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Full Length Article

An intelligent procedure for updating deformation prediction of braced excavation in clay using gated recurrent unit neural networks

Jie Yang [a,*], Yingjing Liu [b], Saffet Yagiz [c], Farid Laouafa [d]

[a] Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hong Kong, China
[b] Zhongtian Construction Group Co. Ltd., Hangzhou, 310008, China
[c] School of Mining and Geosciences, Nazarbayev University, Nur-Sultan, 010000, Kazakhstan
[d] National Institute for Industrial Environment and Risks (INERIS), Verneuil-en-Halatte, France

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A B S T R A C T

This paper aims to establish an intelligent procedure that combines the observational method with the existing deep learning technique for updating deformation of braced excavation in clay. The gated recurrent unit (GRU) neural network is adopted to formulate the forecast model and learn the potential rules in the field observations using the Nesterov-accelerated Adam (Nadam) algorithm. In the proposed procedure, the GRU-based forecast model is first trained based on the field data of previous and current stages. Then, the field data of the current stage are used as input to predict the deformation response of the next stage via the previously trained GRU-based forecast model. This updating process will loop up till the end of the excavation. This procedure has the advantage of directly predicting the deformation response of unexcavated stages based on the monitoring data. The proposed intelligent procedure is verified on two well-documented cases in terms of accuracy and reliability. The results indicate that both wall deflection and ground settlement are accurately predicted as the excavation proceeds. Furthermore, the advantages of the proposed intelligent procedure compared with the Bayesian/optimization updating are illustrated.

1. Introduction

Braced excavation has been widely used in the urban constructions. However, damages may be produced to the adjacent buildings and underground structures induced by lateral wall deflection and ground movement (Shen et al., 2014, 2017; Xu et al., 2016; Jin et al., 2018; Zhang et al., 2018). During the braced excavation, it is crucial to estimate the lateral wall deflection and the ground movement before the excavation of the next stage. However, the conservative estimation will increase the cost while the underestimation will increase the risk and even result in accidents. Therefore, in engineering practice, it is vital to develop an accurate and reliable methodology to predict the lateral wall deflection and the ground movement during the braced excavation. The stage-updating prediction methodology carried out stage by stage, based on field observations, is useful in engineering practice.

The core of staged-updating prediction methodology is how to calculate the deformation caused by excavation. The common way to obtain the deformation response is to adopt finite element method (FEM) (Ou et al., 2000; Hashash et al., 2010; Jiang and Yin, 2014; Zhang et al., 2019, 2020a). For the calculation by FEM, many factors can affect the prediction accuracy, such as (1) the drainage condition (Costa et al., 2007; Zhao et al., 2015; Yang et al., 2019a, b, c, d; Goh et al., 2020), which is difficult to be considered in the calculation, since most excavations are performed in partially drainage condition; (2) the selection of an appropriate constitutive model (Kung et al., 2007a; Hejazi et al., 2008; Lim et al., 2010; Chang and Yin, 2011; Zhang and Ai, 2012; Jiang and Yin, 2014; Yin et al., 2018a), which is important for predicting the deformation responses; (3) the determination of reasonable parameters (Calvello and Finno, 2004; Baroth and Malecot, 2010; Hashash et al., 2011; Juang et al., 2012; Jin et al., 2016, 2017, 2019a); and (4) the spatial variability of soil (Guillaumot et al., 2003; Jin et al., 2019b, c; Goh et al., 2019). Combining FEM simulation with optimization/Bayesian methods, the stage-updating prediction can be achieved.

* Corresponding author.
E-mail address: doc.jie.yang@gmail.com (J. Yang).
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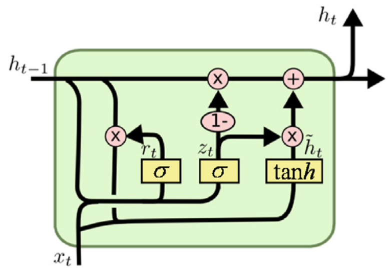

Fig. 1. Structure of GRU (from https://primo.ai/index.php?title=Gated_Recurrent_Unit_(GRU)).

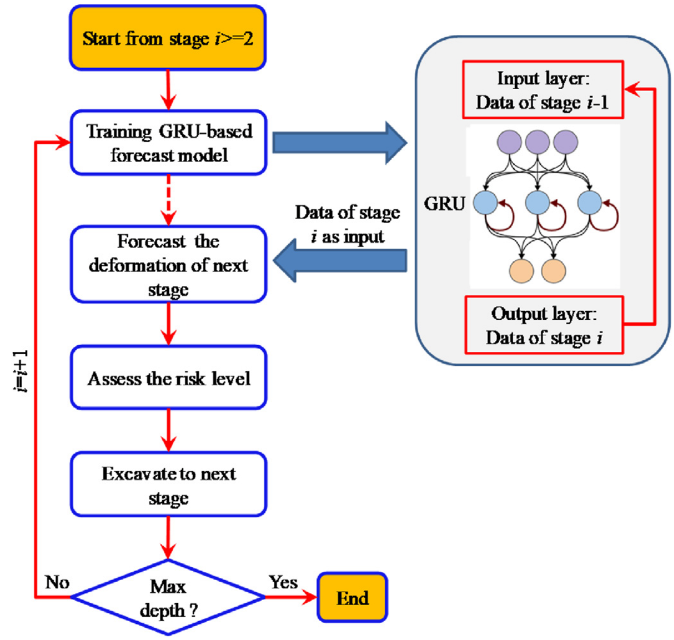

Fig. 3. Combination of model training and updating the prediction process.

However, numerous calculations are required (Huang et al., 2014; Zhao et al., 2015; Jin et al., 2019a), making it impractical for use. Another approach to predict the deformation responses is the semi-empirical model (Kung et al., 2007b), of which the drawback is that only the maximum ground surface settlement and the maximum lateral displacement can be predicted. Compared to the FEM simulation or semi-empirical model, the machine learning approach attracts a lot of attention in predicting the deformation responses of excavation, such as artificial neural networks (ANN) (Goh et al., 1995; Jan et al., 2002; Ambrožič and Turk, 2003; Leu and Lo, 2004; Chua and Goh, 2005; Kung et al., 2007c; Tan et al., 2011; Lü et al., 2012; Zhang et al., 2020b, c). Compared with traditional methods, the machine learning methods can dig the trend of field data, which can learn the characteristics of the field data generated by excavation and then predict the deformation of the following excavation. The soil mechanism behind the field data is therefore learned and considered implicitly instead of using explicitly a soil constitutive model. The updating of machine leaning-based procedure can be regarded as the direct updating from measured data to predicted data, therefore, no soil constitutive model or soil parameter is needed. The advantage of the deformation prediction using machine learning-based methods is that it does not require plenty of numerical calculations (Al-Ani et al., 2009; Obead et al., 2021; Zhang et al., 2021a, b). Furthermore, the inaccuracy induced by the choice and calibration of soil constitutive model and parameters can be avoided, neither extra field monitoring or field sampling nor laboratory testing is required. However, the accuracy of machine learning-based methods heavily relies on the preformation of the used algorithm. Traditional machine learning methods are no longer sufficient for such problems, such as the ANN with few layers. Thus, the use of advanced machine learning

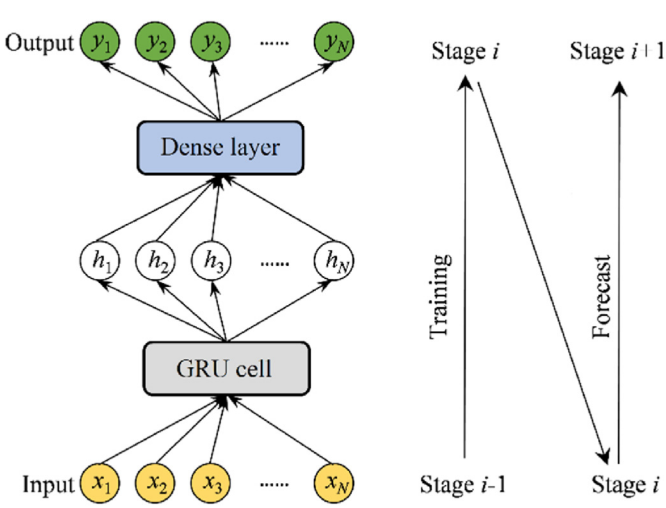

Fig. 2. Schematic view of the GRU-based forecast model.

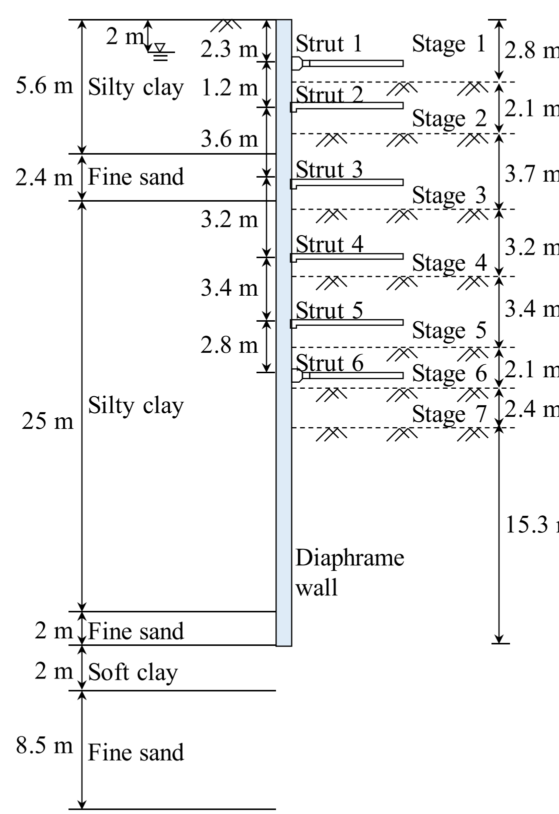

Fig. 4. Soil profile and the excavation depth in TNEC.

(deep learning) algorithm to predict the deformation response of excavation is worth trying.

The gated recurrent unit (GRU) belongs to the family of recurrent neural network (RNN). In principle, RNN is more suitable for capturing relationships among sequential data types. This important feature has made RNN versatile among many applications that require learning from temporal data such as the real-time predictions of mechanized tunnelling processes (Freitag et al., 2018; Zhang et al., 2020a, d, 2021c, d), the rainfall-runoff modeling (Kratzert et al., 2018), the response of caisson foundation (Zhang et al., 2020e), and the soil behavior modeling (Byun and Song, 2018; Wang and Sun, 2018; Wang et al., 2019; Zhang et al., 2020f, 2021a,e). Bengio et al. (1994) showed that, using such simple RNN, it is difficult to capture long-term dependencies due to the vanishing or explosion of (stochastic) gradients. To solve the "vanishing" or "exploding" gradient problems, the long-short-term memory (LSTM) unit RNN (Hochreiter and Schmidhuber, 1997) and GRU-RNN (Chung et al., 2014) have been proposed. In GRU, input gate and forget gate that appear in LSTM are merged into one gate operation. This change makes the GRU have fewer weights and thus less computation cost while preserving the similar performance to LSTM on many applications (Wang, 2017).

