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DETERMINATION OF ULTIMATE BEARING CAPACITY OF SHALLOW FOUNDATIONS USING LSSVM ALGORITHM

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Abstract. Accurate determination of the ultimate bearing capacity (UBC) of shallow foundations is vital for the safety of structures and buildings. Due to the inherent spatial variability characteristics of soil properties, some new approaches are needed to accurately determine the UBC of shallow foundations. The objective of this study is to develop a hybrid least squares support vector machine (LSSVM) and an improved particle swarm optimization (IPSO) algorithm for determining the UBC of shallow foundations. To validate the hybrid IPSO-LSSVM model, a comparison of the predictions was carried out among different models and theoretical methods. Three statistical indexes, namely the root-mean-square error (RMSE), the mean absolute error (MAE) and the correlation coefficient (R) were employed to measure and evaluate the performance of these models. The results showed that the developed hybrid IPSO-LSSVM model can be used for determining the UBC of shallow foundations with high accuracy.

Keywords: ultimate bearing capacity, uncertainty, spatial variability, algorithm.

Introduction

It is vital to accurately determine the ultimate bearing capacity (UBC) of shallow foundations for the reason that it is directly related to the safety of structures and buildings (Shahnazari & Tutunchian, 2012; Sadrossadat, Soltani, Mousavi, Marandi, & Alavi, 2013; Cicek & Guler, 2015). In 1943 Terzaghi suggested a general bearing capacity theory which can be applied for a strip foundation (Terzaghi, 1943). Afterwards, Meyerhof (1963), Hansen (1970) and Vesic (1973) have also developed many theories of UBC of shallow foundations. Althouth there are many different theories of UBC, they have the same basic form and can be written as follows:

$$q_u = \gamma D N_q S_q d_q + 0.5 B N_\gamma S_\gamma d_\gamma; \tag{1a}$$

$$N_q = e^{\pi \tan\varphi} \tan^2\left(45^\circ + \frac{\varphi}{2}\right); \tag{1b}$$

$$N_\gamma = \left(N_q - 1\right)\tan\left(1.4\varphi\right); \tag{1c}$$

$$S_q = S_\gamma = \begin{cases} 1 + 0.2\tan\left(45^\circ + \frac{\varphi}{2}\right)^2 \frac{B}{L} & \varphi > 10^\circ \\ 1 & \varphi = 0^\circ \end{cases}; \tag{1d}$$

$$d_q = d_\gamma = \begin{cases} 1 + 0.1\sqrt{\tan\left(45^\circ + \frac{\varphi}{2}\right)^2} \frac{D}{B} & \varphi > 10^\circ \\ 1 & \varphi = 0^\circ \end{cases}, \tag{1e}$$

where q_u – UBC of footing; B – foundation width (m); D – foundation depth (m); L – foundation length (m); γ = soil unit weight (kN/m^3); φ – internal friction angle (°). N_q and N_γ are the surcharge and density factors, respectively. S_q and S_γ are the nondimensional shape factors; d_q and d_γ are the nondimensional depth factors.

As can be seen from Eqns (1a)–(1e), there are many factors that can potentially affect the accurate determination of UBC of shallow foundations, such as the foundation geometry and physical properties of the soil beneath it. These factors have the inherent characteristics of uncertainty and spatial variability. Furthermore, the establishment of these classical formulae needs to meet some simplifying assumptions, which always provides inaccurate determination of UBC. Therefore, it is necessary to develop some new methods to accurately determine the UBC of shallow foundations. The objective of this study is to develop a hybrid least squares support vector machine

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(LSSVM) and an improved particle swarm optimization (IPSO) algorithm for determining the UBC of shallow foundations. To validate the hybrid IPSO-LSSVM model, a comparison of the predictions was conducted among different models and theoretical methods. Three statistical indexes, namely the root-mean-square error (RMSE), the mean absolute error (MAE) and the correlation coefficient (R) were employed to measure and evaluate the performance of these models. The research of this study can provide reference for determining the UBC of shallow foundations.

