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Prediction of Bearing Capacity of a Footing Resting on Geo-synthetic Reinforced Soil Wall Using Artificial Neural Network

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Abstract. Increased recent application of geo-synthetic reinforced soil (GRS) walls as bridge abutments to support bridge beams over shallow foundations is pervasive in place of deep foundations. Understanding the behaviour of footing resting on the backfill of the GRS wall is necessary and finding out the bearing capacity of the footing is essential. Many researchers have calculated the bearing capacity of the footing resting on GRS walls by using numerical analysis through various softwares. In the present study, numerical analysis is performed to estimate the effects of various factors, namely embedment depth of footing, angle of internal friction, offset distance of footing, width of footing, and length of reinforcement on bearing capacity. Consequently, an artificial neural network (ANN) is applied to predict the bearing capacity of the footing. For this, 190 data points collected from previous research articles and others processed in PLAXIS 2D software are used in the present analysis. A model equation for the determination of the ultimate bearing capacity of the footing resting on the GRS wall has been developed from the best fit ANN model. Finally, sensitivity analysis was performed to determine the order of importance of input parameters on the output parameter.

Keywords: GRS Wall, Footing, Bearing Capacity, PLAXIS 2D, ANN.

1 Introduction

Geo-synthetic reinforced soil (GRS) has been successfully used to construct many earth structures, such as slopes, retaining walls, and embankments. In recent years, Bridge abutments have been increasingly constructed using GRS walls. Bulky gravity walls are usually employed to construct bridge abutments, which must be supported by piles or groups of piles. However, similar situations do not exist when GRS walls are used as bridge abutments, which is why GRS walls are preferable for such a structure. For embankments of bridge approaches, highways, and railways subjected to traffic loads, GRS walls are used as abutments to support bridge beams on the shallow footings placed directly on the backfill. The main benefits of this technology are that it eliminates pile foundations, thus lowering overall construction cost and decreasing bumps at bridge ends. As a result, it is essential to comprehend the behaviour of a footing resting on the GRS wall's backfill. To decrease the bridge span, footings are usually placed near to the wall facing. Furthermore, as the footing position changes, i.e., near or distant from the face of the wall, the load bearing capacity, and footing settlement change, making the analysis difficult. So, finding out the bearing capacity of the footing is necessary.

In this paper, the bearing capacity of the footing has been predicted by adopting an Artificial Neural Network (ANN). Numerical analysis has been done to evaluate the effect of parameters such as embedment depth of footing, angle of internal friction, offset distance of footing, width of footing, and length of reinforcement on bearing capacity.

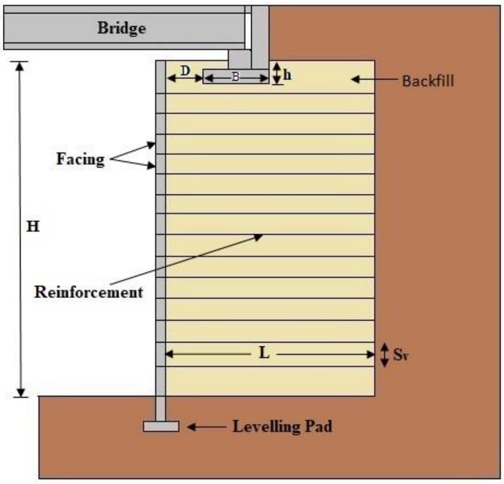


Fig. 1. Schematic illustration of GRS Wall

2 Numerical Analysis

PLAXIS 2D, a finite element program, was used to do the numerical analysis. This software can design geotechnical structures, such as dams, excavations, embankments, and tunnels. The finite element analysis was carried out with 15-node triangular elements in planar strain conditions. The geometry of the structure, soil properties, and other required parameters for modeling were collected from the literature. The structure was modeled by variable parameters like offset distance of the footing from the face of the wall (D), embedment depth of the footing (h), the width of footing (B), length of reinforcement (L), and friction angle of backfill (ϕ) while all other parameters were unchanged. In PLAXIS 2D software, force can be incorporated either by means of prescribed force or displacement. The footing has been kept on the wall by varying the parameters. Fine mesh has been used for every case to make the analysis easier and get instant results. The water table has been taken to be at the bottom surface of the wall. Analysis gives the results in terms of pressure vs displacement. The external stability check for the wall has been done for every wall height, and they are a factor of safety against sliding, overturning, and bearing pressure.