The aim of this paper is to develop a GRU-based updating procedure using the filed data for deformation prediction in the braced excavation in clay. The GRU neural network is adopted due to the ability of memory. It is used to learn the potential rules in the field observations using the Nesterov-accelerated Adam (Nadam) algorithm. The framework of the GRU-based updating procedure using the filed data is first presented with a brief introduction of GRU. Then, the proposed framework is verified by analysing two typical

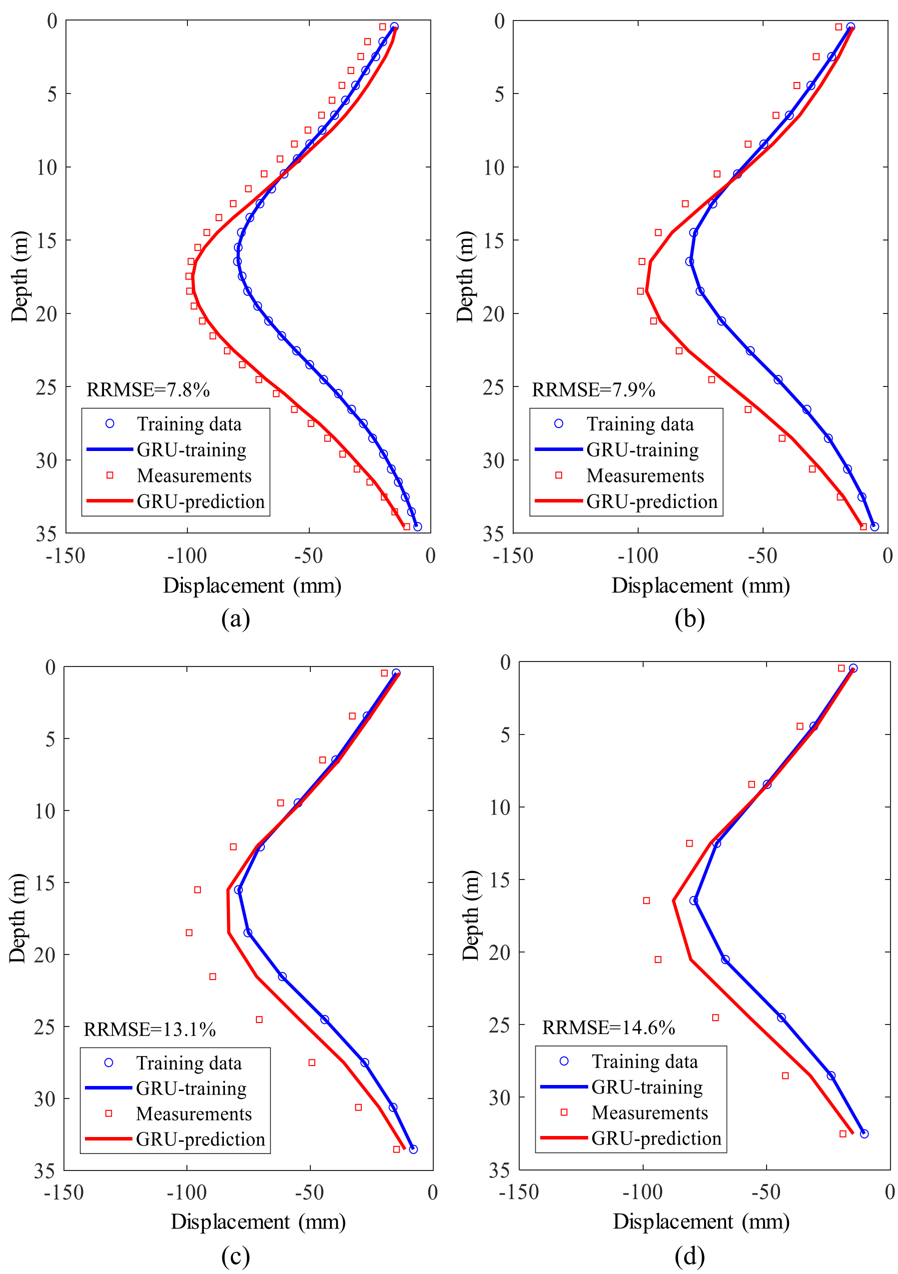

Fig. 5. The influence of the number of data points: (a) 35 points, (b) 18 points, (c) 12 points, and (d) 9 points.

cases of excavation. The accuracy and reliability of the proposed procedure are evaluated. The advantages and limitations of the proposed updating framework are further discussed.

2. A framework of GRU-based updating procedure

2.1. GRU network

Fig. 1 shows that, at t time step, there are two kinds of gate operations in one hidden node of GRU: the update gate z_t and the reset gate r_t. Similar to LSTM, the current hidden output h_t is computed based on the current input $\boldsymbol{x}_t$ and the previous hidden output h_{t-1}.

The reset gate is given as

$$r_t = \sigma(\boldsymbol{W}_r\boldsymbol{x}_t + \boldsymbol{U}_r h_{t-1} + b_r) \tag{1}$$

The update gate is expressed as follows:

$$z_t = \sigma(\boldsymbol{W}_z\boldsymbol{x}_t + \boldsymbol{U}_z h_{t-1} + b_z) \tag{2}$$

The hidden state (memory) is presented as

$$\left.\begin{aligned} h_t &= (1-z_t)\odot h_{t-1} + z_t\odot\tilde{h}_t \\ \tilde{h}_t &= \tanh[\boldsymbol{W}\boldsymbol{x}_t + \boldsymbol{U}(r_t\odot h_{t-1}) + b] \end{aligned}\right\} \tag{3}$$

In Eqs. (1)–(3), $\boldsymbol{W}_r$, $\boldsymbol{W}_z$, $\boldsymbol{W}$ and $\boldsymbol{W}_o$ are the weight matrices of GRU neural networks related to the input $\boldsymbol{x}_t$; $\boldsymbol{U}_r$, $\boldsymbol{U}_z$, and $\boldsymbol{U}$ are the weight matrices of GRU neural networks related to hidden state h_{t-1}; b_r, b_z, b and b_o are the biases; $\boldsymbol{x}_t$ is the input vector; the operation $\odot$ stands for the Hadamard product; σ represents the logistic sigmoid function; and tan$h$ represents the hyperbolic function.

Then, the output from the fully-connected layers to the output layer is expressed as

$$\boldsymbol{y}_t = \text{ELU}(\boldsymbol{W}_o h_t + b_o) \tag{4}$$

where $\boldsymbol{y}_t$ is the output vector, and ELU is the exponential linear unit.

Herein the logistic sigmoid function σ and the hyperbolic function tanh are defined as follows:

$$\sigma(x) = 1/(1+\mathrm{e}^{-x}) \tag{5}$$

$$\tanh(x) = (\mathrm{e}^{x} - \mathrm{e}^{-x})/(\mathrm{e}^{x} + \mathrm{e}^{-x}) \tag{6}$$

The exponential linear unit ELU is defined as

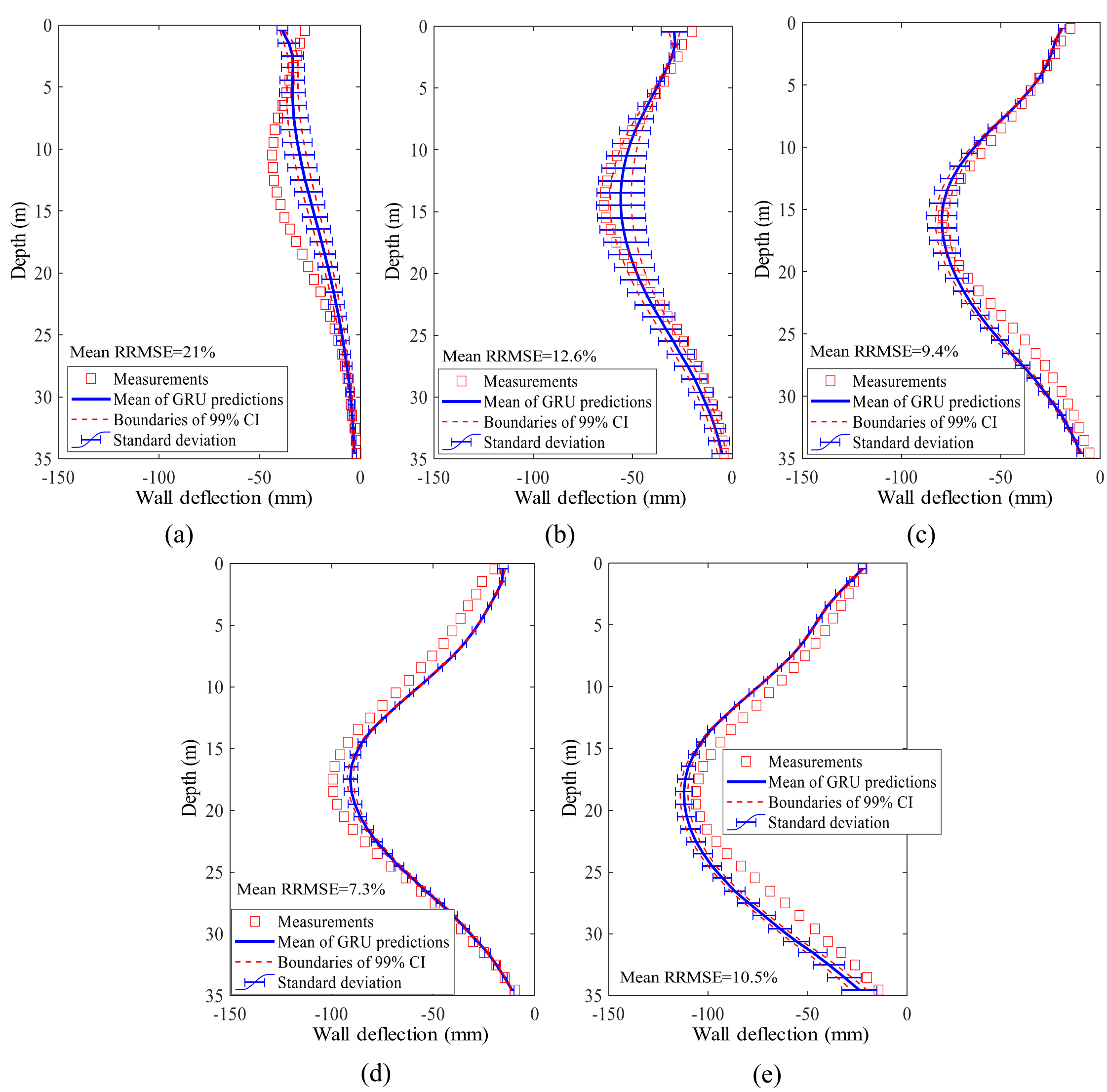

Fig. 6. Predicted and measured wall deflections of TNEC excavation at different stages: (a) Stage 3, (b) Stage 4, (c) Stage 5, (d) Stage 6, and (e) Stage 7.

$$f(x) = \begin{cases} x & (x > 0) \\ \alpha(e^x - 1) & (\text{otherwise}) \end{cases} \tag{7}$$

where α is a hyper-parameter, and $\alpha = 0.01$ in this study.