1. Literature review

As stated above, the complexity of analysis of UBC of shallow foundations calls for new and innovative approaches. With the vast developments in computational software and hardware recently, several alternative artificial intelligence (AI) approaches such as artificial neural networks (ANNs) have emerged and been used widely in many regards (Shahin, Maier, & Jaksa, 2001). For example, Neaupane and Achet (2004) investigated the slope movements by utilizing back-propagation neural network (BPNN). They concluded that the BPNN model can provide a satisfactory result for landslide monitoring. Das and Basudhar (2006) proposed an ANN model to estimate the lateral load capacity of piles in clay. They concluded that the proposed ANN model outperforms the available empirical methods. Lin, Chang, Wu, and Juang (2009) investigated the failure potential of highway slopes by utilizing ANN model. They concluded that the ANN model can be employed for prediction of the stability of slopes. Kalinli, Acar, and Gunduz (2011) proposed two methods to estimate the UBC of shallow foundations. They concluded that the ANN model outperforms the other models. Khanlari, Heidari, Momeni, and Abdilor (2012) investigated the shear strength parameters of soils by utilizing ANN and multivariate regression (MR) methods. They concluded that these methods can be used for estimation of shear strength parameters of soils. Baziar, Kashkooli, and Azizkandi (2012) developed two ANN and nonlinear multi regression models to predict the pile shaft resistance by utilizing cone penetration tests (CPT) results. They concluded that the ANN and nonlinear multi regression models have superiority over traditional approaches in predicting pile shaft resistance. Alkroosh and Nikraz (2012) investigated pile capacity under axial loads by utilizing soft computing methods. They concluded that the developed intelligent model has high accuracy for prediction of pile capacity. Mustafa, Rezaur, Rahardjo, and Isa (2012) estimated the pore-water pressure by utilizing radial basis function (RBF) neural network. They concluded that the developed RBF neural network model is suitable for estimation of pore-water pressure responses to rainfall. Shoaei, Alkarni, Noorzaei, Jaafar, and Huat (2012) reviewed and discussed three approaches including the classical method, finite element method (FEM) and ANN for prediction of UBC of two-layered soils. They concluded that there is still plenty of room for the application of ANN in predicting the UBC of two-layered soils. Alkroosh and Nikraz (2014) developed a new evolutionary model to predict the pile dynamic capacity. They concluded that the developed evolutionary model outperforms the traditional models in estimating the pile capacity. Esamaldeen, Wu, and Abdelazim (2014) modeled the uniaxial compressive strength (UCS) of anisotropic amphibolite rocks by utilizing several intelligent technologies, i.e., ANN, fuzzy inference system (FIS) and multivariate regression (MR). They concluded that the ANN outperforms the other two models, namely FIS and MR. Momeni, Nazir, Jahed Armaghani, and Maizir (2014) developed a genetic algorithm (GA) based ANN model to determine the pile bearing capacity. They concluded that the GA-ANN model can be used for estimating the pile bearing capacity. Ng, Yuen, and Lau (2015) developed a predictive model for estimation of UCS of rocks. They concluded that the proposed model shows satisfactory performance. Armaghani, Shoib, Faizi, and Rashid (2017) proposed a hybrid particle swarm optimization (PSO) based ANN model to estimate the UBC of rock socketed piles. They concluded that the proposed PSO-ANN model outperforms conventional ANN model. Nejad and Jaksa (2017) presented an ANN model to estimate pile behavior by utilizing the CPT data. They concluded that the ANN model has superiority than other traditional methods. Yilmazkaya, Dagdelenler, Ozcelik, and Sonmez (2018) investigated the performance parameters of mono-wire cutting machine by utilizing ANN models. They concluded that the ANN models can be a feasible tool for predicting the parameters of mono-wire cutting operations.

Although the ANN is successful in many regards, it may have some disadvantages (e.g. difficulty in convergence, less generalizing performance, etc.) (Park & Rilett, 1999). Except for ANNs, the least squares support vector machine (LSSVM) is also one of the widely used machine learning techniques presently (Suykens, Vandewalle, & De Moor, 2001; Pardo & Sberveglieri, 2005; Ren & Bai, 2011). In this study, an improved particle swarm optimization (IPSO) based LSSVM algorithm was developed for determining the UBC of shallow foundations. To validate the hybrid IPSO-LSSVM model, a comparison of the predictions is conducted among different models and theoretical methods. The research of this study can provide reference for determining the UBC of shallow foundations.

2. Methodology

2.1. LSSVM

Consider a given data sets $\left[x_i, y_i\right]$ $\left(i=1,2,\ldots,N\right)$, the optimization problem of LSSVM can be formulated as (Suykens et al., 2001):

$$\text{Minimize } J\left(w,e\right)=\frac{1}{2}w^{\mathrm{T}}w+\frac{1}{2}\gamma\sum_{i=1}^{N}e_i^2 \quad (2)$$

$$\text{Subjected to } y_i=w^{\mathrm{T}}\varphi\left(x_i\right)+b+e_i \quad i=1,\ldots,N, \quad (3)$$

where $\varphi(x)$ – nonlinear function that maps the input data points to a high dimensional feature space; w – weight matrix; $\gamma > 0$ denotes a regularization constant; e_i – error; b – bias.

