Examination of ground settlement prediction using machine learning

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ABSTRACT
The purpose of this study is to construct a consolidation settlement prediction method using machine learning, and examine the prediction accuracy when new observation data were applied to the trained model. Regarding the input / output relationship of the neural network, the method of learning the settlement rate was adopted by using the input value as the elapsed time and the amount of settlement at that time and the output value as the settlement rate. It is found that the trained model had high prediction accuracy, the average ratio of the predicted value to the measured value were in the range of 1.04 to 1.10, when different data from the training data were used and the difference in the final settlement amount was small. However, when the final settlement amount during training was larger than the final settlement amount of the data used for prediction, the prediction accuracy improved as the data used for prediction increased.

RÉSUMÉ
Le but de cette étude est de construire une méthode de prédiction de tassement de consolidation à l'aide de l'apprentissage automatique et d'examiner la précision de la prédiction lorsque de nouvelles données d'observation sont appliquées au modèle formé. En ce qui concerne la relation entrée/sortie du réseau neuronal, la méthode d'apprentissage du taux de règlement est adoptée en utilisant la valeur d'entrée comme le temps écoulé et la quantité de règlement à ce moment et la valeur de sortie comme taux de règlement. On constate que le modèle formé a une précision de prédiction élevée, le rapport moyen de la valeur prédite à la valeur mesurée est compris entre 1,04 et 1,10, lorsque différentes données du temps de formation sont utilisées et que la différence dans le montant du règlement final est petit. D'autre part, lorsque le montant de règlement final pendant l'apprentissage est supérieur au montant de règlement final des données utilisées pour la prédiction, la précision de la prédiction s'améliore à mesure que les données utilisées pour la prédiction augmentent.

1 INTRODUCTION

The settlement of embankment structures built on soft ground has long been a geotechnical problem and has been extensively studied by many researchers. Soft ground continues to settle down over a long period of time due to its high compressibility and low permeability. Therefore, the management of ground settlement is extremely important for maintaining the function of facilities and ensuring the safety of people. In recent years, research has been conducted on a consolidation settlement prediction method using a neural network as a method based on dynamic observation results. At present, it is known that this method can be used to make predictions with higher accuracy than existing methods such as the hyperbola method, and that predictions can be made with relatively high accuracy for initial settlement data.

Recent research works have been performed on ground settlement prediction using an artificial neural network (ANN). Wang et al. (2007) presented a novel method, combining FEM and an improved back-propagation neural network, for correction of soil parameters in the numerical prediction of embankment settlement. They showed that the proposed numerical back-analysis framework is very efficient in practical engineering applications to calculate highway settlement. Provenzano (2003) proposed a fuzzy neural network method to predict the behaviour of structures built on complex cohesionless soils. In his results, a numerical example showed the method's effectiveness when soil parameters are uncertain and gave suggestions for successive applications. To obtain more accurate settlement prediction using ANN, Shahin et al. (2002) developed and verified the ANN model from a large database of actual measured settlements, and compared their results with the values predicted by three traditional methods. They showed that their ANN model is a useful technique for predicting the settlement of shallow foundations on cohesionless soils. Nejad et al. (2009) also developed an ANN model for predicting pile settlement based on approximately 1000 data sets of standard penetration tests. They examined the network parameters to obtain the optimum model and demonstrated that their ANN model outperforms the traditional methods and provides accurate pile settlement predictions. Without using a large database, Kanayama et al. (2009 and 2014) examined a neural network model for predicting settlements. Using a learning pattern that focuses on the convergence of the settlement rate, they showed that the prediction values were in good agreement with the measurement values, using measurement records up to a consolidation stage of 60% as teach data for the ANN. The use of ANN for settlement prediction does have difficulties in assessing the pre-consolidation pressure (Çelik and Tan 2005) and the displacement back-analysis to identify soil parameters by using a genetic algorithm (Feng et al. 2004).

In this study, extending the neural network model described by Kanayama et al. (2009 and 2014), the prediction accuracy of the prediction method using the neural network model was examined with the aim of constructing a highly versatile consolidation settlement prediction method.

