

Correction

Correction: Jin et al. A Threshold Model of Tailings Sand Liquefaction Based on PSO-SVM. *Sustainability* 2022, 14, 2720

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The authors would like to make the following corrections about the published paper [1]. The changes are as follows:

1. Replacing the email of the corresponding author Hongzhi Cui, hz.cui@hhu.edu.cn, with hongzhi.cui@126.com
2. The original abstract is replaced. Original abstract:

The liquefaction of tailings sand caused by seismic loads is a major problem in ensuring the safety of tailings ponds. Liquefaction may cause uncontrolled fluidized failure of the dam body, causing considerable damage to the lives, property and environment of people downstream. In this paper, a prototype tailings sand is used as the material to consider the main factors affecting liquefaction (i.e., dynamic load, soil quality, burial and static conditions). By embedding acceleration, pore pressure and earth pressure sensors in the rigid design of the self-designed rigid model box, different types of seismic waves of different ground motion amplitudes (PGA) were induced in a shaking table test of tailings sand liquefaction. The seismic intensity, waveform (class II, III and IV seismic waves) and active earth pressure of the PGA characterizing dynamic factors were obtained, and the static factors were characterized. The dynamic shear stress ratio, the peak acceleration of the earthquake, the pore pressure of the drainage factor and the buried depth (overlying effective pressure) characterize the soil conditions. SPSS software was used to analyze the factor dimension reduction, and the most suitable factors for factor analysis were obtained. Particle Swarm Optimization (PSO) was used to optimize the parameters, and the improved PSO-SVM algorithm was compared with the existing genetic algorithm (GA) and grid node search (GS). The algorithm used in this paper is fast and has a relatively high accuracy rate of 92.7%. The established threshold model method is of great significance to predict the liquefaction of tailings sand soil under the action of ground motions and to carry out safety management in advance, which can provide a certain reference for the project.

Replacement abstract:

The liquefaction of tailings sand during seismic activity poses significant risks to both property and the safety of individuals. This study focused on tailings sand and conducted liquefaction tests using a self-designed rigid test-box. Various factors were considered such as the dynamic factor, static factor, and drainage factor, which were all characterized and obtained. To determine the most influential factors, dimension reduction analysis was performed using SPSS. Additionally, a threshold model for predicting liquefaction was proposed by improving the parameters based on particle swarm optimization (PSO) and incorporating them into the support vector machine (SVM). Comparisons with two other



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established algorithms revealed that the improved algorithm not only exhibited a high accuracy rate of 92.7%, but also demonstrated faster performance. This model can serve as a crucial foundation for preventing earthquake disasters in tailings ponds.

3. In the keyword section, “geotechnical engineering” was deleted. The word “seismic” was added as keyword.
4. Replacing the original Section 1, Introduction, with the following:

Recently, extreme climate change anomalies and frequent earthquakes have resulted in various natural disasters, such as landslides introduced by slope instability [1–3]. The stability problem of tailings dams as artificial slopes has always been a global concern, mainly in terms of preventing property damage and keeping the environment from being threatened [4–6]. At present, the upstream method is generally used in the construction of tailings dams [7], which directly leads to an excessively high flooding rate, even when the tailings sand is completely saturated. The tailings sand is very susceptible to liquefaction and deformation because of its sensitivity to ground movement, which can lead to instability and collapse. According to statistical analysis, since the beginning of the 20th century, there have been more than 200 tailings dam accidents caused by earthquakes in China [5–7]. The main reason is that the saturated tailings sand is very easy to liquefy and deform under the action of earthquakes, resulting in local dam failures [8–10]. Therefore, the crucial study in the area of tailings dam disaster is establishing the liquefaction parameters, liquefaction degree, and failure prediction of saturated tailings sand.

The possibility for sand liquefaction has been assessed using a variety of techniques, up to this point. However, most of these methods use some state to separate the non-liquefaction region from the liquefaction region to establish evaluation criteria [11–16]. However, it is challenging to adopt suitable empirical equations for regression analysis due to the unpredictability, complexity, and uncertainty of a soil mass [17–21]. As a result, many professionals and academics work to construct ways to identify the liquefaction of sandy soil and create simpler, more useful scientific analytical models [22].

