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A regression-based approach to the prediction of crest settlement of embankment dams under earthquake shaking

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Abstract. The settlement of embankment dams is among the many major damages caused by earthquakes that, eventually, leads to dam instability. Therefore, an accurate assessment of the seismic settlement of embankment dams is of particular concern. This study aims to evaluate the settlement of embankment dams subjected to earthquake loads using regression-based methods. wide-ranging cases of real data on crest settlement of embankment dams caused by earthquakes were analyzed. Yield acceleration of dam (a_y), maximum horizontal earthquake acceleration ($a_{\max}$), fundamental period of dam body (T_d), predominant period of earthquake (T_p), and earthquake magnitude (M_w) were considered as the most influential parameters that affect the seismic crest settlement of embankment dams. By applying Support Vector Regression (SVR) and Multiple Linear Regression (MLR) methods, two models were developed to estimate the earthquake-induced settlement of embankment dams. Subsequently, sensitivity analysis was conducted in order to assess the behavior of the proposed models under different conditions. Finally, the accuracy of the proposed models was compared with the existing relationship for the estimation of earthquake-induced crest settlement of embankment dams. Although both MLR- and SVR-based models enjoy acceptable accuracy in the estimation of the crest settlement of embankment dams under earthquake loading, the SVR-based model has higher accuracy.

1. Introduction

An inaccurate assessment of the behavior of embankment dams subjected to seismic vibrations caused by earthquakes can lead to catastrophic damages. The pseudo-static method, sliding block method, and numerical methods are common techniques to estimate seismic deformations of embankment dams [1]. Newmark [2] proposed the sliding block method as the first approach to the evaluation of the earthquake-induced deformations of soil slopes. In this method, the sliding mass was considered as a rigid block such that an input acceleration (caused by the earthquake) greater than the yield acceleration forced the block to move [3]. Makdisi and Seed [4] modified the sliding block model and considered the response acceleration of the sliding mass as the input acceleration. They then used this acceleration to calculate the displacements.

The behavior of embankment dams under earthquake shaking has been studied by many researchers [5–13]. Applying physical modeling and conducting centrifuge experiments, Park and Kim [14] and Kim et al. [15] investigated the behavior of rockfill dams subjected to earthquake loads. Based on the seismic deformations in different embankment dams under

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Table 1. Statistical parameters of database used in the present study.

	Parameter									
Statistical index	a_y (g)	$a_{\max}$ (g)	$a_y/a_{\max}$	T_d (sec)	T_p (sec)	T_d/T_p	M_w	H (m)	S (m)	S/H
Minimum	0	0.004	0	0.05	0.25	0.117	0.7	2.5	0.001	8.3e-6
Maximum	0.55	0.9	50	2.74	0.96	10.96	8.3	235	32	1.359
Mean	0.162	0.285	2.285	0.581	0.378	1.672	6.938	42.221	1.321	0.11
Standard deviation	0.11	0.211	6.428	0.437	0.131	1.391	1.098	40.240	3.757	0.238

earthquake vibrations, Singh et al. [16,17] showed that the yield acceleration of the dam and the maximum earthquake acceleration were among the most important parameters that affect the seismic behavior of embankment dams. They also found that the effect of vertical component of earthquake acceleration was negligible in assessing the behavior of dams.

The accurate assessment of the behavior of embankment dams under various loads is among the important issues to be considered in the initial design of these large structures. Therefore, estimating the settlement of embankment dams subjected to earthquake shaking requires accurate models.

As powerful tools, soft computing methods have been successfully employed in different fields of geotechnical engineering such as predicting dynamic properties of soils [18–21], behavior of stabilized soils [22–24], liquefaction potential of soil deposits [25], ground motion duration [26], scour depth [27–31], soil friction angle [32], and collapse potential of compacted soils [33].

In recent years, the SVR-based models have managed to offer accurate assessments regarding the geotechnical problems (e.g., [34–37]). The phenomena related to soil environments, as well as the earthquake-induced loadings, are highly complex [38–40]. Therefore, the application of advanced computational methods for the estimation of the behavior of embankment dams subjected to earthquake shaking can be an effective step in reducing the uncertainties in the prediction of seismic behaviors and, subsequently, safe designing of dams.

In this study, a large set of seismic crest settlements of different embankment dams was collected and analyzed. The most important parameters affecting the earthquake-induced crest settlement were determined. The Support Vector Regression (SVR) method and Multiple Linear Regression (MLR) method were used to develop models for the prediction of seismic settlement of embankment dams. Subsequently, sensitivity analysis was conducted in order to investigate 1) the behavior of the proposed models under different conditions and 2) the effect of different parameters on the crest settlements caused by earthquake loading. Finally, the proposed models were compared with the existing relationship for the estimation of earthquake-induced crest settlement of embankment dams.