2 MEASUREMENTS AND APPLICATION OF ARTIFICIAL NEURAL NETWORK MODEL TO SETTLEMENT PREDICTION

2.1 Measurements

In this study, the settlement data (BLO) measured at the Bloemendalerpolder near Amsterdam in the Netherlands and the data measured at the settlement plates 1, 4, 5, 8 and 9 (respectively, TAM-1, TAM-4, TAM-5, TAM-8 and TAM-9) in the pre-loaded earth-fill in Tamana City, Kumamoto Prefecture, Japan were used. The former ground is mainly composed of peat, the embankment was constructed in five lifts up to a final level of 3.3 m. Prior to the construction of the embankment, vertical wick drains were installed in the soft soils underneath the embankment to accelerate drainage. The measurements were taken during 1 year, commencing from the start of construction. The latter ground is composed of alluvial clay called Ariake clay. In the Tamana Yokoshima Coastal Conservation Project, the drainage gutter gate, which is the main conservation facility, was completely relocated and renovated. In order to prevent the residual subsidence of the foundation ground due to the embankment backfilling after the construction of the main body of the gutter and the embankment of the mounting embankment, the preload embankment method using the plastic board drain method was adopted as the foundation treatment method. The embankment is divided into four stages, and in this study, the subsidence data for about one year from the completion of the final embankment to the removal of the embankment was used.

Figure 1 shows each settlement behavior. The final settlements of BLO, TAM-1, TAM-4, TAM-5, TAM-8, and TAM-9 were 43.9, 58.9, 44.8, 53.6, 70.1, 25.6 cm, respectively, and the settlement amount of TAM-8 was the largest. BLO, TAM-5, and TAM-8 were used for learning, and TAM-1, TAM-4, and TAM-9 were used for prediction. This is to know the applicability of the network model to different settlement behaviors.

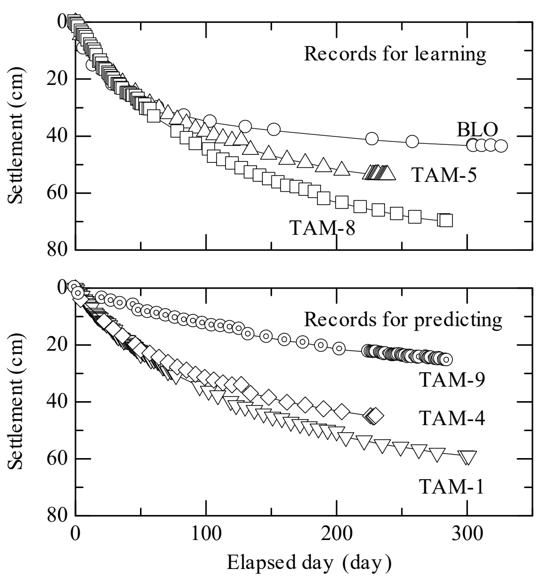

Figure 1. Settlement behavior recorded at each site

2.2 Application of ANN to Settlement Prediction

An artificial neural network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The perceptron model has the ability to recognize patterns, and ground settlement prediction by a neural network is a method that utilizes this ability. Specifically, the network can recognize the mapping relationship from the input layer to the output layer by modifying the weights with known data described here as teach data. The unknown output value can then be estimated by applying the known input value corresponding to the predictive value introduced to the network.

In this paper, the learning pattern and number of divisions for the teach data was adopted from Kanayama et al. (2009 and 2014), as shown in Figure 2. It is notable that the neural network learned the settlement rate, v_i, from the elapsed time, t_i, and the settlement, S_i; the predicted value, S_{i+1}, was calculated as $S_{i+1} = S_i + v_i\,\Delta t$; and the successive time, t_{i+1}, was updated by $t_{i+1} = t_i + \Delta t$. During data processing, the input and output data were normalized by the maximum value in the teach data. The parameters in the neural network were as follows: gain is 1.0, learning

