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Predicting the Displacement of Single Battered Pile in Sandy Soil under Pullout Loading Using Artificial Neural Network

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Keywords:

Artificial neural network; Battered pile; Finite element analysis; PLAXIS 3D; Parametric study; Sensitivity analysis.

Highlights:

- *Battered piles behavior differs from vertical piles.*
- *Accurately predicting their displacement is crucial for designing structures like bridges, wharves, and retaining walls.*
- *The interaction between soil and piles under lateral loading was nonlinear.*
- *Artificial neural networks were well-suited for modeling such complex relationships.*

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Abstract: The displacement of battered piles is one of the most critical parameters in the design of a pile foundation. In this study, an Artificial Neural Network (ANN) algorithm was utilized to predict the displacement of piles in sandy soils subjected to pullout loading. A finite element analysis (FEA) in three dimensions, performed with the PLAXIS 3D program, was utilized to gather 2380 databases, including the length/ diameter of pile, pullout, batter angle, Poisson ratio, friction angle, dilatancy angle, relative density, and Young's modulus as input variables, whereas the displacement of battered piles was considered an output variable. The dataset was divided into three parts: training (80%), validation (10%), and testing (10%). The performance of the Artificial Neural Network (ANN) algorithm was evaluated using the Mean Squared Error (MSE) and the Coefficient of Determination (R^2). This study applied a procedure known as a backpropagation neural network. According to the analysis of relative significance, the pullout load (Pu) and the pile length to its diameter (L/D) were the most effective characteristics among the other inputs. The R-values of the ANN model for the displacement of the battered piles dataset were 0.99 across all three phases of testing, validation, and training. The findings substantiated the viability of employing Artificial Neural Networks as a successful method for obtaining the displacement values of a single battered pile in sandy soil when subjected to pullout loading.

التنبؤ بإزاحة الركيزة المفردة المائلة في التربة الرملية تحت تحميل السحب بإستخدام الشبكة العصبية الاصطناعية

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الخلاصة

يعد إزاحة الركائز المائلة أحد أهم العوامل في تصميم أسس الركائز. في هذه الدراسة تم استخدام طريقة تعرف بخوارزمية الشبكة العصبية الاصطناعية (ANN) للتنبؤ بإزاحة الركائز في التربة الرملية المعرضة لأحمال السحب. تم استخدام تحليل العناصر المحدودة (FEA) ثلاثية الأبعاد، والذي تم إجراؤه باستخدام برنامج PLAXIS 3D، لجمع ٢٣٨٠ قاعدة بيانات. وكانت متغيرات الإدخال عبارة عن طول / قطر الركيزة، حمل السحب، زاوية الخليط، نسبة بواسون، زاوية الاحتكاك، زاوية التمدد، والكثافة النسبية، ومعامل يونغ، في حين تم أخذ إزاحة الركائز المائلة بعين الاعتبار كمتغير مخرجات. تم تقسيم مجموعة البيانات إلى ثلاثة أجزاء: جزء التدريب (٨٠٪)، وجزء التحقق (١٠٪)، وجزء الاختبار (١٠٪). تم تقييم أداء خوارزمية الشبكة العصبية الاصطناعية (ANN) باستخدام متوسط الخطأ التربيعي (MSE) ومعامل التحديد (R2). ولغرض هذه الدراسة، تم تطبيق إجراء يعرف باسم الشبكة العصبية للانتشار العكسي. وفقا لنتائج التحليل ذات الأهمية النسبية، فإن حمل السحب (Pu) وطول الركيزة بالنسبة لقطرها (L/D) كانت الخصائص الأكثر فعالية بين المدخلات الأخرى. تم الحصول على قيم R لنموذج ANN لإزاحة مجموعة بيانات الركائز المائلة لتكون ٠,٩٩ عبر المراحل الثلاث للاختبار والتحقق والتدريب. أثبتت النتائج جدوى استخدام الشبكات العصبية الاصطناعية كوسيلة مثمرة للحصول على قيم إزاحة الركيزة المفردة في التربة الرملية عند تعرضها لأحمال السحب.

الكلمات الدالة: الشبكة العصبية الاصطناعية، الركائز المائلة، تحليل العناصر المحدودة، PLAXIS 3D، الدراسة البارامترية، تحليل الحساسية.

1.INTRODUCTION

Batter piles are driven into the ground at an angle to the vertical to bear massive horizontal loads or side stresses. Batter piles are frequently employed to support bridges, tall buildings, and offshore structures. These structures are a concern due to their vulnerability to overturning and moments brought on by ship impact, waves, and winds. Normally, piles' displacement can be estimated via one of five methods: in-situ testing, dynamic testing, dynamic analysis, static analysis, and pile load testing [1]. In-situ testing is regarded as the way that performs the best overall compared to other options to determine the displacement of battered piles. Nevertheless, this method takes a significant amount of time and cost. In contrast, alternative methods have a lesser level of accuracy. As a direct consequence, several strategies have been devised to either predict the displacement of battered piles or improve the accuracy of such predictions. These methodologies, by their very nature, incorporated some assumptions, empirical approaches, or simplifications regarding the distribution of soil resistance along the pile, interactions between the soil and the pile structure, and soil stratification. In these kinds of research, the findings of the tests were employed as complementary elements to further enhance the accuracy of the forecast. Lopes and Laprovitera [2] suggested a formula for estimating the pile's bearing capacity and displacement for various soil types, including sand and silt. An empirical formula was published by Decourt [3], who considered the different adjusting variables for clayey and sandy soils. Finally, an experimental formula that considered the impacts of soil type was advocated by the Architectural Institute of Japan (AIJ) [4]. In general, the empirical equations or traditional methods have sought to involve a few important parameters to forecast the strength and displacement of the pile. However, if the input parameters of soil characteristics and pile geometry were increased, it was impossible to employ these approaches. A substantial expansion in utilizing information technology in civil engineering recently has prepared the way for numerous promising applications, particularly employing machine learning (ML) methodologies for solving complex engineering problems [5-15]. In addition, various methods that utilize machine learning, such as adaptive neuro-fuzzy inference systems (ANFIS) [16, 17], hybrid artificial intelligence approaches [18-20], decision trees [21], support vector machines (SVM) [22], and artificial neural networks (ANN) [23-28], have been utilized in the process of finding solutions to a wide variety real-world challenges, involving the estimation of the characteristics of piles. To be more specific, Kumar et al. [29] proposed a K-nearest neighbors (KNN) simulation to estimate the soil characteristics necessary for foundation construction. In addition, Refs. [30-33] built an ANN model for drilled shafts and driven piles using several on-site load tests in conjunction with the findings of the cone penetration test CPT. To estimate the friction capacity of driven piles in clays, an artificial neural network (ANN) model that was generated by on-field data recordings was published by Goh [34] and Goh et al. [35]. Additionally, Nejad et al. [36] created a model based on the SPT dataset with 12 input parameters to forecast the pile displacement using ANN. Also, Momeni et al. [37] demonstrated an ANN model that can estimate the tip and shaft resistance of concrete piles. Last but not least, Nawari et al. [38] designed an ANN technique that uses SPT data and shaft geometry to estimate the displacement of drilled shafts. Generally, the ML approach could potentially be regarded as a valuable tool for forecasting the mechanical characteristics of piles. On the other hand, there has not yet been a consensus established over the choice of the model that will be the most accurate in predicting the displacement of piles. In addition, the database is a significant component that significantly impacts the precision of machine learning algorithms and is essential for delivering a trustworthy modeling instrument. Consequently, the primary purpose of this research is to investigate the forecast capability of ANN, considering all possible factors that could influence the displacement of battered piles subjected to uplift loading. To achieve this goal, a significant amount of effort was put into collecting 2380 displacement of battered piles cases from the PLAXIS 3D, which, as far as the authors know, is the biggest database of its kind in the currently available literature. After that, the database was segmented into the training, validation, and testing subgroups, specifically created for the learning and validation phases of the suggested machine learning model. The ability of the algorithms to make accurate predictions was evaluated using several performance indicators, the most prominent of which were the Mean square error (MSE) and the coefficient of determination (R^2). Furthermore, the feature relative importance analysis was suggested to specify the percentage influence of each input variable on the displacement of battered piles subjected to uplift loading.

