

## **PREDICTION OF THE OPTIMUM ASPHALT CONTENT USING ARTIFICIAL NEURAL NETWORKS**

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### **Abstract**

The performance of the asphalt mix is significantly influenced by the optimum asphalt content (OAC). The asphalt content is responsible for coating the aggregate surface and filling the voids between the aggregate particles. Thus, the aggregate gradation has a significant influence on the required asphalt content. The Marshall design process is the most common method used for estimating the OAC, and this process is called the asphalt mix design. However, this method is time consuming, labor intensive, and its results are subjected to variations. Thus, this paper employs the artificial neural network (ANN) to estimate the OAC from the aggregate gradation for the two most common gradations used in asphalt mixes in Egypt (3D, 4C). Results show that the proposed ANN can predict the OAC with a coefficient of correlation of 0.98 and an average error of 0.026%. As a result, a new approach for the Marshall test can be adopted using results of the proposed ANN, and only three specimens, instead of fifteen, are prepared and tested for estimating the remaining parameters. This approach saves the time, effort, and resources required for estimating the OAC. Additionally, the ANN was validated with previously developed models, and the ANN shows promising results.

**Keywords:** Artificial Neural Networks; Asphalt mix design; Early Stopping Technique; Machine Learning; Marshall Design; Optimum asphalt content.

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**Abbreviations:**

OAC	Optimum Asphalt Content
ANN	Artificial Neural Network
%P(I)	percentage passing from sieve i

**Introduction**

Asphalt concrete (AC) was invented to carry heavy loads and the high tire pressures of aircraft, increasing the need for strong and stiff pavements. AC is a composite material that consists of aggregate and bitumen [1]. Generally, pavement consists of different layers to transfer the traffic load to the soil [2]. Road superstructure design can be divided into two main tasks: thickness design of the pavement layers and asphalt mix design [3–8]. The asphalt mix design process is carried out through laboratory tests such as the Marshall design method or Superpave design method. The main target of these tests is to estimate the optimum asphalt content (OAC) [9] because the OAC has a significant influence on the final performance of the mix [10]. High asphalt content leads to rutting, flushing, and insufficient air voids in the asphalt mix, and low asphalt content leads to a harsh mix that is hard to compact and makes durability issues [11].

In 1939, in the Mississippi State Highway Department, Bruce Marshall developed the Marshall Mix design method. The US Corps of Engineers conducted extensive research and studies to improve Marshall test procedures and develop the asphalt mix design criteria [1]. In 1948, the Marshall test was widely adopted in many countries with slight modifications from country to country [9]. Till now, it is the most common asphalt mix design method [12], and it is still used in Egypt for estimating the OAC [13]. During the Marshall test, the designer has to prepare at least 15 samples for five bitumen contents (three samples for every bitumen content) and draw the design curves [14, 15] to find the OAC that satisfies the following criteria: Maximum stability, Maximum density or unit weight, predefined air voids percent, and a min value for voids in mineral aggregate [9]. As a result, the final OAC from the Marshall method is the average value corresponding to the maximum stability, maximum unit weight, and prespecified air voids percentage [14, 15]. Consequently, results are subjected to significant deviations [14]. Also, the Marshall design method requires considerable time for sample preparation and testing [16, 14]. Thus, many studies focused on developing alternatives for the Marshall test to save the testing time using many techniques such as regression analysis and artificial intelligence over the past few years.

Aggregates represent almost 95% of the overall mix weight [17], so characteristics of the asphalt mix mainly depend on the aggregate used and its gradation. Changing the aggregate gradation changes the required asphalt content because the asphalt content is responsible for coating the aggregate surface and filling the voids between the aggregate particles [16]. Thus, fine aggregate requires higher asphalt content [18]. Moreover, the primary sources of the mix strength or stability are the friction between the aggregate particles, interlocking resistance between the aggregate particles, and the consistency of the bitumen used [14, 19]. This paper provides a new approach for estimating the optimum asphalt content resulting from the aggregate gradation using artificial neural networks using Marshall test results conducted in Egypt and validate the results with previously developed models in Egypt.

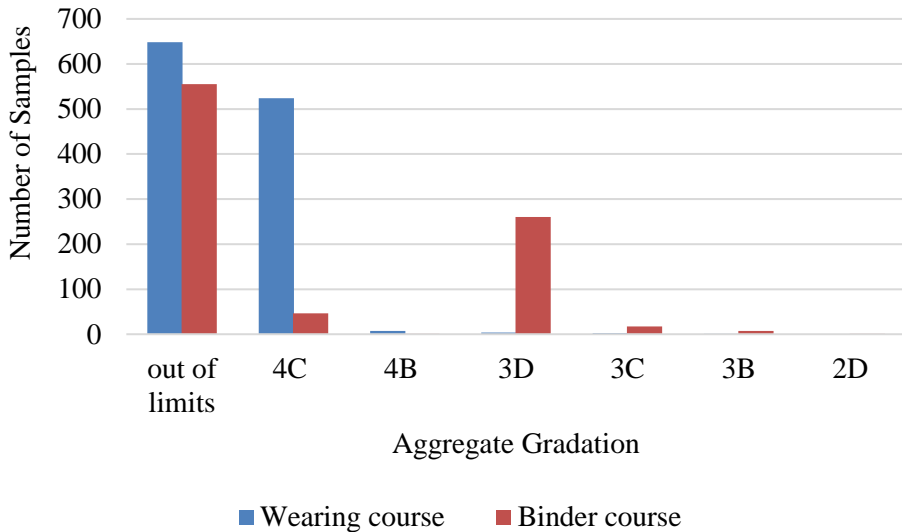
## Historical background of neural network applications in pavement engineering