Note that ELU tries to make the mean activations closer to zero, and speed up the learning. It has been shown that ELU can obtain higher accuracy than rectified linear unit (ReLU) (Clevert et al., 2015):

$$f(x) = \begin{cases} x & (x > 0) \\ 0 & (\text{otherwise}) \end{cases} \tag{8}$$

Note that the activation functions except for the gate operations can be changed according to the practical problems.

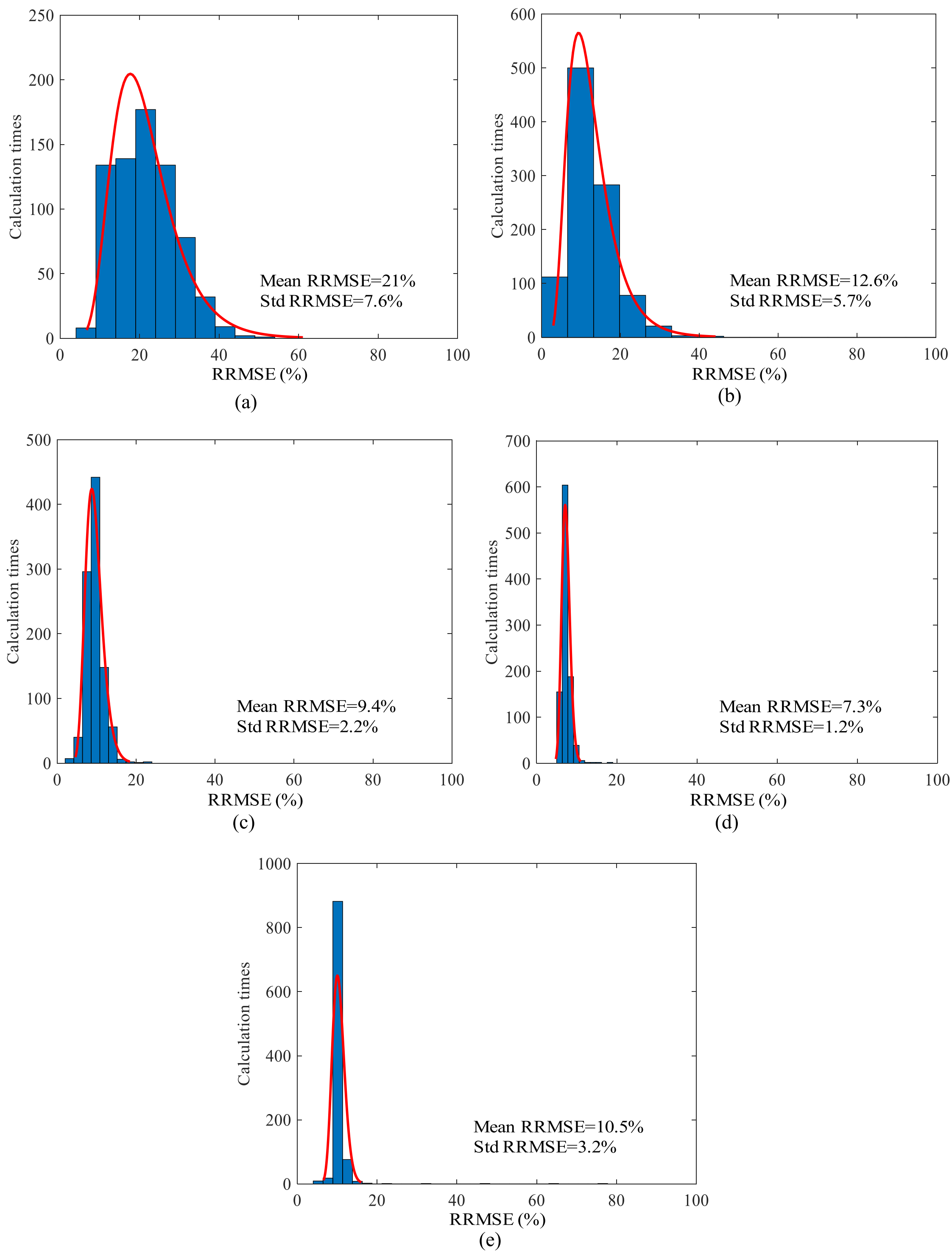

Fig. 7. RRMSE of wall deflection of TNEC excavation at different stages: (a) Stage 3, (b) Stage 4, (c) Stage 5, (d) Stage 6, and (e) Stage 7.

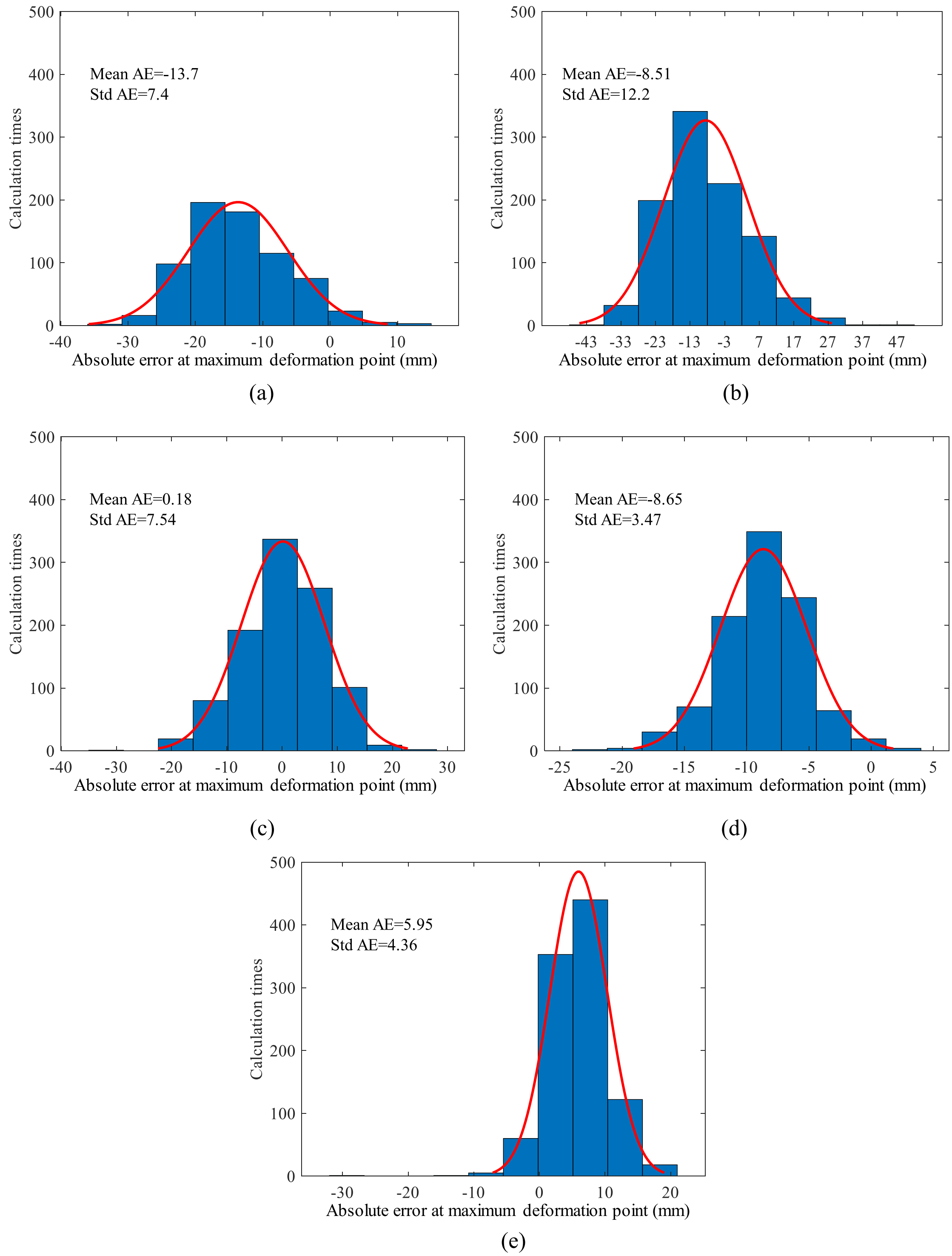

Fig. 8. AE of maximum wall deflection of TNEC excavation at different stages: (a) Stage 3, (b) Stage 4, (c) Stage 5, (d) Stage 6, and (e) Stage 7.

2.2. *Updating procedure using field data*

Figs. 2 and 3 demonstrate the proposed GRU-based procedure of updating predictive deformation. In deep excavation, the ground settlement and wall deflection are measured after the first and second excavation stages. Then, the GRU-based forecast model can be trained with the observed data of the first and second stages as the training dataset. The GRU-based forecast model can learn the deformation pattern of the previous two stages. Then, before the subsequent stages of excavation, the wall and ground responses can be predicted by the trained GRU-based forecast model. If too large deformation is predicted, the precaution measures are needed to protect the adjacent structures. The prediction accuracy is evaluated by comparing the predictions and observations after finishing the next stage of excavation. Next, the observed data of the second stage will act as the training dataset and the newly measured data of the