2. Case histories

In the present study, comprehensive data of crest settlements of embankment dams subjected to past earthquakes in different parts of the world were collected. The results included homogeneous and nonhomogeneous embankment dams, concrete-faced dams, rockfill dams, and also some natural soil slopes. The collected cases were those for which thorough information about their behavior and also earthquake characteristics were recorded and available. The database includes a total of 151 real-world cases. The statistical specifications of the parameters of yield acceleration (a_y), maximum horizontal acceleration of the earthquake ($a_{\max}$), yield acceleration ratio ($a_y/a_{\max}$), fundamental period of the embankment dam (T_d), predominant period of the earthquake (T_p), fundamental period ratio (T_d/T_p), earthquake magnitude (M_w), embankment height (H), crest settlement of the embankment dam (S), and the crest settlement ratio of embankment dam (S/H) are presented in Table 1. The yield acceleration was estimated by pseudo-static slope stability analysis [16]. The values of $a_{\max}$ and T_p were determined from acceleration records from instruments at the dams or embankments sites. The fundamental period of the embankment dam (T_d) was obtained from [41]. In this study, the yield acceleration ratio ($a_y/a_{\max}$), fundamental period ratio (T_d/T_p), and earthquake magnitude (M_w) were considered as the most important parameters that affect the crest settlement of embankment dams. The detailed characteristics of the database are presented in Table A.1.

3. SVR framework

The Support Vector Machine (SVM) has been derived from the machine learning theory, as proposed by Vapnik [42]. The SVM was initially used to classify data; however, its algorithm was then developed further to solve regression problems and predict time series [43].

Assume an experimental dataset $\{(x_1, y_1), ..., (x_n, y_n)\}$ in an n-dimensional space, where x and y denote the input values ($x \in R^n$) and output values ($y \in R$), respectively. In the SVM-based regression model, the objective is to approximate y_i values using function $f(x)$, such that the error is minimized [43]:

$$f(x) = w^T x + b, \tag{1}$$

where b and w represent bias and weight vector, respectively. In order to find the values of w and b, an empirical risk is defined as follows:

$$R = \frac{1}{2}\|w\|^2 + \frac{C}{n}\sum_{i=1}^{n}|y_i - f(x_i)|_\varepsilon, \tag{2}$$

where $C > 0$ controls the error of deviation higher than ε, and $\frac{1}{2}||w||^2$ is the complexity index of the objective function. In fact, the lower the value of $\frac{1}{2}||w||^2$, the simpler the objective function [44].

In the SVR, the ultimate goal is to minimize empirical risk. Therefore, a ε-insensitive loss function was proposed by Vapnik [45]:

$$|y_i - f(x_i)|_\varepsilon = \begin{cases} 0, & |y_i - f(x_i)| \le \varepsilon \\ |y_i - f(x_i)| - \varepsilon, & \text{otherwise} \end{cases} \tag{3}$$

Based on Figure 1, Eq. (3) can be explained as a region with radius, ε, around the hypothetical regression function, such that the upper and lower limits of this region are referred to as the support vector. As long as the data are located inside the limits of the support vectors, the ε-insensitive function remains equal to zero. Any data located outside this region will be penalized with respect to its distance from the support vector [43]. This distance is referred to as violation and denoted by λ. In the 2-dimensional space, one can write:

$$\text{Minimize}: \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\lambda_i^+, \lambda_i^-), \tag{4}$$

$$\text{Subject}: \begin{cases} (w.x_i + b) - y_i \le \varepsilon + \lambda_i^+ \\ y_i - (w.x_i + b) \le \varepsilon + \lambda_i^- \\ \lambda_i^+, \lambda_i^- \ge 0 \end{cases} \tag{5}$$

This problem in a dual space is expressed as follows:

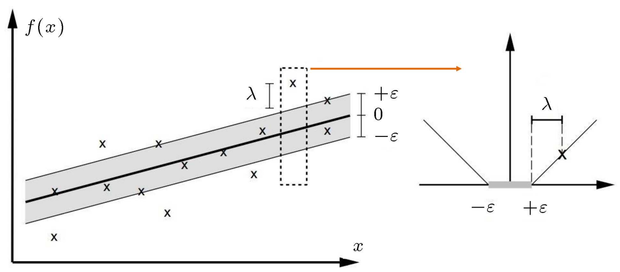

Figure 1. ε-insensitive loss function for the Support Vector Regression (SVR)-based model.

Table 2. Values of the parameters of the proposed Support Vector Regression (SVR)-based model.

Parameter	Optimal value
σ	0.35
C	1000
ε	0.005

$$f(x) = \sum_{i=1}^{n_{sv}}(\beta_i - \beta_i^*)K(x_i, x) + b, \tag{6}$$

where n_{sv} is the number of support vectors, β_i and β_i^* are the Lagrange coefficients, and $K(x_i, x)$ is the kernel function [46]. In nonlinear spaces, the Radial Basis Function (RBF) [47] offers more acceptable results than other functions [48]. Therefore, in this study, the RBF kernel is used as follows:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\rho^2}\right), \rho \in R. \tag{7}$$

The training procedure used 75 percent of the collected dataset, and the remaining 25 percent was used to validate the performance of the SVR-based model. The training and validation data were selected such that the statistical parameters of both categories were as close as possible. Numerous runs were carried out with various initial settings, and the performance of the developed SVR-based models was analyzed for each run. Consequently, the optimal parameters employed in the proposed model (Table 2) were selected.

