Land Reclamation Management Utilizing Artificial Intelligence for Estimating Soil Properties

T. Kumagai[1], T.T.T. Mai[2], K. Bai[3], F. Tsurumi[2], and T. Tashiro[2]
[1]*Institute of Technology, Penta-Ocean Construction Co., Ltd., Tochigi, Japan*
[2]*International Civil Engineering Divisions Group, Penta-Ocean Construction Co., Ltd., Singapore*
[3]*Offshore Wind Farm Business Divisions Group, Penta-Ocean Construction Co., Ltd., Tokyo, Japan*
E-mail: *Takahiro.Kumagai@mail.penta-ocean.co.jp*

ABSTRACT: In use of clayey soils for reclamation, the stability against slip and future consolidation settlement should be examined during and after reclamation. For these purposes, a practical reclamation management system has been developed based on three types of analysis: artificial intelligence (AI) estimation of soil properties such as compression index, consolidation coefficient and undrained shear strength, deposition shape analysis; and consolidation settlement analysis for clayey soils dumped from a hopper barge. The AI estimation of soil properties is characterized by use of a convolutional neural network (CNN) based on information such as soil source, wet density, and photographed image obtained before reclamation works. In this study, the validity of each analysis model has been verified on an actual reclamation project by use of measured data such as deposition shape of dumped soils on the seabed, soil properties in the reclaimed ground and consolidation settlement after reclamation and soil improvement.

KEYWORDS: Neural network, CNN, Machine learning, Centrifuge test, and CPT.

1. INTRODUCTION

When land is reclaimed from the sea for the construction of a port, airport or other development, sandy soils are generally used as ground material. Meanwhile, much of the clayey soil generated by dredging of navigation channels and mooring basins etc. is disposed of in sediment disposal sites. In view of sustainable development of society, it is desirable to utilize clayey soils beneficially, which would reduce waste and minimize the use of sand resources for reclamation fill. Regarding beneficial utilization of dredged clayey soils, many geotechnical methods have been proposed in conventional studies such as stabilization by cement mixing (e.g., Kitazume, 2017), stabilization by mixing with steel slag (Hirai *et al*., 2012), lightweight treatment by adding cement and air bubbles (e.g., Tsuchida and Egashira, 2017), mechanical dewatering (e.g., Kasama *et al*., 2007), and fabrication of particles solidified by cement addition (e.g., Shinsha and Kumagai, 2018). Furthermore, for extending the available period of a sediment disposal site, bulk compression for dredged clays by use of vacuum consolidation method has been proposed by Shinsha and Kumagai (2014).

Regarding the use of dredged clayey soils for reclamation, Kit *et al*. (2020) reported practical examples for the construction of container terminals at the Port of Singapore. The use of clayey soils for reclamation is considered advantageous since large quantities of soil can generally be accepted. In view of the dredged materials that continue to be generated to maintain existing ports, the use of clayey soils for reclamation material is expected to become more prominent in the future’s port maintenance and development. For land that is reclaimed with soft clayey soils, the stability against slip failure during construction and future consolidation settlement of the ground are concerns as engineering problems. The properties on consolidation and shear strength of soft clays to be reclaimed should be ascertained during construction stage; however, it is not practical to conduct detailed in-situ investigations for the formed ground or various soil tests on the soils before reclamation is completed.

In recent years, artificial intelligence (AI) techniques have been utilized in various fields for the treatment of large amounts of data, immediate and accurate evaluation and prediction, labor-saving automatic operation, etc. In the field of geotechnical engineering, conventional studies on application of AI were reviewed by Baghbani *et al*. (2022). In particular, Hanna *et al*. (2007) proposed a neural network model, which learns the relationship between soil and seismic parameters, to assess nonlinear liquefaction potential of soil. Abdalla *et al*. (2015) and Chakraborty and Goswami (2017) proposed neural network models to predict the factor of safety against slope failure in clayey soils based on the inclination and height of slope, the angle of internal friction, cohesion and unit weight of soil, the coefficient of pore water pressure, etc. Jang and Topal (2013) focused on the effects of geological parameters to the overbreak phenomenon in tunnel drilling, and applied a neural network to predict overbreak by use of rock mass rating data. As for an AI model with the performance of image recognition, Hata (2022) applied a multilayer deep neural network (DNN) proposed by Krizhevsky *et al*. (2012) based on a model of the convolutional neural network (CNN) for image recognition, which was originally proposed by LeCun *et al*. (1999), to evaluate a mountain tunnel’s rock mass. The rock mass properties such as degree of weathering, alteration and fracture are estimated from the inputting images of the excavation surface of the mountain tunnel.

The authors proposed a reclamation management system that integrates the AI model to estimate soil properties with the deposition shape analysis model and settlement analysis model in Kumagai *et al*. (2020a). The AI model, which is based on convolutional neural network (CNN), estimates the consolidation properties of clayey soils that are loaded on a hopper barge and dumped for reclamation, from information on soil source, wet density, and photographed images. The main analysis models in the proposed system were developed through accumulated soil test data and experiments by use of a geotechnical centrifuge; however, the system was still relatively conceptual and its applicability in actual reclamation works was not yet verified. In this study, the validity of the models is verified by reproducing actual reclamation work and comparing the analyzed results with the various measured data including deposition shape of dumped soils on the seabed, soil properties in the reclaimed ground, and consolidation settlement after reclamation and soil improvement works.

2. RECLAMATION MANAGEMENT SYSTEM

For reclaiming clayey soils such as dredged clay and excavated clay, the direct dumping method is efficiently applied by use of a hopper barge together with a pusher boat as shown in Figure 1. After soils are loaded into the hopper of a barge and transported to the dumping zone, the hopper is opened to dump the soils. The reclamation management system proposed in Kumagai *et al*. (2020a) has a predictive function of analysis of consolidation settlement of the reclaimed ground based on the AI estimation of properties of clayey soils and the deposition shape of dumped soils at the seabed, which

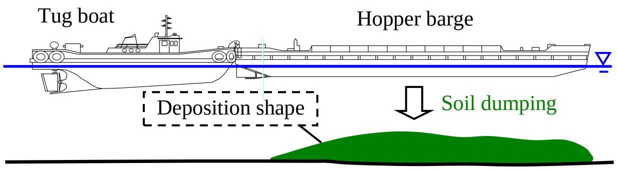


Figure 1 Reclamation method of clayey soils by use of barge

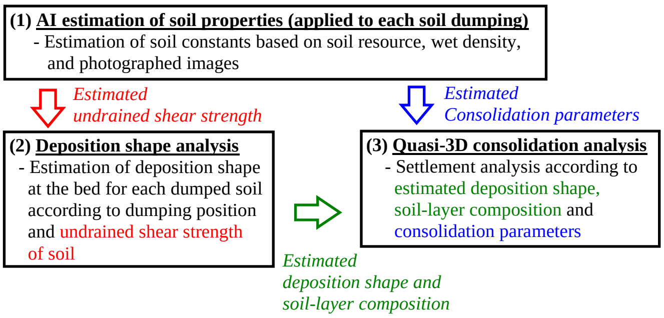


Figure 2 Flowchart of a series of analyses in the reclamation management system

accumulate to form the composition of internal soil layers in the ground. Figure 2 shows the flowchart of a series of analyses in the reclamation management system. First, an AI model is used to estimate soil properties such as the consolidation constant and the undrained shear strength for clayey soils to be dumped from a hopper barge. Next, the shear strength of soil estimated by the AI model is taken into account in the analysis of the deposition shape of the dumped soils at the seabed, and finally, settlement analysis is performed based on the estimated consolidation constants, the deposition shapes, and the composition of internal layers in the reclaimed ground.