The optimization problem of LSSVM can be resolved by introducing the Lagrange function as follows:

$$L(w,b,e,\alpha) = J(w,e) - \sum_{i=1}^{N} \alpha_i \left[w^{\mathrm{T}} \varphi(x_i) + b + e_i - y_i \right], \quad (4)$$

where α_i denotes the multiplier.

The final form of the LSSVM can be obtained as follows:

$$y(x) = \sum_{i=1}^{N} \alpha_i K(x, x_i) + b, \quad (5)$$

where $K(x, x_i)$ denotes the kernel function. Herein, the radial basis function (RBF) is employed and expressed as follows:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2} \right), \quad (6)$$

where σ – the Kernel parameter.

2.2. IPSO

The PSO was first developed by Kennedy and Eberhart (1995). In traditional PSO algorithm, the velocity $(v_{i,j})$ and position $(x_{i,j})$ of each particle is updated through the following formula (Yamagami & Jiang, 1997; Dibike, Velickov, Solomatine, & Abbott, 2001; Sakthivel, Bhuvaneswari, & Subramanian, 2010; Xu & Chen, 2013):

$$x_{i,j}^{t+1} = x_{i,j}^{t} + v_{i,j}^{t+1}; \quad (7)$$

$$v_{i,j}^{t+1} = \kappa v_{i,j}^{t} + c_1 r_1 \left(p_{i,j} - x_{i,j}^{t}\right) + c_2 r_2 \left(g_j - x_{i,j}^{t}\right), \quad (8)$$

where r_1 and r_2 – random numbers; c_1 and c_2 – acceleration coefficients; $p_{i,j}$ and g_j – the best location found by the individual particle and the whole swarm, respectively. κ denotes the inertia weight.

In this study, an improved inertia weight κ was employed and written as follows:

$$\kappa = \kappa_{\min} + \left(\kappa_{\max} - \kappa_{\min}\right)\left(1 - \frac{n_i}{n_{\max}}\right)^2, \quad (9)$$

where $\kappa_{\min}$ and $\kappa_{\max}$ – the minimum and maximum inertia weights, respectively; n_i – the ith iteration number; $n_{\max}$ – the maximum number of iterations.

2.3. Hybrid algorithms

Based on the improved PSO algorithm, a hybrid IPSO-LSSVM model was developed and the flowchart of IPSO-LSSVM is illustrated in Figure 1.

2.4. Performance evaluation

In this study, three statistical indexes, namely the root-mean-square error (RMSE), the mean absolute error (MAE) and the correlation coefficient (R) were employed to measure and evaluate the predicted results. The detailed definition of these three statistical indexes is summarized in Table 1.

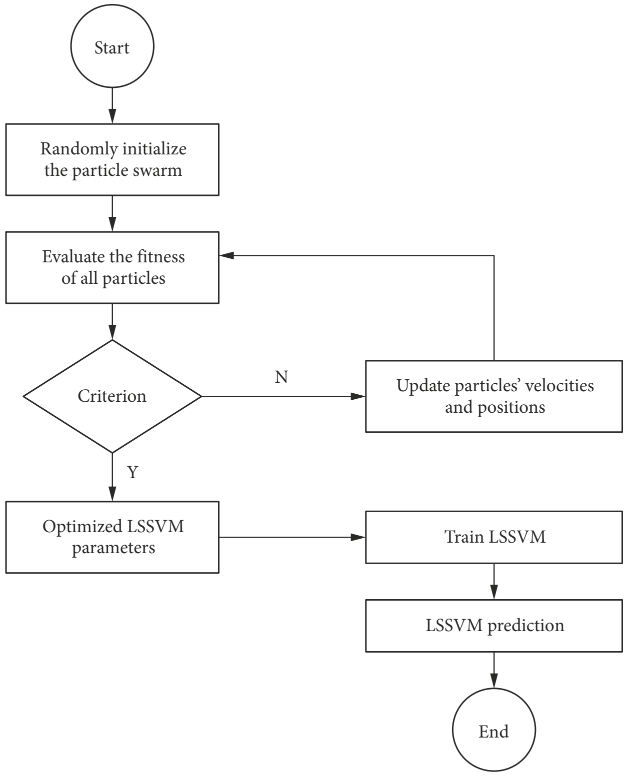

Figure 1. Flowchart of the IPSO-LSSVM algorithm

Table 1. Statistical criteria used for the evaluation of models

Performance index	Mathematical definition
Correlation coefficient (R)	$R = \frac{\sum_{i=1}^{n}(y_i - \bar{y}_i)(\hat{y}_i - \bar{\hat{y}}_i)}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2 \sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}}_i)^2}}$
Root-mean-square error (RMSE)	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$
Mean absolute error (MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i \rvert$

Notes: y_i – the actual value for the ith output; $\hat{y}_i$ – the predicted value for the ith output; n – the number of samples; $\bar{y}_i$ – the average value of the actual outputs; $\bar{\hat{y}}_i$ – the average value of the predicted outputs.