2.IMPORTANCE OF THE RESEARCH STUDY

Accurately forecasting the displacement of battered piles subjected to uplift loads is critical due to the numerous possible benefits and contributions to foundation engineering. In the currently available literature, numerical or experimental strategies still have some limitations, such as the scarcity of dataset samples, i.e., Teh et al. [39] had 37 samples, Bagi'nska and Srokosz [40] had 50 samples, and Momeni et al. [37] had 36 samples; the improvement and evaluation of the accuracy of the ML algorithms; or comparisons with traditional prediction methodologies. Consequently, the contribution of this work may be highlighted by the following four ideas: (i) To the best of the author's knowledge, the largest dataset, consisting of 2380 cases, was employed to create ML models. (ii) The effectiveness of ML algorithms was tested with a randomly divided dataset, which was the best way to determine how well the ML algorithms work. (iii) Through parametric tests, alterations in the values of some parameters enable the model's performance to be validated in simulating the physical behavior of battered pile displacement under uplift loading; and (iv) A sensitivity analysis was conducted to determine the importance of each input parameter in forecasting the displacement of battered piles subjected to uplift loading.

3.DATA PREPARATION AND COLLECTION

The displacement of battered piles subjected to uplift loading was calculated with PLAXIS 3D software, which employs the finite element method. This application may be used in three dimensions to solve problems involving the nonlinear soil and rock properties in addition to the soil-structure interaction problems. Many researchers found a high correspondence between the results of this application and the corresponding practical results [41-43]. The pile used in this study was a concrete pile with specifications indicated in Table 1. An uplift loading was applied axially on the pile, as shown in Fig. 1. An elastic model was applied to the pile, where the elastic model was used to specify the pile material. Based upon the surface roughness of the pile, the strength reduction factor R_{inter} varied from (0.8 to 1.0) [44]; therefore, R_{inter} was assumed to be 0.9 according to the interaction between concrete and sand. Besides, the Elastic-perfectly plastic Mohr-Coulomb model was adopted to model soil behavior. Also, tetrahedral 10-node elements were considered as the type and number of the elements. The testing box's geometry was designed with dimensions of 60 m by 60 m along the x- and y-axes. After determining that the top boundary of the soil layer was at a depth of z = zero, and the bottom boundary was at a depth of z = 50 meters, the soil characteristics were determined to be those of the soil block. The simulation was run assuming drained settings with the phreatic level maintained at the soil's base.

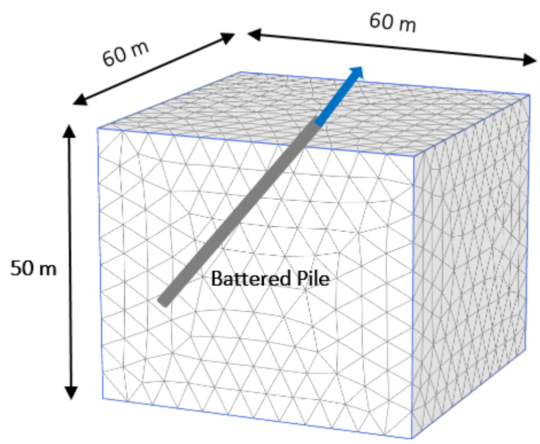


Fig. 1 3D FE Mesh for Soil and Pile.

Table 1 Characteristics of Model Pile.

Length (m)	Diameter (m)	Unit weight (kN/m³)	Young's modulus, E (kN/m²)	Poisson's ratio
10-20-30	0.3-0.4-0.5	24	$25x10^6$	0.21

To make reliable forecasts of the displacement of battered piles, it is necessary to have a detailed understanding of the variables influencing battered piles' displacement. Most traditional displacement of battered piles' determination approaches involved the following factors: pile geometry, properties of pile material, the inclination of the pile, and soil properties [45-47]. As a result, the variables employed in ML simulation were (i) length/ diameter of the pile (L/D); (ii) Pullout Load Pu (kN); (iii) Batter angle, (α˚); (iv) Poisson ratio, (ν); (v) the Friction angle, (ϕ˚); (vi) Dilatancy angle, (ψ˚); (vii) relative Density (RD %); and (viii) Young's modulus, (E) kN/m². The displacement (S) of battered piles was the only variable used as an output in the present investigation. Since the amount of data is huge (2380 samples), the dataset utilized in this investigation is partially presented and summarized in Table 2, which also includes statistical information regarding the input and output variables. In the present research, the obtained dataset was segmented into three datasets: training, validating, and testing. The ML models were trained using the training portion, which made up about 80% of the entire data; the performance of the ML models was validated using 10%; and the model was tested using the testing portion, which made up about 10% of the remaining dataset. With respect to the original data, the scale of the training dataset, which consisted of eight inputs and one output, was set to the range [-1; 1], Table 3. By putting all factors in the same range, the bias between inputs could be kept to a minimum in the dataset. The range [-1; 1] was chosen for the present investigation to represent the non-Gaussian distribution of the input data more accurately. Scaling parameters, like the lowest and highest values of the training data, were also utilized to scale the testing dataset. Equation (1) was utilized to apply the scaling procedure to the input and output variables. Besides, the histograms of all the data, including 8 inputs and 1 output, are presented in Fig. 2.

$$\chi_{scaled} = \frac{2(\chi-\alpha)}{\beta-\alpha} - 1 \qquad (1)$$

where α and β stand for the lowest and highest values of the associated variables, respectively, and χ stands for the value of the input variable chosen to be scaled.

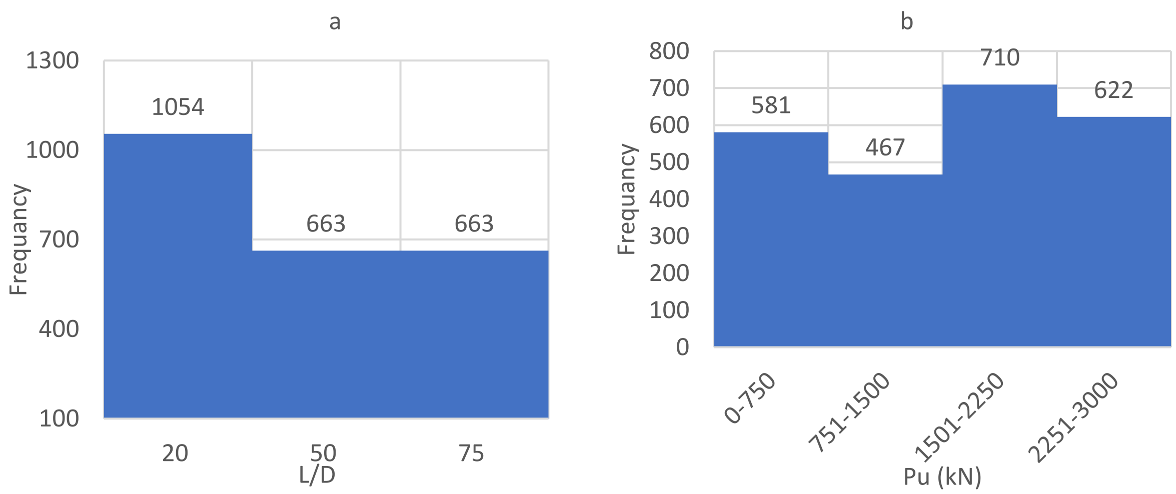
Table 2 The Inputs and Outputs of the Current Research.

No.	L/D	Pu (kN)	α°	ν	ϕ°	ψ°	RD %	(E) kN/m²	(S) mm
1	20	0	0	0.1	30	2	20	10000	0
2	20	750	0	0.1	30	2	20	10000	41
3	20	1500	0	0.1	30	2	20	10000	121
.	-	-	-	-	-	-	-	-	-
.	-	-	-	-	-	-	-	-	-
.	-	-	-	-	-	-	-	-	-
2378	75	1500	40	0.4	40	10	85	30000	6.67
2379	75	2250	40	0.4	40	10	85	30000	16.82
2380	75	3000	40	0.4	40	10	85	30000	29
Min.	20	0	0	0.1	30	2	20	10000	0
mean value	44	1855	20	0.25	35	6	42	12930	130
Max.	75	3000	40	0.4	40	10	85	30000	551
SD	23.08	880.86	14.00	0.15	4.42	3.28	27.17	6317.52	144.32

SD = Standard deviation.