The footing with a larger offset distance on the GRS wall had a higher ultimate bearing capacity than the footing with a smaller offset distance. To attain the maximum value of ultimate bearing capacity, the footing that rests over the backfill of the

GRS wall should be neither too close nor too far away from the wall facing, according to the findings of this study. The footing ultimate bearing capacity was slightly increased as the embedment depth was increased. The increase in the length of the reinforcement and friction angle of the backfill soil has given some improvement in the ultimate bearing capacity, while an increase in the width of the footing decreased the bearing capacity.

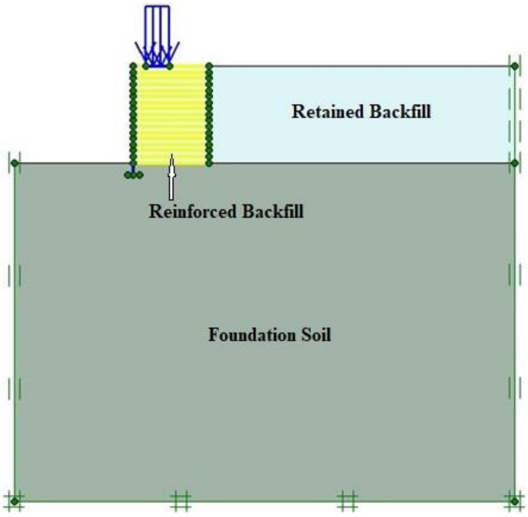


Fig. 2. Placing of the footing and Application of load

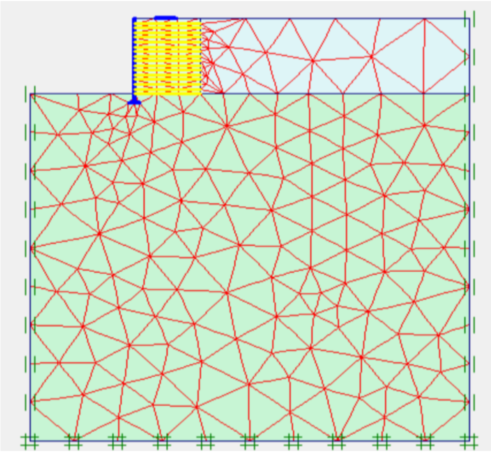


Fig. 3. Deformed mesh after loading

3 Data Collection

A total of 190 data points were collected from various published literature and numerical analysis. 61 of the 190 were taken from published literature, as shown in Table 1, and the remaining 129 were obtained by performing numerical analysis. The offset distance of the footing, embedment depth of footing, width of the footing, friction angle of the backfill, length of the reinforcement, and the related measured ultimate bearing capacity of the footing are all included in each data set.

Table 1. Sources of data collected from the literature

Source	Number of data obtained
Rahmaninezhad, S. M., et al (2020)	14
Srivastava, A., et al (2021)	5
Sakleshpur, V. A., et al (2017)	8
Xiao, C., et al (2016)	30
Kakrasul, J. I. (2018)	2
Xie, Y., et al (2019)	2

Normalization of data has been done to eliminate inaccurate or missing data and enhances prediction accuracy. All data in this study was scaled down between 0 and 1.

$$x_{\text{normalized value}} = \frac{x_{position\ value} - x_{minimum\ value}}{x_{maximum\ value} - x_{minimum\ value}} \quad (1)$$

Where $x_{\text{position value}}$ represents positional value of a specific parameter, $x_{\text{normalized value}}$ represents mapped normalized value, $x_{\text{maximum value}}$ and $x_{\text{minimum value}}$ were maximum and minimum input values of a specific parameter, respectively. Each variable has an n suffix to denote its normalized value. The creation of ANN models was done using normalized input and output data points.

4 Determination of Model Input Parameters

Selection of the optimal number of input parameters is required to be done.

The five input parameters considered for creating ANN models are as follows:

1. Offset distance of the footing from the face of the wall (D)
2. Embedment depth of footing (h)
3. Width of the footing (B)
4. Friction angle of the backfill (ϕ)
5. Length of the reinforcement (L)

5 Division of Data

The entire database must be split into two groups: training and testing. The training set purpose is to help the ANN model understand the underlying patterns in the data, whereas the testing set purpose is to evaluate the trained model, determine the error between the actual and predicted output, and help in model optimization.