In recent years, many scholars have tried to develop a simpler and more practical scientific analysis models in order to predict the possibility of liquefaction, and they have also established many methods for judging sand liquefaction [23]. Based on the GS search method, Zhang [24] et al. searched for the best parameters of the SVM, describing the training set of sand liquefaction with the help of the Libsvm program and then establishing a sand liquefaction prediction model on this basis. Liu [25] et al. selected eight influencing factors of sand liquefaction, including intensity, as predictive factors of the FDA model. Then the FDA discriminant model was established based on Fisher’s discriminant theory. Gao [26] et al. established a BP neural network and Elman network, and obtained a prediction model with faster operation speed and higher accuracy, with the help of Matlab scientific computing software. Yu [27] et al. proposed a gray weighted prediction method with an accuracy rate of up to 90% based on the gray system theory. In order to predict sand liquefaction, Pan [28] et al. applied a regression model and analyzed the sensitivity of different indicators under liquefaction based on the collected 173 sets of sample data. In the multi-index comprehensive discriminant method of sand liquefaction, Zhao [29,30] et al. extracted the initial samples based on KPCA and combined them with GPC to construct the KPCA-GPC model of sand liquefaction. Kurnaz [31] et al. suggested a novel classification-based integrated group data handling (EGMDH) model.

In summary, experts and scholars have conducted a lot of research on sand liquefaction prediction under dynamic load, but tailings sand is neither cohesive soil nor non-cohesive soil, and there are few studies on the liquefaction phenomenon after the complex coupling of solid–liquid–gas chemistry. Therefore, for the liquefaction of ore tailings, there is an urgent need to propose a comprehensive consideration of various factors, and the conver-

gence rate is relatively fast to determine the liquefaction threshold. This article examines the primary liquefaction-causing causes using proto-type tailings sand as the material, and uses SPSS software for factor dimension reduction analysis to determine the most suitable for factor analysis of influencing factors. It then uses the particle swarm method of parameter optimization (PSO) to generate into the support vector machine (SVM) for liquefaction condition prediction. The established threshold model technology provides an important basis for earthquake prevention of tailings ponds, and can provide a reference for engineering applications.

5. Replacing Section 2.1, Test Equipment. Original text:

Given the destructive and unpredictable nature of earthquakes, it is very difficult to perform field tests directly. To study the flow characteristics of tailings after liquefaction under earthquake action, based on the existing research results at home and abroad, a laboratory shaking table test was adopted [37]. The model test of tailings sand liquefaction was carried out by the ANCO R-232H seismic simulator of the Liaoning University of Engineering Technology. The data acquisition system used in the experiment was mainly divided into two parts: a DH-3817K dynamic and static data acquisition instrument was used for pore pressure and earth pressure data acquisition. Acceleration acquisition was performed using a DH-5981 dynamic data acquisition instrument [38].

Replacement text:

Direct field testing is exceedingly challenging because of how destructive and unpredictable earthquakes are. Therefore, based on the findings of the current research conduct, the liquefaction test was carried out through the self-designed rigid test-box [32]. The Liaoning University of Engineering Technology's ANCO R-232H seismic simulator conducted the model test of tailings sand liquefaction. The major components of the data acquisition system employed in the experiment were as follows: A DH-3817K dynamic and static data acquisition equipment was used for the collection of pore pressure and earth pressure data. A DH-5981 dynamic data acquisition tool was used to conduct acceleration acquisition [33].

6. Replacing Section 2.2, Test Material, not including Figure 1 and Table 1, with the following:

Table 1 displays the fundamental mechanical and physical indices of the ore tailings, and Figure 1 depicts the precise grading curve.

According to the research in [34], the dynamic strength of unsaturated tailings sand was higher than saturated tailings sand during the two phases of the tailings sand vibration process.

