

Investigation of Parameters of Compaction Testing

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Abstract

Compaction is one of the most efficient and practical soil improvement techniques that can be applied to earthworks. In the field, compaction control is commonly carried out by sand-cone and nuclear gauge tests. Whether conducted in the field or in the laboratory, these tests are intended to determine optimum water content and dry unit weight parameters, information required for design specifications. In this study, the parameters of field soil densification obtained by various testing methods performed in the same region are compared: unit weight, water content, and densification percentage are measured by nuclear density and sand cone tests. The variations in the outcomes of nuclear density and sand cone tests, namely unit weight, water content, and densification percent, are recorded. It is well-known that the nuclear density test has the advantage of rapid application; nevertheless, this method gives approximate results that should be correlated with a more precise technique, such as sand cone testing. The data at hand are first subjected to statistical analyses. Next, several techniques are used to identify the correlation between the results of the 2 tests. Finally, susceptibility and reliability concepts are considered in evaluating the combined usage of the tests in civil engineering practice.

Key words: Compaction control, Nuclear density test, Sand cone test, Correlation

Introduction

Soil is extensively utilized as a basic material of construction, as witnessed by the existence of earth structure such as dams and road embankments. In these cases, it is desirable that the soil used as in-place material possess reliable properties. The soil should have sufficient strength, be relatively incompressible so that future settlement will not be excessive, maintain a constant volume change against variable water content or other factors, be resistant to deterioration, and possess proper permeability. The requirements can best be achieved by a precise selection of fill material type and proper placement application. The essential properties of a fill can be checked independently, however, desirable charac-

teristics, such as high strength, low compressibility, and stability, are normally associated with density (or unit weight) values that can be fastened through good compaction.

When soil is used for construction purposes, either in embankments or in pavement subgrades, it is distinctively layered to form the final shape. Obviously, each layer is compacted before being covered with the following layer. After proper placement and compaction, the resulting soil mass has the strength and bearing capabilities that are as good as or better than many natural soil formations. To evaluate the degree of compaction, it is common to check soil zones using the in-situ density (or in-situ unit weight) test procedure. Typically, each compacted layer is checked at random locations. Placement

of the next layer begins only after tests indicate a satisfactory compaction level. Therefore, field tests should be well understood and carefully assessed to ensure correct construction.

In the literature, a number of studies have been undertaken to correlate the engineering properties of soils with compaction characteristics. Joslin (1959), after making a number of compaction tests, determined 26 different compaction curves called "Ohio compaction curves". Using the Ohio curves, a compaction curve can be wholly plotted using the water content (ω) dry unit weight (γ_d) point of a single proctor test. Basheer and Najjar (1995) used the artificial neural network (ANN) approach for estimating the optimum water content (ω_{opt}) and maximum dry unit weight (γ_{dmax}) of soils as an alternative to regression analyses. In their study, the consistency limits and the unit weight of soils were input parameters introduced to ANN to determine the w_{opt} and γ_{dmax} of soils. The results of the revised ANN were compared with the regression outcomes, and as a result the ANN method proved to be superior. Najjar et al. (1996) conducted a study to estimate ω and γ_d parameters from other index parameters using the ANN methodology, in comparison with regression analysis. Pandian et al. (1997), in reexamining the compaction characteristics of 3 types of soil, established a simple density-water content-liquid limit relationship. The authors observed that the path of the soil compaction curve for a specific compactive effort could be predicted by determining the liquid limit, the water content, and the coarse fraction. In this regard, the relationship represented by a series of compaction curves for a practical range of liquid limit-water contents; thereby, the entire path of compaction behavior can be determined using discrete dry density-water content data and the liquid limit value.

Another approach to verify the compaction process is through investigating correlative relationships among ω_{opt} , γ_{dmax} , soil classification, index properties, and grain size distribution (Turnball 1948, Davidson and Gardiner 1949). In this context, Ring et al. (1962) investigated the effect of average particle diameter, fineness average, and fines content on compaction behavior. Ramiah et al. (1970) correlated both ω and γ_d with the liquid limit. Jeng and Strohm (1976) correlated the ω and γ_d with the index properties of the soil. Korifiatis and Manikopoulos (1982) developed a model for granular soils to predict the γ_{dmax} by means of factors such as grain size

distribution properties and mean grain size. Wang and Huang (1984) set up a model for the prediction of the ω and γ_d using specific gravity, fines modulus, plastic limit, coefficient of uniformity, and particle diameters corresponding to 10% and 50% passing as independent parameters. All the models listed above exhibited determination coefficients (R^2) ranging between 0.791 and 0.951.