The data set was divided into four different combinations for training and testing algorithms: 90–10 % (90–10 validation), 80–20 % (80–20 validation), 70–30 % (70–30 validation), and 60–40 % (60–40 validation). In the 70-30 validation method, 70% of the database (133 records) has been assigned to the training set, while the remaining 30% (57 records) has been assigned to the testing set. Other validation techniques used similar approaches, and a total of 16 neural network models were developed. According to Shahin et al. [8], Statistical consistency has been maintained for both the training and testing sets, and the statistical parameters used for this purpose are mean and standard deviation; these parameter values of the data in both sets must be as close as possible.

TABLE 2. The statistical parameters for 70-30% validation

Model Parameters and Data set	Mean	Standard deviation	Maximum	Minimum	Range
ϕ					
Training set	36.83	12.78	51	10	41
Testing set	39.86	10.46	51	10	41
L (m)					
Training set	4.99	1.85	8	1.3	6.7
Testing set	4.99	1.76	8	1.3	6.7
B (m)					
Training set	1.87	0.95	4	0.2	3.8
Testing set	1.90	0.98	4	0.2	3.8
D (m)					
Training set	2.43	2.11	8	0	8
Testing set	2.01	1.95	7	0	7
h (m)					
Training set	0.18	0.33	2	0	2
Testing set	0.21	0.45	2.4	0	2.4
q_u (kN/m^2)					
Training set	266.67	135.30	692	11	681
Testing set	266.32	136.79	670	13	657

6 Development of ANN model

ANN has been developed in MATLAB 2014a environment with two-layer feed-forward back propagation neural network and Tan-sigmoid as a transfer function in both the hidden and output layers. The network has been trained using four different learning algorithms: Bayesian Regularization (BR), Levenberg-Marquardt (LM), Gradient descent with momentum (GDM), and Scaled conjugate gradient (SCG).

6.1 Optimizing the Number of Hidden Neurons

The optimal number of neurons in the hidden layer should be determined to get the best performance out of an ANN model. The neurons number in a hidden layer is important for determining network accuracy and the best architecture for an ANN model. The precision of output increases as the number of hidden neurons increases; however, more neurons can lead to overfitting of data, whereas fewer neurons can lead to underfitting. The formula (2i +1), where i is the number of input parameters, can be used to calculate the maximum number of hidden nodes suggested by Hecht-Nielsen [4]. In this study, there are five input parameters. The ANN model with the lowest mean squared error (MSE) was chosen from among those created with a number of hidden neurons ranging from 1 to 11.

6.2 Building the Optimum ANN Model

The Levenberg–Marquardt (LM) algorithm for 70-30% validation, with the six hidden neurons, has been obtained as the optimum ANN model. The architecture of the developed optimum ANN model with six hidden neurons and the variation of hidden neurons with mean square error has been given in Figure 4 and Figure 5, respectively.