2.1 AI Estimation of Soil Properties

2.1.1 Overview

As proposed in Kumagai *et al.* (2020a), the concept of model structure of machine learning using a CNN technique is shown in Figure 3. Once the information on soil source, wet density, photographed images, and firmness (hard or soft) based on tactile feeling is input in the model, the soil parameters such as compression and recompression indexes, consolidation coefficient and undrained shear strength are analyzed based on the correlations obtained in advance by machine learning with training database. The information on soil source means the origin location of soil (e.g., locations of dredging and onshore excavation).

In the processing of the first part of machine learning, feature vectors are extracted from the photographed image, and the extracted feature vectors and other scalar information are integrated. In the latter part, the target variables are estimated by the deep neural network with multiple hidden layers based on the integrated data obtained from the previous process. With regard to the processing of image data in the first part, extracting valid features from images is important. A method of transfer learning is introduced utilizing an existing model that has already been trained by use of a huge data set for extracting valid features from images. In particular, the so-called VGG16 to be classified as a VGG model, which is defined as a model developed by the Visual Geometry Group (VGG) at Oxford University, proposed by Simonyan and Zisserman (2015) is utilized. Once new data are input to the model, which has been developed by optimizing weight parameters in the deep neural network so as to minimize estimation error using training data, the corresponding values of soil parameters are output as the objective variables.

2.1.2 Applicability of Model

The AI model were developed through machine learning of accumulated soil test data. In order to obtain training data for machine learning, 40 cases of standard consolidation tests, 60 cases of liquid limit and plastic limit tests, and vane shear tests for the cases of liquid limit and plastic limit tests were carried out. Dredged marine clays and excavated clays on land are expected to be fill materials for the current reclamation project in almost equal proportions. The specimens of soil tests were photographed from a distance of about 50 cm using a common digital camera with about 10 million pixels. The examples of the images are shown in Figure 4.

At this point, we considered that it was necessary to increase the amount of training data for implementing effective machine learning. The number of photographed images was artificially increased by various processes of multiple cropping, rotating, flipping up/down or left/right, adjusting brightness and contrast, blurring, sharpening, etc. In addition, as the number of photographed images is increased by the above processes, noise is added to the associated input/output numeric data, effectively increasing the variety of numeric data. To add noise to numeric data, a method of statistical treatment was introduced in which the true value obtained from a soil test was taken as the mean value and the data was varied to follow a normal distribution with a coefficient of variation of 0.1. The machine learning was conducted by increasing the number of data points by 400 times, to 16,000, through the above data processing.

Figure 5 shows the frequency distributions of the soil parameters on consistency and consolidation obtained by the tests. Figure 6 shows the relationship between the normalized water content w/w_L, which is water content divided by liquid limit w_L, and undrained shear strength c_u obtained by a vane shear test. The high correlation between these constants is obtained as Equation (1), suggesting that if the liquid limit of a clay is known, it is possible to calculate the water content from wet density and estimate the undrained shear strength using the normalized water content.

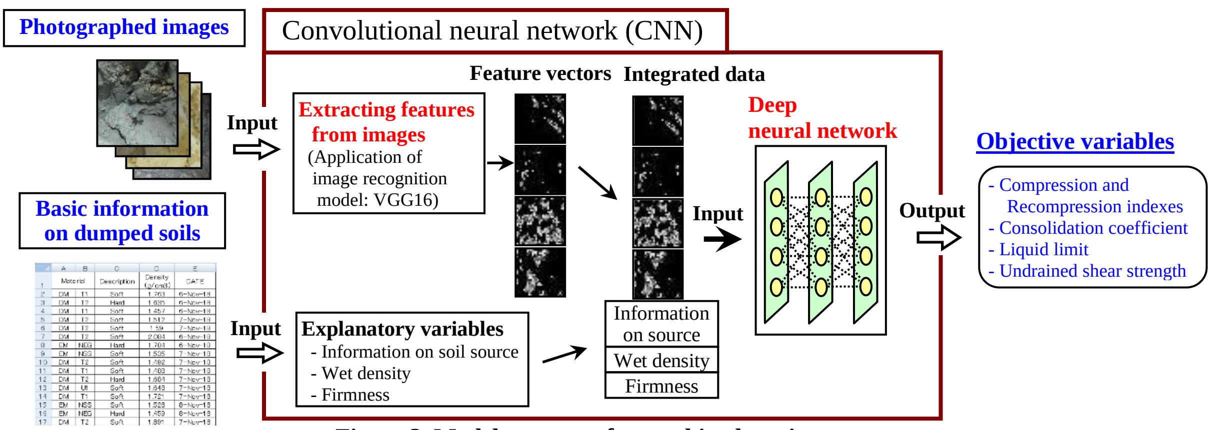


Figure 3 Model structure for machine learning

$$c_u = 1.039\ (w/w_L)^{-4.228} \tag{1}$$

For reference, a conventional formula of Equation (2) proposed by Tsuchida *et al*. (2002) is also shown in Figure 6, indicating that the formula proposed in this study provides results similar to those of a conventional formula.

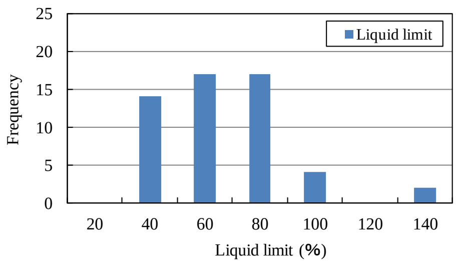
$$c_u = 1.4\ (w/w_L)^{-4.5} \tag{2}$$

In machine learning, the information on soil source, wet density, photographed images, and firmness (hard or soft) based on tactile feeling was set as input data, and compression and recompression indexes, consolidation coefficient, and liquid limit were set as output data, the objective variables. The undrained shear strength can be estimated by obtaining normalized water content from the estimated liquid limit and the previously known wet density, and using the relational equation of Equation (1).

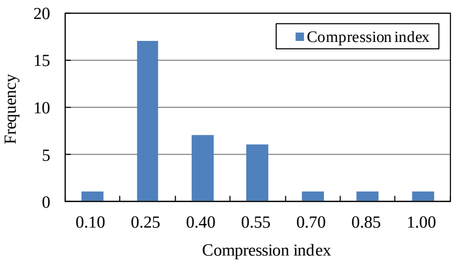
(a) Dredged marine clay

(b) Excavated clay on land

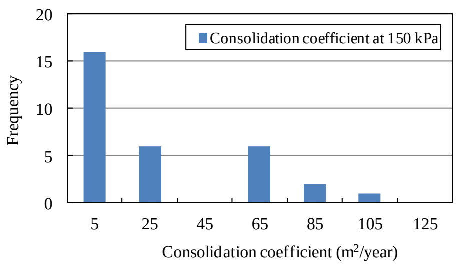
Figure 4 Sample clay images to be used in machine learning