In addition, the preparation method of saturated sand was as follows:

- (1) Before preparing the model, the pore pressure gauge, earth pressure gauge, and accelerometer were arranged at the predetermined position of the test-box by flexible arrangement;
- (2) A certain amount of pure water was injected into the test-box;
- (3) The tailings sand layers were prepared in 10 layers, and the vibrating sand shaker evenly sprinkled the tailing sand from the sand outlet. If there was any unevenness, the surface was quickly leveled to ensure each tailing sand layer was consistent;
- (4) The height of the water surface was controlled at 5 cm above the sand layer in each operation to ensure that the prepared tailing sand was in a saturated state (maximum thickness 75 cm). However, the tailings sand between 75–90 cm from the platform height was not saturated, to guarantee that the tailings sand was in a half-soaked state, in order to more accurately imitate the saturation state of the tailings sand in the actual tailings dam;

- (5) The test was performed after the elements were still for 24 h.
7. Replacing Section 2.3, Test Model Box, not including Equation (1) and Table 2, with the following:

An enhanced new rigid test-box was presented after taking into account the benefits and drawbacks of rigid boxes, flexible boxes, and shearing test-boxes. To ensure that the test-box was applicable, tailings sand was used in the vibrating table model test. According to the experimental findings, the natural frequencies of the test-box before and after the test were 12.25 Hz and 2.36 Hz, respectively. The fundamental frequency of the empty test-box is five times that of the test-box containing tailings. The test-box has no effect on the vibration properties of the model tailings sand's free region and does not cause self-vibration. The vibrating frequency satisfies the vibrating table's test standards.

The boundary of the test-box was processed in accordance with the benefits and drawbacks of the rigid box, flexible box, and shear test-box:

- (1) Treatment of the friction bottom: First, the inner side of the bottom plate was dusted with gravel of various sizes to simulate a friction boundary in order to prevent relative sliding of the test tailings sand and the bottom of the test-box as much as possible and to ensure that they have a good bond.
- (2) Sliding boundary treatment: Lubricating oil was applied to the inner wall of the test-box as the sliding boundary treatment to minimize the frictional resistance and increase the stiffness of the tailings sand.
- (3) Flexible boundary treatment: The sidewall of the test-box was coated with a molded polystyrene foam board as the flexible boundary treatment.

In addition, four rectangular pipes were welded vertically along the four corners of the frame. Each side was welded into an "x" shape with rectangular pipes. The test-box can hardly be bent and deformed. It is difficult for the model floor and the bottom of the tailings to slip relative to each other, but due to the great restraint formed around it, the model tailings sand's free shear deformation in the horizontal direction is inescapably constrained. The tailings sand shall not be twisted or distorted horizontally during the design process based on the rigid box.

The 2-norm method formula is as follows:

where x_i is the reference point acceleration (central acceleration) and x_j is the comparing point acceleration (boundary point acceleration). Both are the maximal acceleration values at these points, and "i" and "j" both represent different time moments.

From the definition, if α is 0, the boundary effect may be entirely avoided because the two signals are equal. Table 2 shows that the boundary norm index for various seismic wave types is less than 10%, which satisfies the test-box's boundary design specifications. Peak acceleration is the one that applies to the box and is the actual acceleration that was collected. The center acceleration serves as the reference point acceleration. The acceleration at the border serves as the comparison point acceleration.

8. Deleting two sentences from Section 2.4, Sensor and Measuring Point Arrangement. The deleted parts read as follows:
 - Considering that the traditional accelerometer arrangement method easily causes deflection and displacement of the sensor position when it is buried, the flexible arrangement sensor technology was used to arrange the sensors at equal intervals and equal depths at various key positions to ensure the scientific accuracy of the test. The test arrangement has five BS-1-type pore pressure sensors, six CE0-type piezoelectric voltage (IEPE) acceleration sensors, and 12 BX-1-type earth pressure sensors.

9. Replacing Section 2.5, Test Loading Scheme, not including Figure 3 and Table 3, with the following:

According to the geological survey report, with a preset seismic acceleration of 0.10 g and a characteristic period of 0.45 s, the corresponding shear wave velocity exceeds 284 m/s, indicating a moderately hard site. A Traft wave is an actual strong earthquake record with a characteristic period of 0.44 s, suitable for the medium hard site. Therefore, this test will explore the dynamic response characteristics of a Traft wave, El Centro seismic wave, and Shanghai seismic wave. The actual situation of the three seismic waves is shown in Figure 3.