In order to assess the performance of the developed models, the coefficient of determination, R^2, Mean Absolute Error, MAE, and Root Mean Squared Error, RMSE, [19] between the measured and predicted S/H were checked.

4. Results

4.1. MLR-based model

In this study, using gathered data (Table 1), an MLR based model was developed using SPSS program for the earthquake-induced crest settlement of embankment dams as Eq. (8):

$$\ln\left(\frac{S}{H}\right) = -1.471\ln\left(\frac{a_y}{a_{\max}}\right) - 1.886\ln\left(\frac{T_d}{T_p}\right) - 0.849M_w, \tag{8}$$

where the earthquake-induced crest settlement ratio of embankment dam (S/H) was developed on the basis of yield acceleration ratio ($a_y/a_{\max}$), fundamental period ratio (T_d/T_p), and earthquake magnitude (M_w), respectively.

The comparison between the measured and predicted crest settlement values using the MLR model

(Eq. (8)) is demonstrated in Figure 2. The values of R^2, MAE, and RMSE for the MLR-based model, developed to assess the seismic crest settlement of embankment dams, were 0.898, 1.746, and 2.305, respectively.

4.2. SVR-based model

In the present study, many SVR based models were investigated by applying different initial parameter values. Ultimately, based on the calculated error parameters, the model with the highest accuracy was selected to predict the crest settlement of embankment dams subjected to earthquake loads.

The accuracy of the proposed SVR-based model in the training and validation stages is respectively compared in Figures 3 and 4 by comparing the measured values and the predicted values of crest settlement ratio (S/H) of embankment dams under earthquake loading. The values of R^2, MAE, and RMSE for the proposed SVR-based model in the training and validation stages were obtained as 0.987, 0.013, and 0.03 (Figure 3) and 0.999, 0.005, and 0.005, respectively (Figure 4). The results indicate the acceptable accuracy of the SVR-based model in estimating the crest settlement of embankment dams under earthquake loadings.

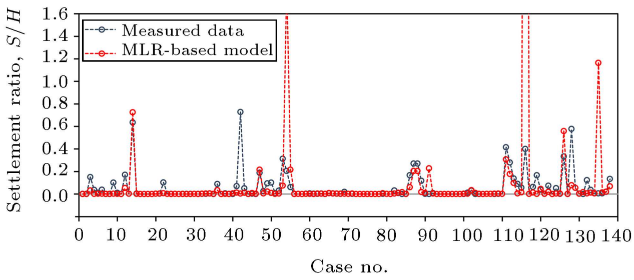

Figure 2. Comparison of measured and Multiple Linear Regression (MLR)-based predicted values of S/H.

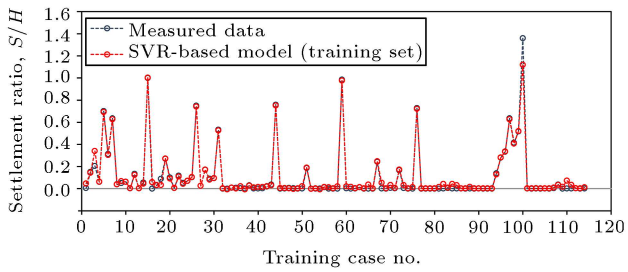

Figure 3. Comparison of measured and Support Vector Regression (SVR)-based predicted values of S/H for training stage.

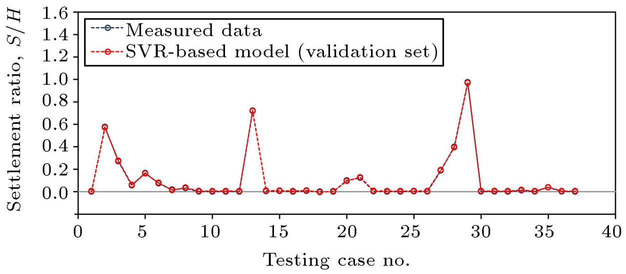

Figure 4. Comparison of measured and Support Vector Regression (SVR)-based predicted values of S/H for validation stage.

5. Sensitivity analysis

Sensitivity analysis was carried out to investigate 1) the effect of each influential parameter on the crest settlement of embankment dams subjected to seismic vibrations and 2) the consistency of the proposed model obtained using soft computations with the real case histories under different conditions. To this end, the effect of changes in each of the input parameters (i.e., M_w, a_y/a_{max}, and T_d/T_p) on the seismic settlement of the crest of embankment dams was investigated, such that the other parameters were fixed at the average value in the dataset (Table 1).

