

Article

Field Observation and Settlement Prediction Study of a Soft Soil Embankment under Rolling Dynamic Compaction

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Abstract: Rolling dynamic compaction (RDC) has been found to be useful for compaction soils and is now widely used globally. Because RDC is not often used in soft soils with poor engineering properties, field monitoring was used to study the soft clay embankment responses under RDC conditions in this study. Analysis of the monitoring data revealed that the response of the soil occurred mainly in the first 20 passes. Field monitoring revealed a strong correlation between settlement, horizontal displacement, and pore water pressure. The depth of impact of RDC on the soft soil embankment was between 3 and 3.5 m. Although settlement prediction is an important issue for construction, there is a lack of prediction methods for RDC-induced soil settlement. In this study, we used three different machine learning algorithms: random forest regression (RFR), multilayer perceptron (MLP), and extreme gradient boosting (XGBoost) to predict the total settlement and uneven settlement induced by RDC on the soft soil embankment. The three prediction models were compared, and the predictive accuracy of these models was assessed. This study analyzes and summarizes the effect of RDC application on a soft clay embankment and explores the machine learning method used for settlement prediction based on monitoring data, which provides some methods and ideas for research on the application of RDC on soft soil foundations.

Keywords: rolling dynamic compaction; impact roller; ground improvement; field monitoring; settlement prediction



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1. Introduction

Soil compaction is important for rapid urban and industrial development. Rolling dynamic compaction (RDC) has been found to be useful for the compaction of soils and is now widely used globally [1]. It involves towing a non-circular module, whose designs have three, four, or five sides, behind a tractor. As the module rotates, it imparts energy and compacts the soil as it falls to the ground [2]. Compared with a conventional smooth drum roller, RDC is able to compact soil to deeper depths (>3 m) with a relatively faster speed [3]. Hence, RDC is extensively used in civil engineering construction, including situ densification of existing fills, airports and land reclamation projects, reconstruction of rural roads, and in the mining and agricultural sectors [4–8].

To assess the effectiveness of RDC, many researchers have conducted field tests of soil settlement [9], soil pressure [10], and vector velocities of the rolling module [11]. Due to the fact that some measurements are difficult to realize or are not fully controlled in field tests, physical scale model tests have been utilized to quantify the performance of RDC with respect to various soil types, roller speeds, and masses [3,12]. Although model tests are more controllable than field tests, small-scale model tests are still impaired by scaling and boundary effects [13]. To complement field and modeling tests, several

researchers have developed numerical models to assess the effectiveness of RDC [2,14–17]. Bradley et al. [14] investigated the behavior of a full-size RDC model using the finite element method (FEM). The numerical results were validated against field results, and they showed encouraging results in terms of simulating soil responses induced by RDC. Nevertheless, since the FEM model is based on continuum rather than particulate analysis, soil particles are difficult to simulate. In order to overcome the limitations of the FEM, several researchers have switched to the discrete element method (DEM) to mimic the behavior of granular materials [18–20]. Chen et al. [15–17] developed a FEM-DEM-based model to simulate the behavior of the RDC of three-sided and four-sided impact rollers. In addition, machine learning algorithms were applied to the study of RDC in some works. Ranasinghe et al. [21,22] suggest an approach to predict density improvement at a specified depth below ground level due to RDC based on artificial neural networks. Despite this research, there is still a dearth of prediction studies of soil settlements induced by RDC. Settlement prediction in a large-construction project is an important issue for rapid and cost-effective construction.

Since machine learning algorithms have proven to be efficient and reliable tools for solving complex geotechnical engineering issues, they have been employed in recent years as prediction models in subterranean geotechnical applications. Many scholars have attempted to predict soil settlements. Park et al. [23] used a genetic algorithm (GA) back-analysis method to predict the settlement of multi-layered thick, soft soil. Wen et al. [24] combined a threshold regression (TR) theory approach with an improved support vector machine (SVM) to establish a dam top settlement prediction model. Han et al. [25] used the sinusoidal algorithm (SA) to optimize a regularized extreme learning machine (RELM) in order to develop a prediction model for ground settlement around a foundation pit. However, existing researches cannot be applied to the prediction of settlement induced by RDC due to the large variation in the effectiveness of different foundation improvement methods. In addition, RDC can cause uneven settlement of soils, which may be detrimental to projects. It is evident that it is necessary to establish an effective prediction method for soil settlements induced by RDC.

In this study, we employed three distinct machine learning (ML) algorithms: random forest regression (RFR), multilayer perceptron (MLP), and extreme gradient boosting (XGBoost) to predict RDC-induced settlement on the Wansong East Road in Ruian, China. The first portion describes the geological conditions, the field test design, and the data gathering process. Given that RDC is not commonly utilized for soft clay upgrading, the impact and effectiveness of RDC reinforcing the soft soil embankment were investigated. Based on field data the relationship between settlement and other metrics was investigated. Then we predicted the total settlement and uneven settlement induced by RDC on the soft soil embankment, and compared the prediction performances of the three models in detail. The main conclusions were stated at the end. The research results help to evaluate the effectiveness of RDC on the reinforcement of soft soil embankments, which is of reference value for engineering practice.

2. Field Test

2.1. Test Setup

A part of Wansong East Road, which is located in Ruian City, China, was selected as the test site. The testing location is shown in Figure 1. The road was built over thick marine soft clay, which is characterized as having a high water content, high plasticity, high sensitivity, high compressibility, low shear strength, and low permeability [26,27]. RDC on a soft clay embankment may increase the risk of excessive settlement and uneven settlement. There is a significant lack of data and engineering experience related to using RDC to improve soft clay embankment, so full-scale field tests are desirable for investigating the influence of the RDC on the soft clay embankment.