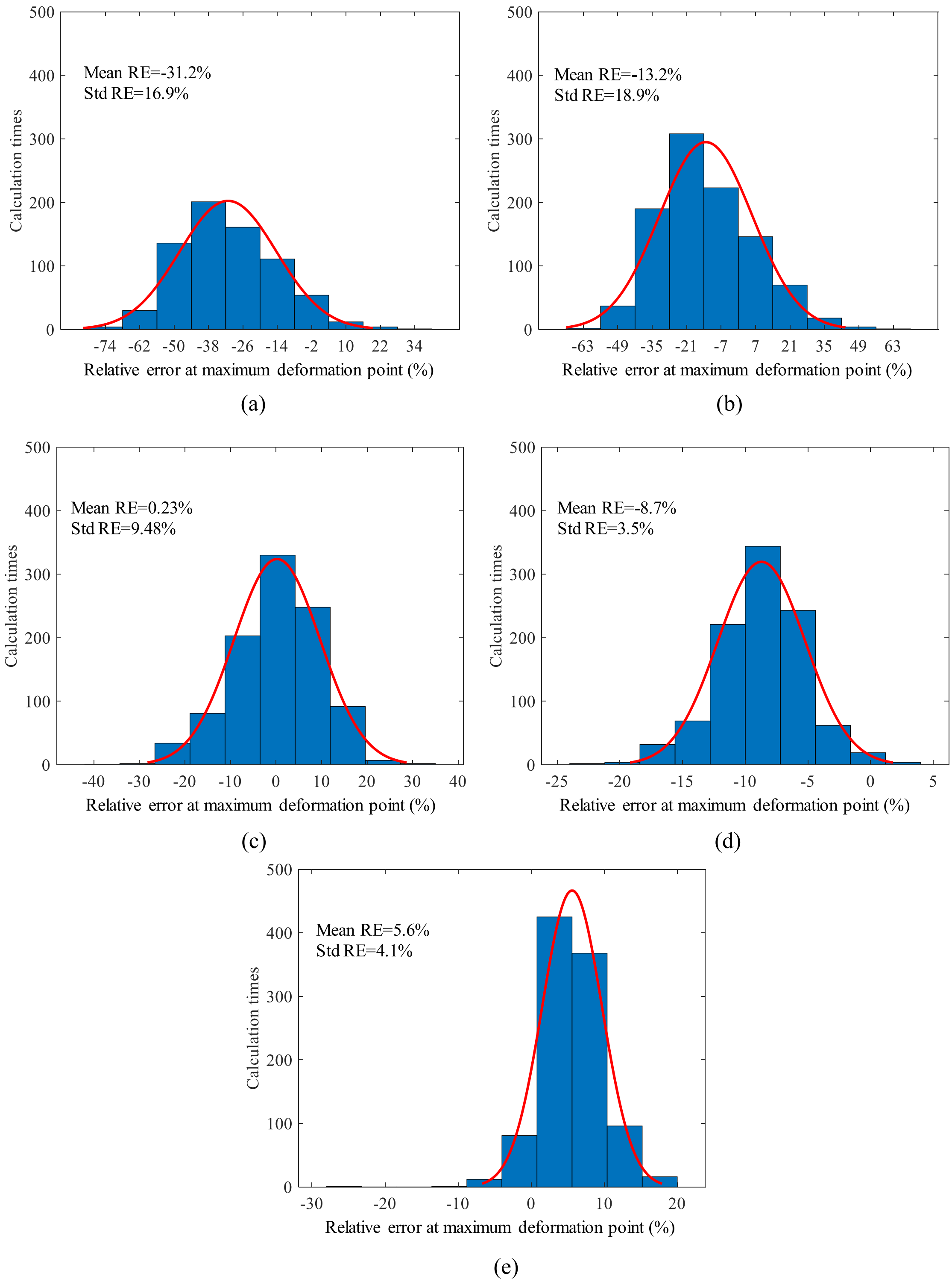

Fig. 9. RE of maximum wall deflection of TNEC excavation at different stages: (a) Stage 3, (b) Stage 4, (c) Stage 5, (d) Stage 6, and (e) Stage 7.

third stage will act as output to retrain a new GRU-based forecast model. After that, the deformation responses of the fourth stage can be predicted. As the excavation proceeds, the training and prediction processes are repeated till the end of excavation.

The training of the GRU-based model is achieved through the algorithm of back-propagation through time (BPTT) with batch gradient descent. The average of the gradients of all the training examples is used to update the weights of the neural network. Nadam, the optimization algorithm proposed by Dozat (2016), is adopted. Compared to stochastic gradient descent (SDG) and Adam, the Nadam takes the advantage of Nesterov-accelerated gradients. This change is an essential approximation of the second derivative of the objective function. The Nadam algorithm has a faster convergence rate than SDG and Adam due to the use of the second-order derivative information, and it has been validated on various benchmarks by Dozat (2016). Note that besides the commonly used deterministic algorithms, the stochastic optimization methods (Yin et al., 2017, 2018b; Jin et al., 2019a; Jin and Yin, 2020) are viable alternatives for the model training.

The goal of the algorithm is to find model parameters (e.g. *weights*) that minimize the model error (*Loss*) on the training dataset. In order to reduce the tedious works on tuning hyper-parameters, the learning rate is set to a fixed value of 0.001 as recommended by Wang and Sun (2018). Overfitting is the modeling error in statistics that occurs when the prediction of the machine learning model is too closely aligned to the training data points but far away from the testing data points. For any data-driven method, overfitting is a frequent problem which makes an overly complex model explain the idiosyncrasies in the data. In view of the excavation problem, the overfitting may also exist because the parameters of the GRU model are much more than the number of training data. The L2 regularization with the coefficient $\lambda = 0.001$ is adopted to avoid the overfitting problem. In order to eliminate the effect of magnitudes of input variables on the model's performance and reduce the computational cost, all training data used in the GRU-based model were normalized into [0, 1]. The *Loss* function is defined as

$$Loss = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{U_{\mathrm{obs}}^{i} - U_{\mathrm{GRU}}^{i}}{U_{\mathrm{obs}}^{i}}\right)^{2} + \lambda\|weights\| \tag{9}$$

where U_{obs}^{i} is the ith point of observed data after normalization, U_{GRU}^{i} is the ith point of predicted data after normalization, and N is the number of points of measured data. Training will stop when the value of *Loss* is smaller than 1×10^{-4} or the number of epochs is greater than 1×10^{4}.

The proposed procedure is similar to the multi-objective optimization updating procedure proposed by Jin et al. (2019c), the Bayesian updating procedure proposed by Juang et al. (2012), the semi-empirical polynomial regression based spreadsheet solver method by Zhang et al. (2015), and the multivariate adaptive regression splines for inverse analysis by Zhang et al. (2017). The optimized parameters of the multi-objective optimization updating procedure are selected from the Pareto front obtained using the multi-objective optimization algorithm. The updated parameters in the Bayesian updating are represented by the posterior distributions and sample statistics obtained through the Markov chain Monte Carlo (MCMC) simulation. It can be seen that for Bayesian/optimization-based updating, the forward prediction is indirectly achieved by updating the soil parameters, while for deep learning based procedure, the updating is directly obtained from the measured data to the predicted data, and no soil parameter is needed. The merits of the proposed procedure realized by using MATLAB (MathWorks, 2016) will be highlighted in two selected real excavation cases.

3. Illustrative examples

3.1. Case 1: Taipei National Enterprise Center excavation

The proposed procedure is first verified by predicting the Taipei National Enterprise Center (TNEC) excavation. The soil testing and field monitoring data have been recorded completely (Ou et al., 1998, 2000; Teng et al., 2014). The width of the excavation is

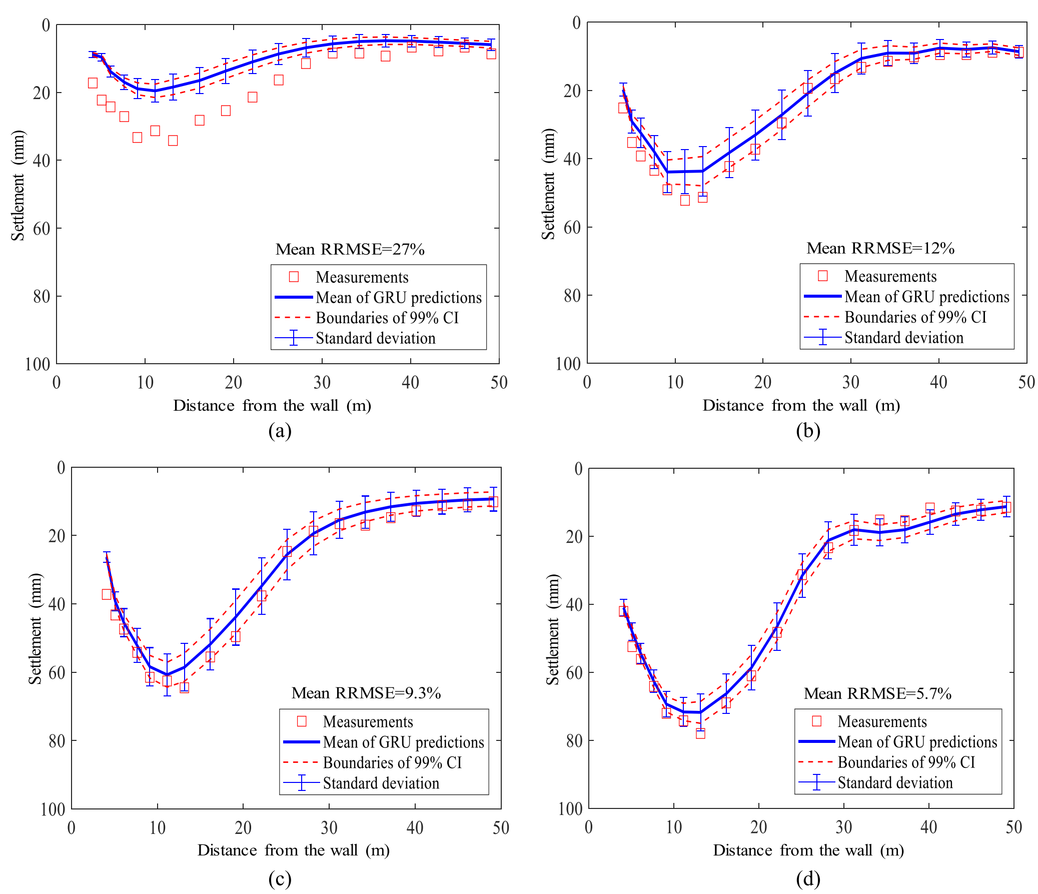

Fig. 10. Predicted and measured ground settlement of TNEC excavation at different stages: (a) Stage 4, (b) Stage 5, (c) Stage 6, and (d) Stage 7.

41.2 m, and the length and thickness of the diaphragm wall is 35 m and 0.9 m, respectively. The excavation was performed by the top-down method in seven stages where the wall was supported by 150-mm thick concrete floor slabs. The total excavation depth is 19.7 m. Fig. 4 shows soil profile and the excavation depth in TNEC excavation. According to Kung et al. (2007a), the site can be considered as a clay-dominant site. The groundwater table is located 2 m below the ground surface. The filed data are recorded by the monitoring instruments including electronic-type piezometers, rebar stress meters on the reinforcement cage, inclinometers in the wall and soil, and earth–water pressure cells on the wall, as well as settlement gauges and heave gauges. The creep behavior of soils has not been considered (Yin and Wang, 2012; Wang et al., 2014; Zhu et al., 2016).

3.1.1. Wall deflection

The performance of the proposed intelligent procedure is first shown on the prediction of wall deflection. As mentioned in the procedure, it starts from stage 2. The measured data of stages 1 and 2 were used to train the GRU-based forecast model. Since there are only a few monitoring points, the hidden size is set to 10 to avoid overfitting. Note that the selection of hidden size is challenging and, in most cases, it should be determined according to the actual situation. To evaluate the performances of the proposed forecast model, three indicators are used: absolute error (AE), relative error (RE) and relative root mean square error (RRMSE), which are defined as

$$AE = Y_{\mathrm{obs}} - Y_{\mathrm{GRU}} \tag{10}$$

$$RE = \frac{Y_{\mathrm{obs}} - Y_{\mathrm{GRU}}}{Y_{\mathrm{obs}}} \times 100\% \tag{11}$$

$$RRMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{Y^{i}_{\mathrm{obs}} - Y^{i}_{\mathrm{GRU}}}{Y^{i}_{\mathrm{obs}}}\right)^{2}} \times 100\% \tag{12}$$

where Y_{obs} is the real observed data, and Y_{GRU} is the real predicted data by the GRU-based forecast model.

To evaluate the influence of the number of points on the performance of the GRU model, four calculations based on the wall deflection prediction of stage 6 were carried out with different numbers of data points, i.e. 35, 18, 12 and 9, respectively. Fig. 5 shows the *RE* of the wall deflection between the results of the GRU model and measurements. It can be found that at least 18 points are needed for training the GRU model, and the overfitting problem (i.e. small training error with large prediction error) occurs when the number of data points is less than 18.