The measured values of crest settlement ratio (S/H) of embankment dams under past earthquakes and the MLR- and SVR-based predicted values with respect to yield acceleration ratio ($a_y/a_{\max}$), fundamental period ratio (T_d/T_p), and earthquake magnitude (M_w) are illustrated in Figures 5, 6, and 7, respectively. Their best fitted curves are also presented in the figures for comparison. As shown in Figures 5 and 6, the crest settlement ratio of the embankment dams decreases by increasing $a_y/a_{\max}$ and T_d/T_p. An increase in the earthquake magnitude also increased the S/H value (Figure 7). Generally, based on the comparison of the variations of S/H ratio and the real results recorded in the past earthquakes, it can be concluded that the proposed MLR- and SVR-based models have appropriate performance.

6. Comparison with Swaisgood's relationship [49]

The relationship proposed by Swaisgood [49] is used for a preliminary assessment of the crest settlement of embankment dams under earthquake shaking. Based on the collected information from 69 different dams, Swaisgood [49] proposed Eq. (9) to estimate the earthquake-induced crest settlement ratio of embankment dams:

$$\frac{S}{H} = 0.01 \exp(6.07 a_{\max} + 0.57 M_w - 8). \quad (9)$$

In Eq. (9), for the calculation of H, the thickness of the alluvial layer is also taken into account. However, in many cases where information on the thickness of the alluvial layer is not available, its value is set to the height of the dam [49]. In this study, the thickness of the alluvial layer is also considered in Swaisgood's

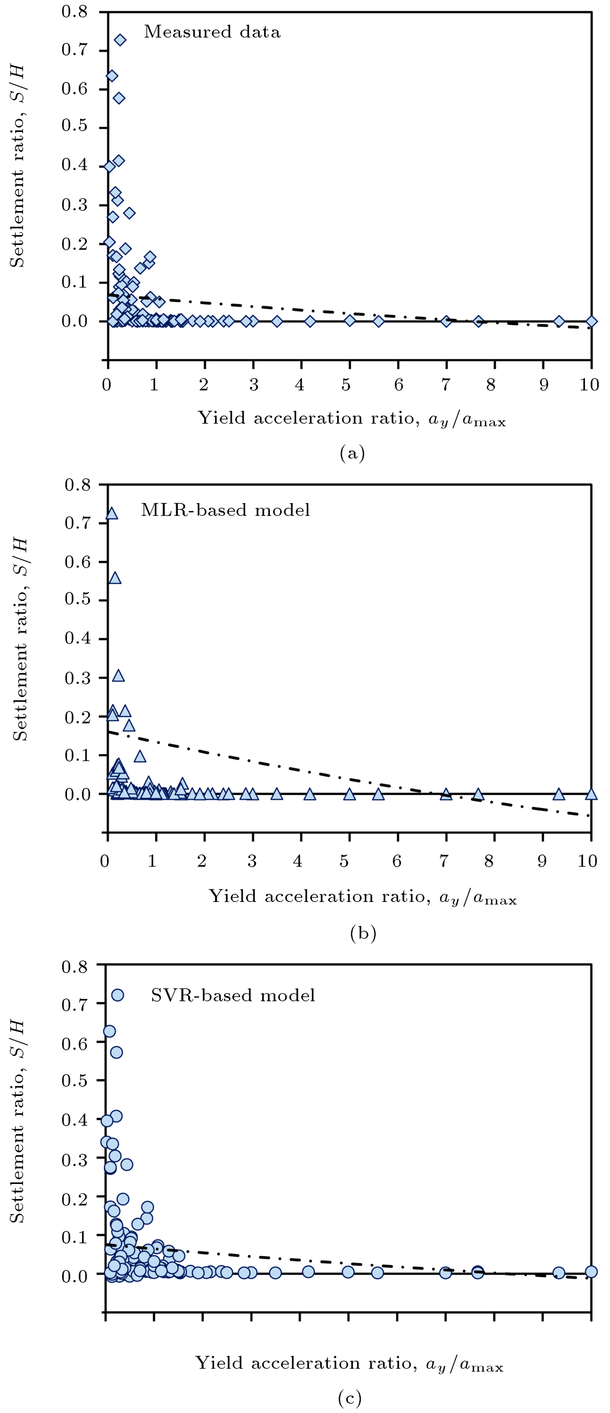

Figure 5. Variations of settlement ratio versus yield acceleration ratio for (a) Measured data, (b) predicted by the Multiple Linear Regression (MLR)-based model, and (c) predicted by the Support Vector Regression (SVR)-based model.