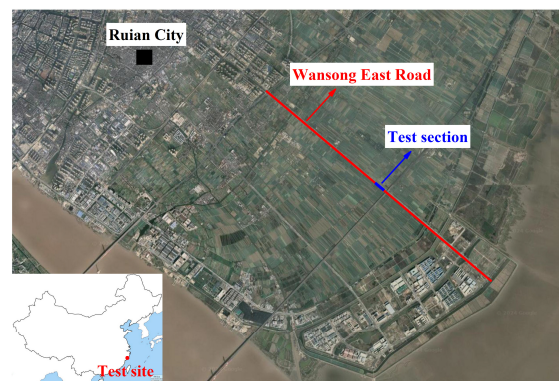


Figure 1. Overview of the field test site.

The upper part of the embankment in the test section consisted of a fill layer with a thickness of 0.6 to 0.8 m of sandy gravel material. Underlying the fill, there was a natural, saturated soft clay with a thickness of 34 to 41 m. The particle size distributions and properties for each of these soils are presented in Figure 2, and Table 1.

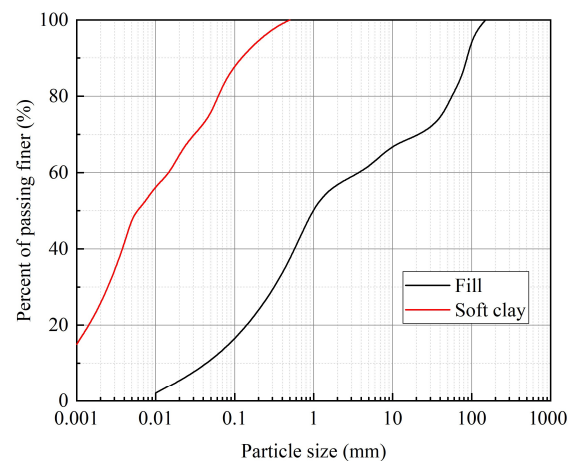


Figure 2. Particle size distributions.

Table 1. Material properties of soil.

Soil Type	Index	Value
Fill soil	Natural moisture content: %	4.8
	Volume moisture content: %	6.7
	Optimum moisture content: %	10.2
	Maximum dry density: g/cm ³	1.50
	Unit weight: kN/m ³	16.5
Soft clay	Silt content: %	12.5
	Natural moisture content: %	45.0
	Volume moisture content: %	54.0
	Liquid limit: %	50.2
	Plastic limit: %	30.5
	Unit weight: kN/m ³	17.9
	Compression index	0.48

At the location shown in Figure 1, the length of the test section was 50 m, with a width of 10 m. Before the field test, preloading was done using a rolling machine with an excitation force greater than 30 tons to level the ground and improve trafficability prior to RDC. The response of the embankment under the influence of the 3YCT32 16-t (each module being 8-t) three-sided impact roller was recorded under typical operating

conditions for the compaction of a controlled fill material (see Figure 3), which involves being drawn behind a tractor performing 40 passes and directed to travel at a speed of approximately 12 km/h.



Figure 3. YCT32 16.5-ton three-sided impact roller.

A monitoring section (see Figure 4) was set up in the test embankment to observe settlement, horizontal displacement, and pore water pressure (PWP). Settlement monitoring was carried out using the embedded settlement device (ESD) [28]. The ESD includes a liquid storage tank, settlement gauges (viz., datum point and measurement point), plastic pipe, and signal output cable, as shown in Figure 5. The settlement gauge consists of a vibrating-wire transducer and a cast iron tank [29]. When the ESD is in operation, the liquid-filled plastic pipe is connected to the settlement gauge at one end and to the atmosphere at the other. The ESD uses a vibrating-wire transducer to measure the surface pressure difference between the datum point and measurement point before and after the settlement, in order to determine their sedimentation value (accuracy of ± 0.05 mm). Three settlement gauges (measurement points) were buried at a depth of 0.25 m within the embankment fill material, as shown in Figure 6a.

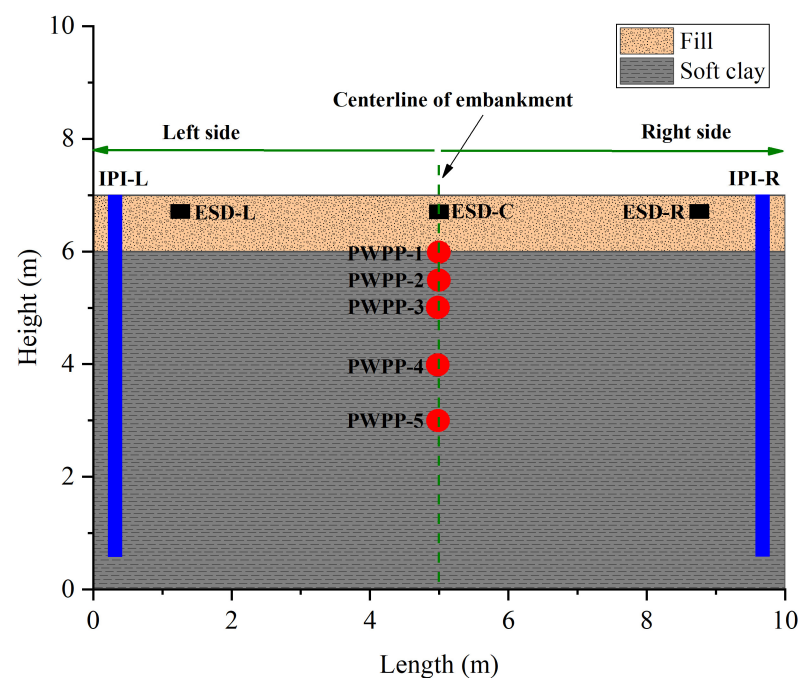


Figure 4. Sketch of monitoring section for test embankment.