(a) Liquid limit



(b) Compression index



(c) Consolidation coefficient at confining pressure of 150 kPa

Figure 5 Frequency distribution of soil constants

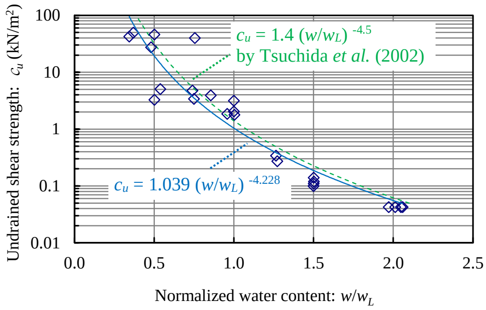


Figure 6 Relationship between normalized water content and undrained shear strength

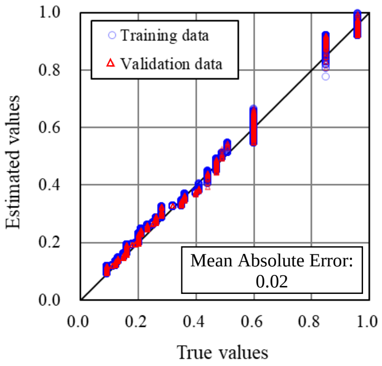
Table 1 Hyper-parameters in the model of deep neural network

Parameter name	Method or value
Method of scale transformation	Min-max normalization
Number of hidden layers	4
Number of neurons in each hidden layer	200
Activation function	ReLU function
Optimization method of weight parameters	Adam
Rate of dropout	0.1

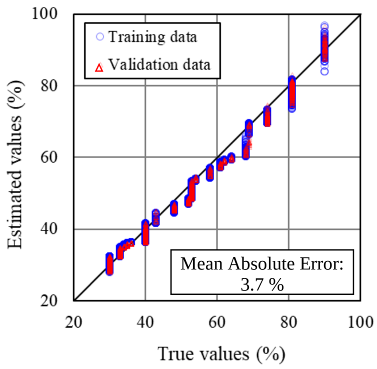
Table 1 lists the hyper-parameters to be used in the deep neural network (DNN) model. As a pre-processing of numeric data, a method of scale transformation called the min-max normalization was applied for non-dimensionalization. The structure of DNN consists of 4 hidden layers with 200 neurons respectively, and the rectified linear activation function (ReLU) is applied for transforming the summed weighted input from the node into the activation of the node or output for that input. For the optimization of weight parameters in a neural network, the Adam algorithm proposed by Kingma and Ba (2014) is applied. This algorithm is an extension to the conventional stochastic gradient descent algorithm and has been recently widely adopted in the field of DNN in recent years. In addition, to enhance generalization performance, it is important for machine learning to avoid overfitting, which is a condition in which the data set is overly fitted only to a specific characteristic data set. Regarding this problem, a method of dropout proposed by Srivastava *et al*. (2014), the concept of which is to randomly drop units (along with their connections) from the neural network during training, is applied. The method of dropout has been demonstrated to be highly effective in improving the performance of a neural network and has been widely adopted in recent years.

In the process of machine learning, 80% of training data to be randomly selected were used for training to optimize the weight parameters, and the remaining 20% were used for model validation based on the hold-out method (Sammut and Webb, 2017), which is widely applied as a validation method evaluating the generalization performance of machine learning models.

Comparisons of the actual values with the estimated results of AI focusing on compression index and liquid limit as representative soil parameters are shown in Figure 7. The mean error of the difference between the actual and estimated values with respect to the validation data was evaluated to be 0.02 for the compressive index and 3.7 % for the liquid limit, which is considered highly accurate. Figure 8 shows examples of estimated results of an AI model trained using only numeral variables such as soil source information and wet density without using photographed images as input data. The average errors for the AI model without images are quite large, indicating that image information is necessary to improve the accuracy of the estimation. At this time, it is not yet clarified how the color and texture of clay in an image contribute to the estimation of soil properties and how much the input parameters are quantitatively weighted in the estimation, which should be addressed in future works.

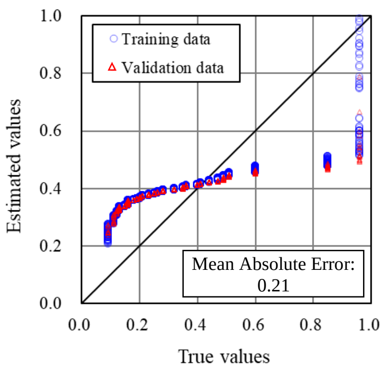


(a) Compression index

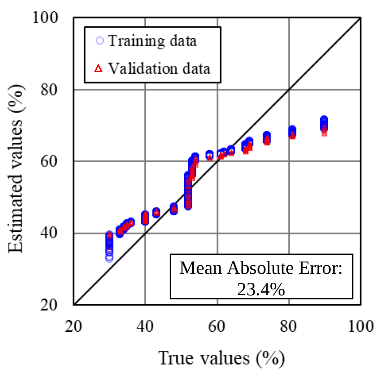


(b) Liquid limit

Figure 7 Comparisons of true values with the AI-estimated results



(a) Compression index



(b) Liquid limit

Figure 8 Comparisons of true values with the estimated results by AI without use of images

2.2 Deposition Shape Analysis

2.2.1 Overview

An analysis model of the deposition shape at the seabed of soils dumped from hopper barges for reclamation was proposed in Kumagai *et al*. (2020a). In this model, after dividing the hold of a barge into small compartments as shown in Figure 9(a), the probability density function $f(x,y)$ shown in Equation (3) is used to evaluate the spreading of soil (deposition shape at the bed) from each compartment of a barge. The overall shape of the soil deposited at the bed for each dumping is then expressed as the sum of the deposition shapes of soil derived from the small compartments.

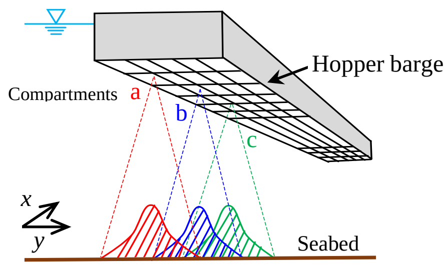
$$f(x,y) = \exp\left[-(x^2 + y^2) / (2\sigma^2)\right] / (2\pi\sigma^2) \tag{3}$$

where σ is the standard deviation (diffusion parameter), which governs the extent of spreading at the seabed.

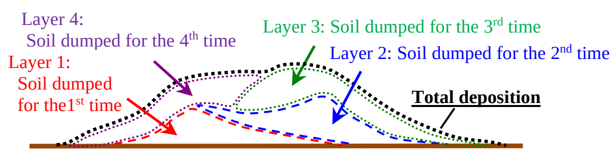
The standard deviation σ is related with undrained shear strength of soil, which is estimated by the AI model. After multiple dumping of soils, the whole deposition shape and the composition of internal soil layers, which are shown in Figure 9(b), are estimated by the model. In addition, the information on soil properties estimated by AI model for each dumping of soil is stored in three-dimensional coordinates on the basis of the results of deposition shape analysis.

2.2.2 Deposition Characteristics and Diffusion Parameter

In order to clarify the deposition characteristics of clayey soils dumped from a hopper barge and to develop an analysis model of the shape to be expressed by Equation (3), centrifuge model experiments were conducted. The set-up of the experiments is shown as Figure 10. A 1/90 model (466 mm long × 113 mm wide × 68 mm high) of a hopper barge with a loading capacity of 1,500 m^3 was used in the experiment, and centrifugal acceleration of 90 G was applied. For the barge model, a device that can open the bottom of the barge was introduced to simulate the actual dumping of soils.