In terms of model training, the Nadam is adopted, whose primary advantage is rapid convergence. However, the limitations also exist, e.g. its optimal solution strongly depends on the initial trial solutions, and it is only capable of searching for a local minimum. A possible solution to avoid such problems is to start the search from

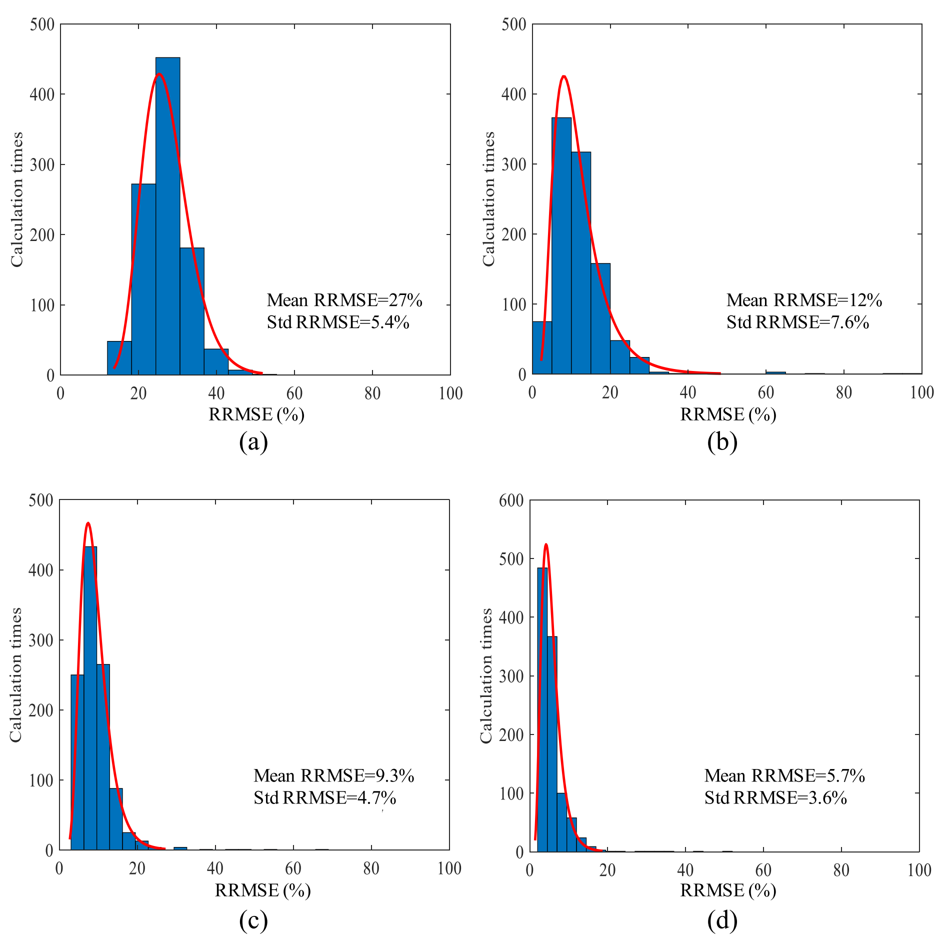

Fig. 11. RRMSE of TNEC excavation at different stages: (a) Stage 4, (b) Stage 5, (c) Stage 6, and (d) Stage 7.

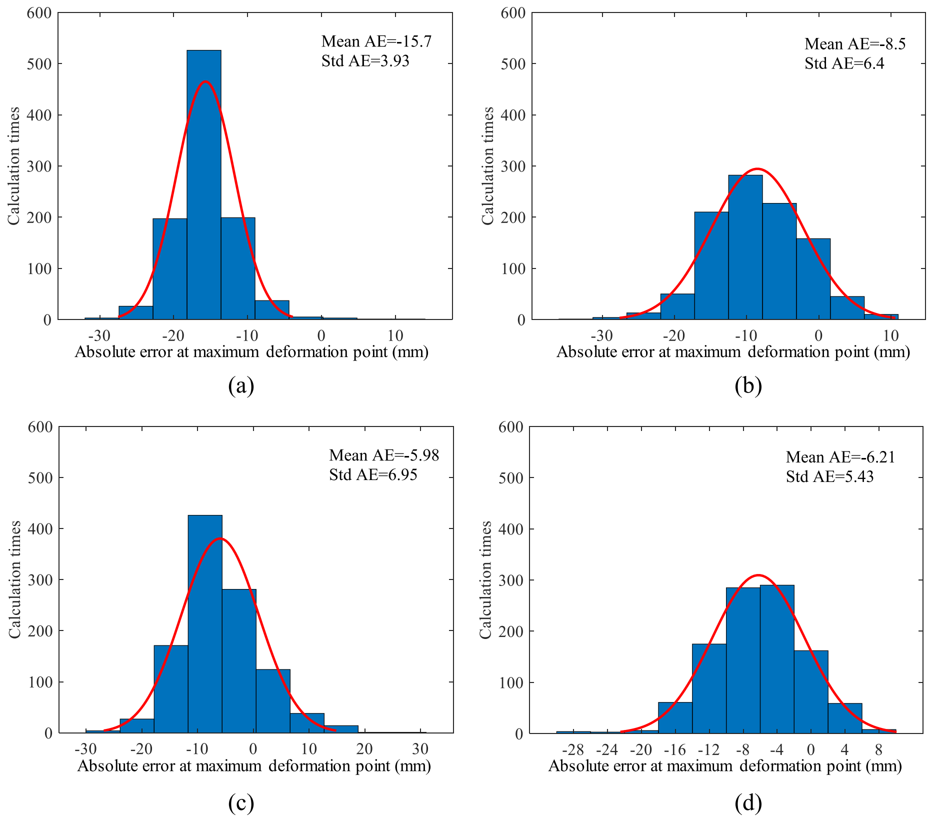

Fig. 12. AE of maximum ground settlement of TNEC excavation at different stages: (a) Stage 4, (b) Stage 5, (c) Stage 6, and (d) Stage 7.

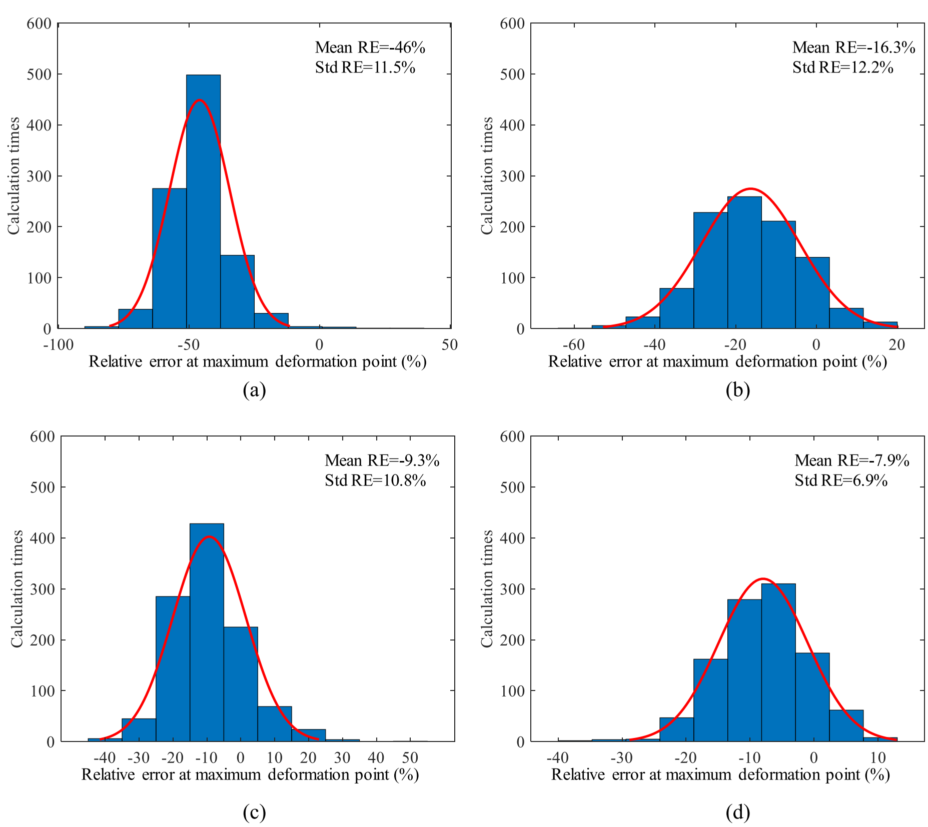

Fig. 13. RE of maximum ground settlement of TNEC excavation at different stages: (a) Stage 4, (b) Stage 5, (c) Stage 6, and (d) Stage 7.

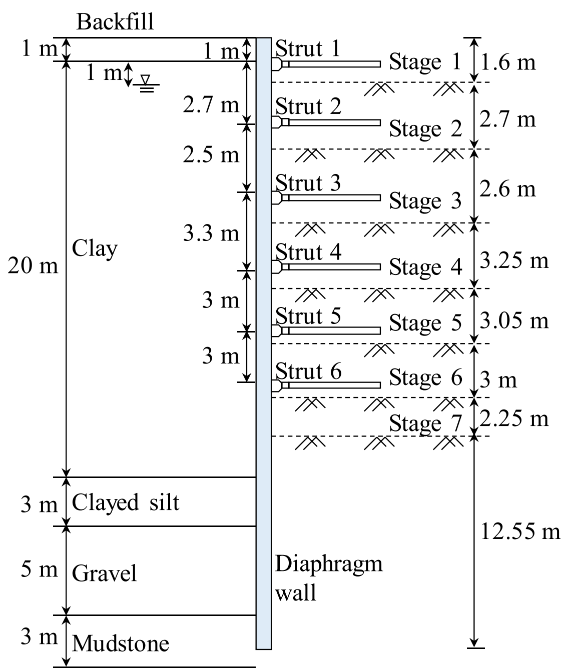

Fig. 14. Soil profile and the excavation depth in Formosa.

different initial positions. Therefore, to avoid randomness and to show the reliability of the proposed procedure, each process of model training and prediction was independently carried out for 1000 times. Based on all calculations, the statistical analysis was performed. The mean, standard deviation and the predictions within 99% credibility interval (CI) for the wall deflection are shown in Fig. 6 (The negative sign of wall deflection denotes the displacement towards the pit). For Stage 3 (Fig. 6a), a large discrepancy between measurement and prediction is found. It is attributed to the inevitable changes in the deformation pattern, consequently, the rules learned by GRU from Stages 1 and 2 fail when predicting the deformation responses of Stage 3. The deformation pattern of the wall generally exhibits a cantilever shape in Stages 2 and 3 for TNEC, and then in later stages, it changes into a concave shape due to the installation of temporary support or the construction of a slab. Furthermore, the effectiveness of the GRU-based forecast model is compromised in the early stages because the excavation responses in these early stages are very small and prone to measurement errors (Juang et al., 2012). Previous studies that use ANN to estimate the wall deflection caused by excavation in clay did not consider the wall deflection data of the first two stages to develop the ANN model. It is because that at least two struts at different levels must be installed before determining the system stiffness (Kung et al., 2007c). Therefore, the predicted performance in the early stages may be inadequate. After Stage 3, the predictions are more accurate compared to the observations, suggesting that the GRU-based model has accurately learned the trend of wall deflection development. Fig. 7 shows the probability distribution of *RRMSE*, representing the distribution of total predicted error. All RRMSE distributions for wall deflection approximate the lognormal distribution. Apart from Stage 3, the errors of other predictions are controlled within 20%, even 10% for Stages 6 and 7.

