other parts.

Differently from ANN, RSM has smoother modelling errors which are closer with each other and around 5% . It was shown that RSM model is more homogenous results which are slightly worse.

A good correlation between the predicted and experimental results resulting from the model was exhibited. Thus, using the proposed procedure, the optimal filler and bitumen rates should be estimated to obtain the better MS values.

In order to investigate the variations in the properties of SMA mixtures under the effect of moisture, mechanical immersion tests were performed. According to the results, the stability loss is lower in the samples have 11% waste granite sludge as filler than the samples included the other filler rates.

Acknowledgements

The author wishes to thank the Scientific Research Projects Coordination Department of Afyon Kocatepe University (AKU BAP) (Project Number: 13.TEF.02) for their financial support.

References

[1] Do Vale, A. C., Casagrande, M. D. T. and Soares, J. B., Behavior of Natural Fiber in Stone Matrix Asphalt Mixtures Using Two Design Methods, J Mater Civ Eng 26 (2014), 457–465.

[2] Akbulut, H., Gürer, C., Çetin, S., and Elmacı, A., Investigation of using granite sludge as filler in bituminous hot mixtures, Constr Build Mater, 36 (2012), 430–436.

[3] Patel, K. A. and Brahmbhatt, P. K., A Comparative Study of the RSM and ANN Models for Predicting Surface Roughness in Roller Burnishing, Procedia Technol 23 (2016), 391–397.

[4] Hafizi, A., Ahmadpour, A., Koolivand-Salooki, M., Heravi, M. M. and Bamoharram, F. F., Comparison of RSM and ANN for the investigation of linear alkylbenzene synthesis over H14[NaP5W30O110]/SiO2 catalyst, J Ind Eng Chem 19, (2013), 1981–1989.

[5] Shojaeimehr, T., Rahimpour, F., Khadivi, M. A., and M. Sadeghi, A modeling study by response surface methodology (RSM) and artificial neural network (ANN) on Cu2+ adsorption optimization using light expended clay aggregate (LECA), J Ind Eng Chem 20 (2014), 870–880.

[6] Sinha, K., Chowdhury, S., Das Saha, P., and Datta, S., Modeling of microwave-assisted extraction of natural dye from seeds of Bixa orellana (Annatto) using response surface methodology (RSM) and artificial neural network (ANN), Ind Crops Prod 41 (2013), 165–171.

[7] Pilkington, J. L., Preston, C., and Gomes, R. L., Comparison of response surface methodology (RSM) and artificial neural networks (ANN) towards efficient extraction of artemisinin from Artemisia annua, Ind Crops Prod 58 (2014), 15–24.

[8] Geyikçi, F., Kiliç, E., Çoruh, S., and Elevli, S., Modelling of lead absorption from industrial sludge leachate on red mud by using RSM and ANN, Chem Eng J 183 (2012), 53–59.

[9] Akbulut, H., Gürer, C., and Çetin, S., Use of volcanic aggregates in asphalt pavement mixes, Proc ICE - Transp 164 (2011), 111–123.

[10] *General Directory of Highways (TCK), Turkish State Highway Specifications*. Ankara: Republic of Turkey, Ministry of Transport, (2013).

[11] Montgomery, D. C., Design and analysis of experiment, Wiley, Hoboken, (2005).

[12] Thepsonthi, T. and Özel, T., Multi-objective process optimization for micro-end milling of Ti-6Al-4V titanium alloy, Int J Adv Manuf Technol 63 (2012), 903–914.

[13] Myers, R. H. and Montgomery, D. C., Response surface methodology: process and product optimization using designed experiments, Wiley, Hoboken, (2002).

[14] Caner, M., Gedik, E. and Keçebaş, A., Investigation on thermal performance calculation of two type solar air collectors using artificial neural network, Expert Syst Appl 38 (2011), 1668–1674.

[15] Suzuki,K. et al, The characteristics of excitation system, In Advances in Power System Control, Operation and Management, APSCOM-91., International Conference on, (1991), 479–484.