A relevant summary of vibration liquefaction in research and soil dynamics is available. In this experiment PGA (0.1 g, 0.2 g and 0.3 g) was used to determine the magnitude. Different local waves (II, III, and IV) made up the waveform, while ground motion duration made up the frequency. Shear strain served as a defining feature of the stress–strain history in soil parameters. Pore pressure variations in the burial components were used to describe the drainage conditions, and buried depth was used to describe the overlying effective stresses. Table 3 displays the precise model test loading circumstances.

10. Replacing the original Section 3.1, Particle Swarm Optimization (PSO). Original text:

PSO is usually based on real coding and, due to the lack of cross-validation and variation, calculates the new speed based on its previous speed and the distance from its current position to its own best historical position and the best position of its neighbor. In general, the value of each component in v_i can be sandwiched within $[v_{\min}, v_{\max}]$ to control excessive roaming of particles outside the search space. The particle then flies to a new position and repeats the process until it reaches its maximum algebra. The main parameters of the PSO algorithm include population size and algebra. The convergence of the algorithm is influenced by the number of particles in the group (larger groups require more iterations to converge) and the topological structure: strongly connected groups (with larger domains, for example) converge faster than loosely connected neighborhoods. Is it possible to find a unique set of algorithm parameters that work well in all cases? Based on the above considerations, the following empirical program is found to work in practice [40].

Replacement text:

PSO typically uses actual coding and determines its new speed based on its prior speed, the distance between its present location, and both its own and its neighbor's best historical positions, in the absence of cross-validation and variation. In order to prevent particles from wandering too far beyond the search area, the values of each component in v_i can often be sandwiched by $[v_{\min}, v_{\max}]$. When the particle achieves its maximum algebra, it travels to a new location and restarts the process. The main parameters of the PSO algorithm include population size and algebra. The topological structure of the group and the number of particles in the group both affect how quickly the algorithm converges. For example, tightly linked groups with bigger domains converge more quickly than weakly connected neighborhoods. Is it feasible to develop a special set of algorithmic parameters that are effective in every situation? The following empirical program is discovered to be effective in practice based on the aforementioned factors [35].

11. Replacing the first original sentence from Section 3.2, Support Vector Machine (SVM). Original text:

The support vector machine is a new type of machine algorithm commonly used for pattern recognition.

Replacement text:

A brand-new class of machine algorithm frequently employed for pattern recognition is the support vector machine.

12. Replacing two sentences from Section 3.3, Algorithm Design. Original text:

- Based on the factor analysis, the parameters of the suitable influencing factors were analyzed, and the corresponding data were normalized.
- The optimal penalty parameter C and kernel function parameter g will be selected at this time.

Replacement text:

- The parameters of the appropriate influencing factors were examined based on the factor analysis, and the relevant results were then standardized.
- At this point, the ideal kernel function parameter g and penalty parameter C will be chosen.

13. Replacing five sentences from Section 4, Factor Analysis of Influence Parameters of Tailings Sand Liquefaction. Original text:

- According to the shaking table test data, the features affecting liquefaction under the action of ground motion were analyzed to obtain the features suitable for the prediction model.
- Through the shaking table test, the liquefaction of tailing sand under an earthquake was studied under the influence of various time–space features.
- Dynamic shear stress ratio (the ratio of shear stress to shear strain) characterized by
- Bartlett’s sphericity test gives an approximate chi-square of 155.182, a companion probability of approximately 0.000, and a significance of less than 0.05. Therefore, the null hypothesis of Bartlett’s sphericity test is rejected, and it is considered suitable for factor analysis, so the next statistical analysis is performed.

Replacement text:

- The factors impacting liquefaction under the influence of ground motion were examined in accordance with the shaking table test results to get features acceptable for the prediction model.
- The liquefaction of tailings sand after an earthquake was investigated using the shaking table test under the effect of different time–space characteristics.
- Dynamic shear stress ratio is characterized by the following:
- According to Bartlett’s sphericity test, the chi-square value is around 155.182, the corresponding probability is roughly 0.000, and the significance is less than 0.05. Bartlett’s sphericity test’s null hypothesis is therefore rejected, and as it is thought to be appropriate for factor analysis. The following statistical analysis is carried out.