Considering that the maximum wall deflection needs more concern in design, the probability distributions of AE and RE at maximum wall deflection were plotted, as displayed in Figs. 8 and 9, respectively. The AE and RE distributions approximate the normal distribution. The absolute difference between observations and predictions are mostly located in the range of -15–15 mm except for Stages 3 and 4. The RE is smaller than 20% except for Stage 3 due to the inevitable changes in the deformation pattern. All errors show a decreasing trend as the excavation proceeds. The results demonstrate that the performance of the proposed GRU-based forecast framework for predicting the wall deflection is satisfactory.

3.1.2. Ground settlement

Compared to the wall deflection, ground settlement is another important and useful indicator in practice for assessing the safety and the risk of the subsequent excavations and adjacent buildings (Hsiao et al., 2008). Thus, the proposed GRU-based forecast model needs to be effective in predicting ground settlement. Fig. 10 shows the comparison of settlement between the observations and predictions. Note that the updating procedure for ground settlement starts from Stage 3 due to the lack of observation of Stage 2. Similar to the results of wall deflection, a discrepancy between the measured and predicted ground settlements is noticed for Stage 4. It is due to the changes in deformation patterns at the early stages. Moreover, the underestimation of ground settlement for early stages (e.g. Stage 4) is due to the slight response of the ground surface at shallow excavation stages. The small settlement can make the training deviate from the right direction. As the excavation proceeds, the prediction is more and more accurate. Although the settlements are always underestimated according to the mean value of prediction, the mean predictions are close to the measurements and the 99% CI predictions mostly cover the measurements. The presented results demonstrate that the proposed GRU model is reliable for predicting the response of excavation and the significant response of settlement can help the GRU mine the accurate rules from the observed data. The total errors represented by RRMSE shown in Fig. 11 are less than 20%. All RRMSE distributions of ground settlement approximate the lognormal distribution.

The distributions of *AE* and *RE* for the maximum settlement are shown in Figs. 12 and 13, respectively. All AE and RE distributions of maximum ground settlement approximate the normal distribution. Except for stage 4, the absolute errors between the observations and predictions are less than 10 mm, equivalent to the 20% RE. All obtained results demonstrate that the accuracy of the predictions of ground settlement by the proposed GRU-based forecast model is acceptable in practice. It also proves the effectiveness of the proposed updating procedure.

3.1.3. Comparison to Bayesian/optimization updating

Obviously, the preliminary results of both wall deflection and ground settlement predictions demonstrate the effectiveness of the proposed updating procedure. However, the efficiency of the procedure is also vital especially in practice where construction is continuously ongoing. Compared to the Bayesian updating (Juang et al., 2012), not only the maximum values of ground settlement and wall deflection can be accurately updated and predicted, but also the evolution of the profiles of wall deflection and ground settlement can be identified and predicted accurately with the proposed GRU-based updating method. However, it is a fact that the uncertainty involved in the braced excavation cannot be accurately quantified. Although the semi-empirical model in place of the FEM model adopted in Bayesian updating can greatly reduce the computational effort, thousands of calculations are unavoidable to derive the posterior distributions of involved parameters of concern. In contrast to optimization-based updating (Jin et al., 2019a), the calculation time for one updating process by the proposed procedure can be completed in 2 h even a few minutes while the computation time of optimization updating is more than 3 d (Jin et al., 2019a). For optimization-based updating, selecting an appropriate soil model is a key

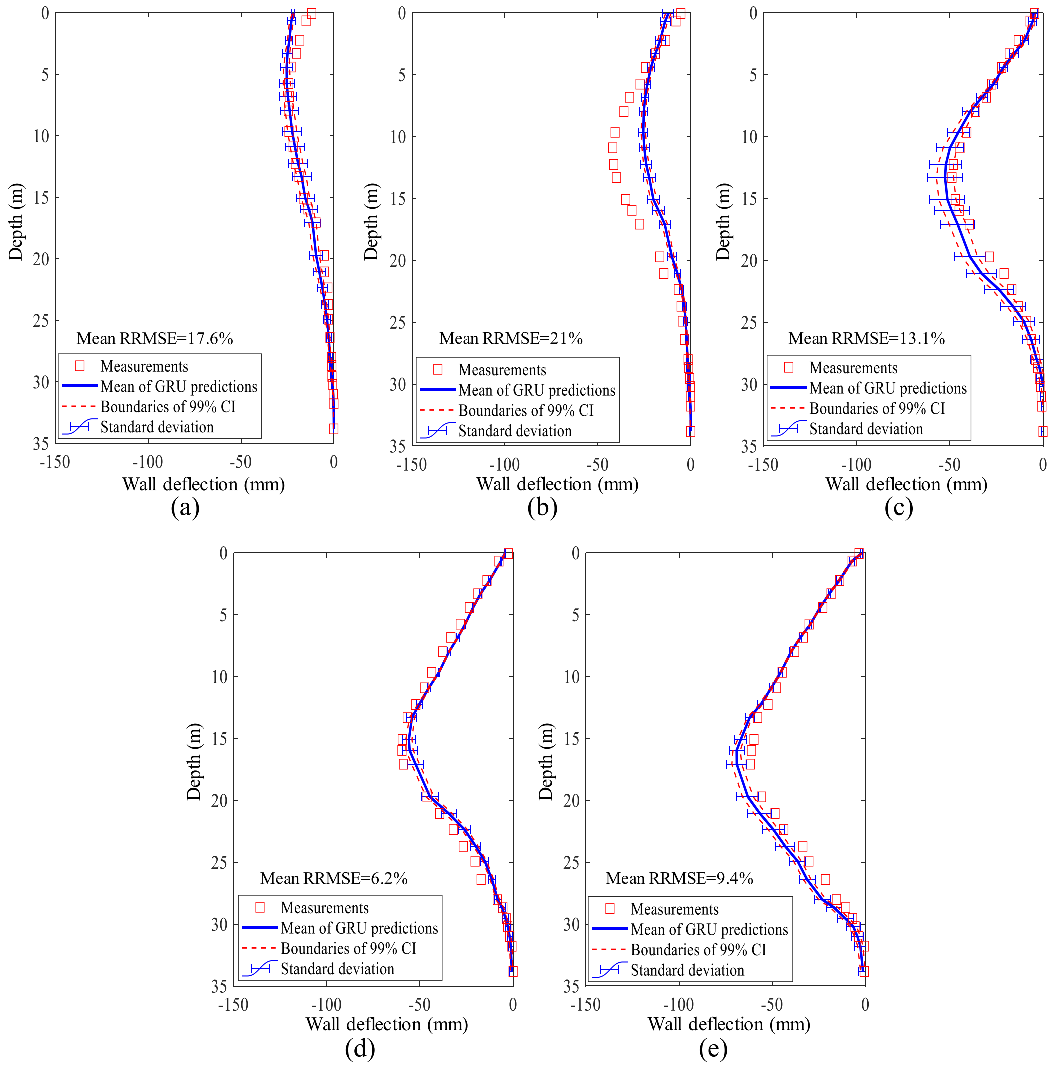

Fig. 15. Predicted and measured wall deflection of Formosa excavation at different stages: (a) Stage 3, (b) Stage 4, (c) Stage 5, (d) Stage 6, and (e) Stage 7.

work that determines the performance of the updating results. At the same time, the more the number of parameters to be updated is, the greater the field observations required are. However, for the proposed GRU-based updating procedure, all the mentioned problems can be avoided.

Therefore, the proposed GRU-based updating procedure is superior to Bayesian/optimization updating in terms of both effectiveness and efficiency.

3.2. Case 2: Formosa excavation

To further validate the proposed GRU-based updating procedure, the Formosa excavation (Ou et al., 1993; Kung et al., 2007a, b) was analyzed. The width of the excavation is 33.4 m, and the length and the thickness of the diaphragm wall is 31 m 0.8 m, respectively. The Formosa excavation was performed by the bottom-up method in seven stages. The total excavation depth is 18.5 m. The soil profile and the excavation depth are shown in Fig. 14. The groundwater table is located 2 m below the ground surface. The monitoring instruments are similar to those in the TNEC excavation case. The wall deflection and ground settlement between predictions and measurements from Stage 2 to Stage 7 are compared in Figs. 15 and 16, respectively. For the wall deflection, the change of deformation pattern leads to the inaccurate prediction of Stage 4. For other stages, the proposed GRU-based updating procedure exhibits a good performance with accurate predictions. For the prediction of the ground settlement in Stage 3, it is normal that the GRU-based forecast model is unable to learn reasonable deformation trends when the wall and ground responses produced in the second stage are too small. While for stage 4, it is difficult for the GRU-based model to learn the underlying laws of the observed data from Stages 2 and 3 since the evolution between the two previous stages is too small, leading to the discrepancy between the measured and predicted ground settlements in Stage 4. Alongside this, the proposed procedure that combines the GRU and the observational method can update the deformation in the braced excavation in clay with success.

3.3. Limitations

Note that neither Bayesian (Juang et al., 2012) or optimization (Jin et al., 2019a) updating nor the proposed GRU-based updating procedure can predict the sudden change of deformation or excavation collapse. The change of the deformation pattern due to the installation of struts cannot be accurately predicted. One of the corrective measures is to establish a database based on a large

