

Research Article

Estimating the Ultimate Bearing Capacity for Strip Footing Near and within Slopes Using AI (GP, ANN, and EPR) Techniques

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Numerical and computational analyses surrounding the behavior of the bearing capacity of soils near or adjacent to slopes have been of great importance in earthwork constructions around the globe due to its unique nature. This phenomenon is encountered on pavement vertical curves, drainages, and vertical infrastructure foundations. In this work, multiple data were collected on the soil and footing interface parameters, which included width of footing, depth of foundation, distance of slope from the footing edge, soil bulk density, slope and frictional angles, and bearing capacity factors of cohesion and overburden pressure determined for the case of a foundation on or adjacent to a slope. The genetic programming (GP), evolutionary polynomial regression (EPR), and artificial neural network (ANN) intelligent techniques were employed to predict the ultimate bearing capacity of footing on or adjacent to a slope. The performance of the models was evaluated as well as compared their accuracy and robustness with the findings of Prandtl. The results were observed to show the superiority of GP, EPR, and ANN techniques over the computational works of Prandtl. In addition, the ANN outclassed the other artificial intelligence methods in the exercise.

1. Introduction

Building substructures are often constructed on or adjacent to slopes owing to the nonavailability of level ground, especially in hilly dominant topography encountered in highway vertical curves, embankments, erosion watersheds, etc. The study of the bearing capacity of loaded slopes is vital because they are more prone to fail than other types of earth structures [1–5]. Shallow foundations on slopes are mainly used for small- to medium-rise buildings. In frictional soils, the bearing capacity is mainly governed by foundation failure, while in cohesive soils, the bearing capacity of the foundation is controlled by the stability of the soil structure [6–9]. Recently, methods proposed by the researchers available to find the bearing capacity of shallow foundations on or near slopes include limit equilibrium analysis [10, 11], slip line analysis [12], variational calculus [13], the method of rigorous characteristics [14], improved movement

optimization [15], finite element analysis [16, 17], and multiblock analysis [9]. Determining the bearing capacity of a shallow substructure is a very important component of geotechnical engineering study and practice. Prandtl [18] is generally credited with some pioneer work in bearing capacity theory, having tried to establish the punching failure mechanism for thick metals based on the theory of plasticity. This theory gave rise to Terzaghi's [19] work, where the effects of soil internal angle of friction, soil cohesion, and surcharge (overburden pressure) were taken into consideration, giving rise to the bearing capacity factors (N_c , N_γ , and N_q). Meyerhof [20] improved on Terzaghi's superimposed theory to account for soil strength, footing size and shape, and slope. Vesic later considered the effects of shallow foundation shape on the ultimate bearing capacity [21]. Nevertheless, despite studies into the effects of foundation shape and depth [19], Meyerhof (1957 and 1974) [20–23], there has been few research works on the bearing capacity of

footings on and/or adjacent to slopes made of $c' - \phi'$ soils. Meyerhof studied general failure mechanisms for bearing capacity on purely cohesionless or cohesive soils adjacent to slopes using an assumed failure pattern based on the empirical observation from model footing tests in the laboratory. However, actual quantifiable results were not available for model verifications. Graham et al. [24] derived an analytical model for bearing capacity and stress distribution for footings placed upon slopes for cohesionless soils that was validated by experimental results. However, his work did not expand to soils with both cohesion and internal friction. Raj and Bharathi reported that Bowles provided a set of revised bearing capacity factors for $c' - \phi'$ soils based on an the assumed failure mechanism resembling that from Terzaghi, but limited to set of strength values. Griffiths [25] used the finite element analysis (FEA) to determine the bearing capacity of $c' - \phi'$ soils on slopes attaining considerable results. However, his N_γ factor recorded pitfall due to a convergence issue. Applying upper bound limits analysis, Kusakabe et al. [26] presented a series of design charts with dimensionless factors showing a reduction in bearing capacity compared to the conventional bearing capacity approach for footings placed on the level of the ground for soils with and without cohesion. A better analysis of the complex, complicated failure mechanism associated with the ultimate bearing capacity of strip footings on slopes requires use of tools that can account for the complex failure kinematics related to the soil-structure interaction and nonintuitive behavior of the soil collapse mechanism [27, 28]; in this case, artificial intelligence (AI) looks a better tool.

Recent discoveries in the field of artificial intelligence (AI) applications have risen in the development of accurate and dependable models for solving engineering problems [29–32]. Advances in the field of AI made it possible to produce models to adapt to difficulties associated with modelling soil and foundation behavior [33–36]. AI has been considered in the field of civil engineering for more than one and a half decade [37]. These models involve a simple black-box model to complex distributed physics-based models. Although there are numerous AI modelling algorithms, namely, genetic algorithm (GA), ant colony (AC), differential evolution (DE), particle swarm (PS), artificial neural network (ANN), genetic programming (GP) [35], and gene expression programming [32], artificial neural network (ANN) [36], genetic programming (GP), and gene expression programming have been widely used [29, 35].

2. Methodology

2.1. Preamble, Data Collection, and Statistical Study. Prantdl [18] proposed a mathematical formula for the ultimate bearing capacity of strip footing in a semi-infinity soil model with a horizontal ground surface based on an experimentally observed failure shape below footing as shown in equation (1). For strip footing near or within the slope, Prantdl suggested modified parameters $N'c = Nc (L1/L0)$ and $N'q = Nq (A1/A0)$, where $L0, L1, A0,$ and $A1$ are

illustrated in Figure 1 and could be calculated from the geometry. N_γ is still the same because the triangular wedges below the footings are the same in all cases. The aim of this research is to develop mathematical formulas for the modified $N'c$ and $N'q$ based on slope geometry and soil properties using different artificial intelligence (AI) techniques.

$$q_{ult} = CNc + qNq + \gamma BN\gamma, \quad (1)$$

where q_{ult} : ultimate bearing capacity of strip footing, C : soil cohesion, q : overburden pressure at foundation depth, γ : bulk density of soil below the footing, B : strip footing width, $Nc, Nq,$ and N_γ are parameters based on the soil internal friction angle ϕ , $Nq: e \pi \tan \phi. \tan 2 (45 + \phi/2)$, $Nc: (Nq - 1) \cot \phi$ ($Nc = 5$ for $\phi = 0$), and $N_\gamma: (Nq - 1) \tan \phi$.