This section reviews the relevant applications of artificial neural networks (ANNs) in the pavement engineering field. Starting with one of the oldest studies using NNs by *Kaseko and Ritchie* (1993) for the detection of pavement cracks based on the image processing technique [20]. *Gagarin, Flood, and Albrecht* (1994) used the strain response readings from bridges to estimate different truck attributes such as axle load and spacing while employing ANNs [21]. *Cal* (1995) used ANNs for estimating the classifications of soils using their plasticity index, water content, and liquid limit [22]. *Roberts and Attoh-Okine* (1998) used ANNs for estimating the pavement condition or the pavement roughness index [23]. Similarly, *Attoh-Okine* (2001) used ANNs for estimating the pavement condition given the pavement characteristics and the surrounding conditions such as weather, age, and traffic condition [24]. *Tapkın et al.* (2010) employed ANNs for estimating Marshalltest results for dense asphalt mixes modified with different types and percentages of an additive, polypropylene [9]. *Khuntia et al.* (2014) used the ANNs and support vector machine for estimating the Marshall test results for the polyethylene modified mixes [25]. *Ozturk et al.* (2016) employed ANNs for estimating the volumetric characteristics of the asphalt mixes prepared following Marshall procedures [26]. *Ivica and Ivan* (2017) used ANN and multiple linear regression for estimating the air voids and the asphalt content of asphalt mixes in Croatia [26]. *Baldo et al.* (2018) used ANNs for estimating the mechanical properties of asphalt mixes (stability and flow) [16]. *Nguyen et al.* (2019) artificial intelligence techniques for estimating the characteristics of the stone matrix asphalt [27].

## Methodology:

### Material selection

According to the Egyptian code for urban and rural roads [28], there are many classes for the aggregate gradations used in the asphalt mix. However, there are two aggregate gradations commonly used in Egypt (4C and 3D). In 2015 and 2016, almost 2073 asphalt mix samples were collected and tested from different locations all over Egypt under the supervision of the highway and research laboratory, Cairo University, Egypt. Out of these 2073 samples, 1186 are wearing course samples, and 887 are binder course samples. Figure 1 shows the number of wearing course and binder course samples for the different aggregate gradations. Gradation 4C is the dominant gradation for the wearing course samples, and gradation 3D is dominant for the binder course samples, followed by grade gradation 4C. Also, it should be mentioned that a significant number of samples do not meet any of the aggregate gradations classified according to the Egyptian code for urban and rural roads, which indicates the poor quality control on site. Similarly, for the bitumen or binder used in Egypt, the most common binder grade used in Egypt is binder 60-70, and it is rare to find a different grade in Egypt. These results comply with a recent study by *Mousa et al.* (2018) in Egypt, which showed that binder grade 60-70 and aggregate 4C and 3D are the most common binder and aggregate gradations used in Egypt [10].



*Fig. 1. The number of wearing course and binder course samples for different aggregate gradations.*

#### *Characteristics of the materials used*

In this study, 106 asphalt mix samples are prepared and tested using bitumen 60-70 and aggregate gradations 4C and 3D. Characteristics of the bitumen and aggregates are shown in Tables 1 and 2. Figure 2 shows the specification limits for the aggregate gradation used in the mixes in the sieve analysis graph.

*Table 1. Specifications of the bitumen used (The Egyptian code for urban and rural roads (ECP, 2008) part (4)).*

Experiment	Specifications
Penetration (0.1 mm)	60-70
Softening point (degree)	45-55
Viscosity (centistoke)	Min 320

Table 2. Aggregate gradations (4C and 3D) used in the mixes (The Egyptian code for urban and rural roads (ECP, 2008) part (4)).

Sieve Size	Limits			
	Wearing Surface (4C)		Binder Layer (3D)	
	Min	Max	Min	Max
% Passing from sieve 1 in	100	100	100	100
% Passing from sieve 3/4 in	80	100	75	100
% Passing from sieve 3/8 in	60	80	45	70
% Passing from sieve number 4	48	65	30	50
% Passing from sieve number 8	35	50	20	35
% Passing from sieve number 30	19	30	5	20
% Passing from sieve number 50	13	23	3	12
% Passing from sieve number 100	7	15	2	8
% Passing from sieve number 200	3	8	0	4