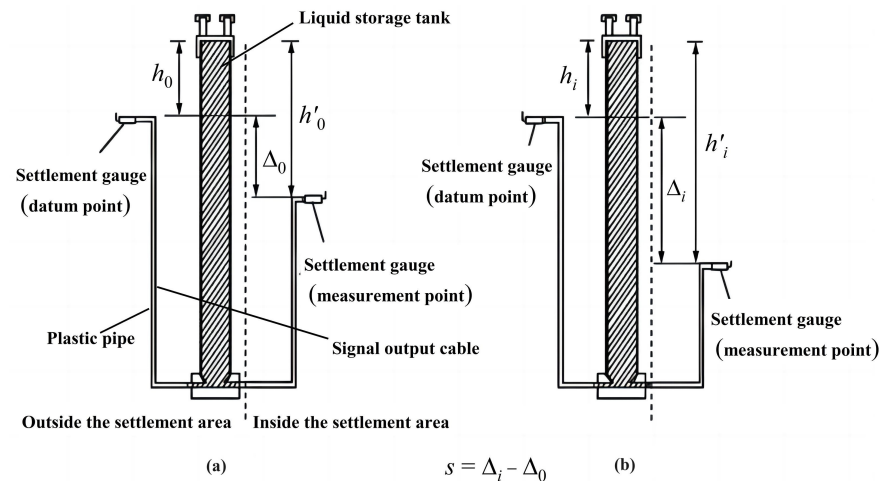


Figure 5. Schematic diagram of embedded settlement device: (a) initial state, (b) monitoring state.

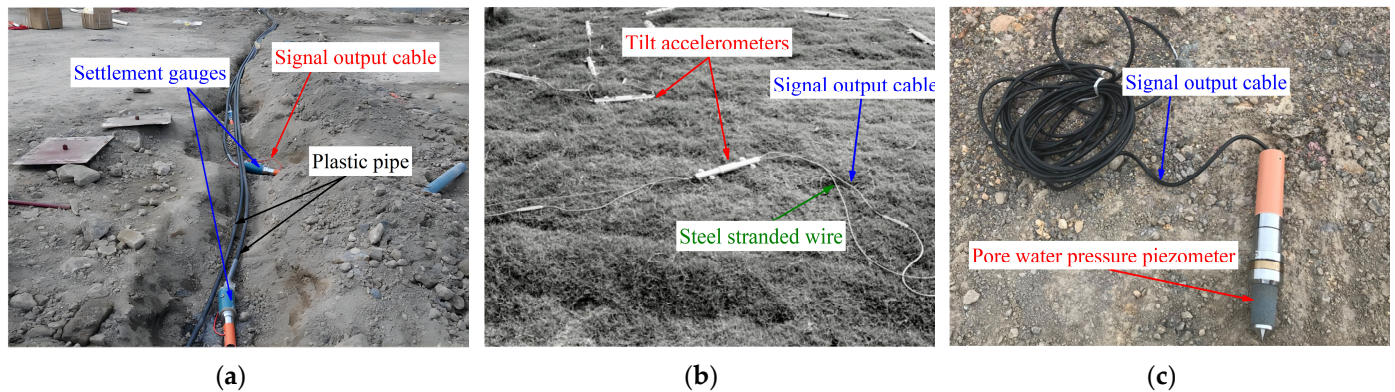


Figure 6. Installation of various instruments: (a) embedded settlement device, (b) in-place inclinometer, (c) pore water pressure piezometer.

To monitor the horizontal displacement of the embankment, two in-place inclinometers (IPIs) [30–33] were installed on both sides of the embankment. The composition of the instrument is shown in Figure 6b. Ten tilt accelerometers (with instrument spacing of 0.5 m) were mounted at 0 to 5 m depths below the ground surface along each IPI casing. For the given spacing of accelerators and tilt angles measured by accelerators, horizontal displacements with accuracy of ± 0.01 mm—at the depth of each accelerometer installed—can be determined. Three pore water pressure piezometers (PWPPs) [34] were installed at the central portion of the embankment to measure PWP at 1 m, 1.5 m, 2 m, 3 m, and 4 m depths (see Figure 6c). The accuracy of each PWPP is 0.2%. The monitoring section was monitored using the above instruments after each pass of the impact roller.

2.2. Monitoring Results

2.2.1. Settlement

The variations of settlement with the number of passes are shown in Figure 7 (including ESD-L, ESD-C, ESD-R, and the average value). Settlement at all measurement points gradually increased with the increase in the number of passes. The increments of settlement were generally greater in the first 10 passes. The maximum settlement reached 159.6 mm after 10 passes. This was due to the compaction of the gravel bedding and a certain depth of soft soil layer under impact loading. Under the action of impact, the pore water pressure of shallow soft soil dissipated rapidly, and the soil consolidated rapidly to form a dense, reinforced layer. After that, the increments of settlement gradually decreased as the number of passes increased. As shown by the variation of the average value with the number of passes, the last 20 passes induced only 17.1% of the total settlement. This was

because the overlying crust formed by the adequately compacted topsoil had the effect of spreading the stresses, making the impact loads less influential.

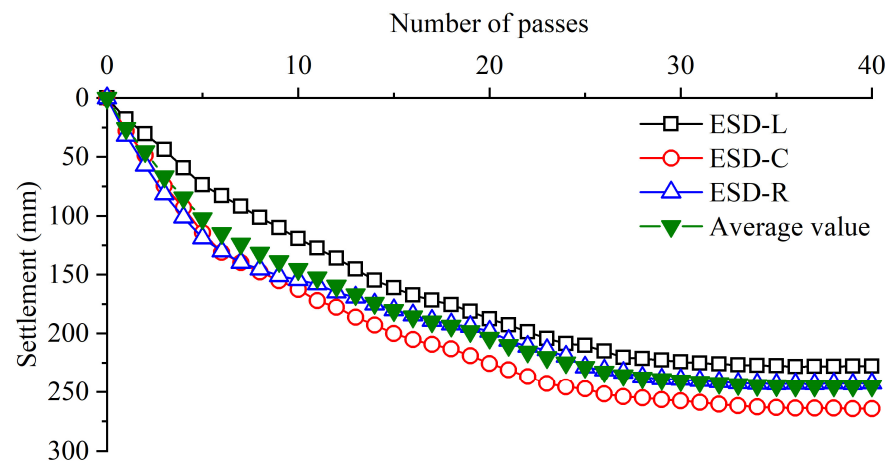


Figure 7. The variation of ground settlements with the number of passes.