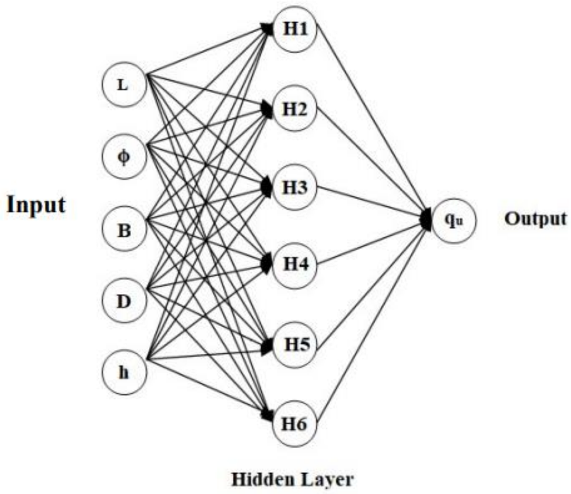


Fig. 4. Architecture of optimum ANN 5-6-1 Model

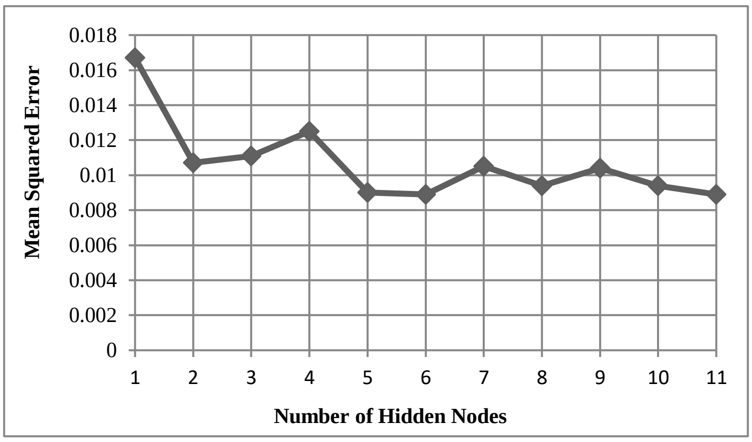


Fig. 5. Graph between the Number of Hidden Neurons and MSE

The following statistical performance functions have been used in this study to evaluate the performance of ANN models:

Mean Squared Error (MSE): MSE = $\frac{\sum(Y_m - Y_p)^2}{N}$

Root mean square error (RMSE): RMSE = $\sqrt{\frac{\sum(Y_m - Y_p)^2}{N}}$

Coefficient of correlation (R): $R = \sqrt{\frac{\sum {Y_m}^2 - \sum (Y_m - Y_p)^2}{\sum {Y_m}^2}}$

Mean Absolute Error (MAE): $MAE = \frac{\sum | Y_m - Y_p |}{N}$

Where Y_m represents actual observed value, Y_p is predicted output value, and N represents number of data points. The relative correlation and goodness of linear fit between the actual target values (Y_m) and the predicted output values (Y_p) are measured by the R. As a result, R should be as high as possible. MSE, RMSE, and MAE are error measures. These error values should be as low as possible.

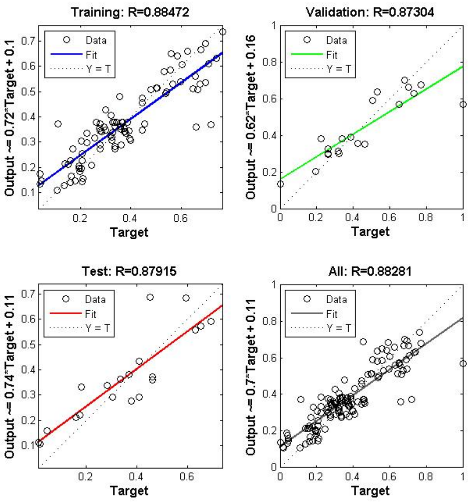
TABLE 3.ANN models statistical error values

ANN Model Combinations	Algorithms	MSE	R	MAE	RMSE	Number of hidden neurons
90-10%	BR	0.01	0.876	0.0752	0.1	5
	LM	0.0095	0.890	0.0713	0.0974	9
	GDM	0.0097	0.863	0.0711	0.0984	8
	SCG	0.0115	0.842	0.0712	0.1072	7
80-20%	BR	0.0095	0.896	0.0708	0.0975	6
	LM	0.0098	0.868	0.0707	0.0989	8
	GDM	0.0099	0.880	0.0741	0.0994	11
	SCG	0.0096	0.899	0.0694	0.0979	9
70-30%	BR	0.0099	0.879	0.0749	0.0995	6
	LM	0.0089	0.884	0.0682	0.0943	6
	GDM	0.0098	0.883	0.0738	0.0989	10
	SCG	0.0095	0.909	0.0712	0.0974	6
60-40%	BR	0.0095	0.856	0.0735	0.0974	6
	LM	0.0093	0.871	0.0692	0.0964	10
	GDM	0.0128	0.834	0.0729	0.1131	7
	SCG	0.0095	0.874	0.0748	0.0974	10

Table 3 indicates that the LM method with a 70–30% validation model gives the lowest MSE, RMSE, and MAE values. As a result, it can be determined that the LM algorithm with a 70–30% validation is the best of all the models considered.