From the foregoing, the methodology was to generate a database of 300 records; each record contains slope angle (β), angle of internal friction of soil (ϕ), ratio between the distance to the slope edge and footing width (b/B), and the ratio between foundation depth and footing width (Df/B) besides the calculated values for both $N'c$ and $N'q$. Table 1 includes the complete dataset, while Tables 2 and 3 summarize their statistical characteristics and the Pearson correlation matrix. Finally, Figure 2 shows the histograms for both inputs and outputs.

2.2. Research Program. Three different artificial intelligent (AI) techniques were used to predict the values of both $N'c$ and $N'q$. These techniques are genetic programming (GP), artificial neural network (ANN), and polynomial linear regression optimized using genetic algorithm which is known as evolutionary polynomial regression (EPR). All the three developed models were based on the generated database. Each model of the three developed models was based on different approaches (evolutionary approach for GP, mimicking biological neurons for ANN, and an optimized mathematical regression technique for EPR). However, for all developed models, prediction accuracy was evaluated in terms of sum of squared errors (SSE).

The following section discusses the results of each model. The accuracies of the developed models were evaluated by comparing the SSE between the predicted and calculated $N'c$ and $N'q$ values.

3. Predictive Model Results

3.1. Prediction of $N'c$ and $N'q$

3.1.1. Model (1)—Using the GP Technique. The developed GP model started with the one level of complexity and settled at five levels of complexity. The population size, survivor size, and number of generations were 10000, 30000, 50000, 75000, and 100000, respectively. Equations (2) and (3) present the output formulas for $N'c$ and $N'q$, while Figures 3(a) and 4(a) show their fitness. The average errors (%) of the total set are 20.7% and 31.6%, respectively, while the corresponding (R^2) values are 0.951 and 0.949.

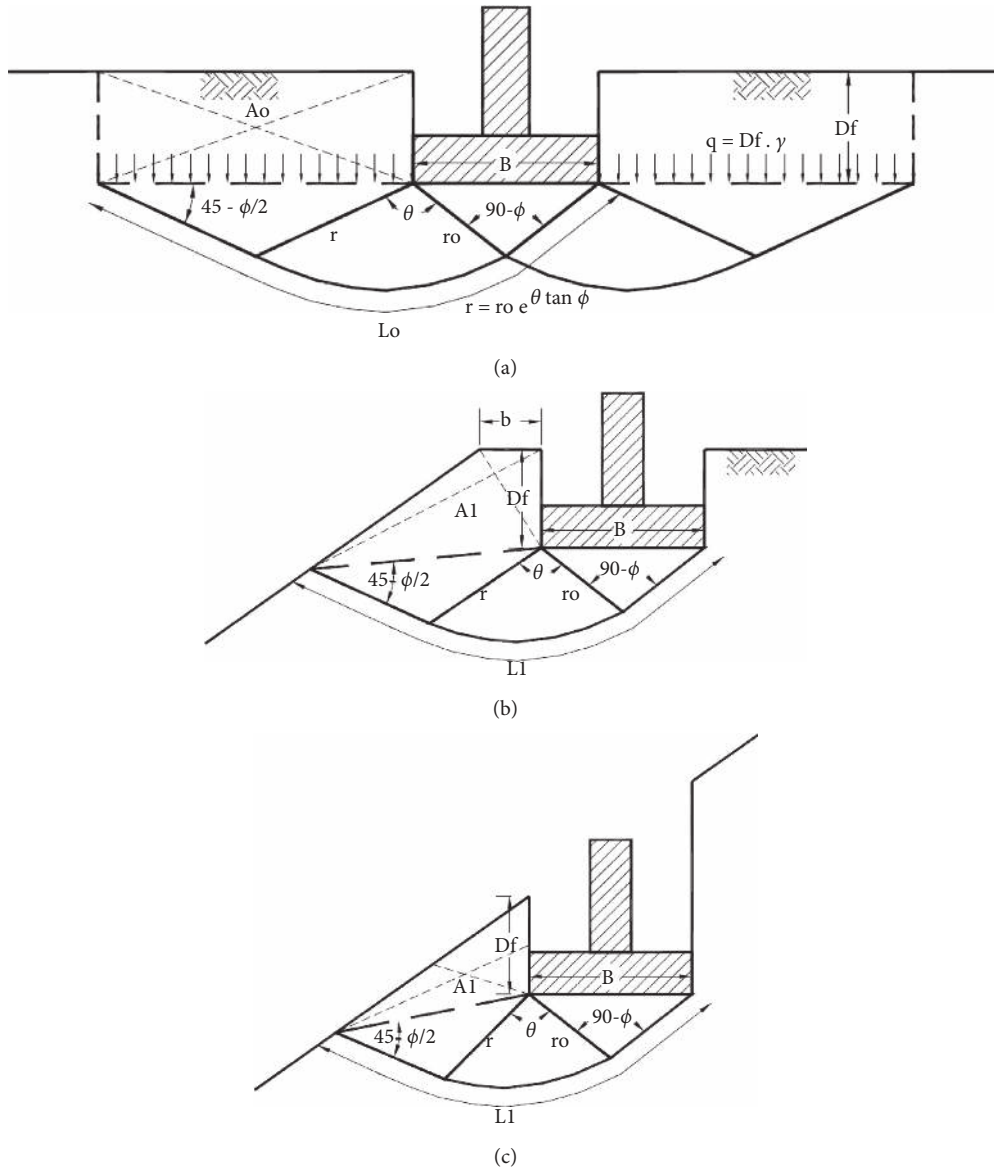


FIGURE 1: Shear failure mechanism for soil below strip footing after Prantdl [18]. (a) Case of strip footing with a horizontal ground surface. (b) Case of strip footing near the slope. (c) Case of strip footing within the slope.

$$N'c = e^{(5+\phi)/11} + \left(7 + \frac{b}{B} + \frac{D_f}{B}\right) - \left(\frac{7 + \beta}{7 + D_f/B}\right), \quad (2)$$

$$N'q = e^{(\phi-11/7+D_f/B)} - \left(\frac{\beta}{11(3 - D_f/B)}\right) + \left((3^{b/B})\left(\frac{D_f}{B(D_f/B)}\right)\right). \quad (3)$$

3.1.2. Model (2)—Using the ANN Technique. A back-propagation ANN with one hidden layer and Hyper Tan activation function was used to predict the values of $N'c$ and $N'q$. The used network layout is illustrated in Figure 5, and its connection weights are listed in Table 4. Since the used ANN has a nonlinear activation function, the equivalent equation is very complicated to be presented mathematically. The average errors in % of this network are 6.9% and 13.0% for $N'c$ and

$N'q$, respectively, while the corresponding R^2 values are 0.995 and 0.991. The relation between the calculated and predicted values is shown in Figures 3(b) and 4(b). The summation of connection weights of each input parameter is a good indication for its importance; accordingly, it was found that ϕ was the most important parameter with 78.6% of the total weights. β came in the second place with 10.1% and then b/B and D_f/B with 7.7% and 3.6%, respectively.