Figure 8 shows the test data for settlement induced by RDC observed in this study as well as in other studies by other researchers [35–38]. The trend of the settlement with respect to the number of passes in this research is basically the same as it is in other studies. However, the settlement of this test is higher than that obtained from other studies with the same number of passes. This indicates that the deformation of soil caused by RDC is more significant in soft clay than in coarse-grained materials such as sand and gravel soils under the same conditions. During the compaction of the large-grained refuse fill materials [37], the surface developed a heave, which may be related to the lower leveling of the compacted materials.

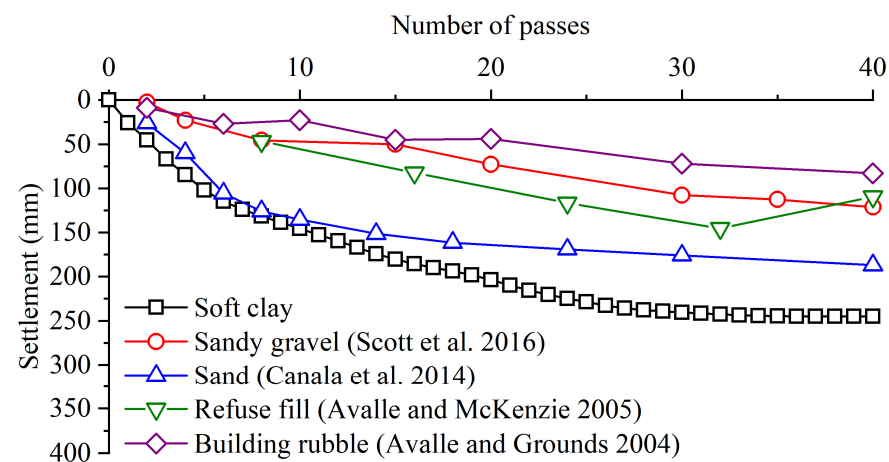


Figure 8. Settlement curves in different soil types [35–38].

The maximum difference in settlement between measuring points was calculated as an uneven settlement value. The variation of the uneven settlement value with the number of passes is shown in Figure 9. At the beginning of rolling, the uneven settlement increased rapidly with the increase in the number of passes. The uneven settlement value reached its maximum, close to 48.2 mm, after the sixth rolling. This was caused by the uneven distribution of the thickness of the soft soil layer in the rolling area. Due to the limitations of the site, the compaction work of the impact mill at different locations of the embankment was different. With the increase in the number of passes, the embankment was consolidated and settled under the action of impact rolling. Part of the uneven settlement was eliminated.

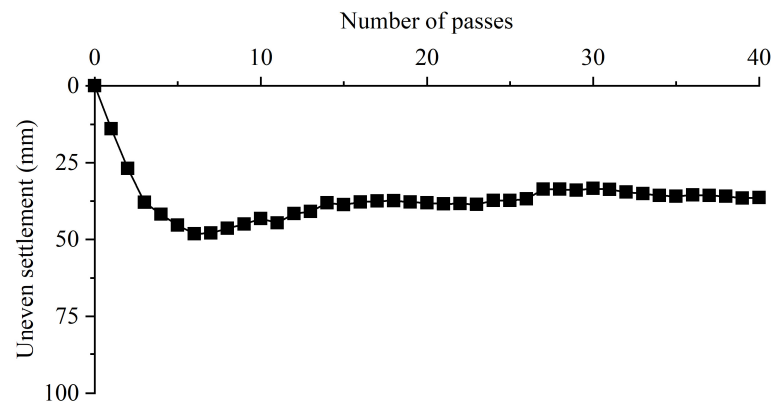


Figure 9. The variation of the uneven ground settlement value with the number of passes.

2.2.2. Horizontal Displacement

Figure 10 shows the effects of RDC on horizontal displacement (including the left and right sides of the embankment) at different depths. The horizontal displacement at all depths of the soil increased as the number of passes increased. The maximum horizontal displacement occurred essentially at the ground level, due to the fact that RDC has the greatest extrusion effect on the ground soil. The difference in horizontal displacement between the two sides of the embankment was small. After compaction, the difference in horizontal displacement at 0 m depth between the two sides of the embankment was about 5 mm. Soil horizontal displacement decreased with increasing depth because the energy generated by the impact dissipated with depth. After 40 passes, the cumulative horizontal displacement at a depth of 3.5 m was <2 mm, so it can be assumed that the effective impact depth of RDC was <3.5 m.

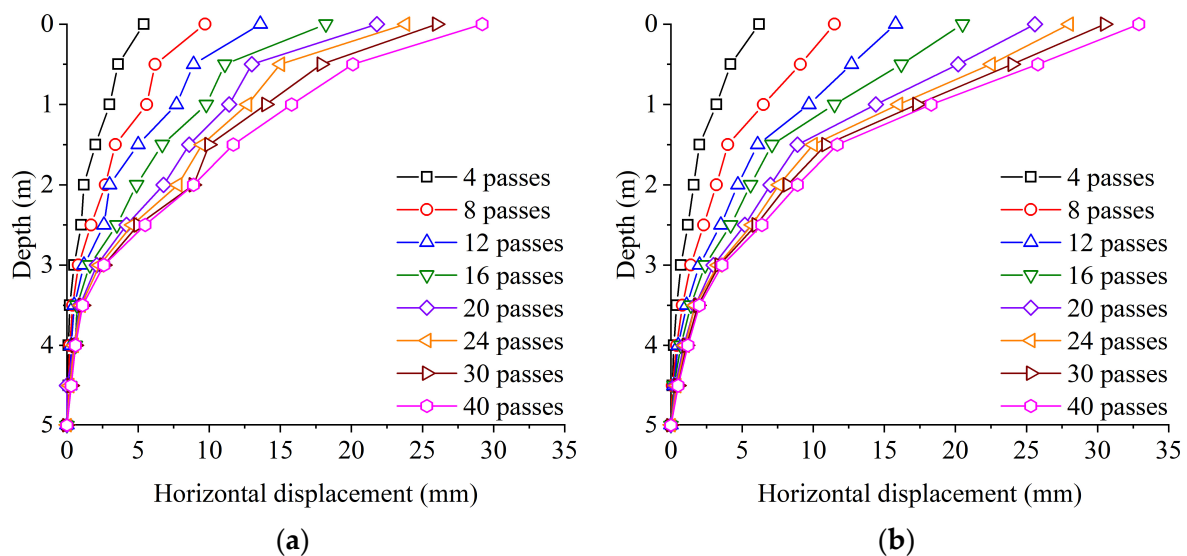


Figure 10. The effect of RDC on horizontal displacement at different depths (a) Left side of the embankment (IPI-L); (b) Right side of the embankment (IPI-R).