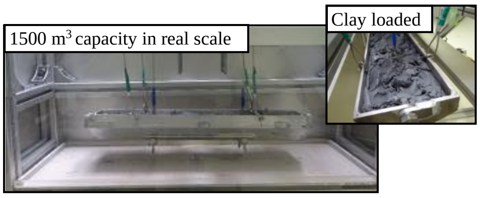


(a) Deposition shape of soil dumped from each compartment

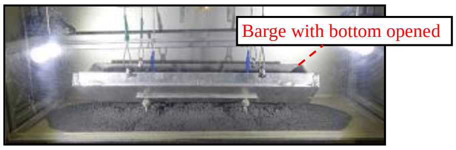


(b) Deposition shape and internal layers of soils formed

Figure 9 Schematic view of deposition shape analysis



(a) Barge model (1/90 scale)



(b) Situation after dumping clay

Figure 10 Implementation of centrifugal model experiments introduced to simulate the actual dumping of soils.

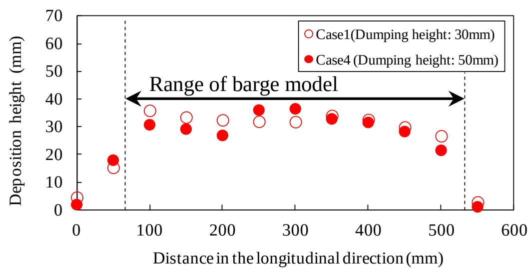
It is also important to set the conditions of water depth considering the distance from the barge bottom to the bed in the assumed conditions at a practical site. The underwater falling behavior of a material dumped from a barge is expressed by Equation (4), which is a one-dimensional equation of motion given in Kumagai *et al*. (2020b).

$$(M + \rho_w k_m V)\, dv/dt = 0.5\rho_w C_D A v^2 + (M - \rho_w V)\, g \qquad (4)$$

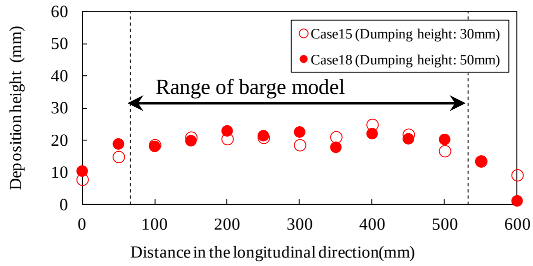
where M is Mass of object, ρ_w is fluid density, k_m is added mass coefficient, V is volume of the object, A is projected area of the object, v is falling velocity of the object, C_D is drag coefficient.

In the analysis of falling behavior, it is assumed that cohesive soils dumped from the barge fall as an integral lump without segregation. A fall velocity at a depth of 20 m in water under an actual condition corresponds to the fall velocity at a depth of 222 m in water or 30 mm in air under the 90 G centrifuge experimental condition assuming that the added mass and drag coefficients are standard values of 0.5 and 1.0 respectively. A fall velocity at a depth of 40 m in water under an actual condition corresponds to the velocity at a depth of 50 mm in air under 90 G centrifugal condition.

In the experiments, four types of clayey soils were used, and the water contents and liquid limits of the soils are shown in Table 2. As shown by Equation (1), once the values of wet density and liquid limit of soil are obtained, the undrained shear strength can be estimated on



(a) Specimen A (Excavated clay on land)



(b) Specimen D (Dredged clay)

Figure 11 Comparison of deposition shapes for the cases with different dumping heights

Table 2 Physical properties of soils to be used in the experiment

Specimen	Source	Natural water content	Liquid limit
A	Excavated clay on land	15.0%	29.9%
B		17.1%	37.5%
C	Dredged clay	57.3%	57.1%
D		43.1%	50.4%

Table 3 List of experimental cases

Case	Specimen	Dumping height	Water content of soil	Falling condition
1	A	30 mm	15.0% (Natural water content)	In air
2			29.9% (1.0* w_L)	
3			44.9% (1.5* w_L)	
4		50 mm	15.0%	
5		222 mm	29.9% (1.0* w_L)	In water
6	B	30 mm	17.1% (Natural water content)	In air
7			37.5% (1.0* w_L)	
8			56.3% (1.5* w_L)	
9		50 mm	17.1%	
10		222 mm	37.5% (1.0* w_L)	In water
11	C	30 mm	57.3% (Natural water content, almost same as w_L)	In air
12			85.7% (1.5* w_L)	
13		50 mm	57.3%	
14		222 mm	57.1% (1.0* w_L)	In water
15	D	30 mm	43.1% (Natural water content)	In air
16			48.3% (1.0* w_L)	
17			75.6% (1.5* w_L)	
18		50 mm	43.1%	
19		222 mm	48.3% (1.0* w_L)	In water

the basis of the normalized water content using water content calculated from wet density. The experimental cases were set to compare the behaviors in water and in air under equivalent conditions of dumping height in terms of fall velocity of soil at reaching the bottom. The conditions of water content were varied to three conditions with respect to liquid limit. The experimental cases are listed in Table 3.

Figure 11 shows the comparison of the deposition shape under the condition of in-air dumping at different heights for the specimens A and D. The conditions corresponding to the dumping of soils at water depths of 20 m and 40 m in actual scale were extracted. In all cases, not just the specimens A and D, it was confirmed that the dumping height, which causes a difference in the fall velocity of soil, had little effect on the deposition shape indicating that it is primarily affected by the strength of soils.

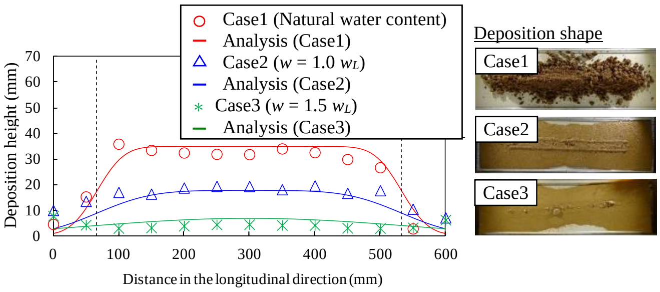
The analysis model is applied to reproduce the deposition shapes obtained in the experiments, setting appropriate values of standard deviation. Figure 12 shows the comparisons between the results of experiments and analyses for the cases of different water contents (undrained shear strengths) of soil. The value of standard deviation in Equation (3) is expected to be set appropriately in relation to the undrained shear strength of soil. By examining appropriate values of standard deviation σ while reproducing the experimental results, including other cases, the relation with the undrained shear strength of soil is obtained as shown in Figure 13 and by Equation (5).

$$\sigma = -2.189\, c_u + 12.16 \qquad (5)$$

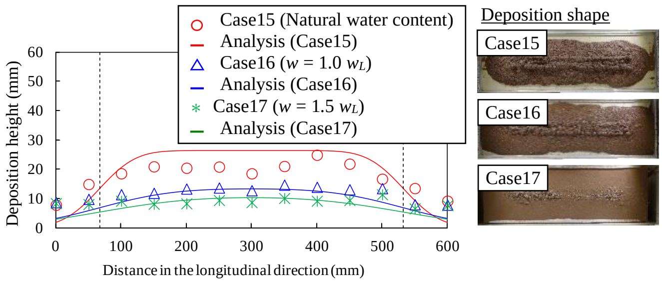
Once the value of the normalized water content, which is the ratio of water content to liquid limit, is obtained, the undrained shear strength can be estimated by use of Equation (1), and the deposition shape analysis can be performed by inputting the value of the standard deviation to be estimated by use of Equation (5) into the model.

