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Artificial Neural Network Model for Predicating Resilient Modulus of Silty Subgrade Soil

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Abstract Recently machine learning is gaining acceptance in different civil engineering applications. In this study, an Artificial Neural Network (ANN) model is proposed to predict resilient modulus (M_R) of a silty subgrade soil for pavement designs. A silty subgrade soil was compacted at the maximum dry density (γ_{dopt}) and optimum moisture content (OMC) according to the standard Proctor compaction. The resilient modulus test was then conducted on at least replicate samples of three groups of samples. The first group of samples were tested directly after compaction, the second group and third groups, after compaction at the standard Proctor effort were left in open air to dry over time or exposed to wetting to gain moisture. The testing results were then used to develop the ANN model. This model predicts M_R of the soil based on water content (Wc), ratio of dry density over the maximum dry density at the optimum moisture content (γ_d/γ_{dopt}) and octahedral shear stress (τ_{oct}). After the ANN model architecture is set, the strengths and weaknesses of the developed model are examined by comparing the predicted versus measured M_R values with respect to goodness-of-fit statistics. In addition, a sensitivity analysis of the model input parameters is performed.

Keywords: *resilient modulus; artificial neural networks, subgrade, proctor compaction, moisture content*

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1. Introduction

The resilient modulus (M_R) has been recognized as an important stiffness parameter that characterizes pavement materials under moving traffic (AASHTO 1993). M_R is defined as the ratio of the deviatoric stress (σ_d) to the resilient strain (ε_r) as shown in Eq. (1) [1].

$$M_R = \frac{\sigma_d}{\varepsilon_r} \tag{1}$$

Uzan's [2] model as presented in Eq. (2) was modified and incorporated in the Mechanistic-Empirical Pavement Design Guide (MEPDG). It is well-known as the universal Witczak model, for predicting M_R for both coarse and fine materials.

$$M_R = k_1 pa(\frac{\theta}{pa})^{k_2}(\frac{\tau_{oct}}{pa}+1)^{k_3} \tag{2}$$

where; k_1, k_2, k_3 are regression parameters, pa is the atmospheric pressure (101.3 kPa), θ is the bulk stress $\theta = \sigma_1 + 2\sigma_3$, σ_1 and σ_3 are the major and minor principal stresses; respectively and τ_{oct} is the octahedral shear stress $= \frac{1}{3}.\sqrt{(\sigma_1-\sigma_2)^{2)}+(\sigma_1-\sigma_3)^2+(\sigma_2-\sigma_3)^2} = \frac{\sqrt{2}}{3}\sigma_d$.

The resilient modulus of soils is affected by numerous factors such as state of stress, variation in moisture content, variation in matric suction, and basic soil properties such as particle gradation, particle shape, maximum particle size, liquid limit (LL), plasticity index (PI) and fines percentage (passing from sieve No. 200) [3,4,5,6,7]. Based on previous studies, research efforts presented that stress state and moisture content are the most significant key factors affecting M_R of soils. Through the last 50 years, many researchers investigated the significant impact of the stress level on M_R of subgrade soils [8,9,10,11] and demonstrated that there is no significant impact of the bulk stress on M_R at low shear stress levels, on the other hand M_R increases when the bulk stress increases at high shear stress levels. However, many studies demonstrated that the octahedral shear stress have a pronounced influence on the M_R of fine materials [3,12,13].

Recently, ANN modeling technique has powerfully stand out for a broad domain of many engineering problems specially its success in featuring geotechnical engineering applications [14,15,16]. ANNs can integrate and associate both literature-based and exploratory data to figure out the best solution. ANNs' applications can be summarized into pattern recognition, anticipation, modeling, and simulation. Such supervised interlinked networks are claimed to be applied in pavement material applications as an alternative to conventional predictive methodologies. For example, Meier et al. [17] built up a computer program, named as WESDEF, with ANN models to back calculate pavement layer moduli. The ANN models were trained to compute the layer moduli based on Falling Weight Deflectometer field data obtained from flexible pavement. As a consequence to continuous research efforts, Sharma and Das [18] were able to use ANN models to backcalculate layer moduli with better accuracy compared with other software, namely, EVERCALC and ExPaS. Moreover according to Far et al. [19], ANN modeling technique was used to estimate the dynamic modulus of the asphalt concrete layer. Very limited ANN models incorporating the influence of moisture together with the stress state for the resilient modulus prediction of fine materials were found in literature.