Besides, many engineers worldwide have developed innovative, statistical approaches to assess compaction in the field. In this regard, Servais and York (1990) and Gabr et al. (1995) compared the precision of nucleodensitometers and sand cone testing.

In the light of previous studies, it should be agreed that, volume-based field tests for measuring compaction process, such as sand cone and balloon, give precise results; nevertheless, these techniques are destructive and quite time-consuming. On the other hand, nuclear density gauges introduce considerable error while recording real-time compaction measurements. Therefore, the common approach for large projects which entail a great number of measurements is to combine usage of both types of tests at the same locations with a certain frequency, thus correcting nuclear gauge measurements by making correlations. In this study, comprehensive statistical analyses have been applied to the data of a highway project obtained by conducting both of the 2 types of tests on the same sites of a highway project. Additionally, multiple regression analyses (linear and nonlinear) and ANN methodology have been applied to identify the correlation between the results of 2 tests. Then, susceptibility and reliability concepts have both been considered in assessing the use of the combined tests for civil engineering practice.

Field Methods for Compaction Control

Compaction quality assessment (CQA) is a vital issue especially for the construction of highways, fills, dikes, and dams. CQA commonly consists of evaluating the densification percentage, which is the ratio of field dry density after compaction to maximum dry density obtained from Proctor tests in the laboratory. It should be noted that the majority of construction projects require densification ratios greater than 90% (Das, 2001). The preferred methods for the CQA in the field are sand cone and nuclear density tests. Seismic velocity, California Bearing Ratio, and plate bearing resistance tests may also be used

to measure field densities. In the sand cone test, a test hole in the compacted field is filled with sand of a known volume. Later, the water content and weight of the material extracted from the hole are measured in the laboratory. Then, field dry density is calculated using these data. However, the water content determination of the fill material needs 24 h, which is rather long for the scheduling of construction projects. Therefore, most engineers overlook the likely measurement error and rely on nuclear density tests, which enable the computation of CQA parameters within a few minutes. The sand cone test has other disadvantages: (a) Sand in the cone is sensible to vibrations due to the construction machinery in the vicinity of the test point; (b) Wet material is prone to cause cone volume errors. On the other hand, nucleodensitometers are sensitive to cobble existence in the test field; its use necessitates great care because the equipment uses hazardous radioactive material. Consequently, the optimal approach is to establish a correlation between the results of fast nuclear gauge tests and those of reliable sand cone tests.

Database and Statistical Analysis

In this study, the nuclear and sand cone test data were collected from the subbase layer of a road construction in Afyon, a city located in the mid-western part of Turkey. In total, 87 test data taken from 3 different locations have been incorporated into models. The soil database demonstrates that the soils are dominantly SM according to USCS. Two of the tested soils are SP-SM. The tests for the database were performed on the soil samples from the same soil class to prevent the adverse effects of variations in engineering properties such as PI and LL. The natural soils tested, having different physical and mechanical properties, were compacted to obtain maximum dry density and optimum water content using standard Proctor compaction. Only 3 geotechnical parameters, namely, dry density, moisture content, and densification percent parameters, were considered in the comparison between sand cone and nuclear density tests. The scattering of the data points in terms of maximum dry density observations and the corresponding optimum moisture content values are plotted in Figure 1.

The water content is found using different methods in the 2 tests. Water content in sand cone test is measured manually, while it is measured automatically by a special mechanism in the nuclear test de-

vice. The water content estimation by the nuclear test is not nearly as precise as that by the sand cone test; therefore, nuclear test based water content estimation can be misleading.