Table 3 Statistical Values of the Training Dataset After the Normalization Process.

No.	L/D	Pu (kN)	α°	ν	ϕ°	ψ°	RD %	(E) kN/m²	(S) mm
Min.	-1	-1	-1	-1	-1	-1	-1	-1	-1
mean value	-0.14	0.24	-0.01	-0.02	-0.08	0.01	-0.32	-0.71	-0.53
Max.	1	1	1	1	1	1	1	1	1



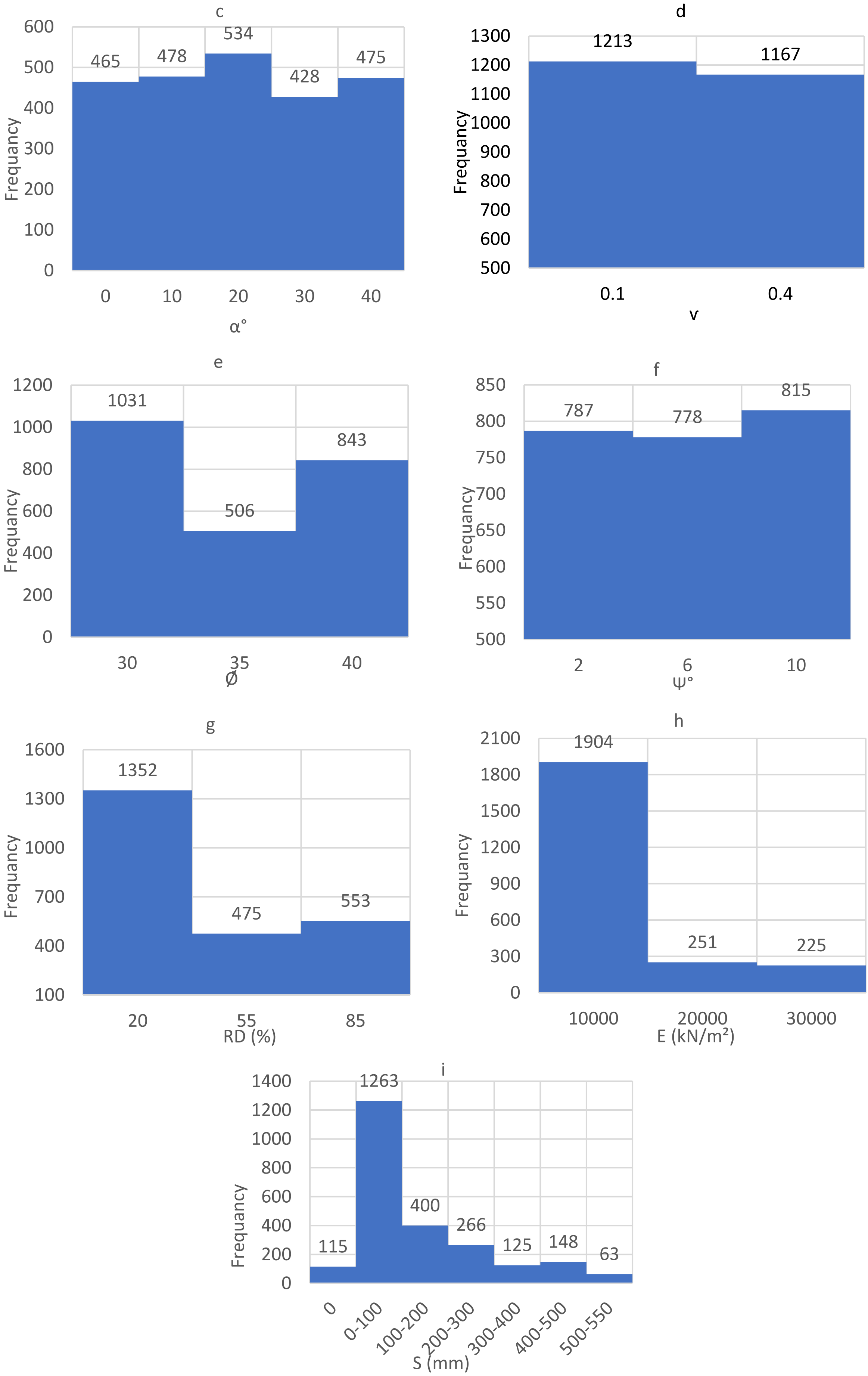


Fig. 2 Histograms of the Dataset in the Study: (a) L/D; (b) Pu; (c) α˚; (d) ν; (e) ϕ˚; (f) ψ˚; (g) RD; (h) E; (i) S.

4.ARTIFICIAL NEURAL NETWORK (ANN)

The term "artificial neural network" (ANN) refers to a strong and multipurpose algorithmic tool that has arisen as a means of organizing and linking knowledge [48]. Many problems, typically challenging to solve using traditional numerical and statistical methodologies, have been successfully predicted using ANN [49]. Mathematician McCulloch and neuroscientist Pitts [50] were the first scientists to develop the concept of ANN. It has been demonstrated that the ANN possesses a powerful capacity to deal with complicated issues in which the interactions between the input(s) and output(s) are either nonlinear or complex [51], which is primarily due to its many interconnected neurons that can handle a lot of information at once [49]. The architecture of an artificial neural network (ANN) comprises multiple layers, i.e., input, hidden, and output layers, interconnected together by various link weights throughout hidden nodes [51]. The activation function is performed in each node of the network. The link weights and a bias are added to obtain the node net input [37]. Among the several learning algorithms, backpropagation is the most used technique for training ANNs [52]. Moreover, numerous additional study concepts have been inserted and expanded to the present time [53, 54]. The above information demonstrates that ANN has numerous benefits and is employed extensively across a variety of fields, particularly in the domain of construction technology [55, 56]. In addition, numerous studies have been conducted to estimate bearing capacity employing ANN [49, 51, 53, 54, 56]. In light of the findings, it can be deduced that the prediction performance provided by ANN appeared more trustworthy than that offered by supporting vector machines (SVM). Furthermore, various studies on the bearing behavior of piles employing ANN revealed superior prediction ability when contrasted with numerical and empirical methodologies [49, 56-58]. Figure 2 illustrates a schematic representation of the neural network. In the ANN algorithm, it has been demonstrated that the multi-layer network functions most effectively since it can mimic nonlinear processes. The fundamental idea behind neural computing is to break down the connection between inputs and output into a number of stages that can be linearly segmented from one another by benefiting from hidden layers. There are three distinct processes for developing an ANN-based answer, which can be summed up as [59]:

Step 1: Data transformation or scaling;

Step 2: Network design is described in terms of the number of hidden layers, the number of neurons in each layer, and the connectivity of the neurons. Figure 3 shows how the network design choice was made.

Step 3: This stage is regarded as the evolution of the neural network since it involves training the network to react appropriately to a particular set of inputs (Fig. 4).

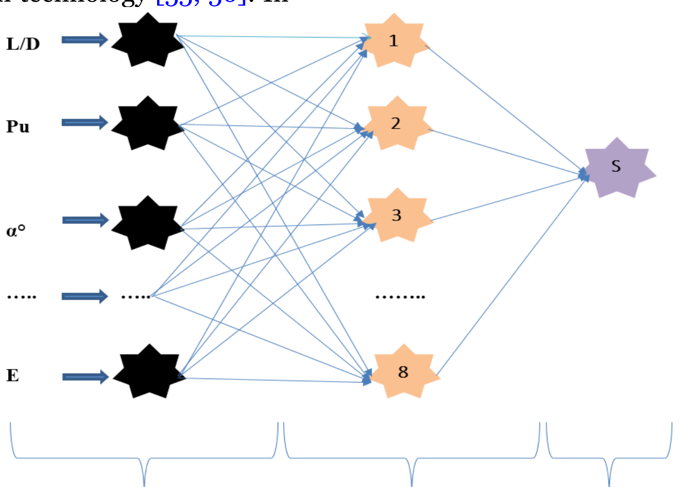


Fig. 3 Choosing an Appropriate Network Architecture.