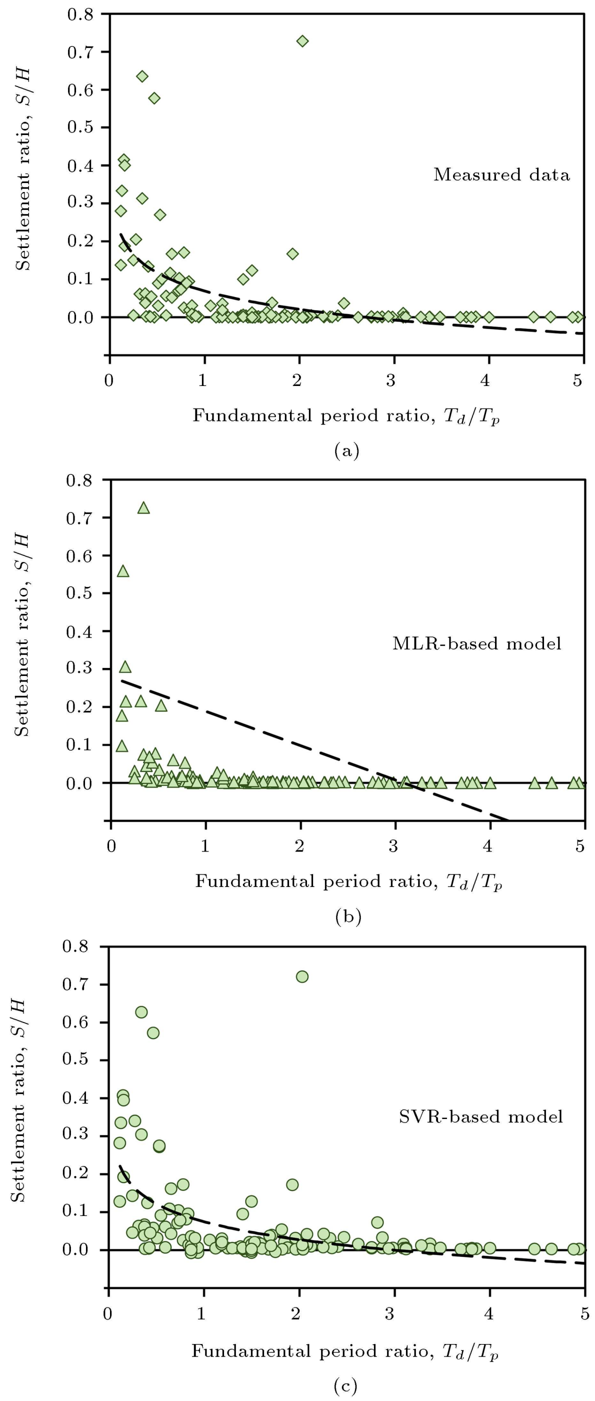

Figure 6. Variations of settlement ratio versus fundamental period ratio for (a) measured data, (b) predicted by the Multiple Linear Regression (MLR)-based model, and (c) predicted by the Support Vector Regression (SVR)-based model.

relationship [49] for the cases where the detailed information about deposits below embankment dam was available.

The comparison between the proposed MLR- and SVR-based models with the Swaisgood's relationship [49] is demonstrated in Figure 8. As depicted in Figure 8, the relationship proposed by Swaisgood [49] underestimates the earthquake-induced crest settlement ratio (S/H) of embankment dams compared to the real values. Moreover, the accuracy of the relationship (Eq. (9)) decreased by increasing the S/H

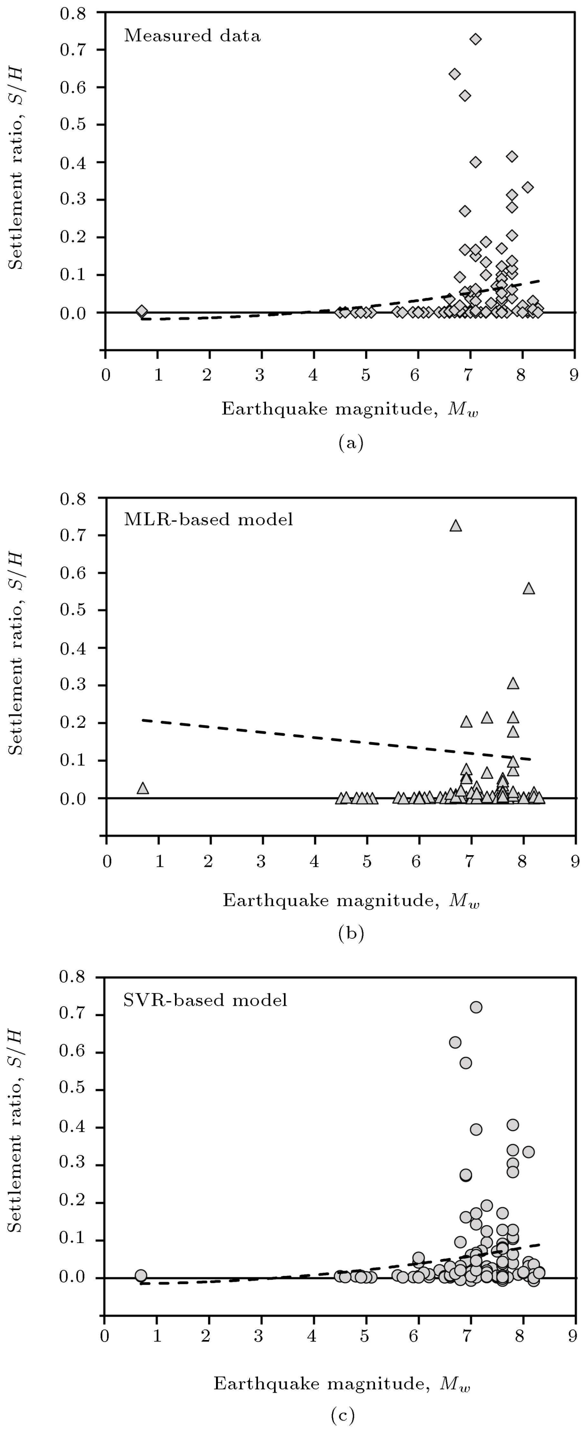

Figure 7. Variations of settlement ratio versus earthquake magnitude for (a) measured data, (b) predicted by Multiple Linear Regression (MLR)-based model, and (c) predicted by Support Vector Regression (SVR)-based model.