Table 4. Best Fit ANN model Performance Characteristics

Data Set	R	MSE	MAE
Training set	0.884	0.0089	0.0682
Testing set	0.879	0.0142	0.0913



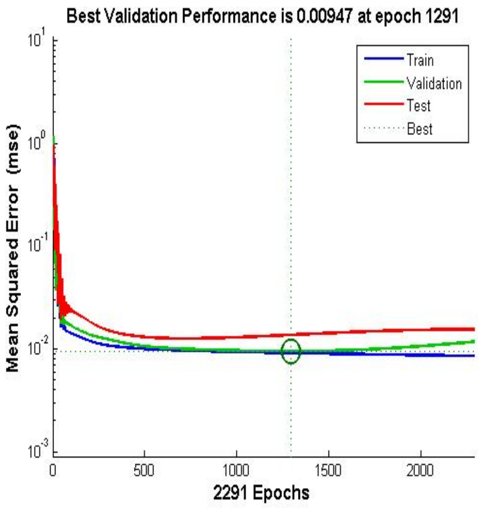


Fig. 6. Fitting Curve between Target and Output values for LM algorithm (70–30% validation)

Fig. 7. Plot of mean square error versus the number of epoch for LM algorithm (70-30% validation)

7 Development of Equation to Predict the Ultimate Bearing Capacity of Footing Resting on GRS Wall on the Basis of the Trained ANN Model

The mathematical equation recommended by Goh et al. [3] that incorporates all of the independent input parameters, as well as the dependent output parameter, is –

$$Y = f_{\text{sigm}}\left\{b_o + \sum_{r=1}^{h}\left[w_r f_{sigm}\left(b_{hr} + \sum_{i=1}^{m} w_{ir} X_i\right)\right]\right\}$$

(2)

Where,

f_{sigm} = Sigmoid transfer function (Tan-sigmoid function in this case).
w_r = The weight of the connection between the hidden layer's r neuron and the output layer's neuron.
b_o = Output layer bias.
b_{hr} = Bias at the hidden layer's rth neuron.
w_{ir} = The weight of the connection between the input variable i and the hidden layer's rth neuron.
X_i = Input parameter.
Y = Output parameter.

TABLE 5. The LM algorithm weights and bias for the ANN-5-6-1 model with 70–30% validation

Hidden Neuron	Input-Hidden Weight					Hidden-Output Weight	Bias	
	$(L)_n$	$(\phi)_n$	$(B)_n$	$(D)_n$	$(h)_n$	$(q_u)_n$	Hidden	Output
1	-1.416	1.1049	-0.8077	0.4837	0.1736	-1.3979	2.4499	-0.1718
2	-0.5767	-0.7910	-0.8501	-1.6840	-1.6252	-0.3636	1.0896	
3	-1.2491	0.0667	-1.5074	-0.6751	-0.3930	0.2233	0.1960	
4	-0.4030	-0.0647	-0.8902	-2.5701	-0.2602	-0.5612	-0.1430	
5	0.4348	1.1053	-1.7041	-0.2979	-0.6917	0.4110	-0.6603	
6	-1.6191	1.0965	-0.8339	2.1251	-1.0491	-1.6425	-3.4234	

By putting the values of weights and bias shown in Table 5 in equation 2, the following equations can be written, and these equations are used to determine the correlation of the output parameter with the input parameters.

$$a = -1.416(L)_n + 1.1049(\phi)_n - 0.8077(B)_n + 0.4837(D)_n + 0.1736(h)_n + 2.4499 \quad (3)$$

$$b = -0.5767(L)_n - 0.791(\phi)_n - 0.8501(B)_n - 1.684(D)_n - 1.6252(h)_n + 1.0896 \quad (4)$$

$$c = -1.2491(L)_n + 0.0667(\phi)_n - 1.5074(B)_n - 0.6751(D)_n - 0.393(h)_n + 0.196 \quad (5)$$

$$d = -0.403(L)_n - 0.0647(\phi)_n - 0.8902(B)_n - 2.5701(D)_n - 0.2602(h)_n - 0.143 \quad (6)$$

$$e = 0.4348(L)_n + 1.1053(\phi)_n - 1.7041(B)_n - 0.2979(D)_n - 0.6917(h)_n - 0.6603 \quad (7)$$

$$f = -1.6191(L)_n + 1.0965(\phi)_n - 0.8339(B)_n + 2.1251(D)_n - 1.0491(h)_n - 3.4234 \quad (8)$$