TABLE 1: The used database.

(b/B)	(D_f/B)	β	ϕ	$N'c$	$N'q$
0.0	0.0	0.0	0.0	5.14	1.03
0.0	0.0	0.0	10.0	8.34	2.47
0.0	0.0	0.0	20.0	14.83	6.40
0.0	0.0	0.0	30.0	30.14	18.40
0.0	0.0	0.0	40.0	75.31	64.20
0.0	0.0	5.0	0.0	5.01	1.03
0.0	0.0	5.0	10.0	8.07	2.47
0.0	0.0	5.0	20.0	14.19	6.40
0.0	0.0	5.0	30.0	28.43	18.40
0.0	0.0	5.0	40.0	69.67	64.20
0.0	0.0	10.0	0.0	4.89	1.03
0.0	0.0	10.0	10.0	7.80	2.47
0.0	0.0	10.0	20.0	13.57	6.40
0.0	0.0	10.0	30.0	26.80	18.40
0.0	0.0	10.0	40.0	64.42	64.20
0.0	0.0	20.0	0.0	4.63	1.03
0.0	0.0	20.0	10.0	7.28	2.47
0.0	0.0	20.0	20.0	12.39	6.40
0.0	0.0	20.0	30.0	23.78	18.40
0.0	0.0	20.0	40.0	55.01	64.20
0.0	0.0	30.0	0.0	4.38	1.03
0.0	0.0	30.0	10.0	6.77	2.47
0.0	0.0	30.0	20.0	11.28	6.40
0.0	0.0	30.0	30.0	21.05	18.40
0.0	0.0	30.0	40.0	55.01	64.20
0.0	0.0	60.0	0.0	3.62	1.03
0.0	0.0	60.0	10.0	5.33	2.47
0.0	0.0	60.0	20.0	8.33	6.40
0.0	0.0	60.0	30.0	14.34	18.40
0.0	0.0	60.0	40.0	28.56	64.20
0.5	0.5	5.0	0.0	5.14	0.83
0.5	0.5	5.0	10.0	8.34	1.85
0.5	0.5	5.0	20.0	14.83	4.41
0.5	0.5	5.0	30.0	30.14	11.67
0.5	0.5	5.0	40.0	75.31	37.38
0.5	0.5	10.0	0.0	5.14	0.94
0.5	0.5	10.0	10.0	8.34	2.03
0.5	0.5	10.0	20.0	14.93	4.73
0.5	0.5	10.0	30.0	30.14	12.17
0.5	0.5	10.0	40.0	74.12	37.80
0.5	0.5	20.0	0.0	5.14	1.03
0.5	0.5	20.0	10.0	8.34	2.34
0.5	0.5	20.0	20.0	14.83	5.19
0.5	0.5	20.0	30.0	29.79	12.66
0.5	0.5	20.0	40.0	65.74	36.91
0.5	0.5	30.0	0.0	5.14	1.03
0.5	0.5	30.0	10.0	8.34	2.47
0.5	0.5	30.0	20.0	14.83	5.36
0.5	0.5	30.0	30.0	27.64	12.40
0.5	0.5	30.0	40.0	58.32	34.02
0.5	0.5	60.0	0.0	5.14	1.03
0.5	0.5	60.0	10.0	8.07	2.13
0.5	0.5	60.0	20.0	12.37	3.92
0.5	0.5	60.0	30.0	20.74	7.83
0.5	0.0	5.0	0.0	5.14	1.03
0.5	0.0	5.0	10.0	8.25	2.47
0.5	0.0	5.0	20.0	14.45	6.40
0.5	0.0	5.0	40.0	70.40	64.20
0.5	0.0	10.0	0.0	5.14	1.03
0.5	0.0	10.0	10.0	8.15	2.47

TABLE 1: Continued.

(b/B)	(D_f/B)	β	ϕ	$N'c$	$N'q$
0.5	0.0	10.0	20.0	14.08	6.40
0.5	0.0	10.0	30.0	27.62	18.40
0.5	0.0	10.0	40.0	65.87	64.20
0.5	0.0	20.0	0.0	5.12	1.03
0.5	0.0	20.0	10.0	6.96	2.47
0.5	0.0	20.0	20.0	13.40	6.40
0.5	0.0	20.0	30.0	25.39	18.40
0.5	0.0	20.0	40.0	57.86	64.20
0.5	0.0	30.0	0.0	5.10	1.03
0.5	0.0	30.0	10.0	7.77	2.47
0.5	0.0	30.0	20.0	12.75	6.40
0.5	0.0	30.0	30.0	23.40	18.40
0.5	0.0	30.0	40.0	51.07	64.20
0.5	0.0	60.0	0.0	4.86	1.03
0.5	0.0	60.0	10.0	7.07	2.47
0.5	0.0	60.0	20.0	10.89	6.40
0.5	0.0	60.0	30.0	18.40	18.40
0.5	0.0	60.0	40.0	35.81	64.20
1.0	0.5	5.0	0.0	5.14	0.86
1.0	0.5	5.0	10.0	8.34	1.95
1.0	0.5	5.0	20.0	14.83	4.70
1.0	0.5	5.0	30.0	30.14	12.53
1.0	0.5	5.0	40.0	75.31	40.33
1.0	0.5	10.0	0.0	5.14	1.01
1.0	0.5	10.0	10.0	8.34	2.26
1.0	0.5	10.0	20.0	14.83	5.35
1.0	0.5	10.0	30.0	30.14	13.94
1.0	0.5	10.0	40.0	75.31	43.57
1.0	0.5	20.0	0.0	5.14	1.03
1.0	0.5	20.0	10.0	8.34	2.47
1.0	0.5	20.0	20.0	14.83	6.40
1.0	0.5	20.0	30.0	30.14	16.29
1.0	0.5	20.0	40.0	68.61	47.76
1.0	0.5	30.0	0.0	5.14	1.03
1.0	0.5	30.0	10.0	8.34	2.47
1.0	0.5	30.0	20.0	14.83	6.40
1.0	0.5	30.0	30.0	29.80	17.81
1.0	0.5	30.0	40.0	62.51	48.90
1.0	0.5	60.0	0.0	5.14	1.03
1.0	0.5	60.0	10.0	8.34	2.47
1.0	0.5	60.0	20.0	14.83	6.40
1.0	0.5	60.0	30.0	24.80	15.66
1.0	0.5	60.0	40.0	47.25	35.82
1.0	0.0	5.0	0.0	5.14	1.03
1.0	0.0	5.0	10.0	8.34	2.47
1.0	0.0	5.0	20.0	14.71	6.40
1.0	0.0	5.0	30.0	29.25	18.40
1.0	0.0	5.0	40.0	71.13	64.20
1.0	0.0	10.0	0.0	5.14	1.03
1.0	0.0	10.0	10.0	8.34	2.47
1.0	0.0	10.0	20.0	14.60	6.40
1.0	0.0	10.0	30.0	29.43	18.40
1.0	0.0	10.0	40.0	67.33	64.20
1.0	0.0	20.0	0.0	5.14	1.03
1.0	0.0	20.0	10.0	8.34	2.47
1.0	0.0	20.0	20.0	14.41	6.40
1.0	0.0	20.0	30.0	26.99	18.40
1.0	0.0	20.0	40.0	60.74	64.20
1.0	0.0	30.0	0.0	5.14	1.03
1.0	0.0	30.0	10.0	8.34	2.47