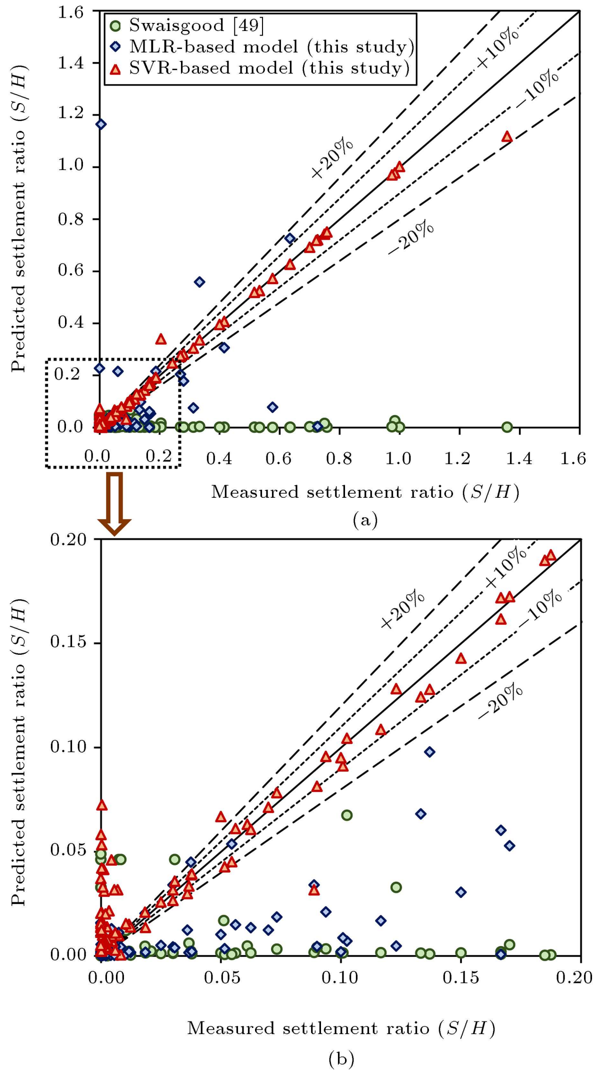

Figure 8. Comparison of Multiple Linear Regression (MLR)- and Support Vector Regression (SVR)-based models with relationship proposed by Swaisgood [49]: (a) General view, and (b) zoomed view.

ratio (Figure 8). Important parameters such as yield acceleration (a_y) and fundamental period of dam (T_d), as the key characteristics in the earthquake-induced behavior of embankment dams, are considered to be one of the main reasons of the low accuracy of Eq. (9).

The comparison presented in Figure 8 indicates the appropriate accuracy of the proposed regressive models in predicting the seismic crest settlement of embankment dams. The correlation coefficient, R^2, MAE, and RMSE for the proposed models and available relationship are presented in Table 3. The statistical indexes (Table 3) indicate that the SVR-based model enjoys higher accuracy in comparison to the MLR-based model in estimating the earthquake-induced crest settlement ratio (S/H) of embankment dams.

The complexity of the geotechnical earthquake engineering problems makes the available models incapable of accurately reflecting all the factors affecting the earthquake-induced settlement of embankment dams. However, note that the available models are still commonly used in the initial designs. Hence,

Table 3. Statistical parameters of various models.

Model	Dataset	R^2	MAE	RMSE
MLR	All data	0.898	1.746	2.305
SVR	Training set	0.987	0.013	0.030
	Validation set	0.999	0.005	0.005
	All data	0.989	0.011	0.028
Swaisgood [49]	All data	0.012	0.109	0.260

employing computational methods can be a worthy step in reducing the uncertainties in estimating the deformation of embankment dams under earthquake vibrations.

7. Summary and conclusion

Evaluating behavior of dams under earthquake vibrations is of great significance. Therefore, the present study attempted to predict the earthquake-induced crest settlement of embankment dams. To this end, wide-ranging data cases of the real earthquake-induced deformations in different types of embankment dams including 151 cases were collected and analyzed. The most important parameters affecting the crest settlement in embankment dams induced by earthquake shaking were determined. The parameters of earthquake magnitude (M_w), maximum horizontal acceleration of the earthquake ($a_{\max}$), predominant period of the earthquake (T_P), fundamental period of embankment dam (T_d), and yield acceleration of embankment dam (a_y) were considered as the most important factors that control earthquake-induced deformations in embankment dams.