2.3 Consolidation Settlement Analysis

As proposed in Kumagai *et al.* (2020a), a quasi-three-dimensional analysis is carried out by dividing the original and reclaimed grounds into three-dimensional elements, as shown in Figure 14, on the basis of integration of one-dimensional consolidation analyses with the c_c (compression index) method. In particular, after the deposition shapes of dumped soils at the seabed, including the composition of internal layers, are obtained by the deposition shape analyses, the newly formed and original grounds are divided into three-dimensional elements. The consolidation settlement analysis is performed by inputting the consolidation constants estimated by the AI model and stored in three-dimensional coordinates.



(a) Specimen A (Excavated clay on land)



(b) Specimen D (Dredged clay)

Figure 12 Reproduction of experimental results by analysis model for cases with different water contents

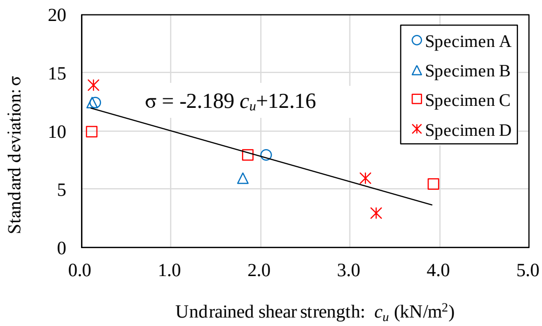


Figure 13 Relationship between undrained shear strength and standard deviation in the analysis model

The settlement is calculated by the following method:

a) The amount of settlement is calculated independently for each soil element. The total settlement of the ground surface is obtained by summing the settlement of each element.

b) Vertical stresses acting on each element in the ground are calculated using wet density of soils following Boussinesq's equation, which assumes the ground to be elastic.

c) The consolidation rate in multi-layered ground may be analyzed by obtaining the equivalent coefficient of consolidation of the ground without vertical drains installed, or by using Barron's theory in case that drains are installed.

3. APPLICABILITY OF ANALYSIS MODELS TO ACTUAL RECLAMATION SITE

The analysis models that consist of the proposed reclamation management system were developed through accumulated soil test data and experiments by use of a geotechnical centrifuge in Kumagai *et al.* (2020); however, the system was still relatively conceptual and its applicability in actual reclamation works was not yet verified. In this study, site investigation data, such as soil parameters of reclaimed materials, deposition shapes of dumped soils on top of seabed by bathymetry survey, monitored consolidation settlements, etc., which were obtained during and after reclamation process in an actual project, has been utilized to verify the validity of analyzed results. In this actual project, clayey soils, originated from various dredging and excavating sources, have been used as reclaimed material in an area of 400 m × 600 m. The practical applicability of the models is verified by comparing site investigation data with the results analyzed by the models reproducing this reclamation work.

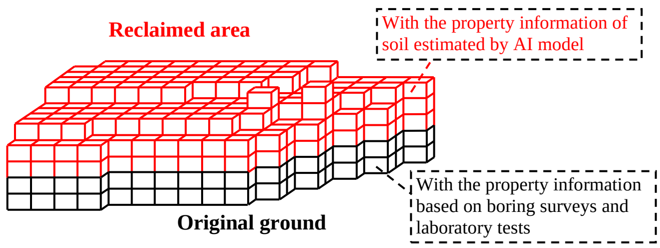


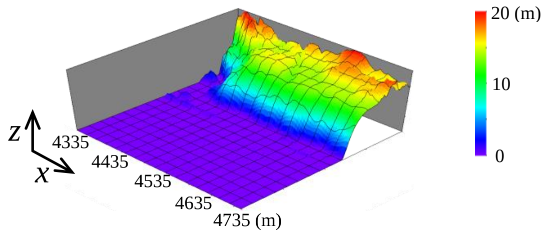
Figure 14 Schematic view of three-dimensional element division of the ground

3.1 Deposition Shape Analysis

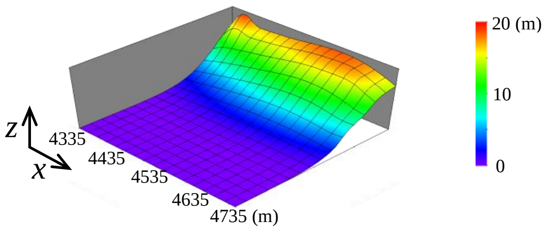
The deposition shape analyses were performed to reproduce the measured deposition shape of the 1.25 million m^3 reclaimed in 6 months by 0.50 million m^3 of dredged clays and 0.75 million m^3 of excavated clays. The reclamation was carried out by dumping of soils 1,000 times by hopper barges, which have loading capacities of 1,000 m^3 and 1,500 m^3.

In the data management system on soil dumping, the information on the plane coordinates and bow direction of a barge at soil dumping, and the source, photographed image, measured wet density and tactile firmness of soil is recorded. The undrained shear strength of soil can be estimated using the normalized water content based on the liquid limit estimated by AI and the water content converted from the wet density measured on the barge. The standard deviation (diffusion parameter) as the input in the model is obtained by Equation (5), and the analysis is performed.

The comparisons between the site measurements and analyzed results by shape model on the deposition shapes in the progress of reclamation are shown in Figure 15. Figure 16 shows a comparison at the cross section to show the profile of maximum deposition height in *x*-direction, indicating that the actual deposition shape can be estimated by the proposed analysis with high accuracy.



(a) Measurement



(b) Analyzed results

Figure 15 Comparison between the measured and analyzed

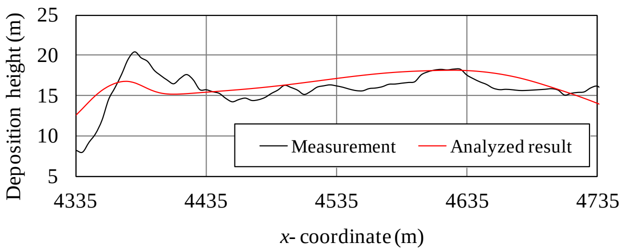


Figure 16 Comparison of measurement and analyzed results on deposition height

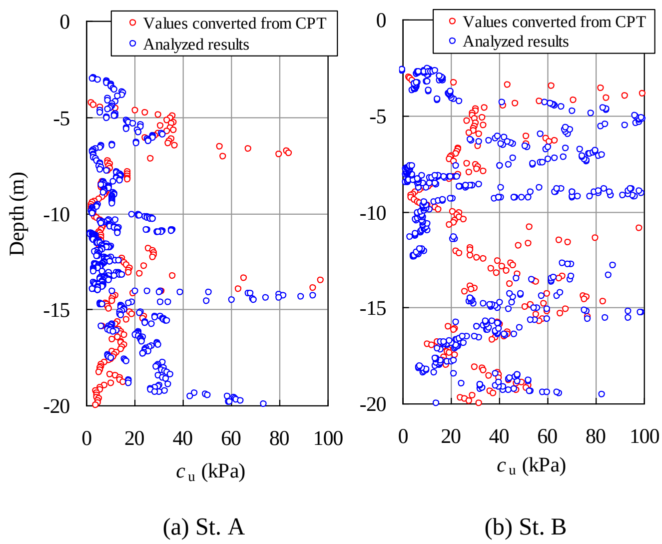


Figure 17 Comparison between the CPT tests and analyzed results on the profile of undrained shear strength

Immediately after reclamation, i.e., before any significant change in soil properties, cone penetration tests (CPT) were conducted at two locations and the undrained shear strength c_u was evaluated from the cone tip resistance q_t and the total vertical stress σ_{v0} using a formula of Equation (6) proposed by Robertson (2012), which is widely applied.

$$c_u = (q_t - \sigma_{v0}) / N_{kt} \qquad (6)$$

where N_{kt} is the cone coefficient (set to 15).