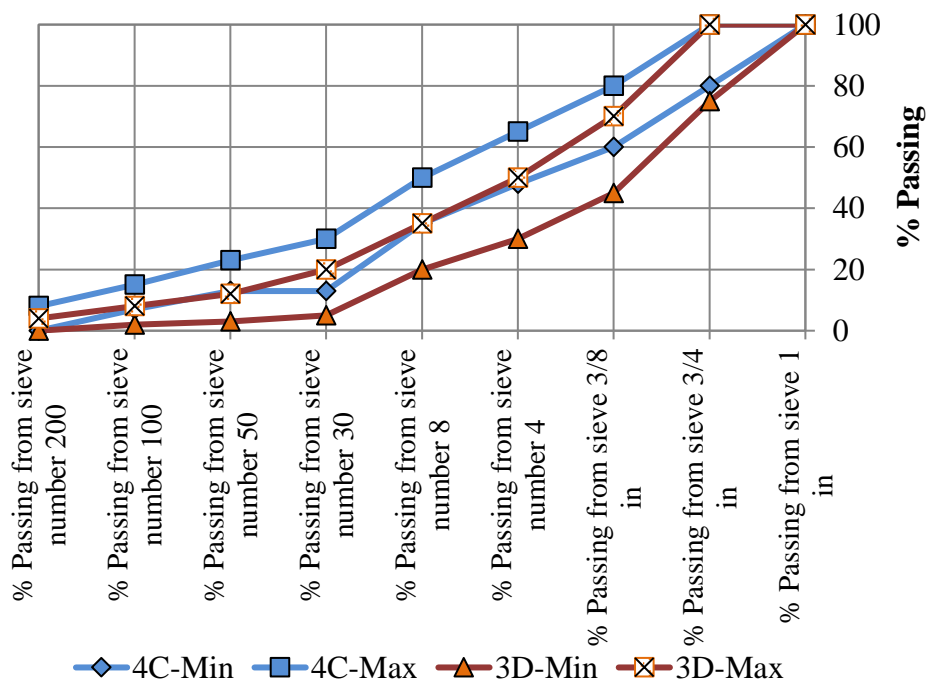


Fig. 2. Aggregate gradation limits for gradations 4C and 3D used in the mixes.

### *Marshall Test*

For each asphalt mix, 15 samples were prepared and tested with five different binder content. For each binder content, three samples were prepared and tested in the standard Marshall test to estimate the flow, stability values, and volumetric characteristics. As three samples are prepared for every binder content, the average value of these three samples was finally used to indicate the stability, flow, and remaining volumetric properties. Then, five curves are drawn to estimate the optimum asphalt content. In this paper, the standard Marshall test is used to estimate the optimum asphalt content for 106 asphalt mixes formed using bitumen 60-70 and aggregates (3D and 4C). Out of these 106 samples, 64 were prepared using aggregate grade 3D, and 42 were prepared using aggregate grade 3C.

### **Background in neural networks**

Basically, ANNs mimic the human brain while performing tasks or functions [29]. ANNs can be defined as parallel distributed processors that have the potential to store the learned knowledge and use it in the future. ANNs resemble a brain in two main aspects: gaining knowledge through a learning process, and interneurons are connected, and their synaptic weights are used to store the learned knowledge [30-31]. The main element of any ANN is the artificial neuron which mimics the biological neuron. Every biological neuron consists of four parts dendrites, synapses, axon, and the cell body. The axon makes connections with the other neurons and forms synaptic connections. The dendrites are responsible for receiving connections from other neurons. The cell body sums the incoming signals from the dendrites and compare the sum of these signals with a threshold to determine whether an impulse is sent to the axons or not [9]. Any artificial neuron consists of three main components: weight, bias, and the activation function. Every neuron receives a number of inputs ( $X_s$ ) and multiplies these inputs by their associated weights ( $W_s$ ) of the neuron connection. The bias ( $b$ ) is a non-zero value that is added to the summations of the weights by the inputs, as shown in equation (1). Then the activation function ( $F$ ) is used to transform the summation, as shown in equation (2).

$$H = b + \sum_i x_i w_i \quad 1$$

$$Y = F(H) \quad 2$$

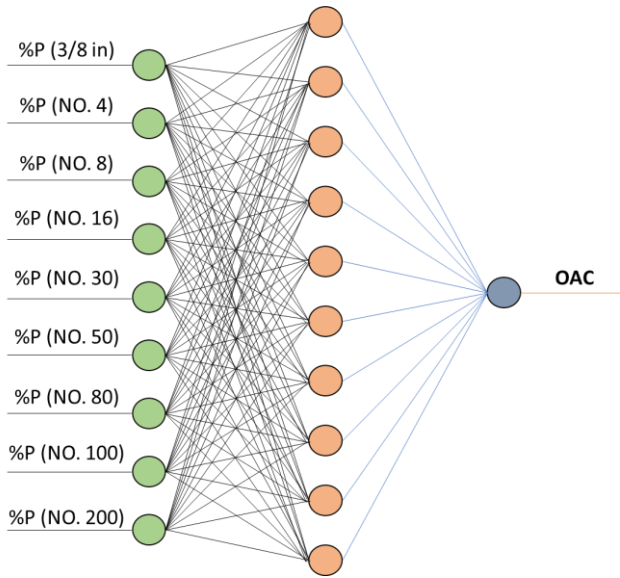
There are many types of neural networks, such as feedforward and feedback. Also, there are many types of training techniques deepening on the data, such as supervised and unsupervised learning. In this study, supervised learning is employed for the proposed ANN. Additionally, the backpropagation learning algorithm is the most common training algorithm used for the training of ANN, so the backpropagation technique is used for the training of the proposed ANN in this paper.