Before substituting in the above equations, the input parameter values must be normalized in the range [0, 1]

$$x = -1.3979\tanh(a) - 0.3636\tanh(b) + 0.2233\tanh(c) - 0.5612\tanh(d) + 0.411\tanh(e) - 1.6425\tan(f) - 0.1718 \quad (9)$$

$$\text{Ultimate Bearing Capacity, } q_u \text{ (normalized)} = \tanh(x) \quad (10)$$

The equation (10) has been de-normalized to equation (11), from which we can obtain the actual predicted ultimate bearing capacity (in kN/m^2).

$$\text{Ultimate Bearing Capacity, } q_u\,(\text{kN/m}^2) = Y_{min} + (Y_{max} - Y_{min})\tanh(x) \quad (11)$$

Where Y_{min} and Y_{max} are the minimum and maximum values of Y, respectively, which can be taken from the dataset.

Table 6. Bounds for the input and output parameters

	L (m)	ϕ	B (m)	D (m)	h (m)	q_u (kN/m^2)
Maximum	8	51	4	8	2.4	692
Minimum	1.3	10	0.2	0	0	11

Within the given limits, the equation (11) established for predicting Ultimate Bearing Capacity works well. Before employing the aforementioned equations, the maximum and lowest values of the input parameters given in Table 6 should be utilised to normalise the input parameters.

The developed equation will be helpful in saving time and cost (monetary and computational) associated with performing model tests and numerical simulations.

8 Validation of ANN Model with PLAXIS 2D and Existing Literature Results

TABLE 7. Comparison of the output values from ANN with the PLAXIS 2D and available literature values

q_u (kPa) value from literature and PLAXIS 2D	q_u (kPa) predicted value from ANN	Absolute Error%
373	371	0.45
190	203	7.07
315	323	2.64
325	301	7.48
203	189	6.97
320	315	1.44
266	307	15.43
270	266	1.56
351	339	3.51
409	331	19.15
143	126	11.58
440	379	13.87
455	389	14.6
152	151	0.570
200	184	8.11
170	187	9.9
100	112	11.76
104	95	9.05

It is noticed from Table 7 that the error is in the range of 0.5% to 20% which is acceptable. We can see that error getting increased with the bearing capacity.

9 Calculation Procedure to find Out the Ultimate Bearing Capacity of the Footing resting on a Geo-synthetic Reinforced Soil Wall with a Numerical Example

The following procedure can be adapted to determine the ultimate bearing capacity of the footing resting on a GRS wall from the derived model equation.

A data set has been taken from numerical analysis results

Height of the wall (H) = 9 m
Friction angle of the backfill (ϕ) = 35
Length of the reinforcement (L) = 6.3 m
Width of the footing (B) = 2 m
Offset distance of the footing from the face of the wall (D) = 2 m
Embedment depth of the footing (h) = 0 m
Ultimate bearing capacity of the footing (q_u) = 268 kN/m^2

Step 1: Normalize the given data using equation 1 in the range [0, 1] and the input parameter limits shown in Table 6.

Table 8. Given and normalized data

	$(L)_n$	$(\phi)_n$	$(B)_n$	$(D)_n$	$(h)_n$
Given Data	6.3	35	2	2	0
Normalized data	0.746	0.609	0.473	0.25	0

Step 2: Substitute the normalized data into the equations (3) – (8) and calculate for a, b, c, d, e and f

$a = -1.4168(L)_n + 1.1049(\phi)_n - 0.8077(B)_n + 0.4837(D)_n + 0.1736(h)_n + 2.4499$
$= 1.804$
$b = -0.5767(L)_n - 0.791(\phi)_n - 0.8501(B)_n - 1.684(D)_n - 1.6252(h)_n + 1.0896$
$= -0.646$
$c = -1.2491(L)_n + 0.0667(\phi)_n - 1.5074(B)_n - 0.6751(D)_n - 0.393(h)_n + 0.196$
$= -1.578$
$d = -0.403(L)_n - 0.0647(\phi)_n - 0.8902(B)_n - 2.5701(D)_n - 0.2602(h)_n - 0.143$
$= -1.547$
$e = 0.4348(L)_n + 1.1053(\phi)_n - 1.7041(B)_n - 0.2979(D)_n - 0.6917(h)_n - 0.6603$
$= -0.543$
$f = -1.6191(L)_n + 1.0965(\phi)_n - 0.8339(B)_n + 2.1251(D)_n - 1.0491(h)_n - 3.4234$
$= -3.826$

Step 3: Substitute the calculated values of a, b, c, d, e, and f into equation (9) and solve for x.