3. Case study

3.1. Data collection

To develop the hybrid IPSO-LSSVM model, the following five parameters, i.e., footing width (B), footing depth (D), length to width ratio of footing (L/B), soil unit weight (γ) and internal friction angle (φ) were employed as inputs, while the UBC of shallow foundations (q_u) was the output. This study uses the database collected by Padmini, Ilamparuthi, and Sudheer (2008), as shown in Table 2.

Table 2. Data used for developing the model (data from Padmini, Ilamparuthi & Sudheer (2008))

Data sets	No.	B (m)	D (m)	L/B	γ_d or γ' (kN/m^3)	φ (°)	q_u (kPa)
Training	1	0.6	0.3	2	9.85	34.9	270
	2	0.6	0	2	10.2	37.7	200
	3	0.6	0.3	2	10.2	37.7	570
	4	0.6	0	2	10.85	44.8	860
	5	0.5	0	1	10.2	37.7	154
	6	0.5	0	1	10.2	37.7	165
	7	0.5	0	2	10.2	37.7	203
	8	0.5	0	2	10.2	37.7	195
	9	0.52	0	3.85	10.2	37.7	186
	10	0.5	0.3	2	10.2	37.7	542
	11	0.5	0.3	2	10.2	37.7	530
	12	0.5	0.3	3	10.2	37.7	402
	13	0.52	0.3	3.85	10.2	37.7	413
	14	0.5	0	1	11.7	37	111
	15	0.5	0	1	11.7	37	132
	16	0.5	0	2	11.7	37	143
	17	0.5	0.029	4	11.7	37	109
	18	0.5	0.127	4	11.7	37	187
	19	0.5	0.3	1	11.7	37	406
	20	0.5	0.3	1	11.7	37	446
	21	0.5	0.5	2	11.7	37	565
	22	0.5	0.5	4	11.7	37	425
	23	0.5	0	1	12.41	44	782
	24	0.5	0	4	12.41	44	797
	25	0.5	0.3	1	12.41	44	1940
	26	0.5	0.3	1	12.41	44	2266
	27	0.5	0.5	2	12.41	44	2847
	28	0.5	0.49	4	12.27	42	1492
	29	0.5	0	1	11.77	37	123
	30	0.5	0	2	11.77	37	134
	31	0.5	0.3	1	11.77	37	370
	32	1	0.2	3	11.97	39	710
	33	0.991	0.711	1	15.8	32	1773.7
	34	3.004	0.762	1	15.8	32	1019.4
	35	2.489	0.762	1	15.8	32	1158
	36	3.016	0.889	1	15.8	32	1161.2
	37	0.0585	0.029	5.95	15.7	34	58.5
	38	0.0585	0.058	5.95	15.7	34	70.91
	39	0.0585	0.029	5.95	16.1	37	82.5
	40	0.0585	0.058	5.95	16.1	37	98.93
	41	0.0585	0.029	5.95	16.5	39.5	121.5
	42	0.0585	0.058	5.95	16.5	39.5	142.9
	43	0.0585	0.029	5.95	16.8	41.5	157.5
	44	0.0585	0.058	5.95	16.8	41.5	184.9
	45	0.0585	0.058	5.95	17.1	42.5	211
	46	0.094	0.047	6	15.7	34	74.7
	47	0.094	0.047	6	16.1	37	104.8
	48	0.094	0.094	6	16.1	37	127.5
	49	0.094	0.047	6	16.5	39.5	155.8
	50	0.094	0.094	6	16.5	39.5	185.6
	51	0.094	0.047	6	16.8	41.5	206.8
	52	0.094	0.047	6	17.1	42.5	235.6
	53	0.094	0.094	6	17.1	42.5	279.6
	54	0.152	0.075	5.95	15.7	34	98.2
	55	0.152	0.15	5.95	15.7	34	122.3
	56	0.152	0.15	5.95	16.1	37	176.4
	57	0.152	0.075	5.95	16.5	39.5	211.2
	58	0.152	0.15	5.95	16.5	39.5	254.5
	59	0.152	0.075	5.95	16.8	41.5	285.3
	60	0.152	0.15	5.95	16.8	41.5	342.5
	61	0.152	0.075	5.95	17.1	42.5	335.3
	62	0.152	0.15	5.95	17.1	42.5	400.6
	63	0.094	0.047	1	15.7	34	67.7
	64	0.094	0.094	1	15.7	34	90.5
	65	0.094	0.047	1	16.1	37	98.8
	66	0.094	0.047	1	16.5	39.5	147.8
	67	0.094	0.094	1	16.5	39.5	191.6
	68	0.094	0.047	1	16.8	41.5	196.8
	69	0.094	0.047	1	17.1	42.5	228.8
	70	0.094	0.094	1	17.1	42.5	295.6
	71	0.152	0.075	1	15.7	34	91.2
	72	0.152	0.15	1	15.7	34	124.4
	73	0.152	0.15	1	16.1	37	182.4
	74	0.152	0.075	1	16.5	39.5	201.2
	75	0.152	0.075	1	16.8	41.5	276.3
	76	0.152	0.15	1	16.8	41.5	361.5
	77	0.152	0.075	1	17.1	42.5	325.3
	78	0.152	0.15	1	17.1	42.5	423.6
Testing	79	0.6	0.3	2	10.85	44.8	1760
	80	0.5	0	3	10.2	37.7	214
	81	0.5	0.3	1	10.2	37.7	681
	82	0.5	0.013	1	11.7	37	137
	83	0.5	0.3	4	11.7	37	322
	84	0.5	0.5	4	12.41	44	2033
	85	0.5	0.5	2	11.77	37	464
	86	0.5	0	4	12	40	461
	87	0.5	0.55	4	12	40	1140
	88	1	0	3	11.93	40	630
	89	1.492	0.762	1	15.8	32	1540
	90	0.0585	0.029	5.95	17.1	42.5	180.5
	91	0.094	0.094	6	15.7	34	91.5
	92	0.094	0.094	6	16.8	41.5	244.6
	93	0.152	0.075	5.95	16.1	37	143.3
	94	0.094	0.094	1	16.1	37	131.5
	95	0.094	0.094	1	16.8	41.5	253.6
	96	0.152	0.075	1	16.1	37	135.2
	97	0.152	0.15	1	16.5	39.5	264.5