### **Neural network architecture:**

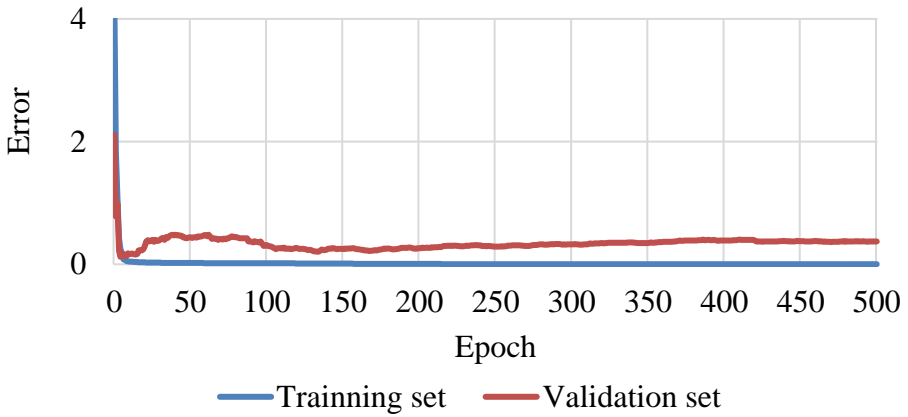
The final performance of any ANN mainly depends on its architecture and the selection of its hyperparameters. However, to the moment, there is no scientific method for defining the optimum ANN structure of hyperparameters, such as the number of

hidden layers and the number of neurons in every layer. As a result, the optimal structure of the ANN is determined based on the trial and error technique. Similarly, the initial weights of the ANN have a significant influence on the performance of the ANN, but still, no specific approach for estimating the best initial weights, so the weights were assigned randomly at the beginning of the training process. Following the trial and error approach makes the process of predicting the optimal structure and parameters of the ANN very time consuming. Thus, reviewing the previous studies in the pavement engineering field and their proposed architectures can provide a good guide and save significant time. Many architectures were tested, and the final architecture used consists of three layers: input layer, one hidden layer consists of ten neurons and output layer, as shown in Figure 3. Additionally, the hyperbolic tangent function (tanh) is employed as the activation function. The dataset was randomly divided into two sets: training set (60%-64 samples) and testing set (40%-42 samples), and the backpropagation technique was used to train the data for 500 iterations. For the testing set, 50% of the testing sample was used to monitor the performance of the training process to avoid overfitting.

In many cases, this segment of the data is called the validation set. Figure 4 shows the training and validation set error during the training process. During the training, the training and validation set error decline until a specific iteration, then the training set error keeps declining, but the validation error increases, which indicates overfitting. As a result, it is better to stop the training process early once the validation set reaches the minimum error to avoid this overfitting. One of the common techniques used in this situation is the early stopping technique, during which the training process stops when the validation set error increases [32, 33]. In the simplest case, the training process stops when the validation set error begins to increase. However, neural network training is a stochastic process, and the error of the validation set might go up or down at any point. Thus, the first overfitting point might not be the perfect point to stop the training. As a result, it is good to delay the training process even when the validation set error increases and monitor the performance for a while. If the validation set error keeps getting higher, the training process is halted. If the validation error declined again, the training process should continue [34]. Figure 5 shows the training and validation set errors during the training process with the application of the early stopping technique.



*Fig. 3. The structure of the proposed ANN.*



*Fig. 4. Training and validation sets error during the training process.*

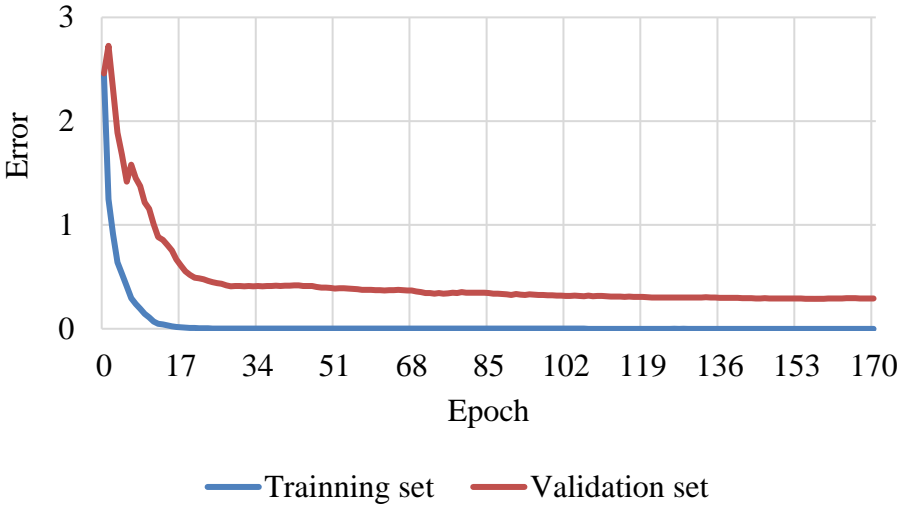


Fig. 5. Training and validation sets error during the training process with the application of the early stopping technique.