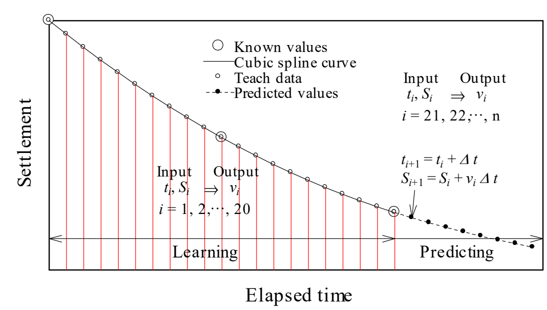

Figure 2. Correction for equal time interval and learning and predicting method (from Kanayama et al. 2014)

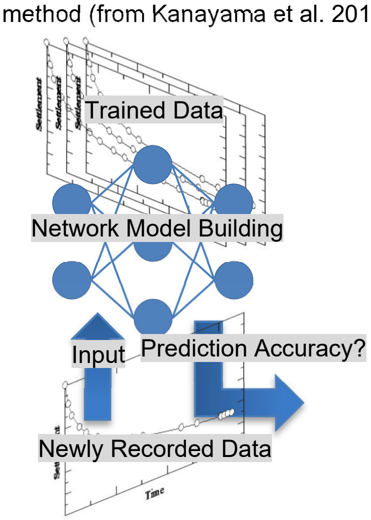

Figure 3. Outline of this study

ratio is 1.0, number of hidden layers is 10, and number of learning iterations is 100,000.

Figure 3 is a diagram showing the outline of the contents of this research. By saving the model obtained by learning, the applicability of the prediction method examined in this study was examined when data outside the learning range was given or when settlement prediction at different points was performed. In this study, teach data with settlement ratio R = 35%, 50%, and 60% were created for learning and prediction. R was defined as the ratio of each measured value to the final settlement, and the effect of the number of data used for learning on the prediction results was examined. The average prediction ratio, APR, and coefficient of variance, CV, were used as evaluation indexes for the accuracy of settlement prediction. APR was the average value of the prediction ratio. If it was larger than 1, it indicated an overestimation, and if it was smaller than 1, it indicated an underestimation. CV was an index showing the variation of APR, and the closer the value was to 0, the smaller the variation.

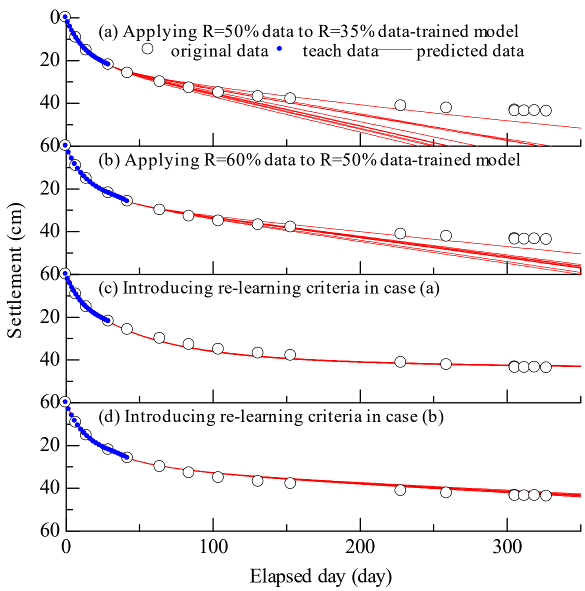

Figure 4. Prediction results and accuracy improvement of trained-model with same point data

3 RESULTS AND DISCUSSION

3.1 Applicability of ANN model to settlement data at same point

The applicability of the network model to settlement prediction was examined, when data outside the learning range was given at the same point. Ten sets of predictions were derived for each calculation. Because the initial weights on the hidden and output layers were set by random numbers, the reproducibility of prediction accuracy should be confirmed.

Figure 4 shows the results of the settlement predictions using the basic neural network model, applying R = 50 % data to a trained model with R = 35 % data (case (a)) and R = 60 % data to a trained model with R = 50 % data (case (b)). Additionally, the figures of case (c) and (d) show that the prediction accuracy of case (a) and (b) was improved, respectively. According to the results of the case (a) and (b), as the APR values are 1.23 and 1.10 and the CV values were 7.4 and 2.8 %, respectively, it is found that the both predictions were overestimated vary widely and the accuracy were low.