The Support Vector Regression (SVR) and Multiple Linear Regression (MLR) methods were used to develop the models for the assessment of seismic settlement of embankment dams, S. The yield acceleration ratio ($a_y/a_{\max}$), fundamental period ratio (T_d/T_p), and earthquake magnitude (M_w) were considered as the input parameters, while the crest settlement ratio of the dam (S/H) was considered as the output parameter. Assessing the accuracy of the proposed regressive models indicates that although both the SVR-based model ($R^2 = 0.989$, MAE = 0.011, and RMSE = 0.028) and the MLR-based model ($R^2 = 0.898$, MAE = 1.746, and RMSE = 2.305) offered acceptable accuracy, the SVR-based model had higher accuracy. Then, sensitivity analysis was conducted to assess the behavior of the developed models under different conditions and the effect of each of the input parameters on the crest settlement ratio of the embankment dams (S/H). Finally, the performance of the proposed models was compared to the available relationship for the assessment of crest settlement of embankment dams subjected to earthquake loading. Certainly, recording more results on the real deformations of the embankment dams under real earthquake vibrations can lead to the development of more accurate computational models.

Nomenclature

a_y	Yield acceleration of dam
$a_{\max}$	Maximum horizontal earthquake acceleration
T_d	Fundamental period of dam body
T_p	Predominant period of earthquake
M_w	Earthquake magnitude
S	Crest settlement of embankment dam
H	Embankment height
SVM	Support Vector Machine
SVR	Support Vector Regression
RBF	Radial Basis Function
MLR	Multiple Linear Regression
b	Bias
w	Weight vector
R	Empirical risk
λ	Distance from the support vector
n_{sv}	Number of support vectors
β_i	Lagrange coefficient
K	Kernel function
R^2	Coefficient of determination
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error

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Appendix A

Table A.1 presents 151 case histories that were used to develop SVR based model.

Table A.1. Summary of datasets used to develop Support Vector Regression (SVR)-based models.

No.	M_w	$a_y/a_{\max}$	T_d/T_p	S/H	No.	M_w	$a_y/a_{\max}$	T_d/T_p	S/H
1	7.1	1.52	0.25	0.004	11	7.6	0.96	0.382	0.0017
2	7.1	0.85	0.25	0.15	12	7.3	0.23	0.406	0.13
3	7.8	0.029	0.275	0.205	13	7.6	1.30	0.418	0.003
4	7.8	0.108	0.315	0.061	14	6.9	0.318	0.437	0.05
5	7.8	0	0.325	0.7	15	7.9	0	0.437	1
6	7.8	0.20	0.343	0.312	16	7	1.31	0.468	0.00005
7	6.7	0.083	0.343	0.634	17	7.6	0.23	0.509	0.031
8	7.6	0.285	0.375	0.037	18	7.6	0.23	0.509	0.08
9	7.1	1.06	0.375	0.05	19	6.9	0.10	0.531	0.27
10	7.1	0.878	0.375	0.062	20	7.6	0.53	0.55	0.1008

Table A.1. Summary of datasets used to develop Support Vector Regression (SVR)-based models (continued).