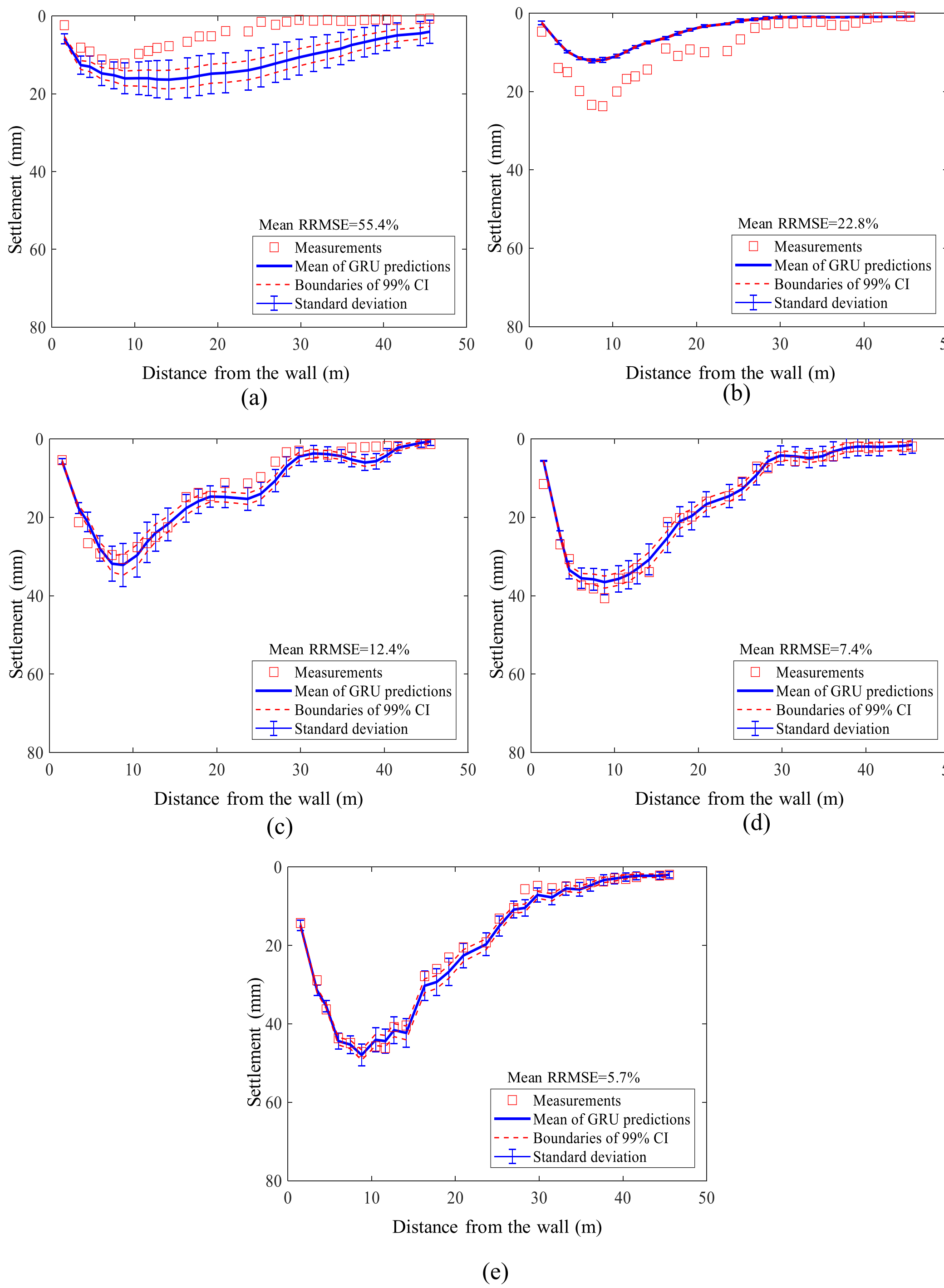

Fig. 16. Predicted and measured ground settlement of Formosa excavation at different stages: (a) Stage 3, (b) Stage 4, (c) Stage 5, (d) Stage 6, and (e) Stage 7.

number of FEM analyses to develop the intended ANN model. Moreover, the excavation depth for each stage should be as same as possible; otherwise, the trends of deformation learned from the data of previous stages are not suitable to predict the response of the next stage. Furthermore, during the excavation, a reasonably detailed construction plan is needed, and the engineers should follow the law of construction strictly to avoid unforeseen human factors. More importantly, the deformation and ground responses during the whole excavation stages should be monitored in real-time, from which the data are used as the source for training the GRU-based forecast model.

In addition, the influence of the uncertainty of the measured data was not considered in the present updating procedure. It can be improved by implementing Bayesian deep learning (Zhang et al., 2021f) into the proposed GRU-based prediction procedure in future work.

4. Conclusions

An intelligent procedure for updating the deformation of braced excavation in clay using deep learning has been proposed. In the proposed procedure, the GRU neural network was employed to build the forecast model. The observed data of the previous and current stages were used to train the GRU-based forecast model by Nadam algorithm. After that, the deformation response of the next stage was predicted by the trained GRU-based forecast model with the observed data of the current stage as the inputs. The deformation updating cycled until the excavation finished.

The performances of the proposed intelligent procedure for updating deformation were verified by analyzing two well-documented excavations (i.e. TNEC and Formosa), in which the wall deflection and the induced ground movement were examined. The errors of predicted results corresponding to the profiles and the maximum values of the ground settlement and the wall deflection were analyzed and found to be conformed to lognormal and normal distributions, respectively. Furthermore, the advantages of the proposed intelligent procedure compared to the Bayesian/optimization updating were illustrated. The proposed GRU-based updating procedure was superior to Bayesian/optimization updating in terms of both effectiveness and efficiency. However, it should be noted that neither Bayesian nor optimization updating nor the proposed GRU-based updating procedure can predict the sudden change of deformation or excavation collapse. The influence of the uncertainty of measured data was not considered in the present updating procedure. The corrective measures are needed, which are, however, beyond the scope of this paper.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Al-Ani, M.M., Fattah, M.Y., Al-Lamy, M.T., 2009. Artificial neural networks analysis of treatment process of gypseous soils. Eng. Technol. J. 27 (9), 1811–1832.
Ambrožič, T., Turk, G., 2003. Prediction of subsidence due to underground mining by artificial neural networks. Comput. Geosci. 29 (5), 627–637.
Baroth, J., Malecot, Y., 2010. Probabilistic analysis of the inverse analysis of an excavation problem. Comput. Geotech. 37 (3), 391–398.
Bengio, Y., Simard, P., Frasconi, P., 1994. Learning long-term dependencies with gradient descent is difficult. IEEE Trans. Neural Network. 5 (2), 157–166.
Byun, H., Song, J.J., 2018. Prediction of the stress-strain curve of materials under uniaxial compression by using lstm recurrent neural network. Tunn. Undergr. Space Technol. 28 (3), 277–291.
Calvello, M., Finno, R.J., 2004. Selecting parameters to optimize in model calibration by inverse analysis. Comput. Geotech. 31 (5), 410–424.
Chang, C.S., Yin, Z.Y., 2011. Micromechanical modeling for behavior of silty sand with influence of fine content. Int. J. Solid Struct. 48 (19), 2655–2667.
Chua, C.G., Goh, A.T.C., 2005. Estimating wall deflections in deep excavations using Bayesian neural networks. Tunn. Undergr. Space Technol. 20 (4), 400–409.
Chung, J.Y., Gulcehre, C., Cho, K.H., Bengio, Y., 2014. Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling. Comput Sci. arXiv, p. 14123555.
Clevert, D.A., Unterthiner, T., Hochreiter, S., 2015. Fast and accurate deep network learning by exponential linear units (elus). Comput Sci. arXiv, p. 151107289.
Costa, P.A., Borges, J.L., Fernandes, M.M., 2007. Analysis of a braced excavation in soft soils considering the consolidation effect. Geotech. Geol. Eng. 25 (6), 617–629.
Dozat, T., 2016. Incorporating nesterov momentum into adam. Workshop track - ICLR.
Freitag, S., Cao, B.T., Ninić, J., Meschke, G., 2018. Recurrent neural networks and proper orthogonal decomposition with interval data for real-time predictions of mechanised tunnelling processes. Comput. Struct. 207, 258–273.
Goh, A.T.C., Zhang, W.G., Wong, K.S., 2019. Deterministic and reliability analysis of basal heave stability for excavation in spatial variable soils. Comput. Geotech. 108, 152–160.
Goh, A.T.C., Wong, K., Broms, B.B., 1995. Estimation of lateral wall movements in braced excavations using neural networks. Can. Geotech. J. 32 (6), 1059–1064.
Goh, A.T.C., Zhang, R.H., Wang, W., Wang, L., Liu, H.L., Zhang, W.G., 2020. Numerical study of the effects of groundwater drawdown on ground settlement for excavation in residual soils. Acta Geotech 15 (5), 1259–1272.
Guillaumot, V.M., Durango-Cohen, P.L., Madanat, S.M., 2003. Adaptive optimization of infrastructure maintenance and inspection decisions under performance model uncertainty. J. Infrastruct. Syst. 9 (4), 133–139.
Hashash, Y.M.A., Levasseur, S., Osouli, A., Finno, R., Malecot, Y., 2010. Comparison of two inverse analysis techniques for learning deep excavation response. Comput. Geotech. 37 (3), 323–333.
Hashash, Y.M.A., Song, H., Osouli, A., 2011. Three-dimensional inverse analyses of a deep excavation in Chicago clays. Int. J. Numer. Anal. Methods GeoMech. 35 (9), 1059–1075.
Hejazi, Y., Dias, D., Kastner, R., 2008. Impact of constitutive models on the numerical analysis of underground constructions. Acta Geotech 3 (4), 251–258.
Hochreiter, S., Schmidhuber, J., 1997. Long short-term memory. Neural Comput. 9 (8), 1735–1780.
Hsiao, E.C., Schuster, M., Juang, C.H., Kung, G.T., 2008. Reliability analysis and updating of excavation-induced ground settlement for building serviceability assessment. J Geotech Geoenviron 134 (10), 1448–1458.
Huang, Z.H., Zhang, L.L., Cheng, S.Y., Zhang, J., Xia, X.H., 2014. Back-analysis and parameter identification for deep excavation based on pareto multiobjective optimization. J. Aero. Eng. 28 (6), A4014007.
Jan, J.C., Hung, S.L., Chi, S.Y., Chern, J.C., 2002. Neural network forecast model in deep excavation. J. Comput. Civ. Eng. 16 (1), 59–65.
Jiang, M.J., Yin, Z.Y., 2014. Influence of soil conditioning on ground deformation during longitudinal tunneling. Compt. Rendus Mec. 342 (3), 189–197.
Jin, Y.F., Yin, Z.Y., 2020. Enhancement of backtracking search algorithm for identifying soil parameters. Int. J. Numer. Anal. Methods GeoMech. 44 (9), 1239–1261.
Jin, Y.F., Yin, Z.Y., Shen, S.L., Hicher, P.Y., 2016. Investigation into MOGA for identifying parameters of a critical-state-based sand model and parameters correlation by factor analysis. Acta Geotech 11 (5), 1131–1145.
Jin, Y.F., Yin, Z.Y., Shen, S.L., Zhang, D.M., 2017. A new hybrid real-coded genetic algorithm and its application to parameters identification of soils. Inverse Probl. Sci. Eng. 25 (9), 1343–1366.
Jin, Y.F., Yin, Z.Y., Wu, Z.X., Daouadji, A., 2018. Numerical modeling of pile penetration in silica sands considering the effect of grain breakage. Finite Elem. Anal. Des. 144, 15–29.
Jin, Y.F., Yin, Z.Y., Zhou, W.H., Horpibulsuk, S., 2019a. Identifying parameters of advanced soil models using an enhanced transitional Markov chain Monte Carlo method. Acta Geotech 14 (6), 1925–1947.
Jin, Y.F., Yin, Z.Y., Zhou, W.H., Shao, J.F., 2019b. Bayesian model selection for sand with generalization ability evaluation. Int. J. Numer. Anal. Methods GeoMech. 43 (14), 2305–2327.
Jin, Y.F., Yin, Z.Y., Zhou, W.H., Huang, H.W., 2019c. Multi-objective optimization-based updating of predictions during excavation. Eng. Appl. Artif. Intell. 78, 102–123.
Juang, C.H., Luo, Z., Atamturktur, S., Huang, H.W., 2012. Bayesian updating of soil parameters for braced excavations using field observations. J. Geotech. Geoenviron. Eng. 139 (3), 395–406.
Kratzert, F., Klotz, D., Brenner, C., Schulz, K., Herrnegger, M., 2018. Rainfall–runoff modelling using long short-term memory (LSTM) networks. Hydrol. Earth Syst. Sci. 22 (11), 6005–6022.
Kung, G.T.C., Hsiao, E.C.L., Juang, C.H., 2007a. Evaluation of a simplified small-strain soil model for analysis of excavation-induced movements. Can. Geotech. J. 44 (6), 726–736.
Kung, G.T.C., Juang, C.H., Hsiao, E.C.L., Hashash, Y.M.A., 2007b. Simplified model for wall deflection and ground-surface settlement caused by braced excavation in clays. J. Geotech. Geoenviron. Eng. 133 (6), 731–747.
Kung, G.T.C., Hsiao, E.C.L., Schuster, M., Juang, C.H., 2007c. A neural network approach to estimating deflection of diaphragm walls caused by excavation in clays. Comput. Geotech. 34 (5), 385–396.
Leu, S.S., Lo, L., Hsien-Chuang, L., 2004. Neural-network-based regression model of ground surface settlement induced by deep excavation. Autom. ConStruct. 13 (3), 279–289.
Lim, A., Ou, C.Y., Hsieh, P.G., 2010. Evaluation of clay constitutive models for analysis of deep excavation under undrained conditions. J. Geoeng. 5 (1), 9–20.