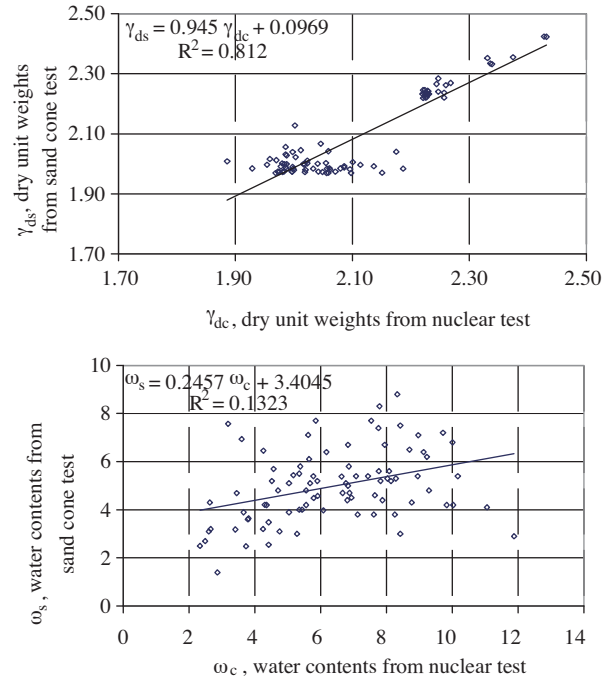


Figure 1. Scattering of (a) dry unit weight values and (b) corresponding water content values.

As can be seen in Figure 1a, which demonstrates the scatter of dry unit weight data, there is a small gap around the 2.10 level. Frequency histograms of the same parameter (Figures 2a and 2b) indicate the same data behavior. Moreover, dry density distribution of nuclear tests indicated that the data is bimodal with a considerable gap between the 2.10 and 2.20 levels. This distinct feature is not acute in sand cone distribution (Figure 2b). In other words, there is no measurement recorded by the nuclear tests around 2.15 level. This can be explained by the physical characteristics of the tests. In addition, as emphasized in the text, the nuclear test is a real-time measurement methodology, which allows instant quality control. However, the consistency as well as the reliability of nuclear testing is lower than the sand cone test. The aim of this study is to represent the deviation between the results of the 2 methodologies and to establish a correlation between them. In this way, it is aimed to improve the use of rapid means of assessing in-situ density.

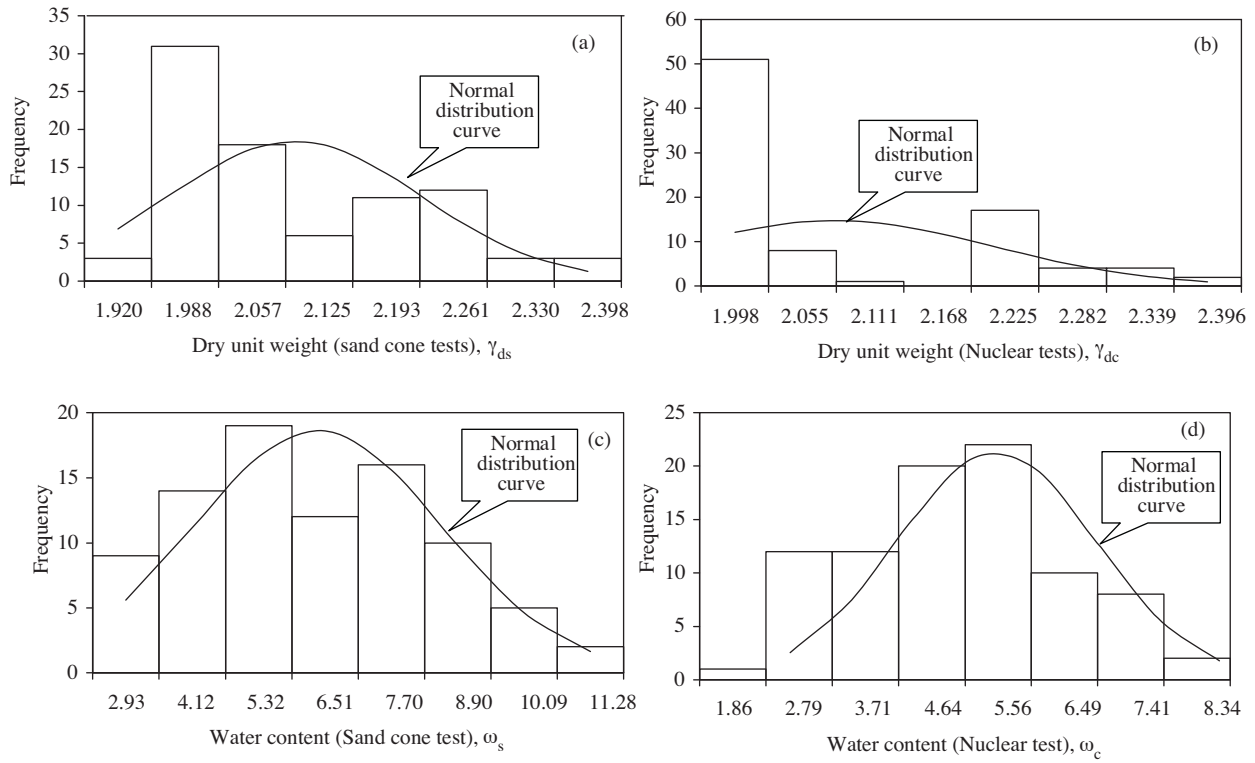


Figure 2. Histograms of (a) γ_{ds} , (b) γ_{dc} , (c) ω_s , and (d) ω_c parameters.