Considering that RDC has the greatest effect on the ground, the average horizontal displacement at the surface is plotted versus the number of passes (Figure 11). As the number of passes increased, the increments of horizontal displacement decreased. Horizontal displacement of the soil occurred mainly within the first 20 passes. The last 20 passes induced only 19.4% of the total horizontal displacement. The pattern was similar to the variation of soil settlement with the number of passes.

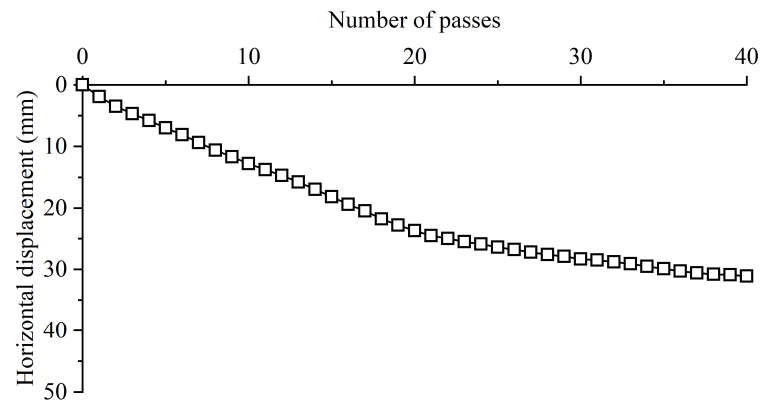


Figure 11. The variation of the average horizontal displacement at the surface with the number of passes.

2.2.3. Pore Water Pressure

Figure 12 shows the evolution of excess PWP measured by pore water pressure piezometers. The excess PWP was measured at five predetermined depths (viz., 1, 1.5, 2, 3, and 4 m) at the measurement point. As can be seen from the figure, the excess PWP at all depths increased with the increased number of passes. RDC had a significant effect on the PWP of the soil in the upper part of the embankment. The impact resulted in excess PWP of about 15 kPa, 12 kPa, and 7 kPa at depths of 1.0 m, 1.5 m, and 2.0 m, respectively. Little excess PWP was generated in the soil at a depth of 3 m. This was essentially the same as the depth of impact influence obtained through horizontal displacement observations. The excess PWP at 1 m depth is plotted versus the number of passes, as shown in Figure 13. Excess PWP was generated mainly within the first 20 passes. As the number of passes increased, the increments of PWP decreased. The PWP increase tends to level off toward a limit value. This trend was similar to the monitoring results for settlement and horizontal displacement. When the test embankment was compacted, the soft soil was compressed, and the additional stresses resulting from the impact caused the PWP to rise. After compaction, the excess PWP gradually dissipated. To maintain the original equilibrium, the effective stress increased. The soil structure of the test embankment improved.

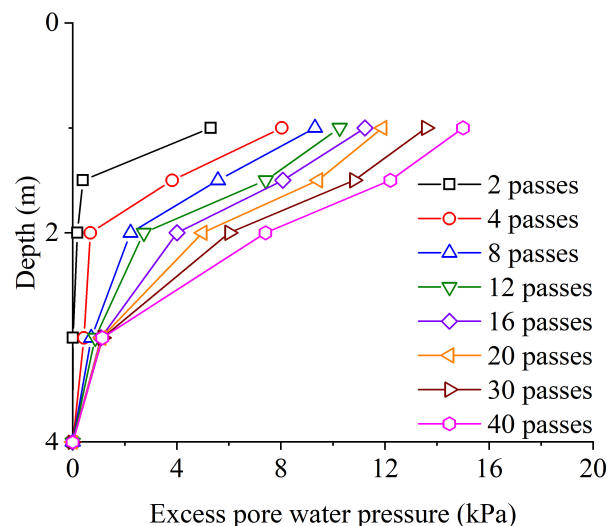


Figure 12. The effect of RDC on excess PWP at different depths.

A combination of monitoring data reveals that RDC can cause soil deformation (ground settlement and extrusion of the sides), and elevated PWP. Settlement is closely related to other factors observed, hence methods for predicting settlement using site monitoring data can be established.

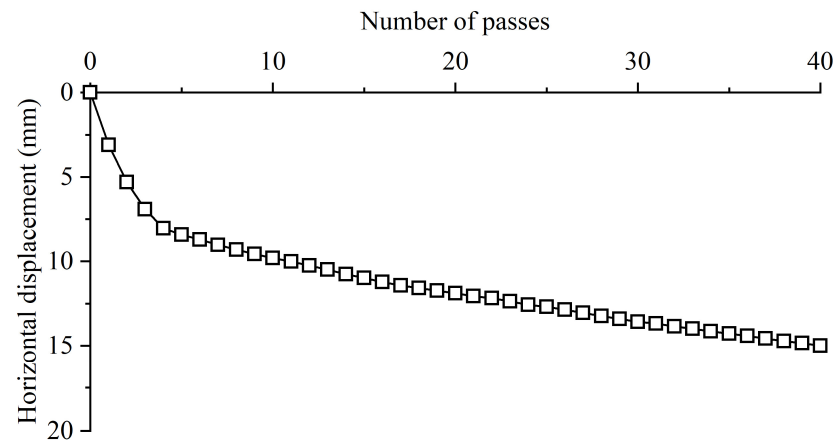


Figure 13. The variation of the excess PWP at 1 m depth (i.e., PWP-1) with the number of passes.