No.	M_w	$a_y/a_{\max}$	T_d/T_p	S/H	No.	M_w	$a_y/a_{\max}$	T_d/T_p	S/H
21	0.7	1.15	0.598	0.005	68	6	0.6	1.8	0.00034
22	7.8	0.25	0.63	0.117	69	6.5	2.85	1.82	0.00002
23	7.6	0.80	0.657	0.052	70	6.8	1	1.84	0.00698
24	7.5	0.31	0.72	0.07	71	6.9	0.34	1.87	0.0019
25	7.8	0.378	0.73	0.10	72	7.1	0.86	1.92	0.167
26	6.8	0	0.75	0.75	73	8.1	0.83	1.95	0.0056
27	7.4	0.56	0.78	0.02	74	5	50	1.96	0.00002
28	7.6	0.10	0.78	0.17	75	8.3	0.188	2.03	0.00004
29	7.6	0.51	0.81	0.09	76	7.1	0.25	2.03	0.728
30	6.8	0.28	0.83	0.094	77	6.6	23	2.03	0.00001
31	5.3	0	0.84	0.53	78	5	20	2.04	0.00002
32	7.7	9.33	0.86	0.00001	79	4.9	28.58	2.04	0.00002
33	8.2	0.138	0.86	0.00003	80	4.9	40	2.04	0.00002
34	8.2	0.176	0.86	0.0075	81	6.1	1.15	2.08	0.00003
35	8.2	0.338	0.86	0.008	82	6	0.58	2.08	0.0012
36	6.8	1	0.90	0.003	83	7	0.441	2.125	0.0045
37	7	0.5	0.93	0.0006	84	8.1	0.65	2.25	0.00033
38	7.1	0.5	1.06	0.03	85	7.3	1	2.32	0.0014
39	6.2	0.77	1.15	0.0007	86	5.9	2.077	3.37	0.0003
40	7.3	1.37	1.18	0.0008	87	6.2	0.65	3.375	0.0002
41	6.8	0.9	1.18	0.0026	88	7	1.30769	3.37500	0.00056
42	6.8	0.18	1.18	0.0184	89	6.6	7.66667	3.69697	0.00001
43	6.6	0.289	1.18	0.036	90	7.3	1.00000	4.64706	0.00041
44	7cs	0	1.3125	0.758	91	6	1.53333	4.88000	0.00001
45	7.3	1.33	1.35	0.00002	92	5.1	7.66667	4.88000	0.00001
46	6.7	0.25	1.41	0.0008	93	7.5	1.00000	4.93750	0.00014
47	6.6	0.316	1.41	0.006	94	7.8	0.66667	0.11667	0.13696
48	7	0.348	1.44	0.0039	95	7.8	0.44444	0.11667	0.28000
49	7.5	5.6	1.46	0.00001	96	8.1	0.15000	0.12857	0.33333
50	6.4	0.72	1.48	0.0004	97	7.7	0.00000	0.13333	0.63500
51	5.5	0	1.48	0.185	98	7.8	0.22222	0.15000	0.41538
52	7.6	0.138	1.5	0.00003	99	7.9	0.00000	0.18519	0.51600
53	7.6	0.18	1.5	0.00004	100	7.9	0.00000	0.23333	1.35870
54	7.6	0.288	1.5	0.0003	101	5.9	2.50000	3.76000	0.00040
55	7.6	0.48	1.5	0.0118	102	5.7	23.00000	3.81250	0.00001
56	7.1	1.038	1.5	0.00002	103	6.5	0.70833	3.85714	0.00115
57	7.1	7	1.51	0.00001	104	7	1.53333	4.46875	0.00020
58	7.1	1	1.53	0.00003	105	5.9	1.00000	4.64706	0.00027
59	7.2	0	1.53	0.985	106	6	1.90909	10.96000	0.00003
60	7.3	1.17	1.56	0.0019	107	7	0.28889	2.40625	0.00414
61	7	1.03	1.59	0.00002	108	7	0.36207	2.46875	0.03670
62	7.3	0.31	1.608	0.0009	109	8	1.12121	2.62000	0.00001
63	6.8	0.66	1.65	0.0124	110	7.2	1.08333	2.82143	0.00044
64	7.1	3.5	1.67	0.00002	111	7.6	0.82609	2.87273	0.00086
65	6.9	1.31	1.68	0.00004	112	7.5	5.00000	2.93750	0.00200
66	7.6	3	1.71	0.00022	113	4.6	1.00000	3.12000	0.00014
67	6.6	0	1.78	0.24238	114	6.7	0.94444	3.28000	0.00031

Table A.1. Summary of datasets used to develop Support Vector Regression (SVR)-based models (continued).

No.	M_w	$a_y/a_{\max}$	T_d/T_p	S/H	No.	M_w	$a_y/a_{\max}$	T_d/T_p	S/H
115	7	1.50000	4.00000	0.00001	134	7.3	0.53333	1.40625	0.10000
116	6.9	0.22727	0.46875	0.57692	135	7.6	0.22500	1.50000	0.12308
117	6.9	0.10000	0.53125	0.27000	136	6.6	0.71429	2.25000	0.00273
118	7	0.48485	0.59375	0.05607	137	7	0.58140	2.34375	0.00020
119	6.9	0.17500	0.65625	0.16667	138	6	2.16667	2.76000	0.00001
120	7.6	0.21429	0.75000	0.07333	139	5.6	0.57692	2.76000	0.00188
121	8	0.72000	0.84000	0.01859	140	7.6	2.39130	2.87273	0.00031
122	8.2	0.36250	0.86667	0.03077	141	7.3	0.36364	0.15625	0.18750
123	7.5	1.75000	0.93506	0.00090	142	7.1	0.03030	0.15625	0.40000
124	0.7	1.54545	1.12121	0.00005	143	7.8	0.00000	0.40000	0.97474
125	8.2	4.18182	1.25000	0.00003	144	7.6	1.50000	0.42857	0.00125
126	6.5	1.00000	1.29630	0.00004	145	8.1	0.84615	2.98113	0.00075
127	7	0.00000	1.31250	0.72273	146	7	1.20000	3.09375	0.00002
128	7.9	1.47368	1.38333	0.00412	147	8.3	0.21053	3.09375	0.01039
129	6.9	0.46875	1.50000	0.00457	148	6.6	0.90909	3.12000	0.00028
130	7.3	0.61111	1.68750	0.00003	149	7.8	0.30000	1.71154	0.03788
131	6.7	0.34375	1.70370	0.00600	150	4.9	1.33333	3.48148	0.00040
132	6.8	0.65455	1.75000	0.00045	151	4.5	7.66667	3.81250	0.00001
133	4.8	10.00000	2.04000	0.00002					

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