In order to show the variation of the data set, descriptive statistical analysis of the model variables is performed (Table 1). Regarding the statistical properties of sand cone dry density (γ_{ds}) parameter, it should be emphasized that normal distribution of this parameter is right-skewed, and negative kurtosis coefficient indicates that the data is cumulated below the mean value. Analyzing the dry density values obtained from nuclear density tests (γ_{dc}), similar characteristics are obtained. The average of the γ_{ds} is somewhat greater than the average of γ_{dc} , while a reverse arrangement is observed for standard deviation parameters. Parallel to dry unit weights, the average of water contents of sand cone tests (ω_s) is greater than that obtained from nuclear gauge tests (ω_c). Relatively low values were obtained for skewness coefficients of ω_s and ω_c values calculated from both tests; therefore, a right-tailed normal distribution curve is indicated. Besides, the negative kurtosis coefficients demonstrate that most of the data are below the average value. Investigation of average densification percentage values obtained from the 2 tests (S_s and S_c) leads to the conclusion that a denser

structure is measured from sand cone tests. Again, right-skewed distributions are obtained with positive kurtosis coefficients, indicating a cumulative behavior of data above the average.

In Figure 2, histograms of considered parameters are given. To evaluate the goodness-of-fit of the 6 model parameters to selected probability distributions, Anderson-Darling tests are employed. The Anderson-Darling test is a goodness of fit statistic for the maximum likelihood and the least squares estimation methods, which are helpful for comparing the fit of predetermined competing distributions. The statistic measures the weighted square distance between plot point and fitted line in a probability plot, which utilizes larger weights in the tails of the distribution. Smaller Anderson-Darling values indicate a better-fit distribution to the data in hand. Therefore, the low Anderson-Darling values given in Table 2 indicate that lognormal, normal, and lognormal distributions are fit to dry unit weight, water content, and densification percent parameters, respectively.

Table 1. Descriptive statistics of the database.

Parameter	γ_{ds}	γ_{dc}	ω_s	ω_c	S_s	S_c
Number of Data	87	87	87	87	87	87
Average	2.100	2.081	6.376	4.971	102.164	101.212
Median	2.057	2.002	6.180	4.800	101.260	100.820
Mode	1.988	1.974	6.830	5.400	100.280	100.760
Minimum	1.886	1.696	2.330	1.400	95.800	100.000
Maximum	2.432	2.424	11.880	8.800	111.080	108.070
Standard Dev.	0.127	0.133	2.196	1.484	2.646	1.292
Skewness	0.719	0.978	0.132	0.279	1.183	2.460
Kurtosis	-0.466	-0.509	-0.636	-0.191	1.673	8.961

Table 2. Anderson-Darling values for the determination of goodness-of-fit.

Distribution	γ_{ds}	γ_{dc}	ω_s	ω_c	S_s	S_c
Normal	3.719	9.174	0.498	0.568	4.398	4.710
Weibull	4.290	8.620	0.390	0.630	6.790	10.330
Lognormal	3.514	9.040	1.126	0.584	4.205	4.550
Extreme	4.570	8.717	1.158	2.129	7.079	10.660
Exponential	35.17	35.24	16.95	20.07	37.71	38.63

Figure 3 demonstrates the best fit distributions to these parameters, in accordance with the maximum likelihood estimation method. The graphs are solely a graphical representation of the percentiles, corresponding to the selected distribution. Percentage values in Figure 3 are transformed to associated probabilities. Besides, in order to indicate the degree of relationship between the measured dry unit weights of the 2 tests, the Spearman, Pearson and Kendall coefficients are also calculated as 0.6443, 0.9011, and 0.4716, respectively. Therefore, it can be concluded that a nonlinear equation between dry unit weights is not sufficient to characterize the target behavior.