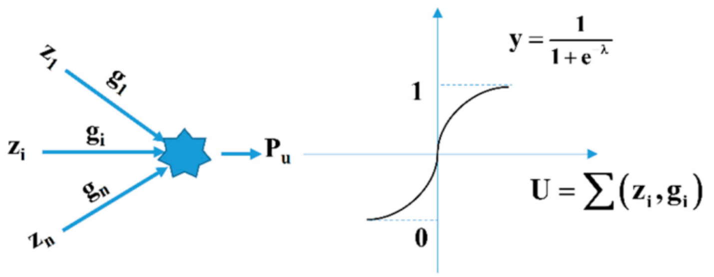


Fig. 4 The Typical Procedures for Developing Neural Networks [60].

5.RESULTS AND DISCUSSION

5.1.Performance Evaluation

In this section, the performance of the ANN model is analyzed and evaluated. The amounts of the battered piles' displacement were predicted using a multilayered feed-forward neural network using a backpropagation technique. The well-known software package [MATLAB 2020] was utilized during the development of ANN [61]. The Levenberg–Marquardt (LM) backpropagation algorithm is a potent enhancement approach adopted into the neural network research because it gave ways that speed up the algorithm's training and convergence processes. Since the mean square error (MSE) was employed as an indicator of performance for the training of neural networks, the (LM) technique is the most suited one that may be employed [62] and [63]. As a result, it was decided to include this technique as part of the research. Convergence in the training process is reached by lowering the mean squared error (MSE) within each training iteration and monitoring the overall performance of the trained stages by comparing the results. This procedure is repeated until the MSE is reduced to an acceptable level. The parameters of ANN applied in this investigation are tabulated in Table 4. Figure 5 compares the results of displacement of the battered pile sand to the neural network prediction for training, validation, testing, and all datasets, using a model of ANN with eight hidden nodes. This comparison, as shown in the figure, demonstrates an excellent match between the ANN and the battered piles' displacement results. The ANN model's correlation coefficient R values determined for the battered pile's displacement dataset were 0.998 for each training, validation, and testing phase. Also, the mean square error (MSE) was 0.0005, which is an excellent value.

Table 4 ANN Parameters.

Parameters	Value and Description
Number of neurons in the input layer	8
Number of hidden layers	1
Number of neurons in the hidden layer	8
Number of neurons in the output layer	1
Activation function for the hidden layer	Tan sigmoid
Activation function for the output layer	Linear
Training algorithm	Levenberg-Marquardt (LM)
Mean Square Error (MSE)	0.0005

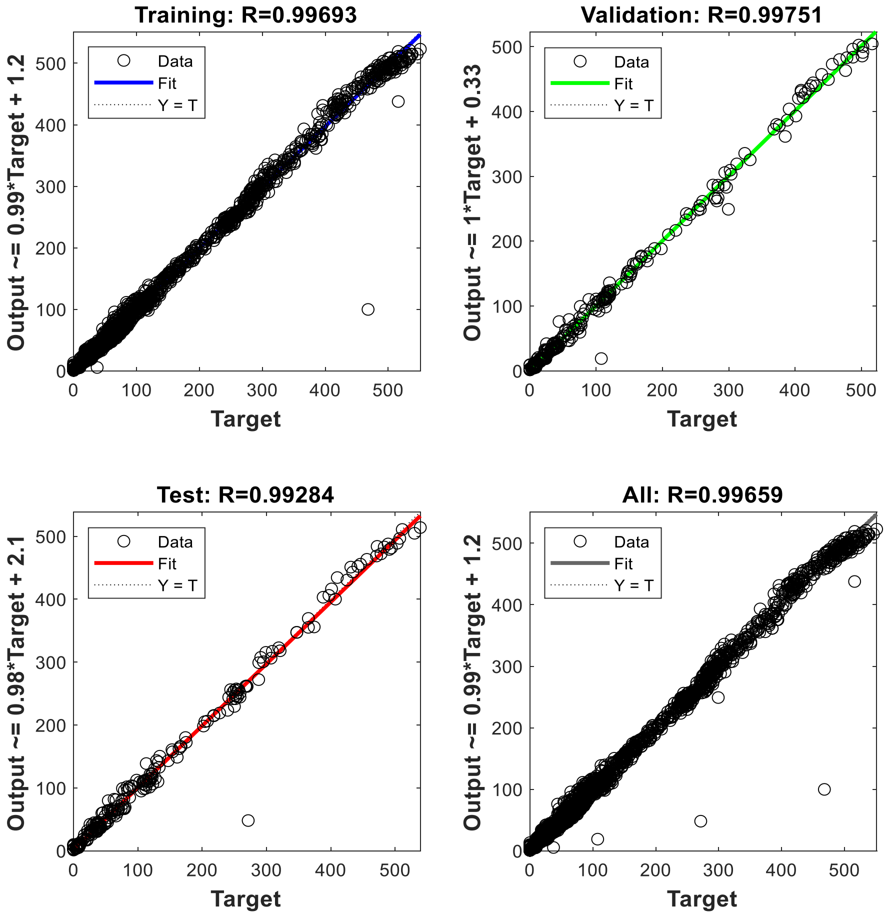


Fig. 5 Regression Graphs Comparing Measured S and Predicted S for the (a) Training, (b) Validation, (c) Testing, and (d) All Datasets.

5.2. Sensitivity Analysis

An operation known as sensitivity analysis investigates the cause-and-effect relationships between a data set's inputs and outcomes [64]. When the neural network has been trained, it is vital to identify the impact and understand how each input parameter individually affects the outcome. If any input pathway yields a small sensitivity value, it can be presumed unnecessary. It can be eliminated, reducing the amount of difficulty and time needed for the training, which will, in turn, improve the performance of the network and vice versa since the backpropagation neural network (BPNN) weight is not straightforward and directly understandable in the form of a digital system. So, it will be turned into a percentage value by dividing the weight of every input variable by the total sum of all the weights of the input variables [65], producing the relative importance of each input parameter to the output parameter. Figure 6 depicts the relative importance of each input parameter obtained. Amongst the 8 introduced parameters to obtain the displacement of the battered piles under pullout loading, the Pullout Load (Pu) was the most significant parameter, as seen by a 39% rise in relative importance, Fig. 6. Indeed, Pu is a substantial indicator of obtaining the displacement of the battered piles. The length/ diameter of the pile (L/D) was the second significant parameter, confirmed by the relative importance value, equal to 18%. The variable RD was ranked as the third significant parameter, with a relative importance of 12%. According to soil mechanics, this meant that with a slight alteration in the properties of the soil, the relative density significantly impacted the displacement of the battered piles; such a parameter is involved in the resistance of the pile. The parameters ϕ°, E, and α° were rated as the fourth to the sixth significant variables, with relative importance ranging from 6% to 9%, Fig. 6. Other parameters in the model (ψ°, and ν) showed a relative importance of less or equal than 5%.