To improve this prediction accuracy, the acceptance criterion for utilizing predicted values as teach data was introduced (Kanayama et al. 2014). Figure 5 shows the schematic depiction about improving the network and the criterion for adding average predicted values to teach data. The criterion was based on the coefficient of variance, CVP, for the predicted values, and the discrimination was conducted in terms of relative variation. The value of CVP was specified by less than 1.0 %. The calculation in this network model was done as shown in Figure 5. At first, the network could learn about initial teach data 100,000 times and compute the 10 sets of settlement prediction. Using these predicted settlements, the CVP was checked whether satisfied the criterion or not. In the part of the predicted settlements that the parameter satisfied the criterion, the average value was calculated from 10 sets of

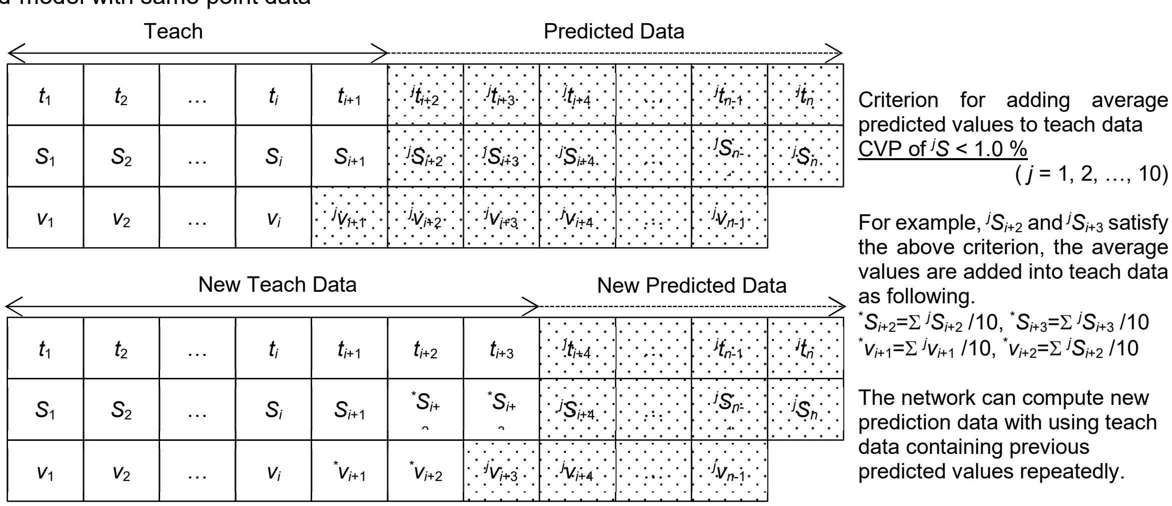

Figure 5. Improvement of network model and criterion for adding average predicted values to teach data (from Kanayama et al. 2014)

predicted values and added into teach data as new teach data. When not satisfied, the corresponding data was turned down. Then the network could continue to learn and predict again and again. Finally, the calculation was stopped if the parameter of all predicted settlements satisfied the criterion.

As can be seen from the case (c) and (d), the prediction accuracy improved significantly for both 35 % and 50 % data. Because of prescribing the variance of predicted settlement and using as teach data, the resultant prediction values had less variance. Focusing on the high accuracy of short-term settlement prediction, the improvement was done for installing the short term predicted values that satisfied the clear criterion to the network teach data.

From this result, it was found that the trained model can be applied to the data at the same point.