The maximum likelihood estimation method is used to calculate the best fit distributions for the 6 parameters in question. These distribution plots are best fit to the input and output data. The fitted line is a graphical representation of the percentiles. Initially, percentiles are calculated for the various percents, based on the chosen distribution. The associated probabilities are then transformed and used as y variables. The percentiles may be transformed, depending on the distribution, and are used as the x variables. The transformed scales, chosen to linearize the fitted line, differ depending on the distribution used.

Correlation Analyses

At the beginning of the correlation analyses, linear and nonlinear regression analyses are applied to the data set to determine the relationships between the dry unit weight (γ_{ds}) of sand cone test by means of γ_{dc} and ω_c parameters obtained from nuclear density tests. Among the 85 equations established, 2 regression equations (linear and the best nonlinear) were selected based on the Fisher (F) and coefficient of determination (R^2) values. The resulting linear regression equation including the γ_{ds} , γ_{dc} , and ω_c is:

$$\gamma_{ds} = 0.36 + 0.846 \times \gamma_{dc} - 0.004 \times \omega_c \quad (1)$$

The R^2 and F values were calculated as 0.813 and 183.8, respectively. These values indicate a meaningful correlation among model parameters. The best nonlinear regression equation between the free parameters addressed in the preceding paragraph is given in Eq. (2):

$$\gamma_{ds} = 15.617 - \frac{52.281}{\gamma_{dc}} - \frac{2.572}{\omega_c} + \frac{50.234}{\gamma_{dc}^2} + \frac{0.487}{\omega_c^2} + \frac{4.848}{(\gamma_{dc}\omega_c)} \quad (2)$$

The coefficient of determination of this equation is 0.836, which is an acceptable value. The F value is determined as 82.48, which is genuinely greater than the critical Fisher value (F_{cr}) of 3.10. The F value surpassing the critical value demonstrates the effectiveness of the regression equation. Figure 4 better