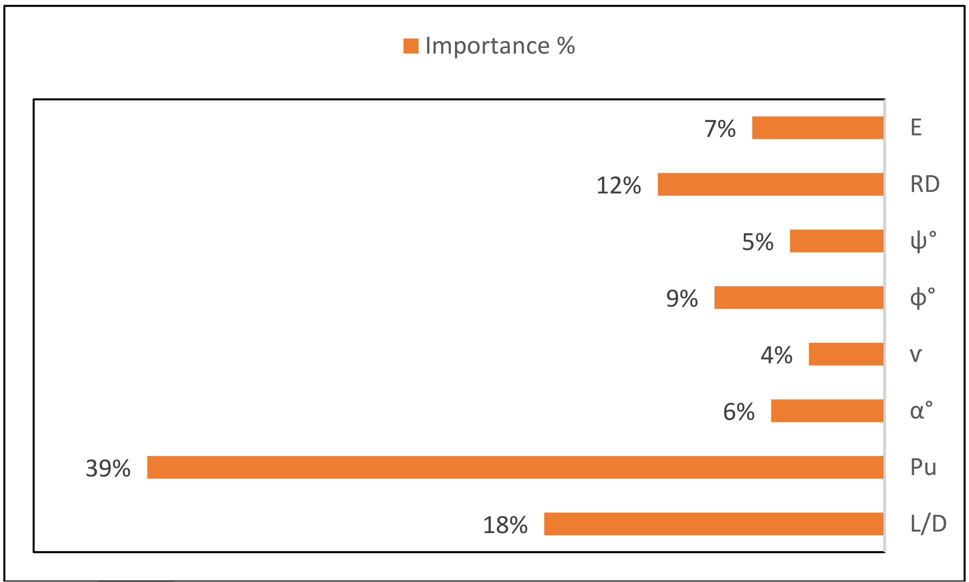


Fig. 6 The Significance of 8 Factors Utilized in this Investigation.

5.3. Parametric Analysis

To obtain how the input parameters individually change the response of the model, a set of parametric studies has been done. The parametric study can be conducted by adjusting just one of the input variables while holding the values of the rest of the input parameters as constant, i.e., all input variables, except one, were fixed to particular values. A set of synthetic data between the maximum and minimum values was generated for the input not installed to a fixed value. The response of the model was then examined. This method is returned utilizing another input variable and so on until the model response is tested for all input variables. Through a parametric study, the model efficiency can be validated by mimicking the physical behavior of the displacement of battered piles under pullout loading due to varying other parameter values.

5.4. The Influence of Axial Pullout Load

The relationship between axial pullout load and displacement is depicted in Figs. 7 - 9 for piles with various length-to-diameter ratios and batter angles in soils with varying relative densities. The domain of battered angle values was 0 – 40, whereas the axial pullout load values range was (0 to 3000) kN. Of course, as presented in such figures, the displacement of battered piles increased with the pullout load, keeping other parameters constant. The findings obtained are near the conclusion Al-Tememy et al. predicted [41].

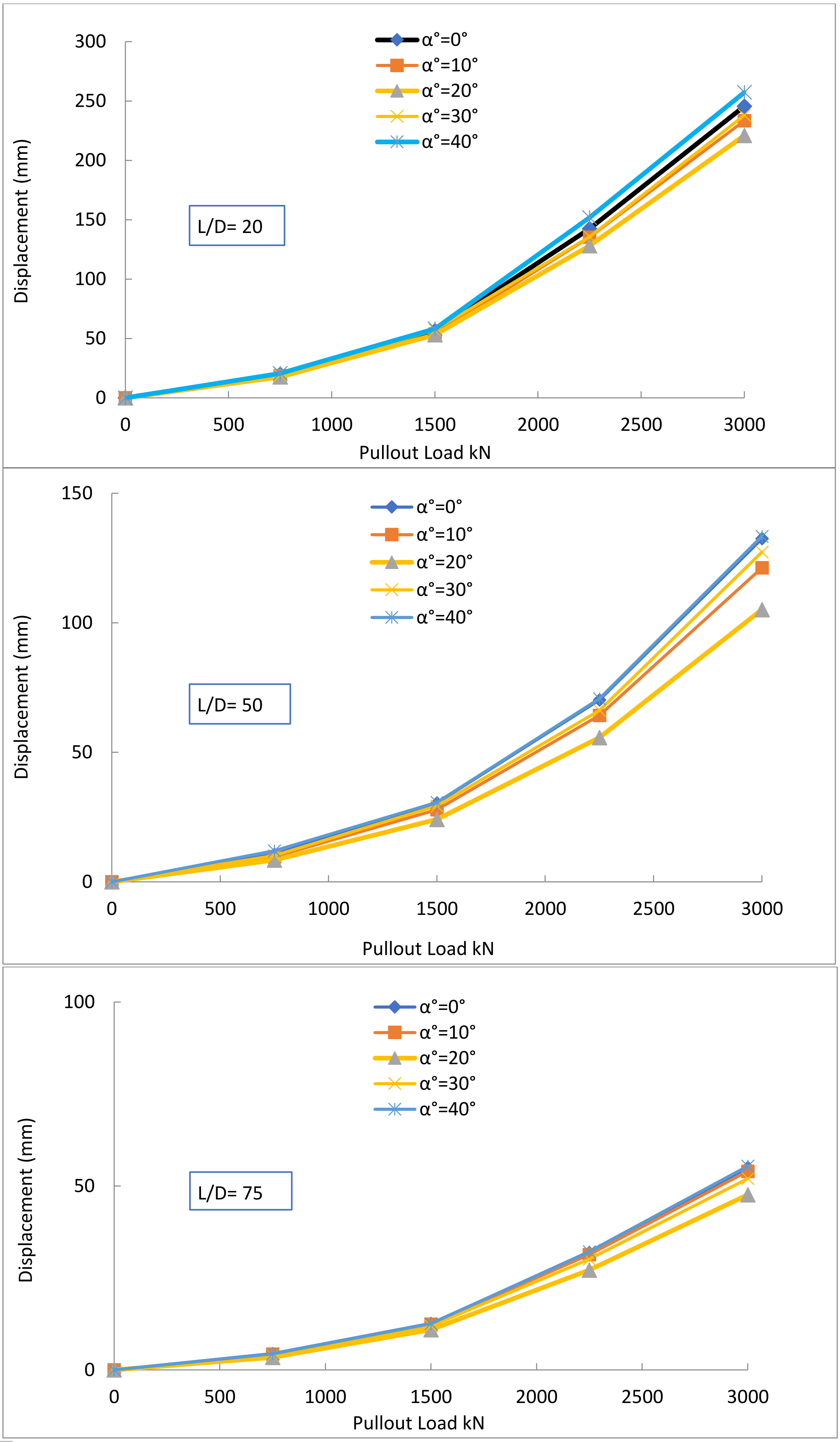


Fig. 7 The Load-Displacement Curve for Vertical and Batter Piles under Different Embedment Ratios in Loose Sand RD = 20%.