2. Objectives

The main objective of this paper is to use the ANN modeling technique for anticipating M_R of common Egyptian silt as a pavement subgrade soil.

3. Material and Testing Program

A common Egyptian subgrade material was investigated in this study. This subgrade soil was sourced from an open excavation site located in El-Mahalla Al-Kubra, Gharbia, Egypt. The routine properties of the investigated soil, such as California Bearing Ratio (CBR), compaction characteristics, plastic limit, liquid limit, and fines percentage, were determined in the laboratory and the results are listed in Table 1. The data in the table show that the soil is classified as A-4 according to the American Association of State Highway and Transportation Officials (AASHTO) and ML according to the Unified Soil Classification System (USCS) methods. The standard compaction energy level was used to define the moisture-density relationship for the investigated silty soil. According to ASTM D698 - 12e2 (2012) [20], the standard volumetric energy density was estimated by 589.3 kJ/m^3 (12300 ft-lbs/ft3) to generate the moisture-density curve at standard compactive effort presented in Figure 1.

Table 1. Routine Properties of the Investigated Subgrade Soil

Measured Property	Test Result	Test Specification
Maximum Dry Density (g/cm3)	1.63	[20]
Optimum Moisture Content (%)	21.2	[20]
California Bearing Ratio (%)	6.3	[21]
Liquid Limit (%)	30	[22]
Plastic Limit (%)	25	[22]
Plasticity Index (%)	5	[22]
Percent Passing Sieve No. 200	82	[23]
Unified Soil Classification System	ML	[24]

It should be noted that laboratory test specimens were prepared simulating similar moisture changes to those occurring in the field. Test specimens were initially compacted at optimum water content and maximum dry density. After that, the samples were allowed to dry in open air to simulate drying condition or soaked in water to simulate wetting condition. By measuring the weight of the samples, the loss or gain of water was estimated. When the desired change in moisture was achieved, the M_R test could be carried out. Several series of triaxial tests under cyclic loading conditions were conducted according to AASHTO T307 (2017) [25] on cylindrical soil specimens of 100 mm in diameter and 200 mm in height. According to the M_R test protocol, each prepared specimen was conditioned at a confining pressure of 103.4 kPa over 500 cycles before applying the 15 testing sequences on the specimen. After all, a data set of 45 points covering three levels of moisture content (dry, optimum, and wet) and one compactive effort (standard) for one type of subgrade soil (low plasticity silt) were used in the modeling approach.

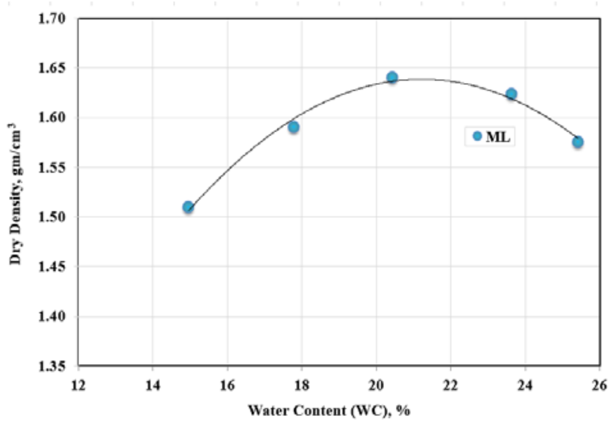

Figure 1. Standard Compaction Curve for the Low Plasticity Silty Subgrade Soil

4. Modeling Technique

In this study, researchers applied the Multilayer Perceptron Neural Networks tool in SPSS statistics software for predicting the M_R values. To develop the ANN model, the available data set was rearranged randomly and divided into two separate data subsets for training and testing the proposed ANN model as shown in Table 2.

Table 2. Data Set Processing Structure for ANN Modeling Approach

Technique	Data Set			
ANN Model	Training	Testing	Valid	Excluded
	76.6%	24.4%	100.0%	0

Several ANN architectures were examined with different combinations of hidden layer numbers (neurons) and algorithm types to reach out the best modeling prediction. By using a hyperbolic tangent function, the best prediction was accomplished as shown in Figure 2. The proposed model is based on three input parameters that mostly affect M_R for fine materials (Wc, γ_d/γ_{dopt}, and τ_{oct}). The different inputs with the adopted algorithm architectures are illustrated in Table 3 for the proposed ANN model.