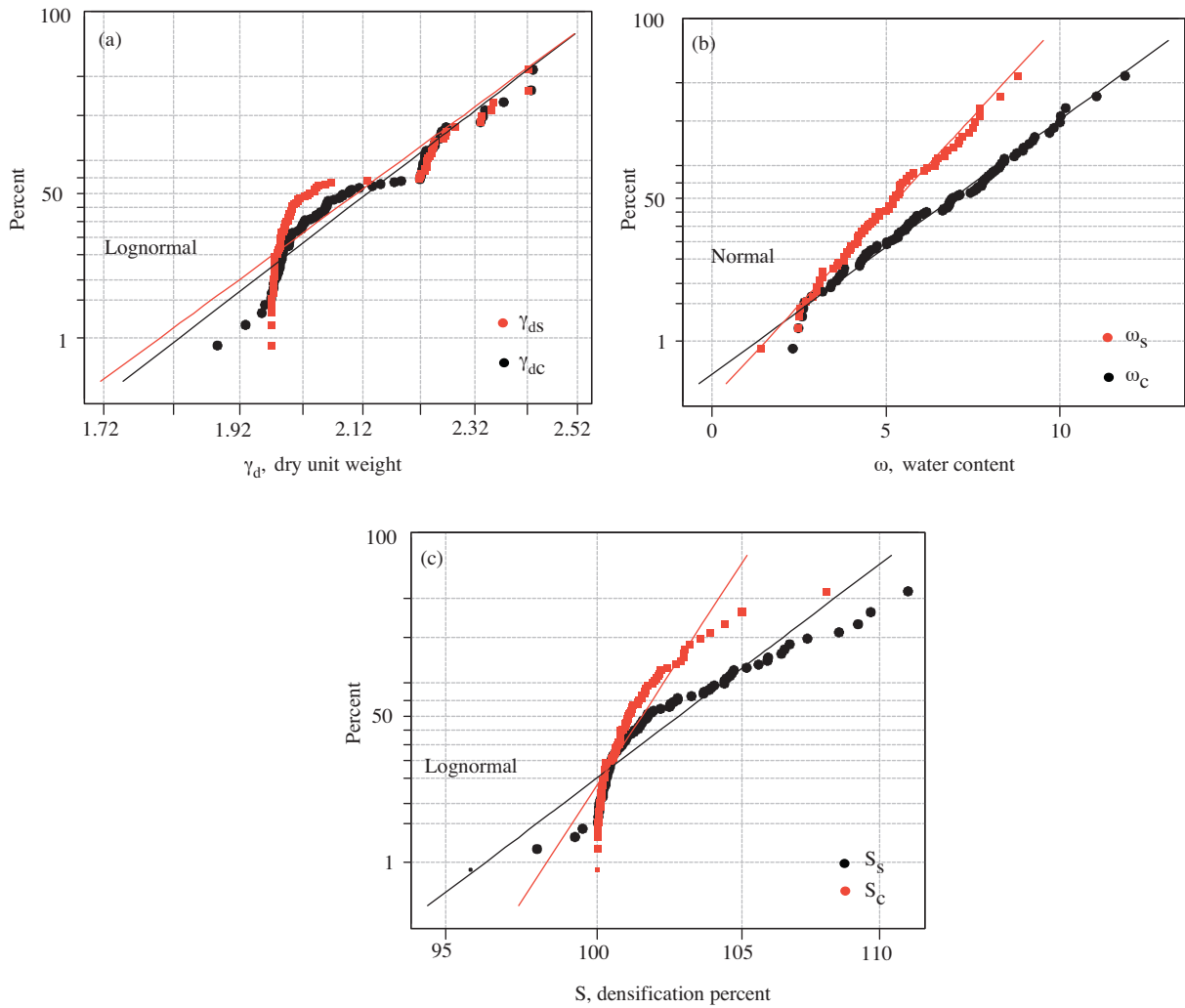


Figure 3. Probability plots of best fit distributions for (a) γ_{ds} and γ_{dc} ; dry unit weights obtained from sand cone and nuclear tests, (b) ω_s and ω_c , water contents obtained from sand cone and nuclear tests, (c) S_s and S_c , densification percent values obtained from sand cone and nuclear tests.

highlights the performance of regression equations and established mappings. It can be concluded that linear and nonlinear regression analyses exhibit similar achievements.

In the second of the study ANN based correlation models are considered to establish desired mapping described by the data. ANNs, powerful universal approximators, are superior in extracting relationships between known input and output patterns, imitating the processing logic of the biological neuron (Civalek and Çatal, 2004). ANNs, which are used in classification, clustering, modeling and estimation, are particularly good at modeling nonlinear systems utilizing a parallel processing logic. Among the several types of ANNs, Back-propagation neural networks (BPNNs)

are probably the most popular type, possessing feed-forward structure and utilizing a supervised learning algorithm. In this study, as an alternative to regression analyses, BPNN is employed to establish target mapping between design parameters. Since the literature is full of ANN discussions, no further explanation on ANN methodology is given here (Russell and Norving, 1995; Haykin, 1999; Kecman, 2001).

Two-layered BPNN structure is constituted for the estimation γ_{ds} using ω_c and γ_{dn} parameters that are collected from nuclear density tests. Tangent hyperbolic activation function, the sum of mean-square error function, Lavenberg-Marquardt learning technique, and the following normalization equation are used in developed BPNN models.

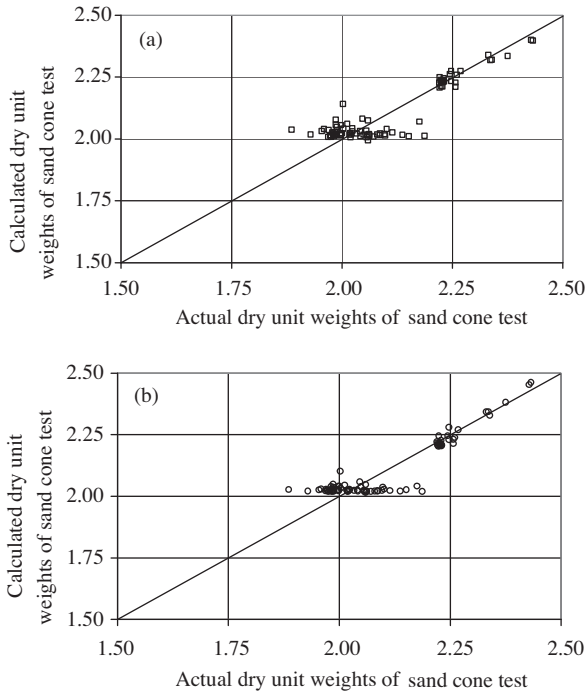


Figure 4. Mappings of (a) linear and (b) nonlinear regression analyses.