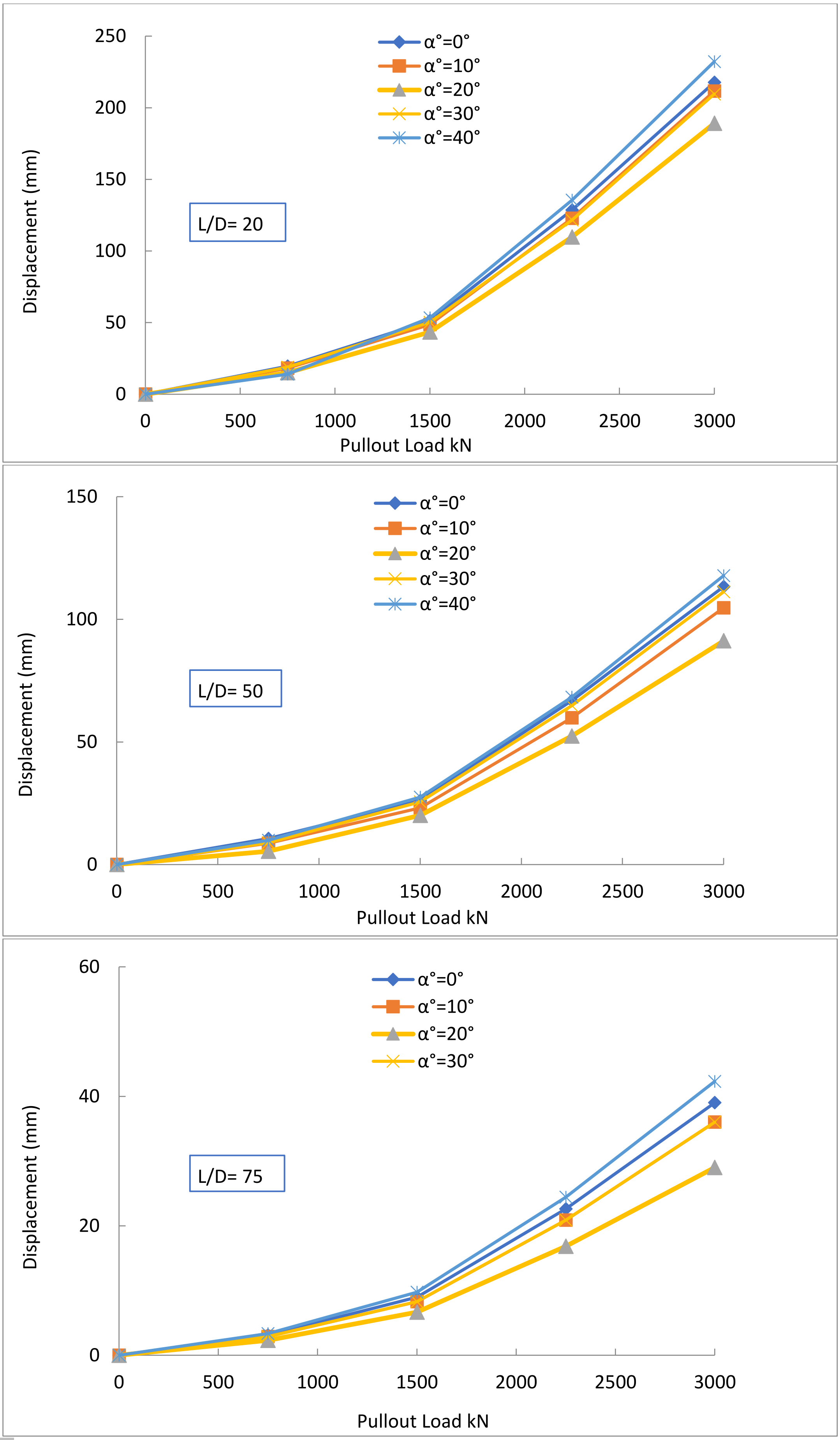


Fig. 8 The Load-Displacement Curve for Vertical and Batter Piles under Different Embedment Ratios in Medium Sand RD = 55%.

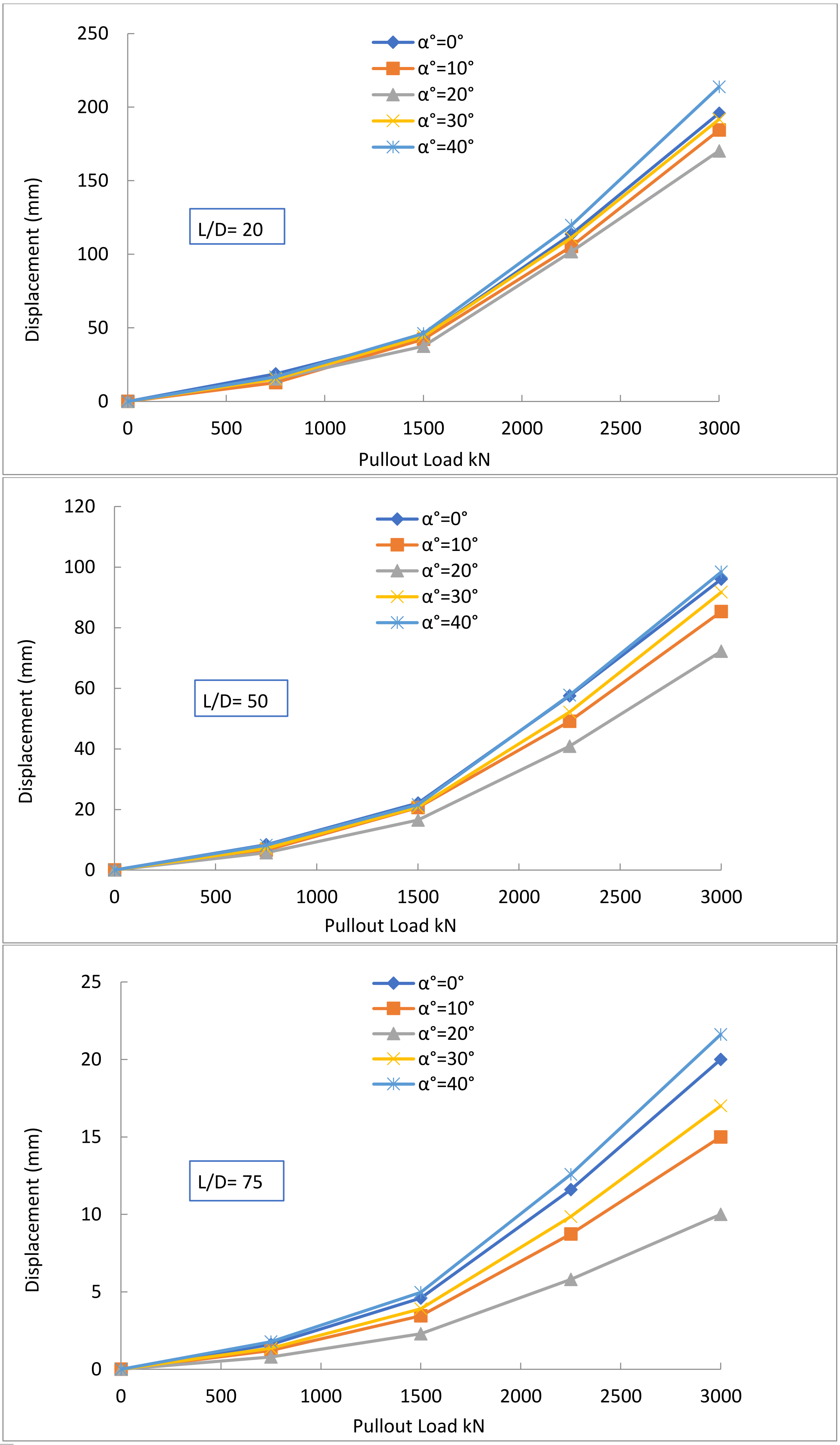


Fig. 9 The Load-Displacement Curve for Vertical and Batter Piles under Different Embedment Ratios in Dense Sand RD = 85%.

5.4.The Influence of Pile Batter Angle

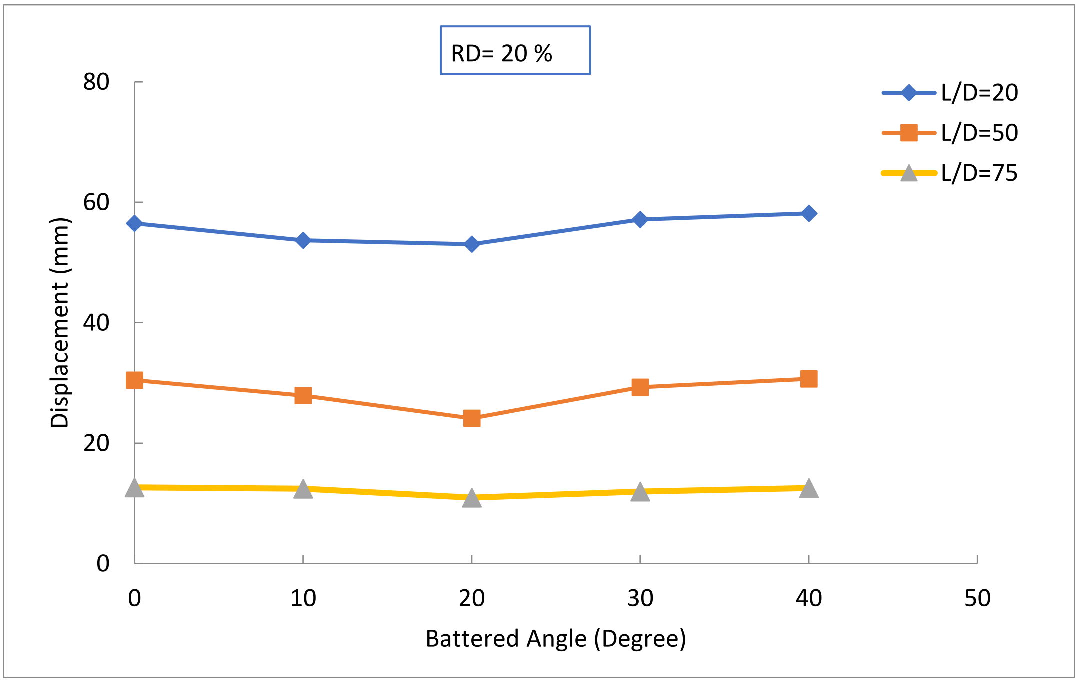
The impact of battered angle (α) on the displacement of battered piles under pullout loading was studied using a selection of vertical and inclined piles with angles of (0°, 10°, 20°, 30°, and 40°). These piles were installed in loose, medium, and dense sand at embedment ratios of 20, 50, and 75. The batter angle affects the displacement of battered piles, as shown in Fig. 10. It can be seen that as the batter angle increased, the displacement of battered piles reduced until it reached a minimal value, at which point it started to rise. For all L/D ratios, the minimum value was reached at a batter angle of 20°, and it was between 6.1 and 20.8% lower than the value for the vertical pile placed in loose sand when RD = 20%. The minimal value was between 15 and 50 % less for piles placed in medium and dense sand than for vertical piles. The findings obtained were quite near to the conclusion predicted by Mohanty et al. [63] and Al-Tememy et al. [41].