3. Overview of ML Algorithms

This section presents a brief introduction to the three surrogate models (viz., RFR, MLP, and XGBoost methods) that were used in this research.

3.1. RFR

RFR is an algorithm, proposed by Breiman in 2001 [39], that integrates multiple trees through the idea of ensemble learning, which consists of multiple classification and regression trees (CARTs). These CARTs are trained using randomly selected data and randomly combined feature types. Some data will be used repeatedly in the training of different CARTs [40]. Certain improvements can be made based on the characteristics of individual CARTs so that the correlation between the different CARTs in the final construction is as small as possible, thus significantly improving the performance of the final model. The final output is acquired by averaging all tree predictions. After growing to W trees $\{\zeta(x)\}$, the random forest regression predictor is calculated using the following equation:

$$\varphi(x) = \frac{\sum_{w=1}^W \zeta(x)}{W} \quad (1)$$

where $\varphi(x)$ is the final output, and w represents the w th tree. The RF method is widely used in geotechnical engineering. Zhou et al. [41] use an RFR approach for the prediction of ground settlements induced by the construction of a shield-driven tunnel. Xie and Peng [42] used a random forest (RF) model for estimating tunnel excavation damaged zones (EDZs), and the results indicated that the RF model has a good prediction capability.

3.2. MLP

MLP is a feedforward artificial neural network (ANN) that can be used to represent a variety of nonlinear logical discriminative functions [43,44]. It consists of input, output, and hidden layers, where each layer may have a number of nodes [45]. The nodes are known as neurons, which perform basic operations. The overall operation is the weighted sum of these basic operations. MLP has to be trained so that a known set of inputs yields the desired results. Training is often accomplished by feeding teaching or instructional patterns into the network and allowing the network to alter its weighting function based on previously set learning rules. The learning can be supervised, semi-supervised, or unsupervised.

In MLP, the neurons are organized in layers, and the connections are always directed from the lower layers to the upper layers. The neurons in the same layer are not interconnected. During the iterative process of training the learning algorithm, these weights are continuously adjusted to minimize prediction error and improve prediction accuracy. MLP has strong data self-driving capability and the ability to handle high-dimensional nonlinear

problems. Thus, it is able to fully reveal the high-dimensional nonlinear relationships between different data.

3.3. XGBoost

XGBoost is a novel extension based on the commonly used gradient tree boosting method developed by Chen et al. in 2016 [46]. In order to overcome the deficiency of a single tree, XGBoost employs a tree ensemble model composed of several trees to create input-output mapping [47]. The main idea of this algorithm is to transform features to grow a tree and add constantly trees [48–50]. Actually, a new function is trained to fit the residual of the previous prediction each time a new tree is added. The prediction output function of the XGBoost model is as follows:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i), f_k \in F \quad (2)$$

where K is the total number of trees, k represents the k th tree, x_i is the features corresponding to sample i , $\hat{y}_i$ corresponds to the predicted score from this tree, and F is the space of regression trees. As indicated by Equation (2), $\hat{y}_i$ is essentially a summation of the predicted value obtained from each tree. For a given set of training data, the total number of trees contained in F (i.e., K), and the optimal structure of each tree can be obtained by optimizing the predefined objective function. The regularization term that XGBoost appends to the objective function can control the complexity of the model. The regularization term contains the number of leaf nodes in the tree and the square sum of the L2 modulus of the score output on each leaf node. From the perspective of bias trade-off, the regularization term reduces model variance, which results in a simpler learning model, prevents overfitting, and improves the generalization ability of the model. For these reasons XGBoost is superior to the traditional gradient boost decision tree (GBDT) method. In the geotechnical engineering field, Zhang et al. [48] adopted XGBoost to predict the surface settlement induced by earth pressure balance shield tunneling.

4. Predictions Using ML Algorithms

This section compares the comprehensive performance of ML algorithms, including RFR, MLP, and XGBoost. The database for settlement prediction includes the results of field monitoring. Field monitoring data were considered, with 80% of the data used in the training phase and the remaining 20% in the testing phase to assess the performance of the various machine learning models. The ML algorithms were implemented in PyTorch, a DL framework written in Python 1.12.0, which runs on an NVIDIA 4070 GPU (Nvidia, Santa Clara, CA, USA). The computational times for each of the three methods are all within 1 s, while the efficiency difference is marginal.

4.1. Predictions for Settlement

Figures 14a and 15a show the training and testing results of the prediction of the average value of settlement by RF, MLP, and XGBoost, where the solid line indicates equality. It is clear that the accuracy of the testing model is close to that of the training model. As can be seen from the plots, all three methods have learned the input/output mapping effectively, with the XGBoost and RFR models outperforming the MLP model. As shown in the plots, the MLP model gives fairly reasonable predictions for settlements less than 150 mm, but has slightly incorrect estimations for settlements exceeding 150 mm. The training and testing results of the settlement predictions at measurement points ESD-L, ESD-C, and ESD-R are shown in Figures 14b–d and 15b–d. Similar to the prediction results for the average values of settlements, the XGBoost and RFR models predicted the settlement values of measurement points ESD-L, ESD-C, and ESD-R more effectively than the MLP did.