14. Authors would like to change the last column from Table 4, changing the words “unliquefied” and “liquefied” to symbols as displayed below:

	PGA (g)	Type of Earthquake	Buried Depth (cm)	Peak Acceleration (g)	Holding Time (s)	Peak Pore Pressure (MPa)	Peak Earth Pressure (MPa)	Dynamic Shear Stress Ratio	Liquefaction State
1	0.1	Taft	−75	0.12	30.9	0.0001	—	—	Unliquefied
2	0.1	Taft	−60	0.224	31.52	0.0008	1.2932	0.6578	liquefied
3	0.1	Taft	−45	0.141	29.38	0.0012	0.8931	0.8068	liquefied
4	0.1	Taft	−30	0.139	35.02	0.0013	1.0849	0.84a91	liquefied
5	0.1	Taft	−15	0.149	38.46	0.0011	1.0104	0.8117	Unliquefied
6	0.1	El Centro	−75	0.199	24.12	0.0002	—	—	liquefied
7	0.1	El Centro	−60	0.143	33.26	0.0007	1.8774	0.9701	liquefied

8	0.1	El Centro	−45	0.261	30.46	0.0005	1.4663	1.3297	Unliquefied
9	0.1	El Centro	−30	0.147	32.22	0.0008	1.7283	1.5168	Unliquefied
10	0.1	El Centro	−15	0.201	39.66	0.001	2.139	1.5355	Unliquefied
11	0.1	Shanghai wave	−75	0.138	16.82	0.0001	—	—	Unliquefied
12	0.1	Shanghai wave	−60	0.134	18.56	0.0008	1.3646	1.4841	liquefied
13	0.1	Shanghai wave	−45	0.135	16.88	0.001	2.4964	1.7746	liquefied
14	0.1	Shanghai wave	−30	0.12	22.92	0.0014	1.9191	1.7892	liquefied
15	0.1	Shanghai wave	−15	0.128	19.84	0.001	1.018	1.9084	Unliquefied
16	0.2	Traft	−75	0.226	38.82	0.0002	—	—	liquefied
17	0.2	Traft	−60	0.218	31.82	0.001	1.2664	1.3091	liquefied
18	0.2	Traft	−45	0.222	27.48	0.0013	1.026	1.6283	liquefied
19	0.2	Traft	−30	0.209	36.38	0.0015	1.3019	1.5671	liquefied
20	0.2	Traft	−15	0.278	41.68	0.0018	2.0589	1.7761	liquefied
21	0.2	El Centro	−75	0.255	23.84	0.0002	—	—	liquefied
22	0.2	El Centro	−60	0.215	25.48	0.0006	1.3066	1.0313	liquefied
23	0.2	El Centro	−45	0.269	26.04	0.0008	2.1932	1.53	Unliquefied
24	0.2	El Centro	−30	0.234	32.3	0.0009	2.0239	1.5746	Unliquefied
25	0.2	El Centro	−15	0.225	27.34	0.0011	1.6395	1.627	Unliquefied
26	0.2	Shanghai wave	−75	0.214	19.04	0.0001	—	—	Unliquefied
27	0.2	Shanghai wave	−60	0.322	22.44	0.0007	1.1371	1.5094	liquefied
28	0.2	Shanghai wave	−45	0.271	21.58	0.0012	2.8246	1.9063	liquefied
29	0.2	Shanghai wave	−30	0.25	32.3	0.0018	2.2371	1.843	liquefied
30	0.2	Shanghai wave	−15	0.322	27.34	0.001	0.8388	1.7258	Unliquefied
31	0.3	Traft	−75	0.316	29.64	0.0005	—	—	Unliquefied
32	0.3	Traft	−60	0.303	29.96	0.0009	2.8406	1.7432	liquefied
33	0.3	Traft	−45	0.35	29.64	0.0014	1.7487	2.2737	liquefied
34	0.3	Traft	−30	0.289	30.48	0.0017	2.0538	2.2511	liquefied
35	0.3	Traft	−15	0.33	31.2	0.0018	3.6069	2.2024	liquefied
36	0.3	El Centro	−75	0.466	23.7	0.0002	—	—	liquefied
37	0.3	El Centro	−60	0.493	24.7	0.0006	0.5975	2.8199	liquefied
38	0.3	El Centro	−45	0.349	25.16	0.001	1.1091	3.2321	liquefied
39	0.3	El Centro	−30	0.313	28.62	0.0016	1.0587	3.6079	liquefied
40	0.3	El Centro	−15	0.416	28.46	0.0009	1.323	3.9402	Unliquefied
41	0.3	Shanghai wave	−75	0.451	17.4	0.0001	—	—	Unliquefied
42	0.3	Shanghai wave	−60	0.378	20.58	0.0005	1.1371	2.4138	Unliquefied
43	0.3	Shanghai wave	−45	0.359	21.94	0.001	2.8246	2.779	liquefied
44	0.3	Shanghai wave	−30	0.318	26.22	0.0013	2.2371	2.8106	liquefied
45	0.3	Shanghai wave	−15	0.37	26.86	0.0009	0.8388	2.8	Unliquefied