**ANN performance and results**

This study aims to estimate the OAC with high accuracy, so various statistical measures are used to estimate the accuracy and error of the ANN results. In this section, the performance of the ANN will be testing using the 42 samples in the testing set because the data in the training set is already used during the training process, and the ANN will predict the OAC for these samples with high accuracy, so the training set should be excluded during the testing set. Thus, four statistical measures are used to estimate the error and accuracy of the ANN as follows:

- 1- Coefficient of correlation (R)

$$R = \frac{n[\sum_i X_{actual}(i) * X_{prediction}(i)] - [\sum_i X_{actual}(i) * \sum_i X_{prediction}(i)]}{\sqrt{[n \sum_i X_{actual}(i)^2 - (\sum_i X_{actual}(i))^2][n \sum_i X_{prediction}(i)^2 - (\sum_i X_{prediction}(i))^2]}}$$

- 2- Mean absolute error, which indicates the average error in the prediction.

$$\epsilon_{mean} = \frac{1}{N} * \sum_i |X_{actual}(i) - X_{prediction}(i)|$$

- 3- Maximum absolute error which captures the maximum error in the prediction.

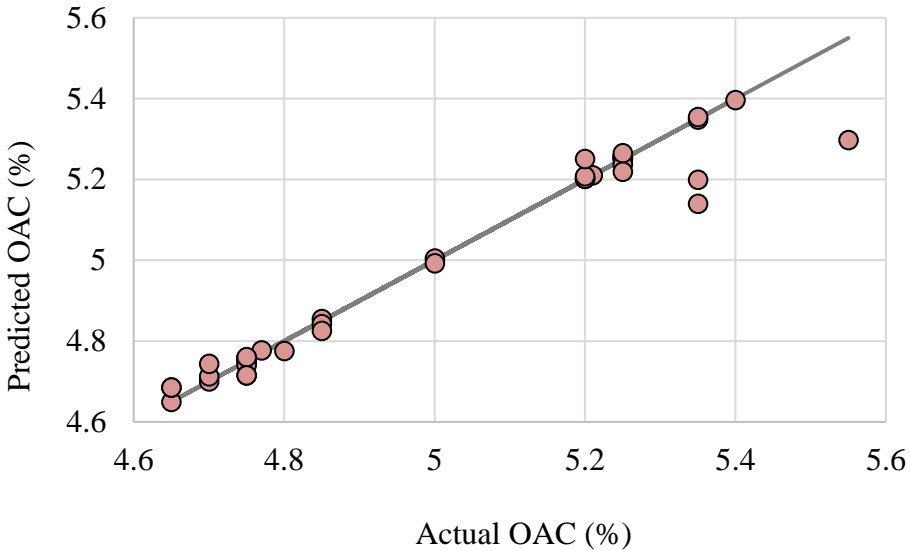
$$\epsilon_{max} = \max (|X_{actual}(i) - X_{prediction}(i)|)$$

Table 3 provides a summary of the performance of the ANN based on the previous statistical estimates. Results indicate that the ANN can estimate the OAC with high

accuracy. The ANN has a very high R-value which in turn means that the predictions are close to the actual values. Also, the mean error value indicates that, on average, the ANN makes an error of 0.025% in every prediction of the percentage of the OAC, which is a very low error value. Additionally, the maximum error of the ANN in the prediction of the OAC is 0.25%. Further investigation of the maximum error shows that the ANN can predict the OAC for 39 samples with a maximum error of 0.05% in predicting the OAC, and three predictions have higher error percentages (2.8%, 3.94%, and 4.55%). Figure 6 shows the predictions of the ANN in the 45-degree graph, and the three samples with the higher errors in the predictions are apparent in the figure.

*Table 3. summary for the statistical measures of the ANN performance.*

	R	$\epsilon_{\text{mean}}$ (%)	$\epsilon_{\text{max}}$ (%)
Value	0.98	0.025912	0.252579



*Fig. 6. Prediction of the ANN and the actual OAC using a 45-degree line.*

**Comparison between the wearing course (4C) samples and the binder course (3D) samples**

From Figure 2, the wearing course samples (4C) limits are higher than the limits for the binder course (3D), which means that the wearing course aggregate particles are finer or smaller. This can be translated into a higher surface area for the wearing course. As a result, the wearing surface mixes require more bitumen content to coat the aggregate particles. This phenomenon can be illustrated in figure 6 as the data can be divided into two sets as follows:

- Set for OAC = 4.6% to 5%, which represent the binder course mixes.
- Set for OAC = 5.2% to 5.6%, which represent the wearing course mixes.

**Comparison between the ANN results and the previous MLR model**

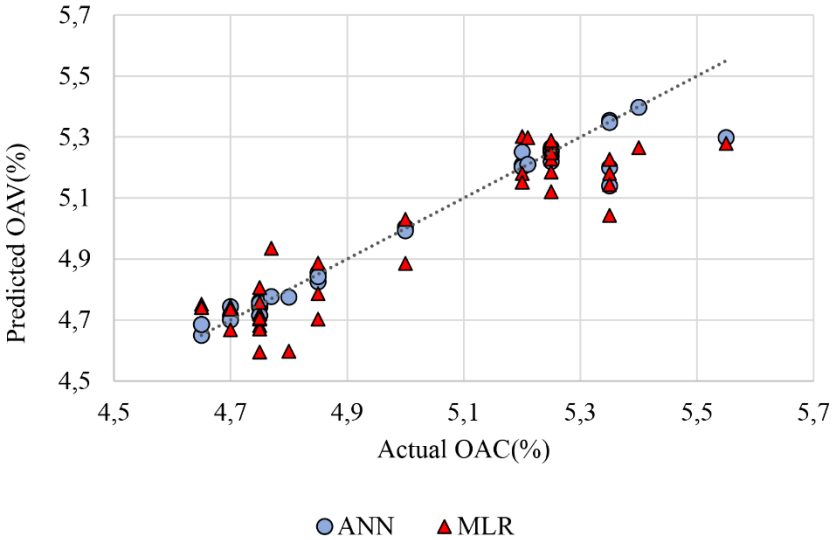
In 2018, Mousa et al. developed a multiple linear regression model for predicting the OAC for the same materials used in this study: aggregate gradations (4C, 3D) and bitumen 60-70. The model developed is as follows:

$$OAC (\%) = 2.816 + 0.023 * \%P\left(\frac{1}{2}inch\right) + 0.017 * \%P(\# 16) - 0.026 * \%P(\# 30) + 0.055 * \%P(\#80)$$

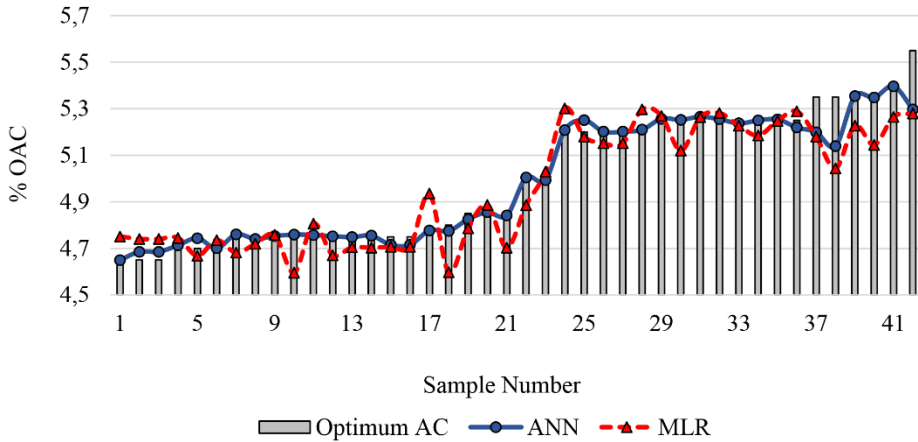
In this section, the results of this model are compared with the results of the developed ANN using the previous statistical measures used in the analysis section: coefficient of correlation, mean absolute error, maximum absolute error, and mean and the maximum percentage of the error. The results of the two models are summarized in table 4. Figures 7 and 8 show a comparison between the predictions of the two models. In general, the ANN performs better than the multiple linear regression model. For example, the ANN coefficient of correlation is higher than the correlation coefficient for the multiple linear regression mode. Additionally, the mean error indicates that the ANN makes a much lower error in its predictions. On average, the ANN makes an error of 0.025% in every prediction, but the multiple linear regression model makes an error of 0.085%, which is almost 3.5 times the error in the predictions of the ANN. Moreover, the maximum error in the predictions if the ANN is lower than the maximum error in the predictions of the multiple linear regression model.

*Table 4: Performance of the ANN vs. the previous multiple linear regression model developed by Mousa et al.*

	R	$\epsilon_{mean}$ (%)	$\epsilon_{max}$ (%)
ANN	0.98	0.025912	0.252579
Multiple linear regression model (Mousa et al., 2018)	0.92	0.085063	0.30717



*Fig. 7. ANN results vs. the multiple linear regression model results using the 45-degree line.*



*Fig. 8. ANN results vs. the multiple linear regression model results.*

**Aggregate surface area:**

It is important to investigate the influence of the aggregate surface area on the required OAC. Table 5 shows the standard surface area factors for different sieves. These factors can approximately estimate the overall surface area of the aggregate used in the mix by multiplying the factors by the corresponding percentage of the sieve. Then, a correlation between the OAC and the aggregate surface area can be developed. Figure 9 shows the relationship between aggregate surface area and the OAC. The required OAC increases with the increase in the aggregate surface area, which complies with section 7

(Comparison between the wearing course (4C) samples and the binder course (3D) samples). Additionally, the data can be divided into two sets according to their surface area and OAC as follows:

- Set with surface area = 3 to 5 m<sup>2</sup>/kg, and OAC= 3.6 to 5%, and this set represents the binder course mixes.
- Set with surface area = 6.5 to 8 m<sup>2</sup>/kg, and OAC= 5.2 to 5.6%, and this set represents the wearing course mixes.

Table 5. Surface area factors for standard sieves.