TABLE 1: Continued.

(b/B)	(D_f/B)	β	ϕ	$N'c$	$N'q$
1.0	0.0	30.0	20.0	14.23	6.40
1.0	0.0	30.0	30.0	25.74	18.40
1.0	0.0	30.0	40.0	55.26	64.20
1.0	0.0	60.0	0.0	5.14	1.03
1.0	0.0	60.0	10.0	8.34	2.47
1.0	0.0	60.0	20.0	13.43	6.40
1.0	0.0	60.0	30.0	22.46	18.40
1.0	0.0	60.0	40.0	43.06	64.20
0.0	1.0	0.0	0.0	5.14	1.03
0.0	1.0	0.0	10.0	8.34	2.47
0.0	1.0	0.0	20.0	14.83	6.40
0.0	1.0	0.0	30.0	30.14	18.40
0.0	1.0	5.0	0.0	5.14	0.99
0.0	1.0	5.0	10.0	8.34	2.13
0.0	1.0	5.0	20.0	14.83	4.92
0.0	1.0	5.0	30.0	30.14	12.55
0.0	1.0	5.0	40.0	75.31	38.59
0.0	1.0	10.0	0.0	5.14	1.03
0.0	1.0	10.0	10.0	8.34	2.19
0.0	1.0	10.0	20.0	14.83	4.91
0.0	1.0	10.0	30.0	30.14	12.16
0.0	1.0	10.0	40.0	75.31	36.24
0.0	1.0	20.0	0.0	5.14	1.03
0.0	1.0	20.0	10.0	8.34	2.17
0.0	1.0	20.0	20.0	14.83	4.63
0.0	1.0	20.0	30.0	30.14	10.88
0.0	1.0	30.0	0.0	5.14	1.03
0.0	1.0	30.0	10.0	8.34	1.89
0.0	1.0	30.0	20.0	14.83	4.04
0.0	1.0	30.0	30.0	29.17	9.05
0.0	1.0	30.0	40.0	61.39	24.02
0.0	1.0	60.0	0.0	5.06	0.45
0.0	1.0	60.0	10.0	7.33	0.77
0.0	1.0	60.0	40.0	36.93	6.27
0.0	0.5	0.0	0.0	5.14	1.03
0.0	0.5	0.0	10.0	8.34	2.47
0.0	0.5	0.0	20.0	14.83	6.40
0.0	0.5	0.0	30.0	30.14	18.40
0.0	0.5	5.0	0.0	5.14	0.79
0.0	0.5	5.0	10.0	8.34	1.69
0.0	0.5	5.0	20.0	14.83	4.03
0.0	0.5	5.0	30.0	30.14	10.65
0.0	0.5	10.0	0.0	5.14	0.79
0.0	0.5	10.0	10.0	8.34	1.70
0.0	0.5	10.0	20.0	14.83	3.94
0.0	0.5	10.0	30.0	30.14	10.15
0.0	0.5	20.0	0.0	5.14	0.79
0.0	0.5	20.0	10.0	8.34	1.62
0.0	0.5	20.0	20.0	14.83	3.58
0.0	0.5	20.0	30.0	28.19	8.79
0.0	0.5	30.0	0.0	5.14	0.72
0.0	0.5	30.0	10.0	8.34	1.43
0.0	0.5	30.0	20.0	13.83	3.03
0.0	0.5	30.0	30.0	25.11	7.09
0.0	0.5	60.0	0.0	4.34	0.28
0.0	0.5	60.0	10.0	6.33	0.50
0.0	0.5	60.0	20.0	9.81	0.95
0.0	0.5	60.0	30.0	16.68	1.98
0.5	1.0	5.0	0.0	5.14	1.03
0.5	1.0	5.0	10.0	8.34	2.25

TABLE 1: Continued.