5.5.Influence of the Pile Embedment Ratio

To examine the impact of the pile embedment ratio of vertical and inclined piles, three L/D ratios, i.e., 20, 50, and 75, were employed. The link between the displacement of battered piles and their embedment ratios L/D at relative densities of 20%, 55%, and 85% is depicted in Fig. 11. Additionally, the batter angles employed in this illustration are also shown. Regarding the displacement of battered single piles, the embedment ratio is also a crucial factor to consider. As the embedment ratio increased, the displacement of battered single piles subjected to pullout loading considerably increased. The findings obtained are near the conclusion predicted by Gaaver [66].

5.6.Influence of Sand Relative Density

Variation in battered pile displacement as a function of batter angle and sand density is depicted in Fig. 12. The graph confirmed that for all L/D values, a rise in relative density reduced the displacement of vertical and batter piles. When the relative density of sand increased from 20% to 55%, the displacement of battered piles decreased by about 9-29% for vertical piles and by approximately 17-39% for inclined piles at an angle of 20°. If the RD of sand increased from 55% to 85%, the displacement of battered piles reduced by 14-49% for vertical piles and 14-66% for piles at a 20° angle. As a result of increasing the L/D, the angle of friction between the soil and the pile increased. Hence, effective stress and skin friction also increased, decreasing the buttered pile's displacement when subjected to uplift loading. These findings are consistent with predictions by Al-Neami et al. [67].



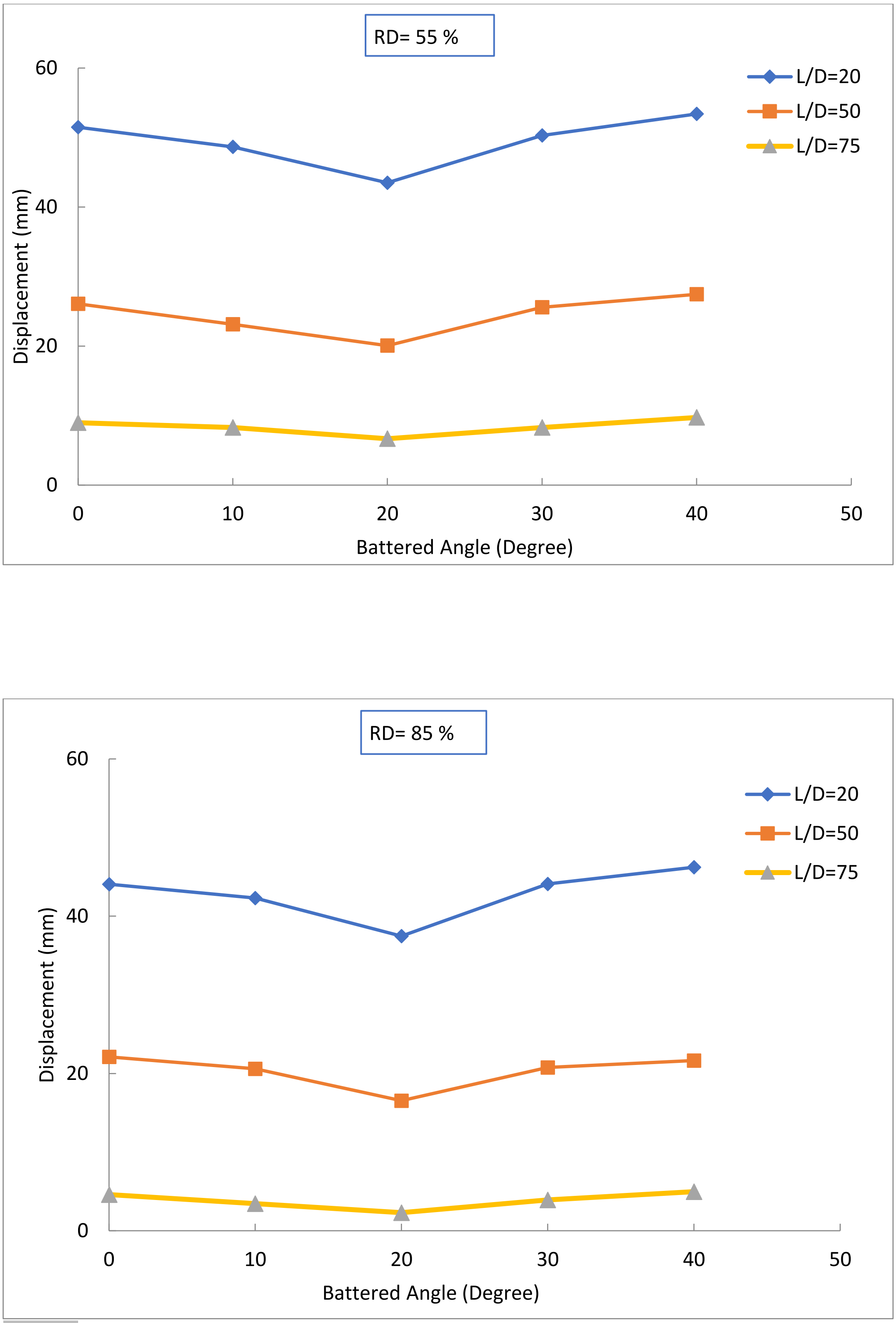


Fig. 10 The Displacement Variation with Batter Angle under Different Embedment Ratios.