With

	PGA (g)	Type of Earthquake	Buried Depth (cm)	Peak Acceleration (g)	Holding Time (s)	Peak Pore Pressure (MPa)	Peak Earth Pressure (MPa)	Dynamic Shear Stress Ratio	Liquefaction State
1	0.1	Traft	−75	0.12	30.9	0.0001	—	—	×
2	0.1	Traft	−60	0.224	31.52	0.0008	1.2932	0.6578	○
3	0.1	Traft	−45	0.141	29.38	0.0012	0.8931	0.8068	○
4	0.1	Traft	−30	0.139	35.02	0.0013	1.0849	0.84091	○
5	0.1	Traft	−15	0.149	38.46	0.0011	1.0104	0.8117	×
6	0.1	El Centro	−75	0.199	24.12	0.0002	—	—	○
7	0.1	El Centro	−60	0.143	33.26	0.0007	1.8774	0.9701	○
8	0.1	El Centro	−45	0.261	30.46	0.0005	1.4663	1.3297	×
9	0.1	El Centro	−30	0.147	32.22	0.0008	1.7283	1.5168	×
10	0.1	El Centro	−15	0.201	39.66	0.001	2.139	1.5355	×
11	0.1	Shanghai wave	−75	0.138	16.82	0.0001	—	—	×
12	0.1	Shanghai wave	−60	0.134	18.56	0.0008	1.3646	1.4841	○
13	0.1	Shanghai wave	−45	0.135	16.88	0.001	2.4964	1.7746	○
14	0.1	Shanghai wave	−30	0.12	22.92	0.0014	1.9191	1.7892	○
15	0.1	Shanghai wave	−15	0.128	19.84	0.001	1.018	1.9084	×
16	0.2	Traft	−75	0.226	38.82	0.0002	—	—	○
17	0.2	Traft	−60	0.218	31.82	0.001	1.2664	1.3091	○
18	0.2	Traft	−45	0.222	27.48	0.0013	1.026	1.6283	○
19	0.2	Traft	−30	0.209	36.38	0.0015	1.3019	1.5671	○
20	0.2	Traft	−15	0.278	41.68	0.0018	2.0589	1.7761	○
21	0.2	El Centro	−75	0.255	23.84	0.0002	—	—	○
22	0.2	El Centro	−60	0.215	25.48	0.0006	1.3066	1.0313	○
23	0.2	El Centro	−45	0.269	26.04	0.0008	2.1932	1.53	×
24	0.2	El Centro	−30	0.234	32.3	0.0009	2.0239	1.5746	×
25	0.2	El Centro	−15	0.225	27.34	0.0011	1.6395	1.627	×
26	0.2	Shanghai wave	−75	0.214	19.04	0.0001	—	—	×
27	0.2	Shanghai wave	−60	0.322	22.44	0.0007	1.1371	1.5094	○
28	0.2	Shanghai wave	−45	0.271	21.58	0.0012	2.8246	1.9063	○
29	0.2	Shanghai wave	−30	0.25	32.3	0.0018	2.2371	1.843	○
30	0.2	Shanghai wave	−15	0.322	27.34	0.001	0.8388	1.7258	×
31	0.3	Traft	−75	0.316	29.64	0.0005	—	—	×
32	0.3	Traft	−60	0.303	29.96	0.0009	2.8406	1.7432	○
33	0.3	Traft	−45	0.35	29.64	0.0014	1.7487	2.2737	○
34	0.3	Traft	−30	0.289	30.48	0.0017	2.0538	2.2511	○
35	0.3	Traft	−15	0.33	31.2	0.0018	3.6069	2.2024	○
36	0.3	El Centro	−75	0.466	23.7	0.0002	—	—	○
37	0.3	El Centro	−60	0.493	24.7	0.0006	0.5975	2.8199	○
38	0.3	El Centro	−45	0.349	25.16	0.001	1.1091	3.2321	○
39	0.3	El Centro	−30	0.313	28.62	0.0016	1.0587	3.6079	○
40	0.3	El Centro	−15	0.416	28.46	0.0009	1.323	3.9402	×