3.2. Parametric determination of IPSO

It is vital to tune the parameters of IPSO to guarantee the fast convergence of the algorithm (Li & Kong, 2014). After many trials, it was observed that the performance of IPSO can achieve ideal results when the acceleration coefficients $c_1 = 2.0$ and $c_2 = 1.5$. Therefore, we can fix $c_1 = 2.0$ and $c_2 = 1.5$ in this study. In order to obtain the optimal values of swarm size and the maximum number of iterations, two sensitivity analysis tests are performed and illustrated in Figure 2.

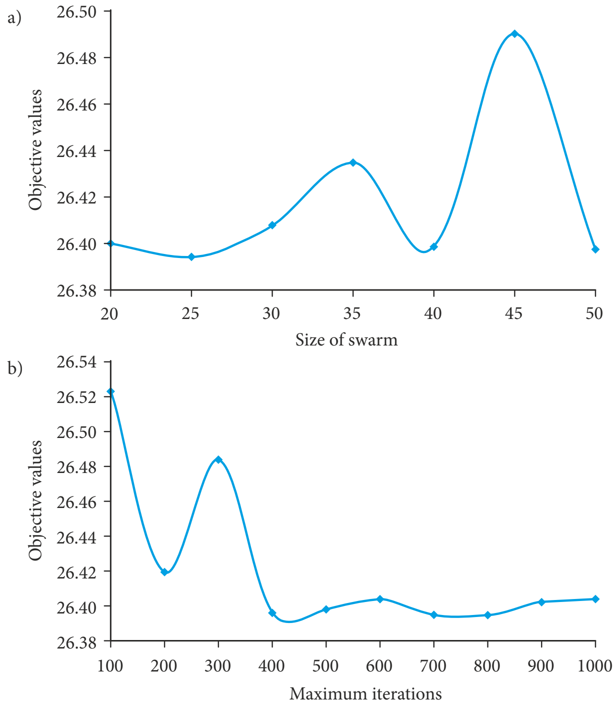

Figure 2. Results of sensitivity analysis tests: (a) swarm size; (b) the maximum iterations

According to the results of sensitivity analysis, the optimal parameters of IPSO can be obtained as follows: the swarm size = 25, the maximum number of iterations = 800, and the acceleration coefficients $c_1 = 2.0$, $c_2 = 1.5$.