$$x_{ni} = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (3)$$

where, x_i is an input value of the data set, x_{ni} is the normalized input value, $\min(x)$ is the minimum of x data set, $\max(x)$ is the maximum of x data vector. It should be noted that a small parametric study is also carried out to determine the optimal size of hidden neurons by trying 10, 30, 50, and 70 neurons. Furthermore, 4 different ANN architectures are trained up to 2000 epochs. Due to the parametric study, the best mapping among the dry density and water content of nuclear tests with the dry density of sand cone test is obtained using 50 hidden neurons. The learning graph of the ANN with 50 hidden neurons is shown in Figure 5. As can be observed from the figure, after 400 epochs, the high rate of decrease in MSE is substituted by a fixed behavior of this parameter at a value of 0.0045. The scatter plot between model outputs and target values is given in Figure 6 evaluating ANN's performance. Consequently, a nearly one-to-one correspondence is attained through ANN methodology, as can be determined from the R^2 value of 0.999 (Figure 7).

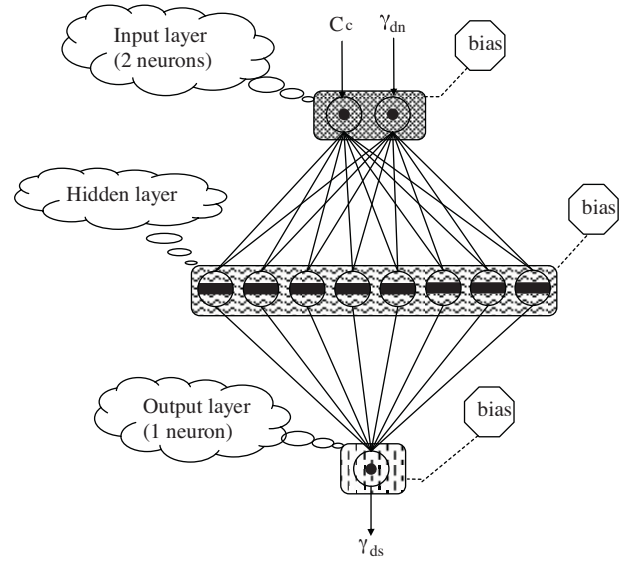


Figure 5. BPNN structure for the estimation of γ_{ds} .

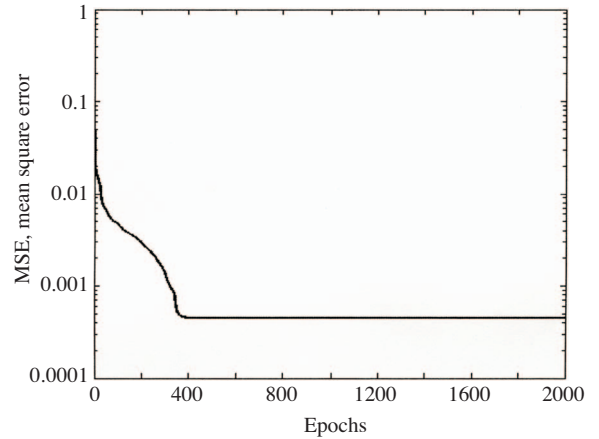


Figure 6. MSE (Mean square error) obtained from learning process for networks possessing a hidden layer constituting 50 neurons.

Finally, in order to observe the performance of NN-based correlation model, the network is tested by unseen data. As generally known, the success of a NN model is highly dependent to the data that is utilized through training sessions. Therefore, it is important to test the network's response to a dataset that was not used in the training phase. In this investigation, a testing database, which consists of 10 data points, is obtained by additional tests to evaluate the network's final performance. The scatter plot given in Figure 8 shows the result of the testing study. As can be seen from the figure, even though it is not successful as training session, the ANN-model exhibits outstanding performance considering the difficulty in the estimation of soil behaviors.

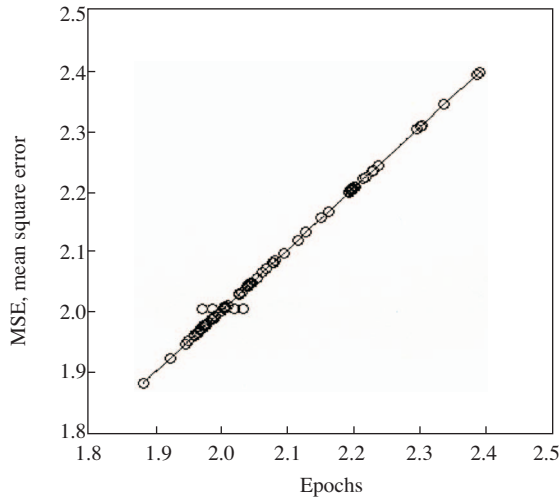


Figure 7. The comparison of dry density values obtained from the ANN of one hidden layer including 50 neurons with actual results of sand cone test.