Lü, Q., Chan, C.L., Low, B.K., 2012. Probabilistic evaluation of ground-support interaction for deep rock excavation using artificial neural network and uniform design. Tunn. Undergr. Space Technol. 32, 1–18.
MathWorks, T., 2016. MATLAB Documentation. Disponıvel em.
Obead, I.H., Omran, H.A., Fattah, M.Y., 2021. Implementation of artificial neural network to predict the permeability and solubility models of gypseous soil. Pertanika J. Sci. Technol. 29 (1), 107–122.
Ou, C.Y., Shiau, B.Y., Wang, I.W., 2000. Three-dimensional deformation behavior of the Taipei National Enterprise Center (TNEC) excavation case history. Can. Geotech. J. 37 (2), 438–448.
Ou, C.Y., Hsieh, P.G., Chiou, D.C., 1993. Characteristics of ground surface settlement during excavation. Can. Geotech. J. 30 (5), 758–767.
Ou, C.Y., Liao, J.T., Lin, H.D., 1998. Performance of diaphragm wall constructed using top-down method. J. Geotech. Geoenviron. Eng. 124 (9), 798–808.
Shen, S.L., Wang, Z.F., Cheng, W.C., 2017. Estimation of lateral displacement induced by jet grouting in clayey soils. Geotechnique 67 (7), 621–630.
Shen, S.L., Wu, H.N., Cui, Y.J., Yin, Z.Y., 2014. Long-term settlement behaviour of metro tunnels in the soft deposits of Shanghai. Tunn. Undergr. Space Technol. 40, 309–323.
Tan, G.J., Liu, H.B., Cheng, Y.C., Liu, B., Zhang, Y., 2011. Prediction method for the deformation of deep foundation pit based on neural network algorithm optimized by particle swarm. In: Proceedings 2011 International Conference on Transportation, Mechanical, and Electrical Engineering (TMEE). Changchun, China, pp. 1407–1410.
Teng, F.C., Ou, C.Y., Hsieh, P.G., 2014. Measurements and numerical simulations of inherent stiffness anisotropy in soft taipei clay. J Geotech Geoenviron 140 (1), 237–250.
Wang, K., Sun, W.C., 2018. A multiscale multi-permeability poroplasticity model linked by recursive homogenizations and deep learning. Comput. Methods Appl. Mech. Eng. 334, 337–380.
Wang, K., Sun, W.C., Du, Q., 2019. A cooperative game for automated learning of elasto-plasticity knowledge graphs and models with AI-guided experimentation. Comput. Mech. 64, 467–499.
Wang, S.H., Qi, J.L., Yin, Z.Y., Zhang, J.M., Ma, W., 2014. A simple rheological element based creep model for frozen soils. Cold Reg. Sci. Technol. 106–107, 47–54.
Wang, W., 2017. R-NET: machine reading comprehension with self-matching networks. Natural Language Computer Group, Microsoft Reserach. Asia, Beijing. China. Technical Report 5.
Xu, Y.S., Shen, S.L., Ren, D.J., Wu, H.N., 2016. Analysis of factors in land subsidence in Shanghai: a view based on a strategic environmental assessment. Sustainability 8 (6), 573.
Yang, J., Yin, Z.Y., Laouafa, F., Hicher, P.Y., 2019a. Hydro-mechanical modeling of granular soils considering internal erosion. Can. Geotech. J. 57 (2), 157–172.
Yang, J., Yin, Z.Y., Laouafa, F., Hicher, P.Y., 2019b. Analysis of suffusion in cohesionless soils with randomly distributed porosity and fines content. Comput. Geotech. 111, 157–171.
Yang, J., Yin, Z.Y., Laouafa, F., Hicher, P.Y., 2019c. Internal erosion in dike-on-foundation modeled by a coupled hydromechanical approach. Int. J. Numer. Anal. Methods GeoMech. 43 (3), 663–683.
Yang, J., Yin, Z.Y., Laouafa, F., Hicher, P.Y., 2019d. Modeling coupled erosion and filtration of fine particles in granular media. Acta Geotech 14 (6), 1615–1627.
Yin, Z.Y., Wang, J.H., 2012. A one-dimensional strain-rate based model for soft structured clays. Sci. China Technol. Sci. 55 (1), 90–100.
Yin, Z.Y., Jin, Y.F., Shen, S.L., Huang, H.W., 2017. An efficient optimization method for identifying parameters of soft structured clay by an enhanced genetic algorithm and elastic–viscoplastic model. Acta Geotech 12 (4), 849–867.
Yin, Z.Y., Wu, Z.X., Hicher, P.Y., 2018a. Modeling monotonic and cyclic behavior of granular materials by exponential constitutive function. J. Eng. Mech. 144 (4), 04018014.
Yin, Z.Y., Jin, Y.F., Shen, J.S., Hicher, P.Y., 2018b. Optimization techniques for identifying soil parameters in geotechnical engineering: comparative study and enhancement. Int. J. Numer. Anal. Methods GeoMech. 42 (1), 70–94.
Zhang, K.Y., Ai, Y.B., 2012. Comparison and application of different elasto-plastic constitutive models in FEM analysis of an excavated soil slope. J. Civ. Eng. Manag. 18 (6), 802–810.
Zhang, P., Chen, R.P., Wu, H.N., Liu, Y., 2020a. Ground settlement induced by tunneling crossing interface of water-bearing mixed ground: a lesson from Changsha, China. Tunn. Undergr. Space Technol. 96, 103224.
Zhang, W.G., Zhang, R.H., Wu, C.Z., Goh, A.T.C., Wang, L., 2020b. Assessment of basal heave stability for braced excavations in anisotropic clay using extreme gradient boosting and random forest regression. Undergr. Space. https://doi.org/10.1016/j.undsp.2020.03.001.
Zhang, W.G., Zhang, R.H., Wu, C.Z., Goh, A.T.C., Lacasse, S., Liu, Z.Q., Liu, H.L., 2020c. State-of-the-art review of soft computing applications in underground excavations. Geosci. Front. 11 (4), 1095–1106.
Zhang, P., Wu, H.N., Chen, R.P., Dai, T., Meng, F.Y., Wang, H.B., 2020d. A critical evaluation of machine learning and deep learning in shield-ground interaction prediction. Tunn. Undergr. Space Technol. 106, 103593.
Zhang, P., Yin, Z.Y., Zheng, Y.Y., Gao, F.P., 2020e. A LSTM surrogate modelling approach for caisson foundations. Ocean Eng. 204, 107263.
Zhang, P., Yin, Z.Y., Jin, Y.F., Ye, G.L., 2020f. An AI-based model for describing cyclic characteristics of granular materials. Int. J. Numer. Anal. Methods GeoMech. 44 (9), 1315–1335.
Zhang, P., Yin, Z.Y., Jin, Y.F., Chan, T.H.T., Gao, F.P., 2021a. Intelligent modelling of clay compressibility using hybrid meta-heuristic and machine learning algorithms. Geosci. Front. 12 (1), 441–452.
Zhang, P., Yin, Z.Y., Jin, Y.F., 2021b. State-of-the-art review of machine learning applications in constitutive modeling of soils. Arch. Comput. Methods Eng. 28, 3661–3686.
Zhang, P., Chen, R.P., Dai, T., Wang, Z.T., Wu, K., 2021c. An AIoT-based system for real-time monitoring of tunnel construction. Tunn. Undergr. Space Technol. 109, 103766.
Zhang, W.G., Li, H.R., Li, Y.Q., Liu, H.L., Chen, Y.M., Ding, X.M., 2021d. Application of deep learning algorithms in geotechnical engineering: a short critical review. Artif. Intell. Rev. https://doi.org/10.1007/s10462-021-09967-1.
Zhang, N., Shen, S.L., Zhou, A.N., Jin, Y.F., 2021e. Application of LSTM approach for modelling stress–strain behaviour of soil. Appl. Soft Comput. 100, 106959.
Zhang, P., Jin, Y.F., Yin, Z.Y., 2021f. Machine learning–based uncertainty modelling of mechanical properties of soft clays relating to time-dependent behavior and its application. Int. J. Numer. Anal. Methods GeoMech. 45 (11), 1588–1602.
Zhang, W.G., Goh, A.T.C., Goh, K.H., Chew, O.Y.S., Zhou, D., Zhang, R.H., 2018. Performance of braced excavation in residual soil with groundwater drawdown. Undergr. Space 3 (2), 150–165.
Zhang, W.G., Goh, A.T.C., Zhang, Y.M., 2015. Updating soil parameters using spreadsheet method for predicting wall deflections in braced excavations. Geotech. Geol. Eng. 33 (6), 1489–1498.
Zhang, W.G., Hou, Z.J., Goh, A.T.C., Zhang, R.H., 2019. Estimation of strut forces for braced excavation in granular soils from numerical analysis and case histories. Comput. Geotech. 106, 286–295.
Zhang, W.G., Zhang, Y.M., Goh, A.T.C., 2017. Multivariate adaptive regression splines for inverse analysis of soil and wall properties in braced excavation. Tunn. Undergr. Space Technol. 64, 24–33.
Zhao, B.D., Zhang, L.L., Jeng, D.S., Wang, J.H., Chen, J.J., 2015. Inverse analysis of deep excavation using differential evolution algorithm. Int. J. Numer. Anal. Methods GeoMech. 39 (2), 115–134.
Zhu, Q.Y., Yin, Z.Y., Hicher, P.Y., Shen, S.L., 2016. Nonlinearity of one-dimensional creep characteristics of soft clays. Acta Geotech 11 (4), 887–900.

Jie Yang obtained his BSc degree in Civil Engineering from Tongji University, China, in 2012, and his MSc-Ingénieur double-degree in Tunnel and Underground Structures from Tongji University and Ecole Centrale de Nantes, France, in 2015. In 2019, his received a PhD degree in Civil Engineering from Ecole Centrale de Nantes, France. He was affiliated as postdoctoral fellow in The Hong Kong Polytechnic University from 2019 till now. His research interests include: 1) constitutive modelling of soils; 2) internal erosion in soils; 3) multi-physics modelling in geotechnical engineering; 4) soil-structure interaction; and 5) artificial intelligence in geotechnical engineering.