At two locations of St. A and St. B in the reclamation site, a comparison of the profiles of undrained shear strength in depth between the results evaluated by cone penetration tests and analyses are shown in Figure 17. Although evaluating undrained shear strengths from CPT tests by use of an empirical formula is not precise, it is confirmed that the distribution of undrained shear strength inside the reclaimed layer tends to be generally in agreement with the measured values in Figure 17, indicating a certain degree of validity of the proposed models of the AI estimation of soil properties and the deposition shape analysis.

By using the models, the total deposition shape and the composition of internal soil layers can be determined. In addition, the property information estimated by the AI model can be labeled and stored in three-dimensional coordinates for each soil dumping.

3.2 Consolidation Settlement Analysis

Since the deposition shape analysis is carried out for each dumping of soil from a hopper barge, each dumped soil is labeled with an ID number of layer, and the composition of soil layers on the seabed shown as Figure 9(b) can be output simultaneously in three-dimensional coordinates with the information on soil properties measured on a barge or estimated by the AI model such as water content (or wet density), liquid limit, compression and recompression indexes, consolidation coefficient and undrained shear strength. After conducting AI estimation of soil properties and deposition shape analysis for each dumped soil, the formed ground is divided into three-dimensional elements as shown in Figure 14, and settlement analysis can be performed by inputting the consolidation constants for each element estimated by the AI model, in accordance with assumed loads.

The work sequences of reclamation and ground improvement are shown in Figure 18. After reclamation was completed for approximately 10,000 m^2 with average reclamation height of 24.5 m, the settlement analysis was conducted considering future surcharge loads during ground improvement by consolidation. Consolidation parameters for this settlement analysis were obtained from output of AI analysis and deposition shape analysis. Regarding ground investigation after reclamation, six surface settlement plates, SP-01 to SP-06, were installed to monitor the actual behaviors of consolidation settlement, and soil investigations (one boring survey and one cone penetration test (CPT) were conducted at the same location as SP-03 to investigate actual soil parameters.

3.2.1 Properties of Deposited Soil

Before improving the reclaimed ground, undisturbed samples of reclaimed soils were taken for every 3 m depth at the location of the boring survey, and laboratory tests were carried out to determine physical and consolidation properties of the soil samples. In particular, the soil parameters of wet density, water content, compression and recompression indexes, consolidation yield stress, and consolidation coefficient were obtained by the tests, and they were compared with analyzed results at the corresponding depths.

Figure 19 shows comparisons of soil parameters in depth between the test results and the results of the AI estimation of soil properties and deposition shape analysis at the location of SP-03. The water content is calculated from wet density measured on a barge before soil dumping, and the test results for sampled soils generally agree with the analyzed results, indicating the validity of the analysis. Compared to the analyzed results, the test results tended to be smaller. Possibly this was because the reclaimed ground was affected by self-weight consolidation after the deposition at the seabed. The results of tests and analyses were in general agreement on consolidation constants of compression and recompression indexes and consolidation coefficients, which shows the validity of the AI estimation of soil properties and deposition shape analysis.

The fact that the reclaimed ground may be affected by self-weight consolidation after the deposition at the seabed suggests that a method for estimating consolidation yield stresses that considers the initial overburden pressure and over-consolidation ratio (OCR) needs to be investigated. Figure 20 shows the comparisons of the consolidation yield stress between the test results, the values directly estimated by the AI model, and the analyzed results assuming the

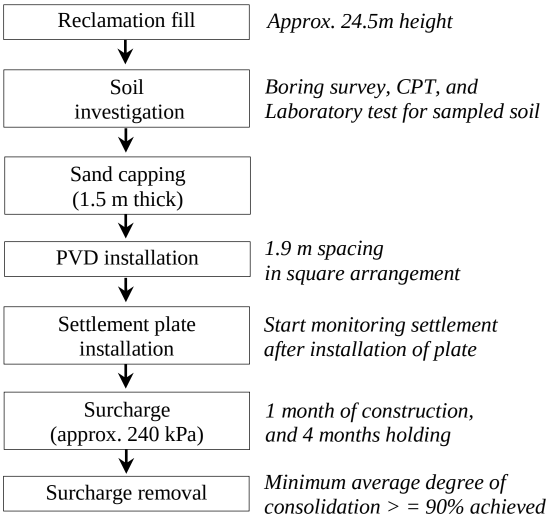


Figure 18 Work sequences in reclamation and ground Improvement

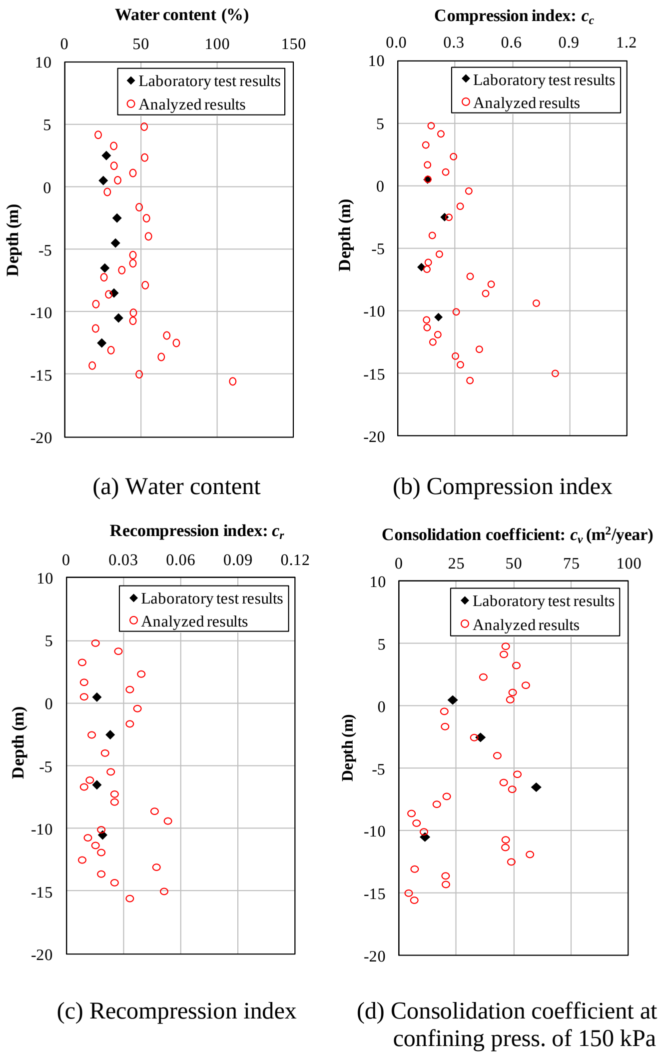


Figure 19 Comparison of soil parameters in depth between the results of tests and analyses at SP-03

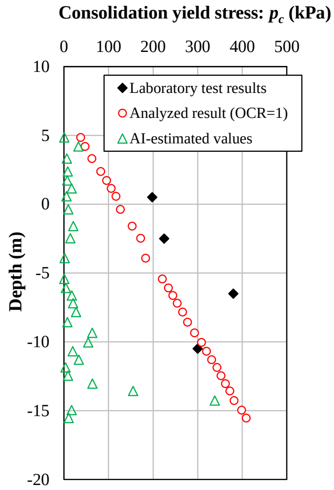


Figure 20 Comparison of consolidation yield stress between the results of tests and analyses at SP-03

change to normal consolidation state with OCR = 1. In the analysis, the initial overburden pressure is calculated by the distribution of estimated wet density of soils. The analyzed consolidation yield stresses, which increase with depth, showed a good agreement with the soil investigation results, which would conclude that the assumption of normal consolidation state is generally valid, while the estimated values by AI are significantly small. Based on these findings, a method is employed for estimating the consolidation yield stress to be input to the settlement analysis by considering the initial overburden pressure and over-consolidation ratio (OCR).