(b/B)	(D_f/B)	β	ϕ	$N'c$	$N'q$
0.5	1.0	5.0	20.0	14.83	5.19
0.5	1.0	5.0	30.0	30.14	13.22
0.5	1.0	5.0	40.0	75.31	40.59
0.5	1.0	10.0	0.0	5.14	1.03
0.5	1.0	10.0	10.0	8.34	2.44
0.5	1.0	10.0	20.0	14.83	5.47
0.5	1.0	10.0	30.0	30.14	13.52
0.5	1.0	10.0	40.0	75.31	40.14
0.5	1.0	20.0	0.0	5.14	1.03
0.5	1.0	20.0	10.0	8.34	2.47
0.5	1.0	20.0	20.0	14.83	5.80
0.5	1.0	20.0	30.0	30.14	13.56
0.5	1.0	20.0	40.0	73.61	37.73
0.5	1.0	30.0	0.0	5.14	1.03
0.5	1.0	30.0	10.0	8.34	2.47
0.5	1.0	30.0	20.0	14.83	5.77
0.5	1.0	30.0	30.0	30.14	12.81
0.5	1.0	30.0	40.0	65.57	33.55
0.5	1.0	60.0	0.0	5.14	1.03
0.5	1.0	60.0	10.0	8.34	2.04
0.5	1.0	60.0	20.0	14.83	3.63
0.5	1.0	60.0	30.0	23.09	7.01
0.5	1.0	60.0	40.0	44.19	15.55
1.0	1.0	5.0	0.0	5.14	1.03
1.0	1.0	5.0	10.0	8.34	2.34
1.0	1.0	5.0	20.0	14.83	5.41
1.0	1.0	5.0	30.0	30.14	13.81
1.0	1.0	5.0	40.0	75.31	42.45
1.0	1.0	10.0	0.0	5.14	1.03
1.0	1.0	10.0	10.0	8.34	2.47
1.0	1.0	10.0	20.0	14.83	5.95
1.0	1.0	10.0	30.0	30.14	14.75
1.0	1.0	10.0	40.0	75.31	43.83
1.0	1.0	20.0	0.0	5.14	1.03
1.0	1.0	20.0	10.0	8.34	2.47
1.0	1.0	20.0	20.0	14.83	6.40
1.0	1.0	20.0	30.0	30.14	16.11
1.0	1.0	20.0	40.0	75.31	44.80
1.0	1.0	30.0	0.0	5.14	1.03
1.0	1.0	30.0	10.0	8.34	2.47
1.0	1.0	30.0	20.0	14.83	6.40
1.0	1.0	30.0	30.0	30.14	16.11
1.0	1.0	30.0	40.0	69.76	43.38
1.0	1.0	60.0	0.0	5.14	1.03
1.0	1.0	60.0	10.0	8.34	2.47
1.0	1.0	60.0	20.0	14.83	6.36
1.0	1.0	60.0	30.0	27.14	12.28
1.0	1.0	60.0	40.0	51.44	27.10
1.5	1.5	5.0	0.0	5.14	1.03
1.5	1.5	5.0	10.0	8.34	2.47
1.5	1.5	5.0	20.0	14.83	6.02
1.5	1.5	5.0	30.0	30.14	14.95
1.5	1.5	10.0	0.0	5.14	1.03
1.5	1.5	10.0	10.0	8.34	2.47
1.5	1.5	10.0	20.0	14.83	6.33
1.5	1.5	10.0	30.0	30.14	15.26
1.5	1.5	10.0	40.0	75.31	43.94
1.5	1.5	20.0	0.0	5.14	1.03
1.5	1.5	20.0	10.0	8.34	2.47
1.5	1.5	20.0	20.0	14.83	6.40

TABLE 1: Continued.

(b/B)	(D _f /B)	β	φ	N' <i>c</i>	N' <i>q</i>
0.5	1.5	20.0	30.0	30.14	15.20
0.5	1.5	20.0	40.0	75.31	41.04
0.5	1.5	30.0	0.0	5.14	1.03
0.5	1.5	30.0	10.0	8.34	2.47
0.5	1.5	30.0	20.0	14.83	6.40
0.5	1.5	30.0	30.0	30.14	14.23
0.5	1.5	30.0	40.0	72.83	36.18
0.5	1.5	60.0	0.0	5.14	1.03
0.5	1.5	60.0	10.0	8.34	2.19
0.5	1.5	60.0	20.0	14.83	3.85
0.5	1.5	60.0	30.0	25.43	7.28
0.5	1.5	60.0	40.0	48.37	15.77
0.0	1.5	0.0	0.0	5.14	1.03
0.0	1.5	0.0	10.0	8.34	2.47
0.0	1.5	0.0	20.0	14.83	6.40
0.0	1.5	0.0	30.0	30.14	18.40
0.0	1.5	5.0	0.0	5.14	1.03
0.0	1.5	5.0	10.0	8.34	2.47
0.0	1.5	5.0	20.0	14.83	5.79
0.0	1.5	5.0	30.0	30.14	14.40
0.0	1.5	10.0	0.0	5.14	1.03
0.0	1.5	10.0	10.0	8.34	2.47
0.0	1.5	10.0	20.0	14.83	5.85
0.0	1.5	10.0	30.0	30.14	14.13
0.0	1.5	20.0	0.0	5.14	1.03
0.0	1.5	20.0	10.0	8.34	2.47
0.0	1.5	20.0	20.0	14.83	5.65
0.0	1.5	20.0	30.0	30.14	12.93
0.0	1.5	20.0	40.0	75.31	35.14
0.0	1.5	30.0	0.0	5.14	1.03
0.0	1.5	30.0	10.0	8.34	2.47
0.0	1.5	30.0	20.0	14.83	5.04
0.0	1.5	30.0	30.0	30.14	10.99
0.0	1.5	30.0	40.0	68.64	28.23
0.0	1.5	60.0	0.0	5.14	0.62
0.0	1.5	60.0	10.0	8.34	1.04
1.0	1.5	5.0	0.0	5.14	1.03
1.0	1.5	5.0	10.0	8.34	2.47
1.0	1.5	5.0	20.0	14.83	6.21
1.0	1.5	5.0	30.0	30.14	15.45
1.0	1.5	10.0	0.0	5.14	1.03
1.0	1.5	10.0	10.0	8.34	2.47
1.0	1.5	10.0	20.0	14.83	6.40
1.0	1.5	10.0	30.0	30.14	16.30
1.0	1.5	10.0	40.0	75.31	46.93
1.0	1.5	20.0	0.0	5.14	1.03
1.0	1.5	20.0	10.0	8.34	2.47
1.0	1.5	20.0	20.0	14.83	6.40
1.0	1.5	20.0	30.0	30.14	17.48
1.0	1.5	20.0	40.0	75.31	46.85
1.0	1.5	30.0	0.0	5.14	1.03
1.0	1.5	30.0	10.0	8.34	2.47
1.0	1.5	30.0	20.0	14.83	6.17
1.0	1.5	30.0	30.0	30.14	17.48
1.0	1.5	30.0	40.0	75.31	44.32
1.0	1.5	60.0	0.0	5.14	1.03
1.0	1.5	60.0	10.0	8.34	2.47
1.0	1.5	60.0	20.0	14.83	6.17
1.0	1.5	60.0	30.0	29.49	11.69
1.0	1.5	60.0	40.0	55.63	25.26

TABLE 2: Statistical analysis of the generated database.

	Minimum	Maximum	Mean	Std. deviation	Variance
<i>b/B</i>	0.00	1.00	0.492	0.412	0.170
<i>D_f/B</i>	0.00	1.50	0.735	0.561	0.315
β	0.00	60.00	23.217	19.403	376.491
φ	0.00	40.00	18.900	13.848	191.763
N' <i>c</i>	3.62	75.31	21.972	21.100	445.201
N' <i>q</i>	0.28	64.20	12.204	16.766	281.101

TABLE 3: Pearson correlation matrix.