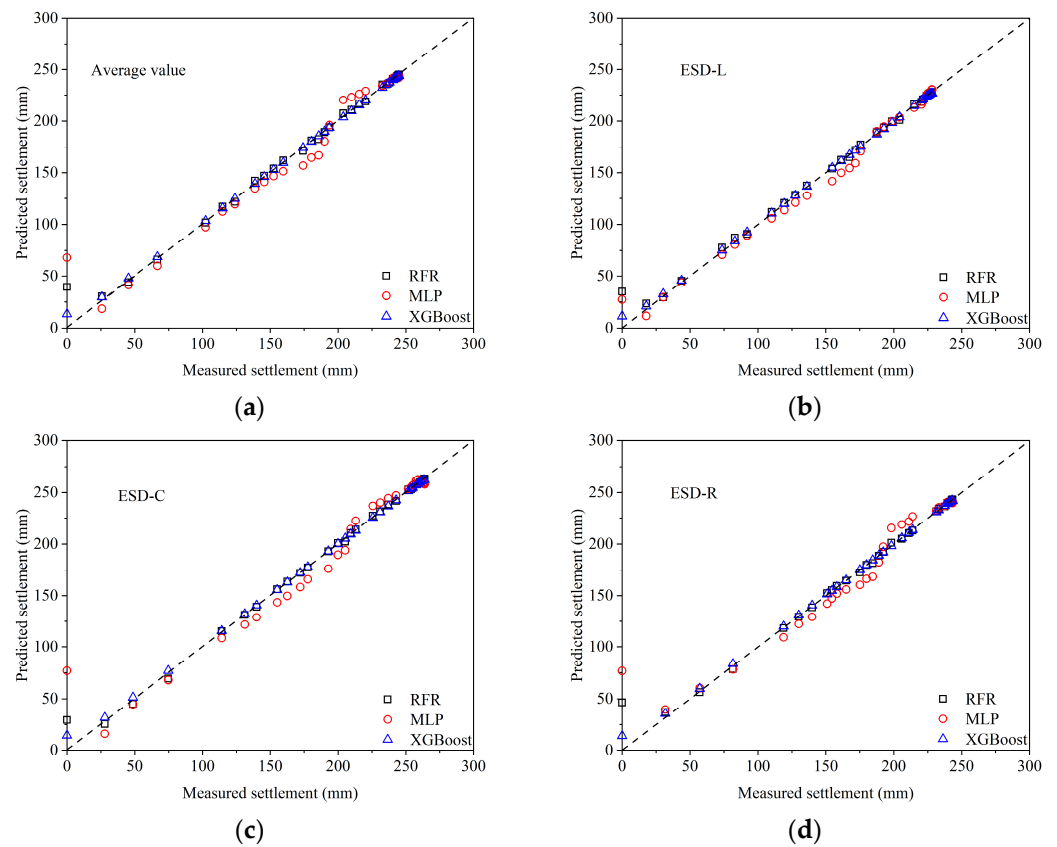


Figure 14. Predictive results using training samples: (a) ESD-L, (b) ESD-C, (c) ESD-R, and (d) average value.

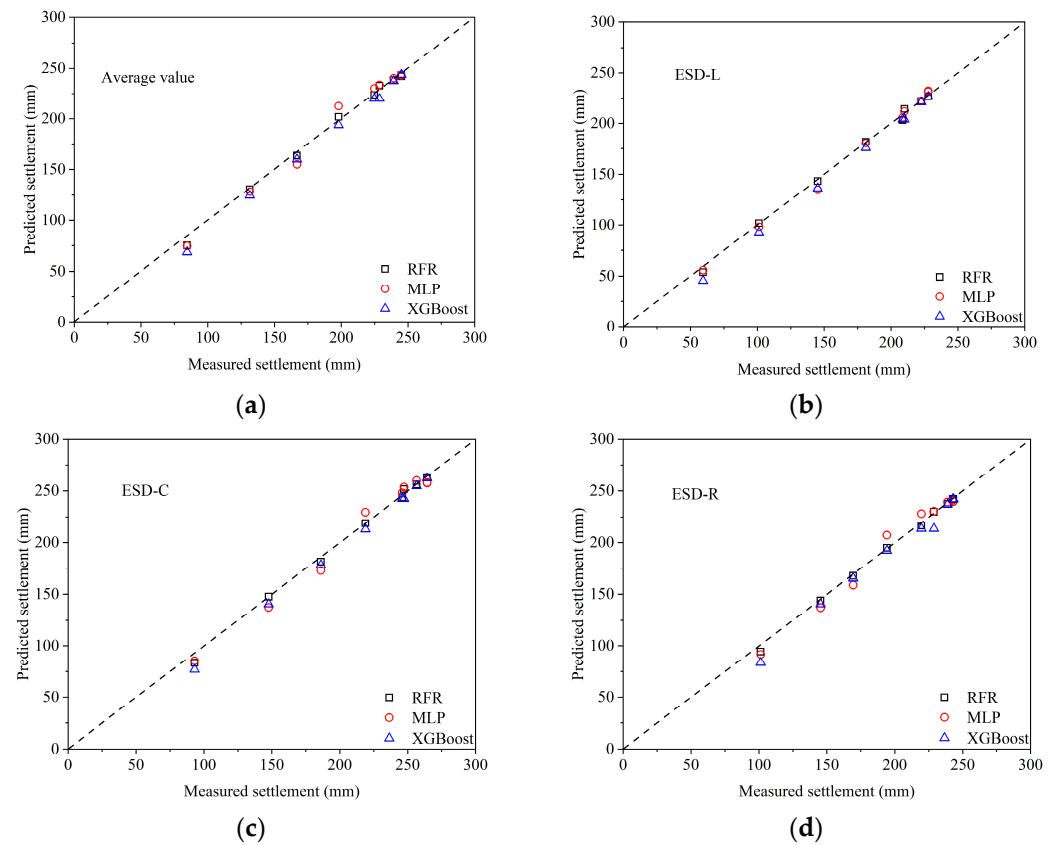


Figure 15. Predictive results using testing samples: (a) ESD-L, (b) ESD-C, (c) ESD-R, and (d) average value.

In this research, the data used for machine learning was obtained from field monitoring. The amount of field monitoring data is small. The XGBoost and RFR models perform more effectively when processing the sparse data. Considering that MLP is a deep learning method, the effect of MLP may improve if the sample continues to expand.