Sieve Size (mm)	Surface area factor (m <sup>2</sup> /kg)
All Aggregates above 4.75 mm	0.41
4.75	0.41
2.36	0.82
1.18	1.64
0.6	2.87
0.3	6.14
0.15	12.29
0.075	32.77

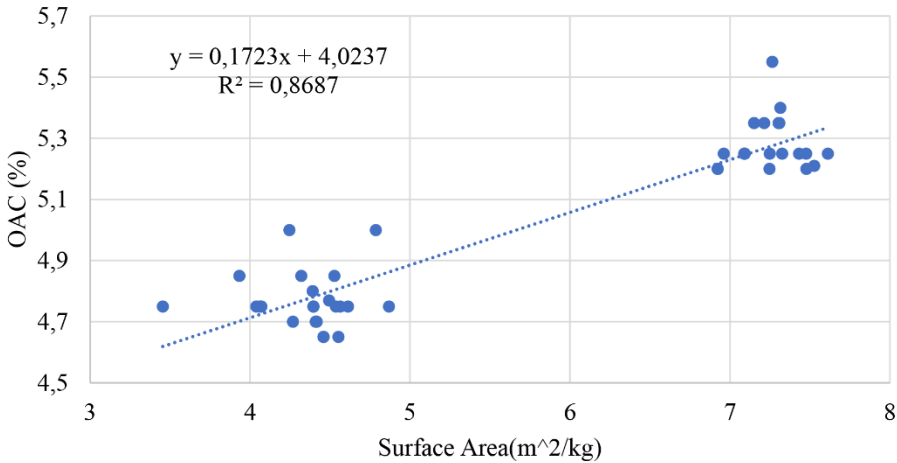


Fig. 9. Relationship between the aggregate surface area and the OAC.

The following model can be used to predict the OAC from the aggregate surface area:

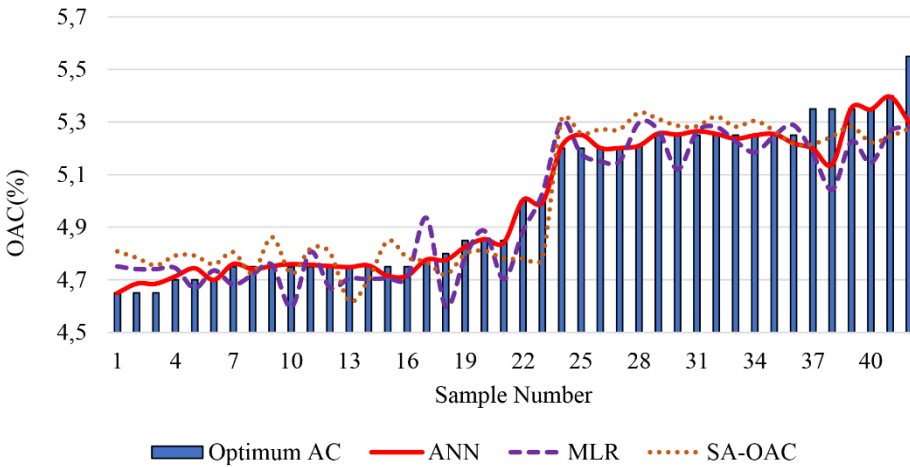
$$OAC (\%) = 0.1723 * \text{surface area (m}^2/\text{kg)} + 4.0237$$

Table 6 summarizes the performance of the surface area model. Results show that the performance of the surface area model is slightly better than the performance of the model developed by Mousa et al. (2018). For example, the surface area model makes an average error of 0.078% in predicting the OAC, which is an error of 1.57%. Mousa et al. (2018) model makes an average error of 0.085% in the prediction of the OAC, which is an error of 1.68%. Also, the maximum error in the predictions of the surface area model is 4.9%, but the maximum error is 4.9% for Mousa et al. model. Thus, the surface area

model performs better than the model developed by *Mousa et al. (2018)*, but not much better. On the other hand, the performance of the ANN is much better than the performance of the other two models, with a higher coefficient of correlation ( $R = 0.98$ ) and a much lower mean error (0.025%) in the predictions of the OAC. Figure 10 shows the predictions of the three models for both the wearing course mixes and the binder course mixes. Predictions of the ANN are much better than the other two models.

*Table 6. Performance of surface area model vs. the ANN and the MLR model.*

	R	$\epsilon_{\text{mean}}$ (%)	$\epsilon_{\text{max}}$ (%)
ANN	0.98	0.025912	0.252579
Multiple linear regression model ( <i>Mousa et al., 2018</i> )	0.92	0.085063	0.30717
Surface area model	0.93	0.078306	0.274616



*Fig. 10. Results of the three models for the binder course mixes.*

**A new approach for the Marshall test**

At least 15 asphalt mix samples are prepared and tested for five different bitumen contents during the Marshall test and draw the design curves. In other words, three mixes are prepared and tested for every bitumen content, then the average values of these three samples are used as the corresponding value for this bitumen content. Then the design curves are drawn, and the OAC is the average value corresponding to the maximum stability, maximum unit weight, and prespecified air voids percentage. As a result, the results of Marshall mixes design are subjected to variations. Thus, instead of the normal design procedures that require the preparation and testing of 15 mix samples, which is time consuming, the ANN can be employed for estimating the OAC with high accuracy, then only three specimens are prepared and tested to estimate the design parameters and make sure they match the design criteria. This approach saves time, resources, and the required effort to estimate the OAC.

## Conclusion

In this paper, a backpropagation ANN was developed for estimating the OAC from the aggregate gradation for the two most common asphalt mixes used in Egypt (3D, 4C). The proposed ANN can estimate the OAC with a coefficient of correlation of 0.98, an average error of 0.026%, and a maximum error of 0.25%. Thus, this paper presents a new approach for estimating the OAC from the aggregate gradation utilizing the proposed ANN. This new approach for the Marshall test can be adopted using results of the proposed ANN, and only three specimens, instead of fifteen, are prepared and tested using the OAC from the ANN to estimate the remaining parameters (stability, flow, air voids, voids in mineral aggregate). This approach saves the time, effort, and resources required for estimating the OAC. Additionally, this approach can be used as a quality control tool to help in identifying issues in the asphalt mix design process.