	<i>b/B</i>	<i>D_f/B</i>	β	φ	N' <i>c</i>	N' <i>q</i>
<i>b/B</i>	1.000					
<i>D_f/B</i>	0.023	1.000				
β	0.119	-0.011	1.000			
φ	0.069	-0.031	0.008	1.000		
N' <i>c</i>	0.104	0.023	-0.090	0.867	1.000	
N' <i>q</i>	0.105	-0.166	-0.044	0.787	0.889	1.000

3.1.3. *Model (3)—Using the EPR Technique.* Finally, the developed EPR models were limited to the pentagonal level, for 4 inputs; there are 226 possible terms ($56 + 35 + 20 + 10 + 4 + 1 = 126$) as follows:

$$\begin{aligned}
& \sum_{i=1}^{i=4} \sum_{j=1}^{j=4} \sum_{k=1}^{k=4} \sum_{l=1}^{l=4} \sum_{m=1}^{m=4} X_i \cdot X_j \cdot X_k \cdot X_l \cdot X_m + \sum_{i=1}^{i=4} \sum_{j=1}^{j=4} \sum_{k=1}^{k=4} \sum_{l=1}^{l=4} X_i \cdot X_j \cdot X_k \cdot X_l \\
& + \sum_{i=1}^{i=4} \sum_{j=1}^{j=4} \sum_{k=1}^{k=4} X_i \cdot X_j \cdot X_k \\
& + \sum_{i=1}^{i=4} \sum_{j=1}^{j=4} X_i \cdot X_j + \sum_{i=1}^{i=4} X_i + C.
\end{aligned} \tag{4}$$

The GA technique was applied on these 126 terms to select the most effective 6 terms to predict the values of N'*c* and N'*q*. The output is illustrated in equations (3) and (4), and their fitness is shown in Figures 3(c) and 4(c). The average errors (%) and R² values were 7.2%–0.994 for N'*c* and 17.3%–0.984 for N'*q*. Both equations (5) and (6) show that φ existed in each term and it got the highest power, which indicated that it is the most effective parameter, and other parameters almost had the same importance. Meanwhile, the results of all the developed models are summarized in Tables 5 and 6.

$$N'c = \frac{\phi^4}{45000} + \frac{\phi}{4.1} + \frac{b \cdot \beta \cdot \phi}{205B} + \frac{D_f \cdot \phi^3}{8250B} - \frac{\beta \cdot \phi^3}{98000} + 5.165, \tag{5}$$

$$\begin{aligned}
N'q = & \frac{\phi^4}{43350} + \frac{D_f^2 \cdot \phi^3}{2140B^2} + \frac{D_f \cdot b \cdot \beta \cdot \phi^2}{4170B^2} - \frac{D_f \cdot \phi^3}{1335B} \\
& - \frac{D_f \cdot \beta \cdot \phi^3}{100000B} + 2.253.
\end{aligned} \tag{6}$$

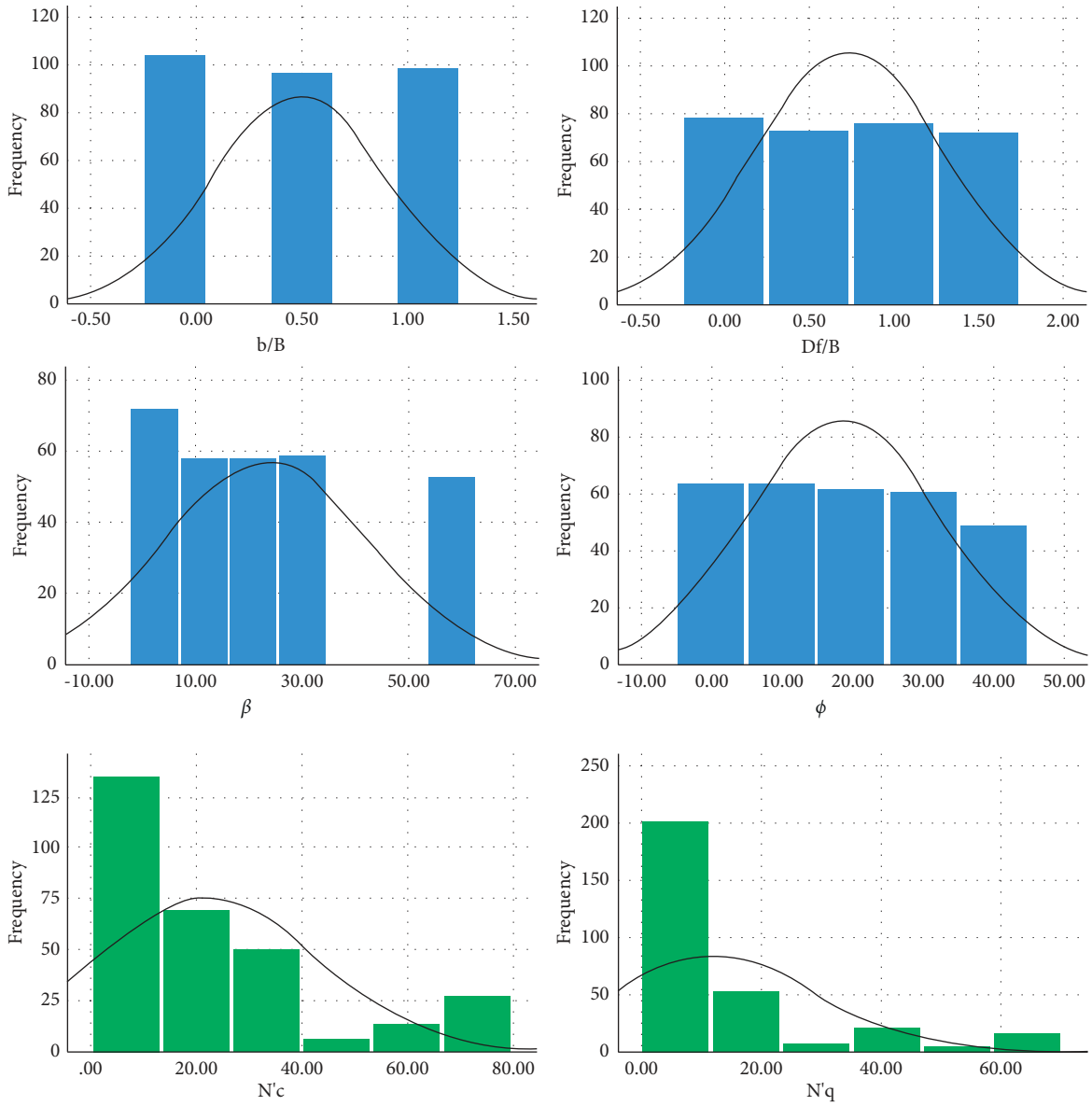


FIGURE 2: Distribution histograms for inputs (in blue) and outputs (in green).