41	0.3	Shanghai wave	−75	0.451	17.4	0.0001	—	—	×
42	0.3	Shanghai wave	−60	0.378	20.58	0.0005	1.1371	2.4138	×
43	0.3	Shanghai wave	−45	0.359	21.94	0.001	2.8246	2.779	○
44	0.3	Shanghai wave	−30	0.318	26.22	0.0013	2.2371	2.8106	○
45	0.3	Shanghai wave	−15	0.37	26.86	0.0009	0.8388	2.8	×

Notes: ○: liquefied; ×: unliquefied.

15. The authors would like to change eight sentences from Section 5.2, Construction of the Tailings Sand Liquefaction Threshold Model. Original text:

- The parameters used in the PSO optimization process are given in Table 7, where the group size (Sizepop) is set to 20, the number of iterations (Maxgen) required is set to 200 and the inertia weight is set to 0.5
- The size of the optimization accuracy depends on the maximum position of the best fitness. After the particle swarm optimization method is completed, the optimal parameters (penalty factor and kernel parameter) are obtained, and then automatically provided to the support vector machine program for corresponding training.
- Through the MATLAB program of PSO-SVM, the global penalty of the factor C and the kernel parameter g of the SVM model are obtained by the population particles. The optimal penalty factor of the SVM model suitable for seismic liquefaction under the experimental conditions is 12.7695.
- In this result, the SVM model is trained using the optimal parameters to generate the final classifier.
- Of the 45 test datasets used, only 3 were misclassified, and the overall classification accuracy rate was 92.7%, as shown in Figure 7. The designed PSO-SVM model has the ability to predict tailings liquefaction.

Replacement text:

- Table 7 lists the parameters that were utilized in the PSO optimization process. The group size (Sizepop), the number of iterations (Maxgen), and the inertia weight were all set to 20.
- The maximum location of the optimal fitness determines how accurate an optimization is. The best parameters (penalty factor and kernel parameter), which are determined once the particle swarm optimization process is finished, are then automatically given to the support vector machine software for the appropriate training.
- The global penalty of the factor C and the kernel parameter g of the SVM model are derived by the population particles using the MATLAB software of the PSO-SVM. Under the experimental conditions, the SVM model's optimal penalty factor for seismic liquefaction is 12.7695.
- In order to produce the final classifier in this outcome, the SVM model is trained using the best parameters.
- Only 3 of the 45 test datasets were incorrectly identified, yielding a classification accuracy percentage of 92.7% overall, as shown in Figure 7. The PSO-SVM model that was created may foresee tailings liquefaction.

16. The authors would like to replace five segments from Section 5.3, Analysis of the PSO-SVM Tailings Liquefaction Threshold Model. Original text:

- To verify the superiority of the PSO-SVM algorithm, the existing genetic algorithm support vector machine (GA-SVM) and grid search method (GS) optimized support vector machine (GS-SVM) algorithm are compared and calculated.

- In this result, the optimal parameters are used to train the SVM model to obtain the final classification results. In the 45 test datasets used, 5 samples were classified incorrectly, and the overall classification accuracy rate was 88.9%.
- The GS algorithm performs an exhaustive search in the given data space to solve the model selection problem (i.e., find the optimal parameters for the dataset). However, since the boundary of the SVM parameter is a priori, the SVM parameter is first searched in the coarse range to find the optimal region of the SVM parameter. Once the coarse mesh search is completed, the fine mesh search is performed, but following the search process. The disadvantage is that the time is relatively long. The parameter ranges of the coarse mesh and fine mesh search are given in Table 8. After the grid search, the parameter with the highest classification accuracy will be selected for use by the SVM.
- In this result, the optimal parameters are used to train the SVM model to achieve the final liquefaction classification purpose.
- The results are compared based on the results of PSO-SVM, GA-SVM and GS-SVM, as shown in Figure 13.
- Therefore, parameter determination and feature selection in PSO-SVM is very valuable. However, due to the limited space, this paper only uses the results database of the vibrating table indoor test to calculate the classification accuracy rate to evaluate the developed model.