## References:

- [1] The Asphalt Institute, Mix design methods for asphalt concrete and other hot mix types, Manual series No. 2, 1988.
- [2] P.G. Rakaraddi, V. Gomarsi: *IJRET*, 4 (2015) 182-188.
- [3] J. L. Feiteira Dias, L. G. Picado-Santos, and S. D. Capitão: *Construction and Building Materials*, 73 (2014) 247–254.
- [4] Q. T. Liu, S. P. Wu: *Key Engineering Materials*, 599 (2014) 150–154.
- [5] A. Garc'ia, J. Norambuena-Contreras, M. Bueno, M. N. Partl: *Journal of Testing and Evaluation*, 42 (2014) 1107-1118.
- [6] A. R. Pasand'in and I. P'erez: *Construction and Building Materials*, 74 (2015) 151–161.
- [7] M. Zaumanis, R. B. Mallick, R. Frank: *Transportation Research Procedia*, 14 (2016) 3493–3502.
- [8] L. Wang, H. Gong, Y. Hou, X. Shu, B. Huang: *Road Materials and Pavement Design*, 18 (2017) 1–11.
- [9] T. Serkan, C. Abdulkadir, U.Ün: *Expert Systems with Applications*, 37 (2010) 4660-4670.
- [10] K.M. Mousa, H.T. Abdelwahab, H.A. Hozayen: *Proceedings of the Institution of Civil Engineers – Construction Materials*, 174 (2021) 69–74.
- [11] P.S. Kandhal, S.A. Cross: *Transportation Research Record*, 1417 (2006) 21–28.
- [12] H. Ozturk, A. Saglik, Demir. B. A. Güngör, “An artificial neural network base prediction model and sensitivity analysis for marshall mix design” <https://www.h-a-d.hr/pubfile.php?id=1033> Accessed 23 April 2021.
- [13] A.E. Gomaa, *Marshall Test Results Prediction Using Artificial Neural Network*, MSc thesis, Arab Academy for Science and Technology, Cairo, Egypt, 2014.
- [14] W. Liu, H. Li, B. Tian: *Applied Mechanics and Material*, 97 (2011) 23–27.
- [15] A. H. Aljassar, M. A. Ali, A. Alzaabi: *Kuwait Journal of Science & Engineering* 29 (2002) 181–195.
- [16] N. Baldo, E. Manthos, M. Pasetto: *Advances in Civil Engineering*, 2018 (208) 1-17.
- [17] E. Sangsefidi, H. Ziari, M. Sangsefidi: *KSCE Journal of Civil Engineers*, 20 (2015) 385–392.
- [18] A. Afaf: *Journal of Engineering Sciences*, 42 (2014) 567–574.

- [19] D. Ridolfi, P. Sebaaly, R. Gangavaram, Impact of Aggregate Gradation on Mixture Performance, Thesis, Pavement/Materials Program, University of Nevada, Reno, NV, USA.1996.
- [20] M. S. Kaseko, S. G. Ritchie: Transportation Research Part C, 1 (1993) 275–291.
- [21] N. Gagarin, I. Flood, P. Albrecht: Journal of Computing in Civil Engineering, ASCE, 8 (1994) 179–200.
- [22] Y. Cal: Advances in Engineering Software, 22 (1995) 95–97.
- [23] C. A. Roberts, N. O. Attoh-Okine: Computer-Aided Civil and Infrastructure Engineering, 13 (1998) 339–348.
- [24] N. O. Attoh-Okine: Computer-Aided Civil and Infrastructure Engineering, 16 (2001) 112–125.
- [25] S. Khuntia, A. Das, M. Mohanty, M. Panda: International Journal of Transportation Science and Technology, 3 (2014) 211-228.
- [26] A. Ivica, M. Ivan: Canadian Journal of Civil Engineering. 44 (2017) 994-1004.
- [27] H. Nguyen, T. Le, C. Pham, T. Le, L. Ho, V. Le, B. Pham, H. Ly: Applied Sciences, 9 (2019) 1-20.
- [28] ECP (Egyptian Code Provisions) ECP (104/4): Egyptian code for urban and rural roads. Part (4): Road material and its tests. Housing and Building National Research Center, Cairo, Egypt, 2008.
- [29] R. Hecht-Nielsen, Neurocomputing. Reading, MA: Addison-Wesley, 1990.
- [30] Highway Technical Specifications, 2006, General Directorate of Highways, Item No. 170/2, Ankara, Turkey.
- [31] S. Haykin, Neural networks, a comprehensive foundation, Prentice Hall, New Jersey, 1994.
- [32] L. Goodfellow, Y. Bengio, A. Courville, Deep Learning (Adaptive Computation and Machine Learning series), MIT press, 2016.
- [33] B. Christopher, Pattern Recognition and Machine Learning (Information Science and Statistics), Springer-Verlag, Berlin, Heidelberg, 2006.
- [34] L. Prechelt, Neural Networks: Tricks of the Trade. Lecture Notes in Computer Science, vol 1524. Springer, Berlin, Heidelberg, 1998, 53-67.



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