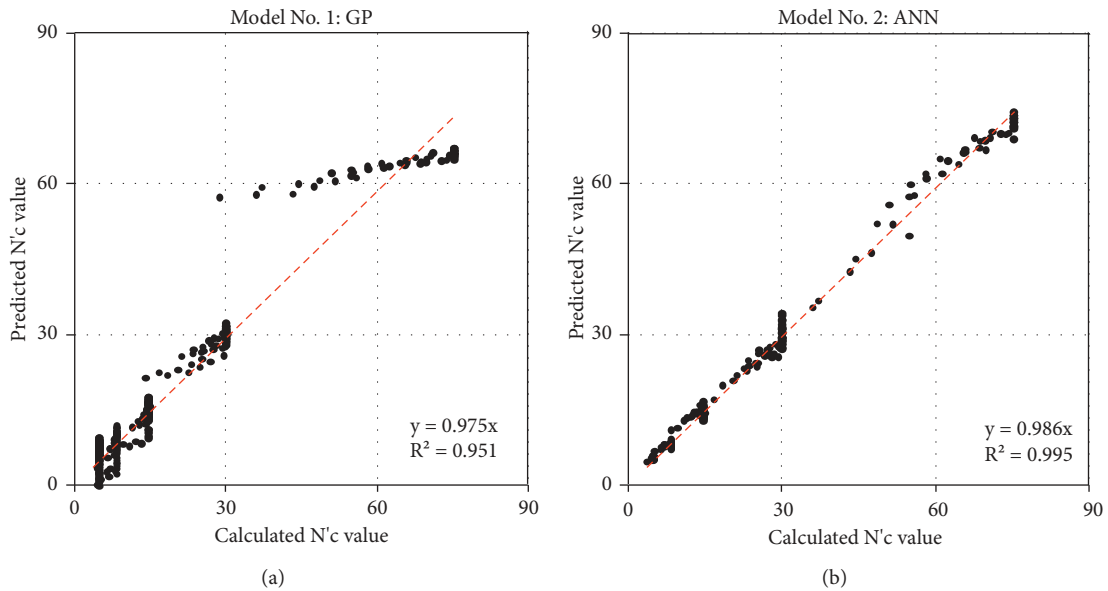
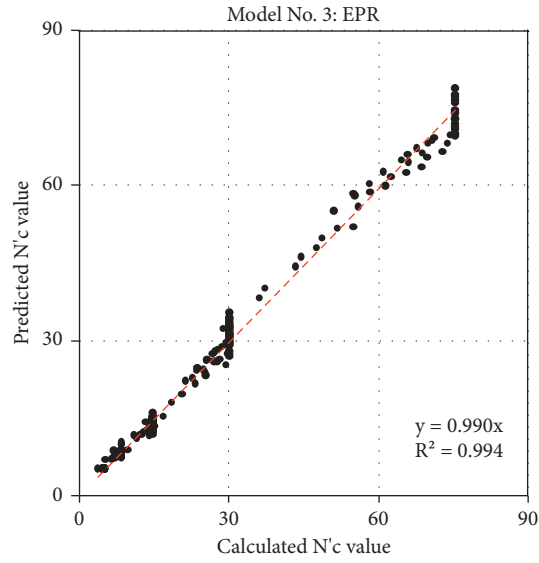
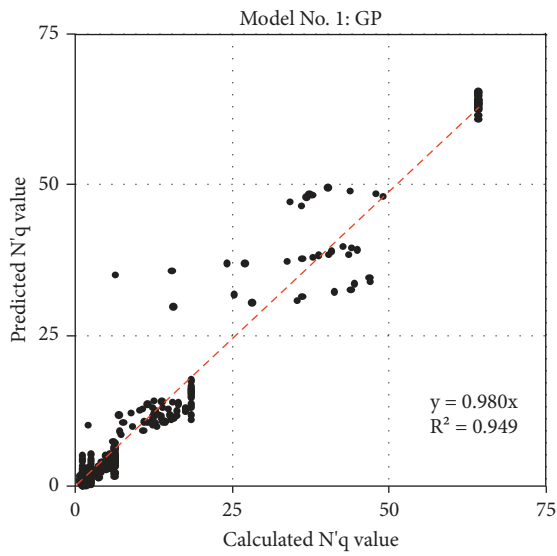


FIGURE 3: Continued.

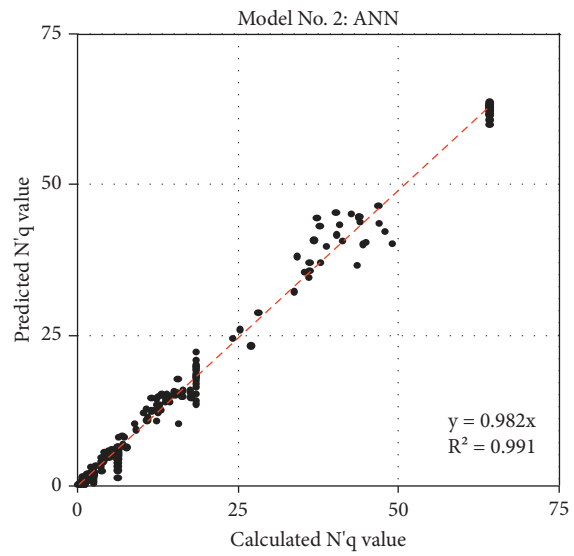


(c)

FIGURE 3: Relation between the predicted and calculated N'_c values using the developed (a) GP, (b) ANN, and (c) EPR models.



(a)



(b)

FIGURE 4: Continued.