3.3. Results and discussion

After performing five independent runs, the performances of training and testing of these five runs are listed in Table 3. From Table 3, it can be seen that the performance of run 3 outperforms other runs. For instance, in run 3, the root-mean-square error (RMSE) for training datasets and testing datasets are 26.3946 and 39.8242, respectively. While the corresponding root-mean-square error (RMSE) values for training datasets and testing datasets in run 1, run 2, run 4 and run 5 are 26.3960 and 39.9875, 26.3963 and 39.8761, 26.4890 and 39.9127, 26.4238 and 39.8976, respectively. Therefore, the regularization constant γ and kernel parameter σ in run 3 are employed in this study, that is, $\sigma = 0.0779$, $\gamma = 682.9488$. Figure 3 shows the run 3 convergence procedure of IPSO. The whole training time of IPSO-LSSVM needs about 15 seconds in this study.

Table 3. Training and testing performance of 5 runs

Run #	RMSE (kPa)		γ	σ
	Training	Testing		
1	26.3960	39.9875	909.3306	0.0239
2	26.3963	39.8761	781.4162	0.01
3	26.3946	39.8242	682.9488	0.0779
4	26.4890	39.9127	404.3915	0.0989
5	26.4238	39.8976	913.4256	0.109

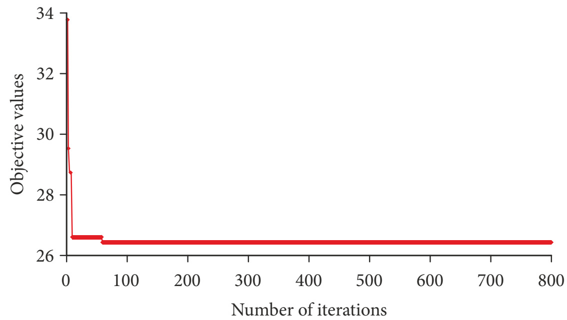

Figure 3. Convergence procedure of IPSO

To validate the performance of the developed IPSO-LSSVM model, a comparison of the predictions is conducted among different models and theoretical methods, i.e., adaptive neuro fuzzy inference system (ANFIS) (Padmini et al., 2008), fuzzy inference system (FIS) (Padmini et al., 2008), back-propagation (BP) neural network model (Padmini et al., 2008), Meyerhof's (1963) method, Hansen's (1960) method and Vesic's (1973) method. In this study, three statistical indexes, namely the root-mean-square error (RMSE), the mean absolute error (MAE) and the correlation coefficient (R) were employed to measure and evaluate the predicted results, as shown in Figure 4 and Table 4. From Figure 4 and Table 4, it can be seen that the performance of IPSO-LSSVM model outperforms other models and traditional theories. For example, the corre-

Table 4. Prediction performance statistics of all the models & theories

Performance index	Models & theories						
	ANFIS	BP	FIS	IPSO-LSSVM	Meyerhof	Vesic	Hansen
R	0.9968	0.9920	0.9899	0.9984	0.9412	0.9496	0.9457
RMSE (kPa)	52.3	77.2	98.0	39.8242	207.3	251.3	305.3
MAE (kPa)	35.758	47.177	75.997	27.474	123.423	156.951	193.771

lation coefficient (R) of the IPSO-LSSVM model is 0.9984, while the corresponding R values calculated by the other six models, i.e., ANFIS, BP, FIS, Meyerhof's (1963), Vesic's (1973) and Hansen's (1960) are 0.9968, 0.9920, 0.9899, 0.9412, 0.9496 and 0.9457, respectively. It can be seen that the correlation coefficient (R) of the IPSO-LSSVM model is the highest among these models and theoretical methods. Clearly, the higher the correlation coefficient (R) values, the better the prediction accuracy, and vice versa. The other two statistical indexes, that is, the mean absolute error (MAE) and the root-mean-square error (RMSE), also confirm it. Table 5 and Figure 5 show the comparison of the UBC of shallow foundations among these models and theoretical methods. From Figure 5 and Table 5, it can be observed that the proposed IPSO-LSSVM model outperforms the other models and theoretical methods.