3.2.2 Consolidation Settlement

In the previous section, the validity of the AI estimation of soil properties and deposition shape analysis is confirmed by comparing the consolidation constants obtained from soil tests. As the next step, settlement analysis was conducted on the basis of the estimated composition of internal soil layers labeled with consolidation constants. For initial conditions of reclaimed ground before imposing surcharge loads, the state of normal consolidation with OCR = 1 was assumed according to the results of the previous section. The analysis reproduced the conditions of reclamation with the soil model shown in Figure 21 where prefabricated vertical drains were installed at 1.9 m spacing in a square arrangement, and

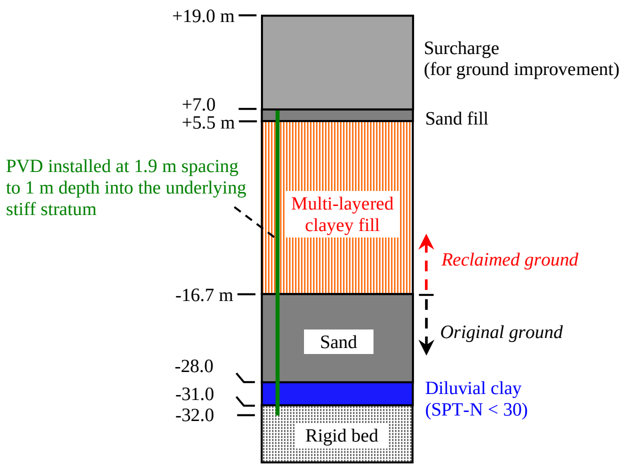
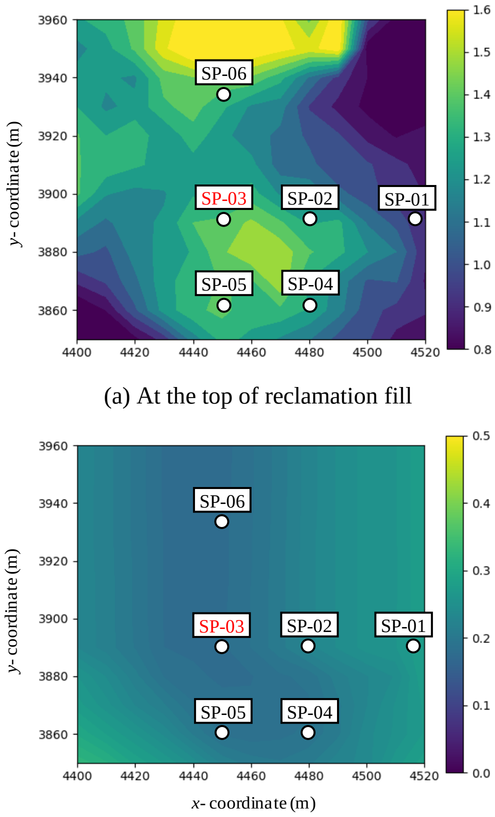


Figure 21 Soil model in the reclamation area



(a) At the top of reclamation fill

(b) At the top of original ground

Figure 22 Planar distribution of analyzed final settlement

surcharge was constructed at a height of approximately 13.5 m with a load of 240 kPa. Since only the 3 m thick diluvium clay lies as a compressible layer in the original ground, the consolidation settlement is expected to occur mainly in the reclamation layer.

Figure 22 shows the planar distribution of analyzed final settlement at the tops of reclamation fill and original ground. It is confirmed that significant settlement appears in the reclaimed layer rather than in the original ground, and there is a considerable variation in the total settlement due to differences in soil properties. Figure 23 compares measured and analyzed settlement curves at the top of fill, including at SP-03, where the results of soil tests and analyses were compared in details. As shown in this figure, after the reclamation by clayey soils was completed, sand coverage was placed at a thickness of 2 m, and surcharge was constructed taking approximately 50 days for ground improvement by consolidation.

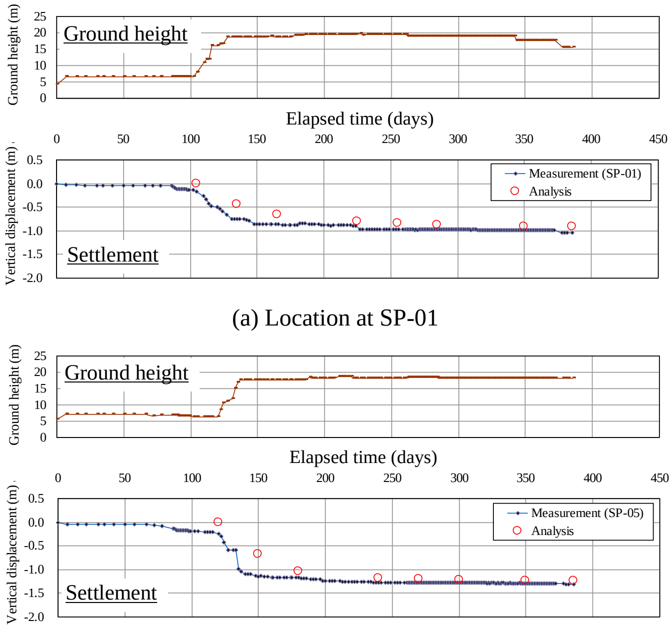
Since consolidation rate of ground with drains installed is analyzed by use of Barron's simplified theory, the settlement behavior of the ground is analyzed with reference to the start of the surcharge construction while adjusting input loads acting on the ground to match the actual loads. In the figure, it turns out that the analyzed settlement behaviors generally agree with the measured data, though the consolidation rate of ground is slightly smaller, which might be due to slightly smaller estimate of consolidation coefficients by the AI model.

Figure 24 show the comparison of final settlements between the site measurement and analysis at all locations of SP-01 to SP-06. It is confirmed that measured settlements are in good agreement with analysis results, with an error of only 10%, which would confirm the validity of the analyses.

4. CONCLUSIONS

A reclamation management system has been developed integrating the artificial intelligence (AI) estimation of soil properties, the deposition shape analysis, and the consolidation settlement analysis for clayey soils dumped from a hopper barge for reclamation. In particular, the consolidation parameters and undrain shear strengths of clayey soils, which are loaded on hopper barges and dumped for reclamation, can be estimated by the AI model from information on soil source, wet density and photographed images without detailed soil testing.