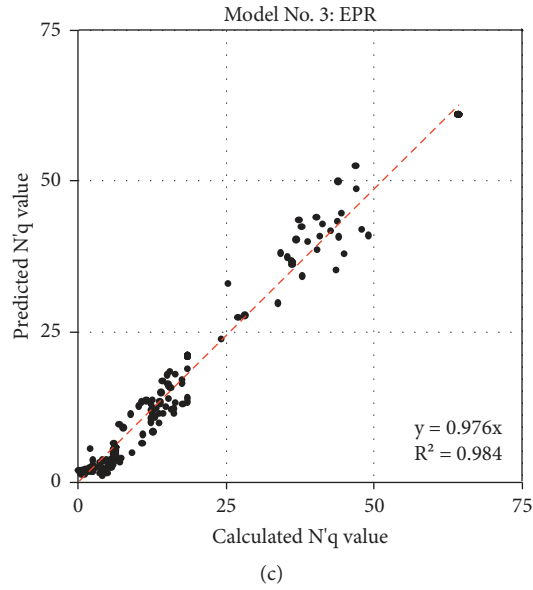


FIGURE 4: Relation between the predicted and calculated $N'q$ values using the developed (a) GP, (b) ANN, and (c) EPR models.

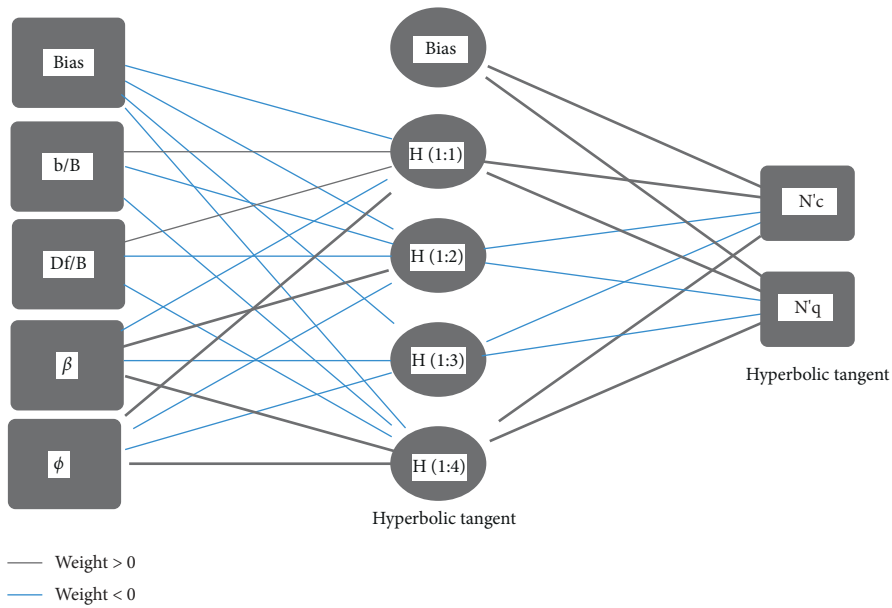


FIGURE 5: Layout for the developed ANN.

TABLE 4: Connection weights of the developed ANN model.

Predictor	Hidden layer 1				Output layer	
	$H(1:1)$	$H(1:2)$	$H(1:3)$	$H(1:4)$	$N'c$	$N'q$
Input layer	(Bias)	-3.177	-0.836	-0.387	-3.987	
	b/B	0.085	-0.333	0.077	-0.177	
	D_f/B	0.237	-0.185	0.035	-1.768	
	β	-0.511	0.563	-0.187	0.415	
	ϕ	2.644	-0.109	-0.750	2.130	
Hidden layer 1	(Bias)				0.365	0.592
	$H(1:1)$				2.027	0.730
	$H(1:2)$				-0.608	-1.372
	$H(1:3)$				-1.283	-1.470
	$H(1:4)$				0.053	2.560

TABLE 5: Accuracies of the developed models for $N'c$.

Technique	Developed equation	Error (%)	R^2
GP	Equation (2)	20.7	0.951
ANN	Table 4	6.9	0.995
EPR	Equation (4)	7.2	0.994

TABLE 6: Accuracies of the developed models for $N'q$.

Technique	Developed equation	Error (%)	R^2
GP	Equation (3)	31.6	0.949
ANN	Table 4	13.0	0.991
EPR	Equation (5)	17.3	0.984

4. Conclusions

This research presents three models using three AI techniques, namely, GP, ANN, and EPR, to predict the modified bearing capacity parameters $N'c$ and $N'q$ using slope angle (β), angle of internal friction of soil (ϕ), ratio between the distance to the slope edge and footing width (b/B), and the ratio between foundation depth and footing width (D_f/B). The results of comparing the accuracies of the developed models could be concluded in the following points:

- (i) Although five levels of complexity (128 genes in the chromosome) were used in the GP model, the achieved accuracy was still low (79.3% and 68.4% for $N'c$ and $N'q$, respectively)
- (ii) The prediction accuracies of ANN and EPR models are close, 93.1% and 92.8% for $N'c$ and 87.0% and 82.7% for $N'q$, which gives an advantage to the EPR model because its output is a simple equation and could be applied either manually or implemented in software unlike the complicated output of the ANN which cannot be applied manually
- (iii) The importance analysis of both ANN and EPR models indicated that ($N'c$ and $N'q$) values were mainly governed by ϕ , while other parameters are minors
- (iv) All developed models showed that $N'c$ and $N'q$ values increase with increasing ϕ , b/B , and D_f/B values and with decreasing β value
- (v) GA technique successfully reduced the 126 terms of the conventional PLR quadratic formula to only 6 terms without a significant impact on its accuracy
- (vi) Like any other regression technique, the generated formulas are valid within the considered range of parameter values; beyond this range, the prediction accuracy should be verified

Abbreviations

AI:	Artificial intelligence
C:	Cohesion
q:	Overburden pressure at foundation depth
γ :	Bulk density of soil below footing
B:	Strip footing width

$L0$:	Length of the failure wedge of normal footing
$L1$:	Length of the failure wedge of slopy footing
$A0$:	Area of a rectangular mass on normal footing
$A1$:	Area of a triangular mass on slopy footing
b :	Distance of the slope from the footing edge
β :	Slope angle
ϕ :	Friction
Nc :	Bearing capacity coefficient of cohesion
Nq :	Bearing capacity coefficient of overburden pressure
$N\gamma$:	Bearing capacity coefficient of bulk density
$N'c$:	Predicted bearing capacity coefficient of cohesion on the slope
$N'q$:	Predicted bearing capacity coefficient of overburden pressure on the slope
ANN:	Artificial neural network
GP:	Genetic programming
GA:	Genetic algorithm
EPR:	Evolutionary polynomial regression
PLR:	Polynomial linear regression
SSE:	Sum of squared errors
R^2 :	Coefficient of determination.

Data Availability

The underlying data supporting the results of this research are reported in the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest in the publication of this research work.

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