$x = -1.3979\tanh(a) - 0.3636\tanh(b) + 0.2233\tanh(c) - 0.5612\tanh(d) + 0.411\tanh(e) - 1.6425\tan(f) - 0.1718$
$= 0.4558$

Step 4: Now, put the value of x into equation (10) and calculate q_u (normalized)

Ultimate Bearing Capacity, q_u (normalized) = tanh(x)
= 0.4267

Step 5: De-normalize the q_u value by substituting in equation (11) with maximum and minimum values of q_u taken from Table 6

Considering Y_{max} = 692 kN/m^2 and Y_{min} = 11 kN/m^2
Ultimate Bearing Capacity, q_u (kN/m^2) = $Y_{min} + (Y_{max} – Y_{min}) \tanh(x)$
= 301kN/m^2

The value of predicted ultimate bearing capacity obtained from equation (11) is 301kN/m^2. The data of the example has been obtained from a numerical analysis whose ultimate bearing capacity was 268kN/m^2**.** As a result, the predicted error is 12.31%, which is acceptable.

10 Sensitivity Analysis

To determine the importance of the input parameters in the prediction of the output parameter, a sensitivity analysis was performed. Garson's approach Goh [2], based on an optimised weight vector, was used to determine the influence of different input parameters on the output parameter. Connection weight values of the trained network for LM algorithm and 70–30% validation model are given in Table 5. A python code was used with Garson’s algorithm to find the relative significance of various input parameters.

The analysis shows that the fourth parameter, the offset distance of the footing from the face of the wall *D*, has the greatest influence on the ultimate bearing capacity of the footing. The width of the footing is the second-factor influencing ultimate bearing capacity. The friction angle of the backfill and footing embedment depth had the least impact on bearing capacity.

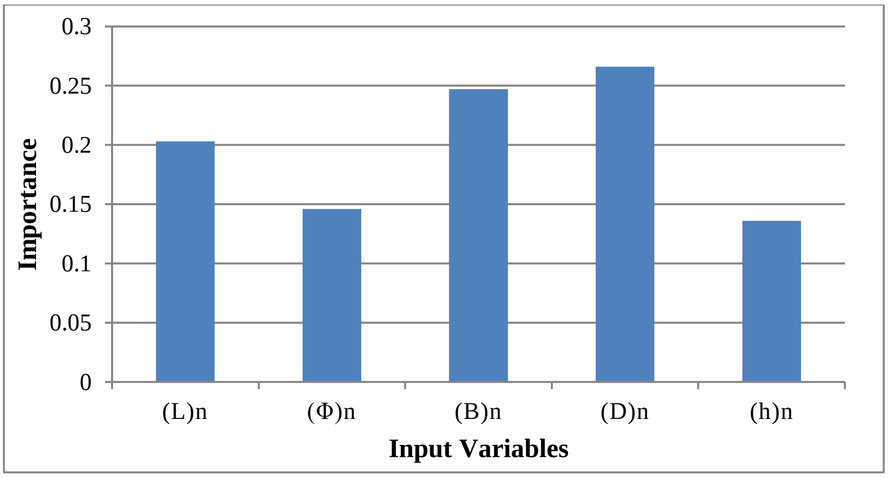


Fig. 8. Histogram for Importance of input parameters

11 Conclusion

The Levenberg–Marquardt (LM) algorithm with the mean square error value of 0.0089 and the corresponding correlation coefficient value of 0.884 for 70-30% validation model with six numbers of hidden neurons outperforms all other algorithms and validation models. The most influencing parameter in predicting the ultimate bearing capacity of the footing is offset distance (*D*), whereas the least influencing parameter is embedment depth (*h*) of the footing, according to sensitivity analysis.

Based on the best fit ANN model, a model equation has been developed to predict the ultimate bearing capacity of the footing resting on the GRS wall. Within the specified limits, the derived equation performs well. The numerical analysis study suggests an optimum offset distance for placing footing above the GRS wall is D = 2 to 4 m to get the maximum bearing capacity and least settlement.

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