To assess the accuracy of the training and testing models quantitatively, three evaluation indicators were introduced. The performance indicators are the coefficient of determination (R^2), the maximum average error (MAE), and the root mean square error (RMSE), expressed as Equations (3)–(5), respectively.

$$R^2 = 1 - \frac{\sum (Y_i - \hat{Y}_i)^2}{\sum (Y_i - \bar{Y})^2} \quad (3)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2} \quad (5)$$

where Y_i is the i th observed element, $\hat{Y}_i$ is the i th predicted element, $\bar{Y}$ is the mean of the observed values of Y_i , and n is the number of datasets used. Theoretically, the MSE and RMSE measure the deviation between the measured and predicted data, and lower MSE and RMSE values suggest better performance. R^2 values that approach 1 indicate a better fit of the model to the data.

The performance indicators of the various models are shown in Table 2. As may be seen when comparing the values of R^2 , MSE, and RMSE, XGBoost performs best in the training models, while RF performs better in the testing models. In general, the best predictive model is RF, followed by XGBoost.

Table 2. Performance indicators of models in predicting settlement.

Model		R^2		MAE		RMSE	
		Training	Testing	Training	Testing	Training	Testing
ESD-L	RFR	99.2%	99.7%	2.42	2.30	6.43	3.11
	MLP	98.9%	99.4%	4.63	3.46	7.24	4.46
	XGBoost	99.8%	98.5%	1.08	5.82	2.23	7.04
ESD-C	RFR	99.5%	99.5%	1.93	2.72	5.42	4.01
	MLP	95.5%	97.9%	9.30	7.45	15.82	8.18
	XGBoost	99.9%	98.4%	1.25	5.79	2.80	7.21
ESD-R	RFR	98.4%	99.7%	2.50	2.04	8.37	2.78
	MLP	94.2%	97.3%	8.82	6.38	15.76	7.71
	XGBoost	99.8%	96.8%	1.14	6	2.68	8.42
average value	RFR	99%	99.4%	2.64	3.15	7.17	4.05
	MLP	95.8%	98%	7.88	6.02	14.33	7.58
	XGBoost	99.8%	98%	1.15	5.87	2.58	7.32

4.2. Predictions for Uneven Settlement

Figure 16 compares the training and testing results of the uneven settlement predictions by RFR, MLP, and XGBoost, respectively. Compared with the MLP model, both the XGBoost and RF models give better predictions. From Figure 10, it is obvious that the data points produced by the RFR and XGBoost models fit well with the reference line. This indicates the ability of these two algorithms to predict the maximum settlement, especially for larger values. As can be seen in Table 3, similar to the prediction results for settlement, the best prediction model is RF, followed by XGBoost. In this study, the data are based on monitoring data from one section, which shows less noise. As a reliable tree-based tool, XGBoost and RFR methods can strike a balance between predictive accuracy and robustness.

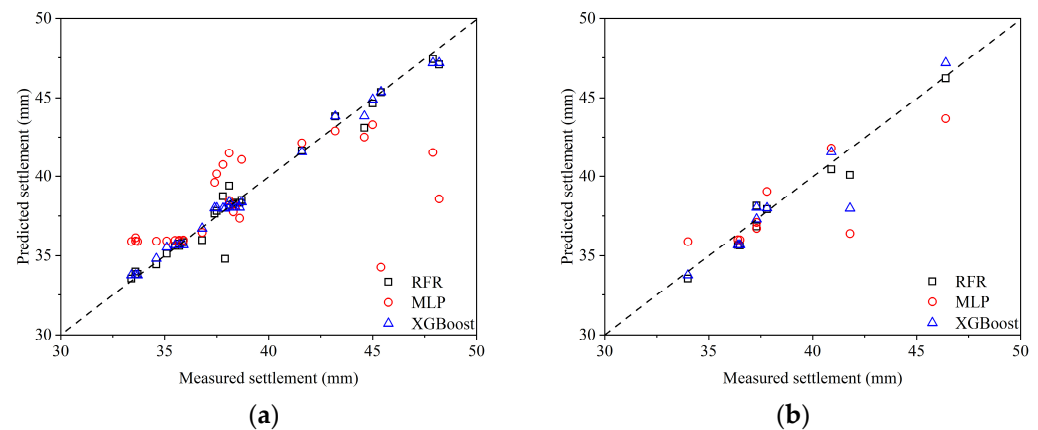


Figure 16. Comparison of predicted results of uneven settlement: (a) Training and (b) Testing.

Table 3. Performance indicators of models in predicting uneven settlement.

Model	R ²		MAE		RMSE	
	Traing	Testing	Traing	Testing	Traing	Testing
RFR	0.94	0.95	0.86	0.65	2.21	0.79
MLP	0.68	0.64	3.07	2.10	5.07	3.69
XGboost	0.99	0.84	0.40	0.89	0.67	1.40

5. Conclusions and Future Research Directions

In this study, the effects of RDC on the settlement of soft soil embankments were analyzed using field test methods, including ground surface settlement, embankment horizontal displacement, and soil PWP. The monitoring results were compared with data from other research to analyze the difference between the application of RDC in soft soils and coarse-grained soils. The relationship between settlement and other metrics was also investigated. We employed three distinct ML algorithms: RFR, MLP, and XGBoost to predict RDC-induced settlement, and the prediction performances of the three models were then compared in detail. The main conclusions of this study are as follows:

- (1) Analysis of the monitoring data revealed that the response of the soil occurred mainly in the first 20 passes. After 20 passes, the settlement of the soil gradually stabilized.
- (2) The deformation of soil caused by RDC is more significant in soft clay than in coarse-grained materials such as sand and gravel soils under the same conditions.
- (3) Field monitoring revealed a strong correlation between settlement, horizontal displacement, and pore water pressure. Based on the horizontal displacement and PWP monitoring results, the depth of impact of the RDC on the soft soil embankment was between 3 and 3.5 m.
- (4) In the prediction of settlement and uneven settlement caused by RDC, the XGBoost and RFR models were found to outperform the MLP model. As a reliable tree-based tool, XGBoost and RFR methods can strike a balance between predictive accuracy and robustness. This study demonstrates the feasibility of using the XGBoost and RFR models for predicting the settlement of soft soil embankments due to RDC and suggests that ensemble learning methods have great potential to predict RDC-induced settlement of complex foundations.

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