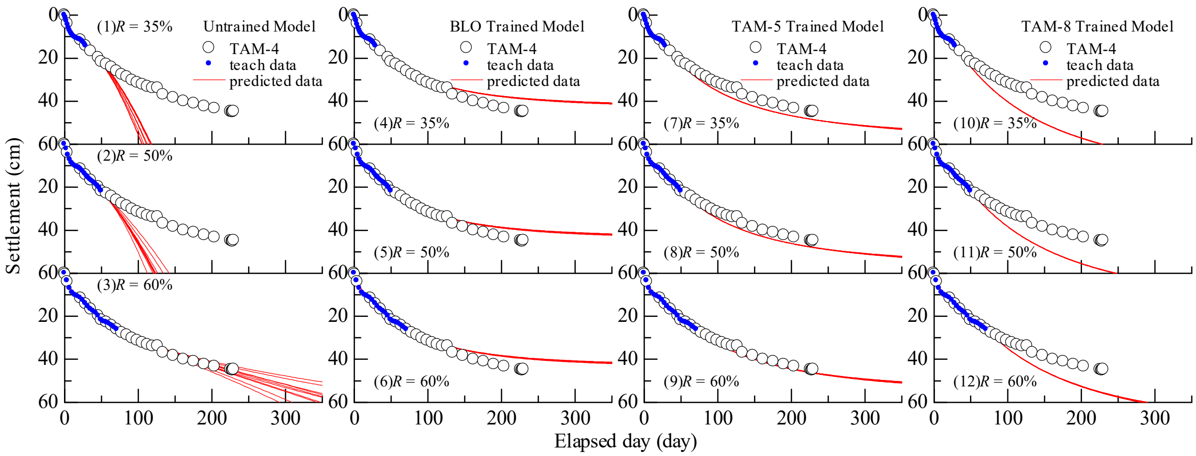

Figure 6. Prediction results of another recorded data (TAM-4) by using the trained models

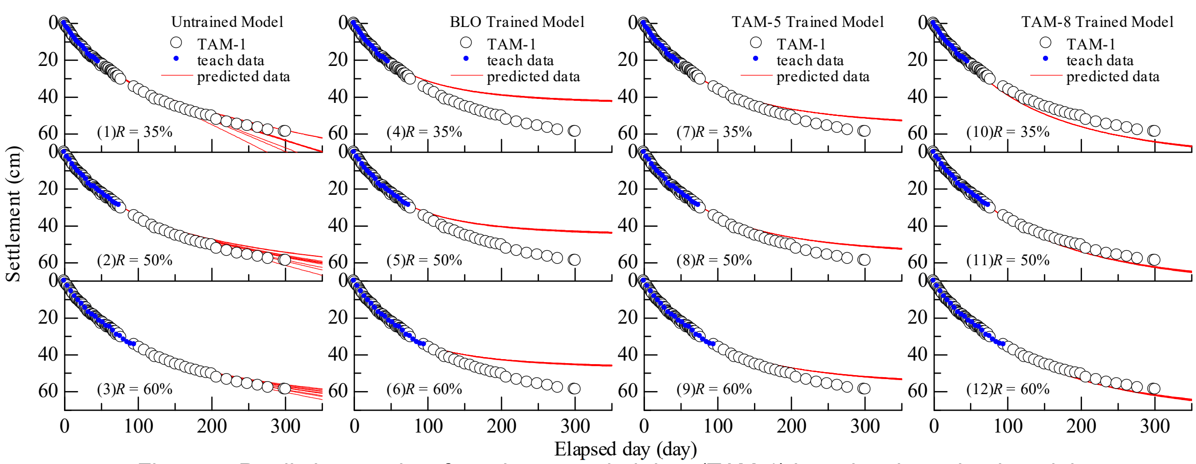

Figure 7. Prediction results of another recorded data (TAM-1) by using the trained models