In this study, the validity of the models in practical application



(a) Location at SP-01

(b) Location at SP-03

Figure 23 Comparison of settlement behaviors under surcharge load between the measurements and analyses

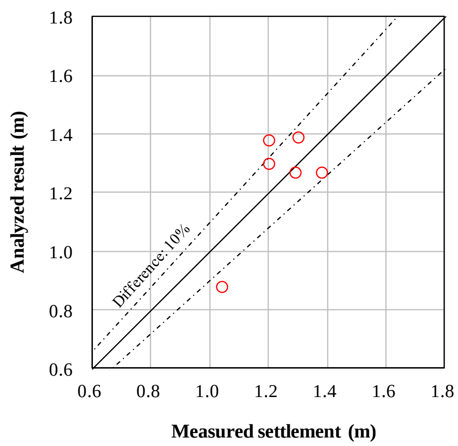


Figure 24 Comparison of final settlements between measurements and analyses for all locations of SP-01 to SP-06

has been verified by reproducing actual reclamation work and comparing the measured data with the results analyzed by the models. Especially, the validity of the AI estimation of soil properties and deposition shape analysis was confirmed by comparing soil parameters obtained from soil tests and reproductive analyses after reclamation, as well as the deposition shapes during reclamation. Since it is found that the reclaimed ground may be affected by self-weight consolidation after the deposition at the seabed, a method is employed for estimating the consolidation yield stress to be input to the settlement analysis by considering the initial overburden pressure and over-consolidation ratio (OCR), instead of using the estimated values by AI. The validity of the settlement analysis is also confirmed by reproducing the measured settlements with an error limited to only 10 %.

In developing the AI model, the machine learning was performed with a limited number of cases (from 40 to 60) of soil test results. Hence, to improve the generalization and practical performance of the AI model, machine learning with use of a larger amount of training data is necessary as a future task. In addition, the analyzed consolidation rate may be slightly smaller than the actual rate. This might be because a single value is used for the consolidation coefficient under a representative confining pressure of 150 kPa, and the analysis model needs to be improved to vary the value according to actual confining pressure as a future task.

By using the proposed system, of which practical applicability has been verified from actual reclamation project, the quality of reclamation is expected to be improved and required construction duration would also be shortened since the three-dimensional distribution of soil properties in the reclaimed ground could be estimated with considerable accuracy without any detailed soil investigations required. In addition, stability analysis and consolidation settlement can be conducted at any time during and after construction, leading to the realization of optimal design and construction management.

5. REFERENCES

Abdalla, J. A., Attom, M. F. and Hawileh, R. (2015). "Prediction of Minimum Factor of Safety against Slope Failure in Clayey Soils using Artificial Neural Network." *Environ. Earth Sci.*, 73 (9), 5463-5477.

Baghbani, A., Choudhury, T., Costa, S., and Reiner, J. (2022). "Application of Artificial Intelligence in Geotechnical Engineering: A state-of-the-art review." *Earth-Science Reviews*, Vol.228, https://doi.org/10.1016/j.earscirev.2022.103991.

Chakraborty, A., and Goswami, D. (2017). "Prediction of Slope Stability using Multiple Linear Regression (MLR) and Artificial Neural Network (ANN)." *Arab. J. Geosci*., Vol. 10 (17), 1-11.

Hanna, A. M., Ural, D. and Saygili, G. (2007). "Neural Network Model for Liquefaction Potential in Soil Deposits using Turkey and Taiwan Earthquake Data." *Soil Dyn. Earthq. Eng.*, Vol. 27 (6), 521-540.

Hata, K. (2022). "Evaluating Tunnel Rock Mass using Deep Learning." *J. of JSCE*, Vol. 10, 260-274.

Hirai, S., Mizutani, T., Kikuchi, Y., Nakashima, S. and Iguchi, K. (2012). "Study on Effect of Mixing Condition on Strength of Mixture of Dredged Soil and Steel Slag." *Advances in Transportation Geotechnics II*, CRC Press, 302-308.

Jang, H. and Topal, E. (2013). "Optimizing Overbreak Prediction Based on Geological Parameters Comparing Multiple Regression Analysis and Artificial Neural Network." *Tunn. Undergr. Space Technol*., Vol. 38, 161-169.

Kasama, K., Zen, K. and Iwataki, K. (2007). "High-Strengthening of Cement-Treated Clay by Mechanical Dehydration." *Soils and Foundations*, Vol. 47, No. 2, 171-184.

Kingma, D. P. and Ba, J. L. (2014). "ADAM: A Method for Stochastic Optimization." *Proc. of the 3rd Int. Conf. on Learning Representations (ICLR)*, San Diego, 1-15.

Kit, L. C., Khoo, E., Huah, S. K., Wei, J. L. P., Tan, T. S., Tsurumi, F. and Kumagai, T. (2020). "Reuse and Recycling of Clayey Soil in Pasir Panjang Terminal Phase 3 & 4 Project in Singapore." *Geotech. Eng. J. of the SEAGS & AGSSEA*, Vol.51, No.1, 32-43.

Kitazume, M. (2017). "The Pneumatic Flow Mixing Method." *CRC Press*, 250.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. "ImageNet classification with deep convolutional neural networks in NIPS2012." *Conf. and Workshop on Neural Information Processing Systems (NIPS)*, Lake Tahoe, Nevada, USA, 1097-1105.

Kumagai, T., Bai, K., Sasaki, Y., Tashiro, T., Kotoura, T. and Tsurumi, F. (2020a). "Reclamation Management System by Use of Artificial Intelligence for Estimating Soil Properties." *J. of Japan Society of Civil Engineers*, Ser B3 (Ocean Eng.), I_720-I_725 (in Japanese).

Kumagai, T., Yanagibashi, T., Tsutsumi, A., Konishi, C. and Ueno, K. (2020b). "Efficient Surface Wave Method for Investigation of the Seabed." *Soils and Foundations*, https://doi.org/10.1016/j.sandf.2020.04.005.

LeCun, Y., Haffner, P., Bottou, L. and Bengio, Y. (1999). "Object Recognition with Gradient-Based Learning." *Shape, contour and grouping in computer vision*, Springer-Verlag Berlin Heidelberg, 319-345.

Robertson, P.K. (2012): "Mitchell Lecture. Interpretation of In-Situ Tests - Some Insight." *4th Int. Conf. on Site Characterization ISC-4*, Porto de Galinhas, Brazil, Vol. 1, 3-24.

Sammut, C. and Webb, G.I. (2017). "Holdout Evaluation." in Encyclopedia of Machine Learning and Data Mining, *Springer*, 624.

Shinsha, H. and Kumagai, T. (2014). "Bulk Compression of Dredged Soils by Vacuum Consolidation Method using Horizontal Drains." *Geotech. Eng. J. of the SEAGS & AGSSEA*, Vol. 45, No. 3, 78-85.

Shinsha, H., and Kumagai, T. (2018). "Material Property of Solidified Soil Grains Produced from Dredged Marine Clay." *Soils and Foundations*, Vol. 58, 678-688.

Simonyan, K. and Zisserman, A. (2015). "Very Deep Convolutional Networks for Large-Scale Image Recognition." *In 3rd Int. Conf. on Learning Representations (ICLR 2015)*, 1-14.

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., and Salakhutdinov, R. (2014). "Dropout: A Simple Way to Prevent Neural Networks from Overfitting." *J. of Machine Learning Research*, Vol.15, 1929-1958.

Tsuchida, T., Watabe Y. and Kang M. (2002). "Evaluation of Structure and Mechanical Properties of Pleistocene Clay in Osaka Bay." R*eport of the Port and Airport Research Institute*, Vol. 41, No. 2, 45-92.

Tsuchida, T. and Egashira, K. (2004). "The Lightweight Treated Soil Method: New Geomaterials for Soft Ground Engineering in Coastal Areas." *CRC Press*, 136.