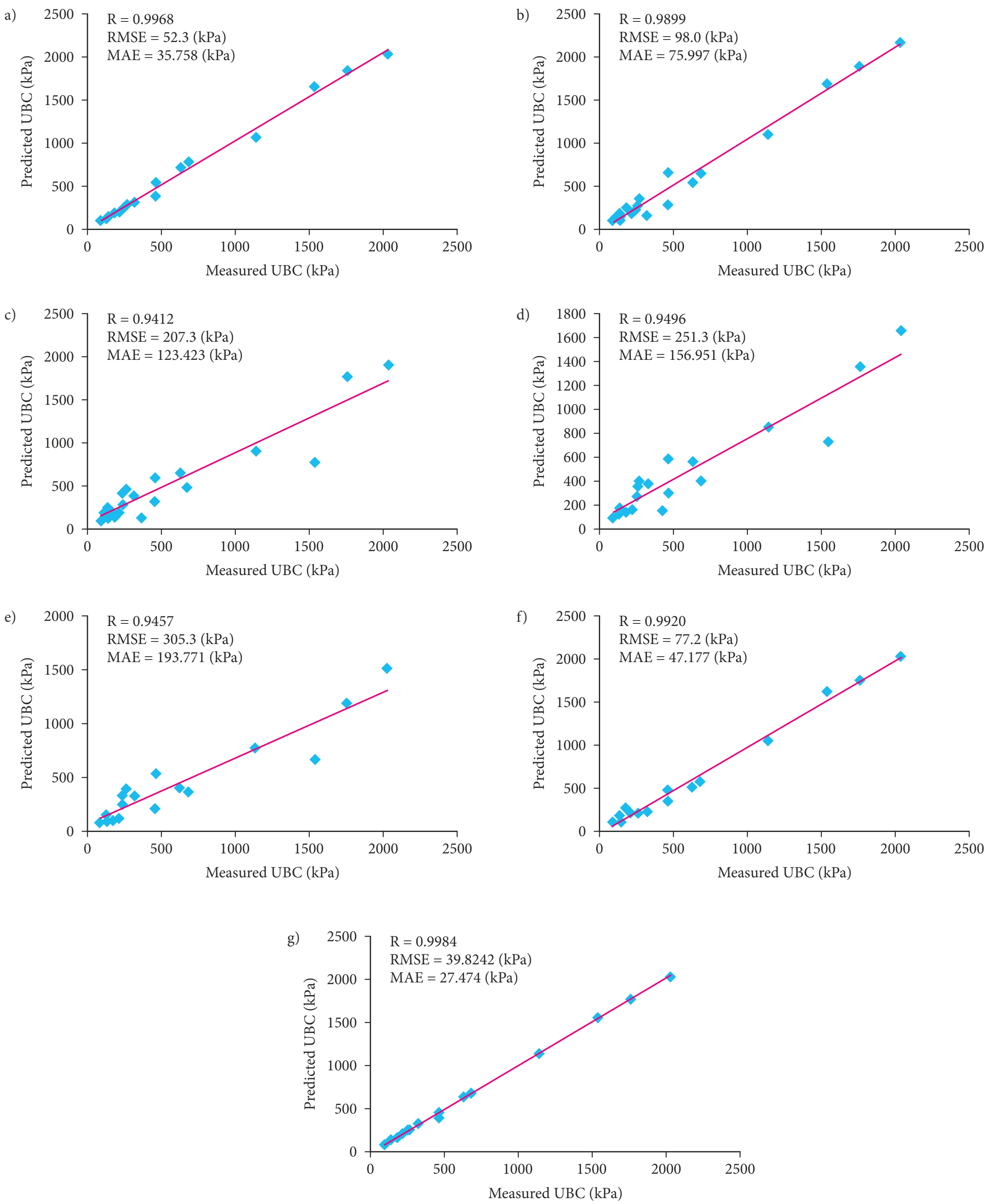

Figure 4. Prediction performance statistics of all the models & theories: (a) ANFIS; (b) FIS; (c) Meyerhof; (d) Vesic; (e) Hansen; (f) BP; (g) IPSO-LSSVM

Table 5. Comparison of the UBC of shallow foundations among different models and theoretical methods