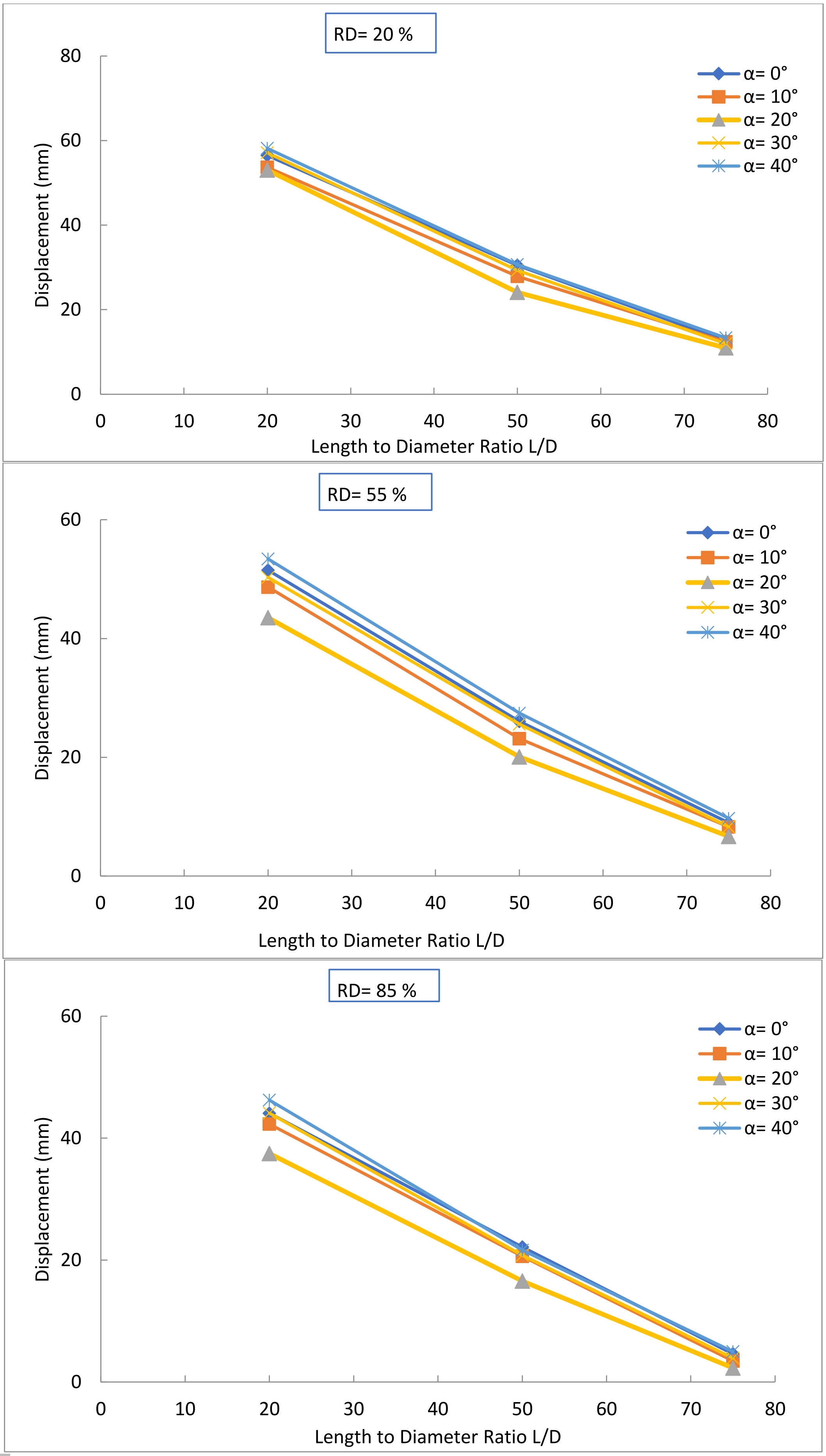


Fig. 11 Variation in the Battered Piles' Displacement with a Length-to-Diameter Ratio under Different Batter Angles.

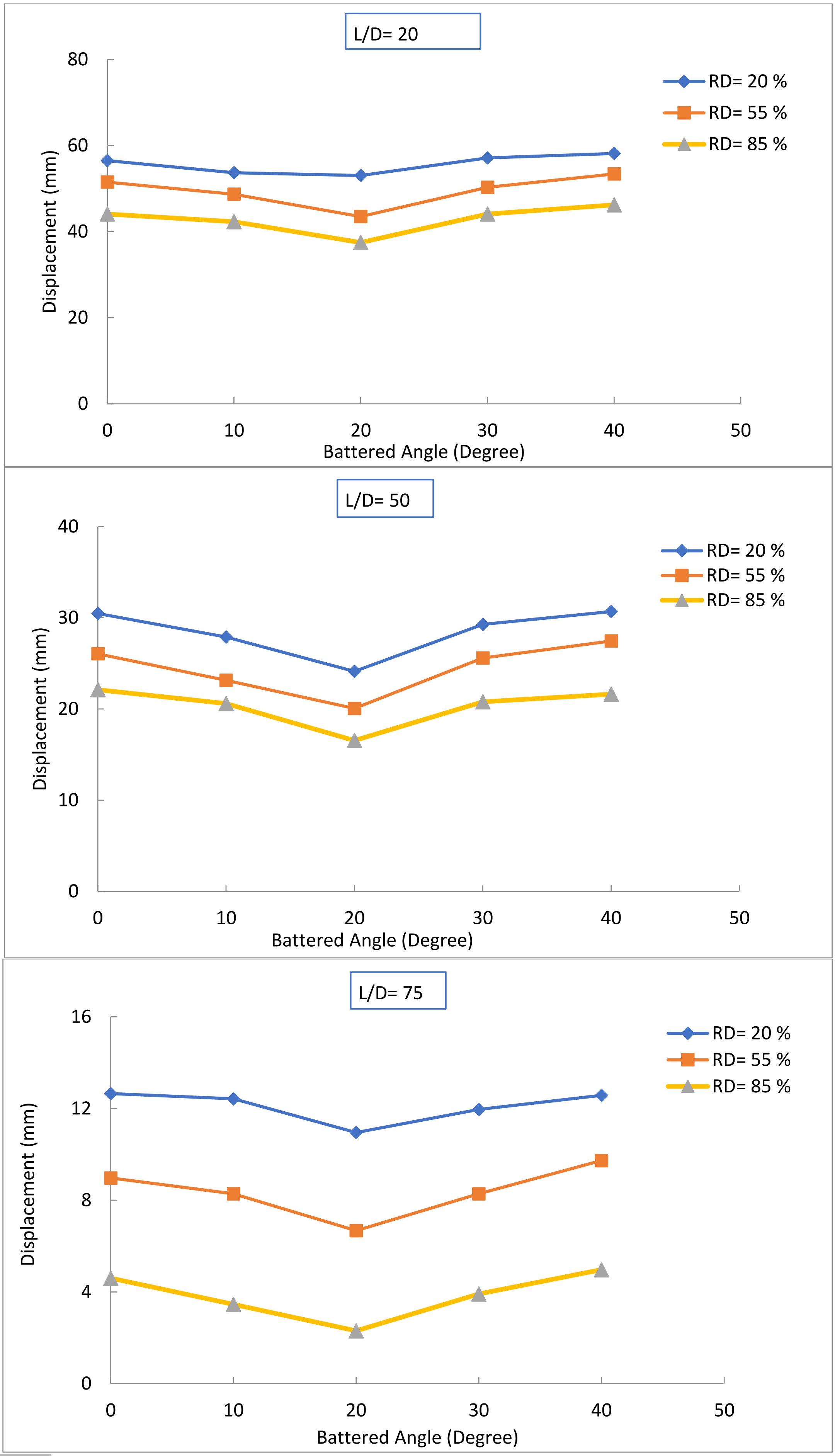


Fig. 12 Variation in the Pile Displacement with Batter Angle under Different Relative Densities.

6.CONCLUSIONS

The ANN algorithm was employed in the present work to test its ability to anticipate the displacement of battered piles when subjected to pullout loading. The proposed machine learning models were developed and evaluated using an unparalleled set of 2380 examples from PLAXIS 3D. The proposed ANN with the 8-8-1 architecture predicted the real value of the displacement of battered piles under pullout loading based on the following data: length/ diameter of the pile, pullout load, batter angle, Poisson ratio, friction angle, dilatancy angle, relative density, and young's modulus. The presented ANN estimates the displacement of battered piles under pullout loading with values of determination coefficient $R^2 = 0.998$, and the mean square error (MSE) was 0.0005. Also, from the present investigation of the displacement of battered piles in sand, the following conclusions can be summarized:

1- As the batter angle α° increased, the displacement of a single battered pile reduced until it reached its minimal value at α =20°, after which it increased.
2- The displacement of battered piles decreased as the L/D ratio and relative density increased due to the increased skin friction resistance between the pile and the soil.
3- The input variables can be arranged according to their relative importance: pullout load, length/ diameter of the pile, relative density, friction angle, Young's modulus, batter angle, dilatancy angle, and Poisson ratio.

In the end, as with many other machine learning techniques, the ANN technique offers an additional benefit over more traditional approaches: after the model is built, it can be applied as a fast, precise numerical tool for calculating the displacement of battered piles subjected to pullout loading. As a result, the accuracy of this kind of numerical tool is essential in the field of foundation engineering. Thus, one aspect of the present effort is to improve prediction accuracy by employing deep neural networks or hybrid machine learning techniques to anticipate the displacement of battered piles.

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