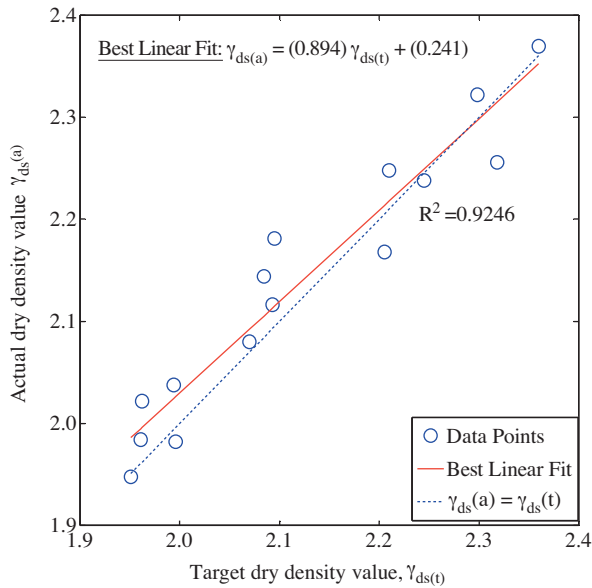


Figure 8. Scatter plot of the actual values of testing data set and the ANN model results.

Results and Discussion

In this study, using the dry density, water content and densification percentage values obtained from sand cone and nuclear gauge tests, relationships between these parameters are investigated via regression analyses and artificial neural networks. Consequently, the computational results regarding the correlation coefficients lead to the conclusion that the

ANN method is more capable of expressing the relationships between the parameters than regression analyses.

The basic objective of the study is the evaluation of the precision and uncertainty in the test methods utilized for compaction control. In this scope, Anderson-Darling tests and histograms of the data set indicate that exponential distribution fits the 6 input data including dry density, water content, and densification percentage values. The given scatter plots, basic statistical parameters, and normal distribution curves of the histograms indicate that dry unit weights are not uniformly distributed. This random behavior necessitates establishing a nonlinear relationship between the CQA parameter, depicted in the preceding paragraphs. Furthermore, because CQA is related to many parameters like reliability of the equipment, accurate application of test procedures, and laboratory distance; an uncertainty analysis is required on the principal test results. This study is conducted to evaluate relationships between reliable sand cone tests and fast applicable nuclear tests. A nearly perfect relationship facilitates the verification of fast nuclear test results via sand cone test results. Initially, linear, nonlinear regression analyses and also artificial neural networks are performed to establish relationships between dry unit weights and water content values of sand cone and nuclear tests, which were performed on a road construction in the Inner Aegean Region of Turkey. A basic statistical approach leads to the conclusion that a linear or nonlinear regression approach does not satisfactorily characterize the behavior between the 6 values, which demonstrate the densification data in the field. Artificial neural networks, which enable the characterization of nonlinear relationships between selected input and output values, produce much better relationships, which are confirmed by the high coefficient of determination values.

In this study, 87 experiments are considered to be sufficient for characterizing the input output mapping. Obviously, more extensive data is always preferable; nevertheless, an analyzer must decide how much data will serve by considering the distribution and scatter diagrams, which are the good demonstrators of data quality. However, the database in this study should be developed with further testing. The established relationship should be updated in order to improve the reliability.

Nomenclature

AI	artificial intelligence	x	input data to ANN
ANN	artificial neural network	x_{ni}	normalized input value
BPNN	backpropagation neural network	γ_d	dry unit weight
CQA	compaction quality assessment	γ_{dmax}	maximum dry unit weight
F	Fisher value	γ_{dc}	dry density obtained from nuclear test
MSE	mean square error	γ_{ds}	dry density obtained from sand cone test
PI	plasticity index	$\gamma_{ds(a)}$	actual dry density value obtained from sand cone test
LL	liquid limit	$\gamma_{ds(c)}$	calculated dry density value from nuclear test
S_c	densification percentage obtained from nuclear test	ω	water content
S_s	densification percentage obtained from sand cone test	ω_c	water content obtained from nuclear test
USCS	unified Soil Classification System	ω_s	water content obtained from sand cone test
		ω_{opt}	optimum water content

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