No.	Actual (kPa)	ANFIS (kPa)	FIS (kPa)	Meyerhof (kPa)	Vesic (kPa)	Hansen (kPa)	BP (kPa)	IPSO-LSSVM (kPa)
79	1760	1841.576	1888.48	1778.48	1361.888	1185.184	1753.048	1822.9
80	214	189.7281	195.1252	174.6454	163.0466	117.165	221.113	234
81	681	773.8407	651.3084	470.3667	401.9943	370.2597	579.728	754.2
82	137	119.1311	100.6128	227.1323	126.9031	94.0779	161.646	126
83	322	308.1959	150.2774	375.3876	376.7078	327.474	226.623	342.1
84	2033	2023.892	2164.129	1913.256	1662.994	1499.338	2047.19	2043.8
85	464	536.0546	657.024	586.496	583.48	539.4	475.066	512.2
86	461	383.3031	274.1106	310.9906	293.4265	213.2586	348.004	425.3
87	1140	1067.222	1097.022	895.584	855.684	775.542	1064.874	1085
88	630	710.7471	541.044	639.513	561.771	408.303	512.1459	684.2
89	1540	1651.404	1683.99	775.082	727.342	660.968	1626.086	1639.5
90	180.5	179.9386	241.4368	135.5194	136.0609	115.0688	269.234	174.3
91	91.5	89.02493	107.0916	78.47955	88.81905	80.3919	99.845	107.7
92	244.6	242.7361	230.3643	272.6801	275.7865	247.7798	233.397	246.5
93	143.3	140.2019	151.7547	127.7663	139.9898	118.6381	108.421	144.1
94	131.5	128.586	156.5113	175.9733	170.1742	161.6793	130.612	133.2
95	253.6	256.1816	275.0038	406.673	348.8775	330.8973	226.109	254.6
96	135.2	131.2332	178.5992	179.0318	149.2878	135.565	128.832	137.7
97	264.5	272.2842	347.2885	443.4607	401.7755	381.1551	198.718	263.4

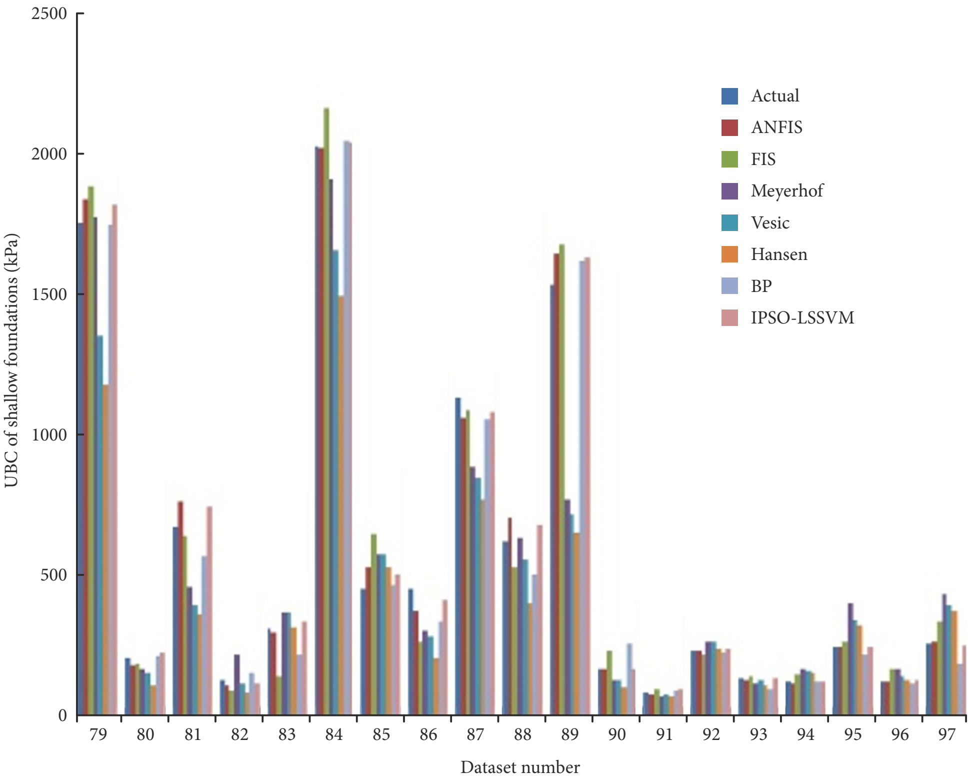

Figure 5. Comparison of the UBC of shallow foundations among all the models & theories

Conclusions

In this study, a hybrid IPSO-LSSVM model was developed to determine the UBC of shallow foundations. To construct the proposed IPSO-LSSVM model, five parameters, namely footing width, footing depth, length to width ratio of footing, soil unit weight and internal friction angle were employed as inputs, while the UBC of shallow foundations was the output. To validate the hybrid IPSO-LSSVM algorithm, a comparison of the predictions was conducted among different models and theoretical methods in terms of three statistical indexes. From the comparison results, it can be seen that the correlation coefficient of the IPSO-LSSVM model is the highest among these models and theoretical methods, while the other two statistical indexes, namely the mean absolute error and the root-mean-square error of the IPSO-LSSVM model are the smallest among these models and theoretical methods. The results confirmed that the developed hybrid IPSO-LSSVM model can be used for the determination of UBC of shallow foundations with high accuracy.

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