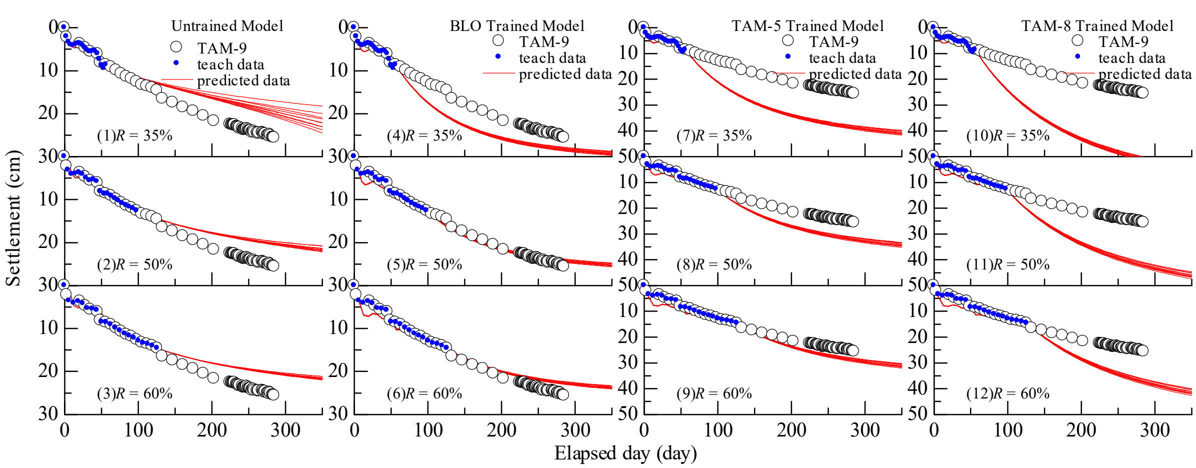

Figure 8. Prediction results of another recorded data (TAM-9) by using the trained models

Table 1. Prediction accuracy of the untrained and trained models

Data	R (%)	Untrained Model		BLO Trained Model		TAM-5 Trained Model		TAM-8 Trained Model	
		APR	CV (%)	APR	CV (%)	APR	CV (%)	APR	CV (%)
TAM-4	35	2.10	6.34	0.93	0.18	1.10	0.10	1.27	0.09
	50	1.94	7.75	0.96	0.21	1.08	0.10	1.23	0.09
	60	1.00	1.93	0.93	0.22	1.04	0.11	1.17	0.15
TAM-1	35	0.99	1.82	0.87	0.20	0.97	0.09	1.07	0.08
	50	0.95	1.42	0.82	0.26	0.92	0.11	1.04	0.14
	60	0.98	0.84	0.86	0.22	0.93	0.10	1.04	0.14
TAM-9	35	0.79	3.42	1.19	0.85	1.56	1.05	1.98	0.99
	50	0.83	0.85	0.99	0.89	1.26	1.30	1.60	1.38
	60	0.82	0.51	0.92	0.79	1.13	1.30	1.41	1.50

3.2 Applicability of ANN model to settlement data at different point

Next, the applicability of the network model that learned the settlement data at other points was examined. Specifically, let the network model train the total settlement data obtained at a certain point. Using the network constructed by the learning, the applicability of the network model was examined when predicting the data newly observed at other points.

Figures 6 to 8 show the results of predicting the settlement data of TAM-4, TAM-1, and TAM-9 using an untrained network model and network models that learned BLO, TAM-5, and TAM-8, and Table 1 shows the prediction accuracy of each result.

From the results of the untrained model in Figures 6(1) to (3), the APR value of case (1) to (3) was 2.10, 1.94, and 1.00, and similarly the CV was 6.34, 7.75, and 1.93 %, respectively. When too little measurements were used as teach data, for cases (1) and (2), clear differences were observed between the predicted and recorded values, and the variance of predicted values became larger with an increase in the elapsed time. In case (3), the predicted settlement was in good agreement with the measured data, but the variance was still large over time.

However, according to the results of the trained model in Figures 6(4) to (12), it can be seen that the variation in the predicted values was eliminated as the CV values were in the range of 0.09 to 0.22. Especially for the TAM-5 and TAM-8 trained model, Figures 6(7) to (12), the larger the R value, the better the prediction accuracy, the APR value tended to be close to 1.00. However, the results of the BLO trained model were in underestimation as the APR value was in the range of 0.93 to 0.96, it is considered that the difficulty existed to expect an improvement in prediction accuracy when making predictions for settlement data larger than the learning range.

From Figures 7(1) to (3), the regularity of the observation data, with less variance in value itself, was high, even the predicted values of the untrained model were in good agreement with the measurements. The APR values were in 0.95 to 0.99 and the CV values were in 0.84 to 1.82 %. From this result, it can be seen that the regularity of the settlement data used for the prediction was important in the settlement prediction using the neural network.