Replacement text:

- The current genetic algorithm support vector machine (GA-SVM) and grid search technique (GS) optimized support vector machine (GS-SVM) algorithms are compared, and calculations are made to demonstrate the superiority of the PSO-SVM methodology.
- In order to get the final classification findings in this result, the SVM model was trained using the optimum parameters. Five samples were incorrectly identified out of the 45 test datasets employed, and the total classification accuracy percentage was 88.9%.
- The model selection problem is solved by the GS method by doing an exhaustive search in the provided data space. To discover the ideal area of the SVM parameter, the parameter is initially searched in the coarse range because the SVM parameter's boundary is known in advance. The fine mesh search is carried out after the coarse mesh search, but in the opposite order. The fact that the time is so lengthy is a drawback. Table 8 lists the parameter ranges for the coarse mesh and fine mesh searches. The SVM will choose the parameter with the best classification accuracy following the grid search.
- In order to attain the ultimate liquefaction classification goal, the SVM model was trained using the ideal parameters in this result.
- As shown in Figure 13, the outcomes are contrasted using the outcomes of the PSO-SVM, GA-SVM, and GS-SVM.
- As a result, choosing features and setting parameters in the PSO-SVM are quite important. To compute the classification accuracy rate and assess the built model, this research only uses the results database of the vibrating table indoor test, owing to space constraints.

17. The authors would like to replace Section 6, Conclusions, with the following:

The primary elements impacting liquefaction were taken into consideration while using the prototype tailings sand as the material for this article. Shaking table tests of tailings liquefaction were carried out with a self-designed rigid test-box. The following conclusions were drawn:

- (1) By performing a large number of factor analyses on the selected factors, the influencing factors suitable for the prediction model were obtained, namely, PGA, type of earthquake, buried depth, peak acceleration, holding time, peak pore pressure, peak earth pressure, and dynamic shear stress ratio.
- (2) The support vector machine (SVM) was utilized to forecast the liquefaction scenario after the parameters were optimized using the particle swarm optimization method (PSO). The liquefaction threshold model's forecast accuracy has increased, and prediction speed has increased.

- (3) In comparison to the current genetic algorithm (GA) and grid node search technique (GS), the revised PSO-SVM algorithm was shown to be not only quickly calculated but also to have a high degree of accuracy, reaching 92.7%, and to have strong application.
18. After completing the Major Correction, 17 citations have been removed [20–36] the references are the following:
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19. The authors added 12 new references in the following citation order [1–3] and [23–31]:
 1. Cui, H.; Ji, J.; Song, J.; Huang, W. Limit state line-based seismic stability charts for homogeneous earth slopes. *Comput. Geotechnics* **2022**, *146*, 104749.
 2. Ji, J.; Cui, H.; Zhang, T.; Song, J.; Gao, Y. A GIS-based tool for probabilistic physical modelling and prediction of landslides: GIS-FORM landslide susceptibility analysis in seismic areas. *Landslides* **2022**, *19*, 2213–2231.
 3. Cui, H.; Hürliemann, M.; Medina, V.; Ji, J. GIS-FSLAM-FORM: A QGIS plugin for fast probabilistic susceptibility assessment of rainfall-induced landslides at regional scale. In Proceedings of the EGU General Assembly 2023, Vienna, Austria, 24–28 April 2023; EGU23-295.

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With this correction, the order of some references has been adjusted accordingly.

The authors state that the scientific conclusions are unaffected. This correction was approved by the Academic Editor. The original publication has also been updated.

Reference

1. Jin, J.; Yuan, S.; Cui, H.; Xiao, X.; Jia, B. A Threshold Model of Tailings Sand Liquefaction Based on PSO-SVM. *Sustainability* **2022**, *14*, 2720. [[CrossRef](#)]

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