Table 3. Summary of the Network Structure of the Proposed ANN Model

Covariates	$Wc_t, \tau_{oct}, \frac{\gamma_d}{\gamma_{dopt}}$
Rescaling Method for Covariates	Standardized
Activation Function	Hyperbolic tangent
Dependent Variables	M_R
Fitting Equation	Y=0.99x+0.01
ANN Architecture	3-2-1
R^2	0.99

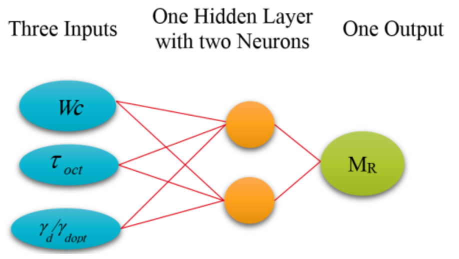

Figure 2. Feed-Forward Neural Network Structure

Table 4 summarizes the goodness-of-fit statistics of the feed-forward ANN model. The ANN model prediction for both training and testing subsets shows excellent results compared with experimental values with coefficient of determination (R^2) of 0.99. Figure 3 confirmed the modeling predictions by graphically showing the relationship between measured and predictive M_R values. The data fits perfectly almost on the line of equality showing highly accurate precision and minimal bias.

Figure 4 shows the sensitivity analysis of the ANN model input parameters. It is found that Wc has significantly higher influence on M_R compared to the other input parameters (γ_d/γ_{dopt} and τ_{oct}).

Table 4. Statistical Parameters for the ANN Model

	n	p	S_e	S_y	S_e/S_y	R^2	R^2_{adj}
Training	45	3	0.020	1.205	0.016	0.99	0.99
Testing	45	3	0.018	1.205	0.015	0.99	0.99

Where:
n = Number of data points,
p = Number of variables,
S_e = Standard error of estimate,
S_y = Standard deviation of the measured resilient moduli,
R^2= Coefficient of determination,
R^2_{adj}= Adjusted coefficient of determination.

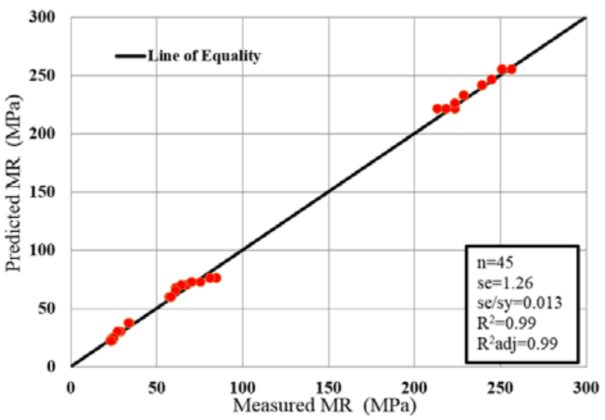

Figure 3. Measured vs. Predicted MR Values using ANN Model

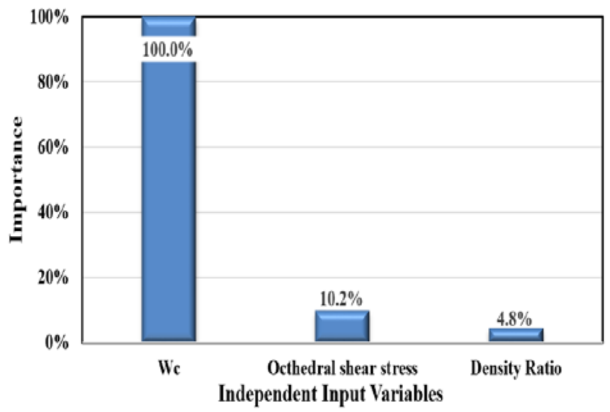

Figure 4. Sensitivity Analysis of ANN Model Input Parameters

5. Conclusions and Recommendations

One low plasticity silty (ML) subgrade soil was used to develop ANN model to predict M_R. Generally, the proposed ANN model was applied for predicting M_R of subgrade soil with state of stress, water content and density ratio. The proposed ANN model was developed based on feed-forward neural network and perceptron technique with ANN structure (3-2-1) representing excellent modeling accuracy ($R^2 = 0.99$).

Though, only ANN methodology is discussed in this paper, results indicate that the use of ANN in this context is promising and merits further consideration and analysis in subsequent work.

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