In the prediction results by the trained models, Figure 7(4) to (12), the TAM-8 trained models produced the better prediction accuracy than the other models, and the APR values were in the range of 1.04 to 1.07 and the CV values were in 0.08 to 0.14. The results by the BLO and TAM-5 trained models were affected by the out of range of the training settlement data and therefore the APR values were less then 1 and seemed to be constant. These results were same trend as the Figures 6(4) to (6).

In the case of the TAM-9 settlement measurement, Figure 8, the behavior of this settlement was unique compared to the other settlement behavior. While the other settlement curves showed a gentle curve shape with the passage of time, the TAM-9 settlement data showed an almost linear increase with the passage of time. Moreover, it can be seen that the irregularities of the observed values were remarkable, and the variations of the measured values were large. The observations with this tendency are not uncommon and are often observed in the field. It is important to use such settlement data in order to understand the application limits of this method.

In the results by the untrained model, Figure 8(1) to (3), the settlement predictions were in underestimation. This is because the gradients at the beginning and end of the observed values were different, and it is shown that the prediction cannot be made accurately only with the information contained at the beginning of the observed values. However, focusing on the teach data and the output value, it can be seen from the figure that the values output from this model reproduce irregular teach data. Thus, it is found that the learning of this model was functioning effectively.

According to the results by the trained models, not good results were achieved in all predictions, Figures 8(4) to (12). The first point is that the output value of the model could not reproduce the teach data. This indicates that the model could not cope with irregular data such as the TAM-9 because the model learned relatively highly regular settlement data. The second is that the predicted value showed a settlement behavior completely different from the observed value. As the predicted settlement showed the gradual curve shape, it is presumed that the training of the model was performed effectively and the output value sufficiently reproduced the settlement data used for training. However, when using the settlement data that tended to be different from the teach data, it is necessary to pay attention to use this model. The APR values of the trained models were in 0.92 to 1.98, the CV values were in 0.79 to 1.50 %, and these values were unacceptable as predicted values.

From the above results, it was found that the accuracy of the settlement prediction using this model depended on the similarity between the settlement data used for training and the settlement data used for prediction. Specifically, if the learned settlement data was larger than the settlement data used for prediction, the output value of the model tended to be equal to or overestimated, and the prediction accuracy tended to improve as the data range used increased. However, when the learned settlement data was smaller than the data used for prediction, the predicted value was underestimated from the observed value, and the prediction accuracy remained constant even if the number of data used for prediction increased. Finally, if the settlement data used for prediction had a large irregularity and the settlement behavior was different from the training data, it was found that this model was not applicable. To improve this difficulty, it is necessary to simply categorize the settlement behavior of the ground into several types and let the model learn them so that the model can determine which pattern the target settlement behavior is suitable for. Further investigation on the applicability of the method should be considered.

4 CONCLUSION

In this paper, extending the neural network model described by Kanayama et al. (2009 and 2014), the prediction accuracy of the prediction method using the neural network model was examined with the aim of constructing a highly versatile consolidation settlement prediction method.

The applicability of the network model to settlement prediction was examined, when data outside the learning range was given at the same point. Introducing the acceptance criterion for utilizing predicted values as teach data, and the prediction accuracy improved significantly, it was found that the trained model could be applied to the data at the same point.

Additionally, the applicability of the network model that learned the settlement data at other points was examined. It was found that the accuracy of the settlement prediction using this model depended on the similarity between the settlement data used for training and the settlement data used for prediction. When the learned settlement data was larger than the settlement data used for prediction, the output value of the model tended to be equal to or overestimated, and the prediction accuracy tended to improve as the data range used increases. However, when the learned settlement data was smaller than the data used for prediction, the predicted value was underestimated from the observed value, and the prediction accuracy remained constant even if the number of data used for prediction increased. Finally, if the settlement data used for prediction had a large irregularity and the settlement behavior was different from the training data, it was found that this model was not applicable.

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