Inversion of damage inducement of wharf pile foundation under heaped load based on parametric model

Liangdong Zuo¹ · Shibao Cao¹ · Shiliang Zhou² · Jun Wu²

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Abstract

Uneven stowage of wharf is one of the main external loads during its service period. The main load-bearing structure of the overhead vertical wharf is the lower pile foundation. Under the action of the upper pile load, the pile foundation will be damaged to varying degrees, and the local damage may cause adverse effects on the overall structural safety of the wharf. In order to realize the inversion analysis of the adverse damage inducement of wharf stowage, the stress detection results of the lower pile foundation are taken as inversion data samples, and 10,000 sets of stress data are obtained by establishing a parameterized numerical calculation model. After normalization and dimension reduction, they are input into the established neural network model, and the action position and strength of stowage damage inducement are identified. The results show that the inversion analysis samples obtained by the parameterized model in this paper have higher accuracy and generalization in the calculation of neural network model.

Article Highlights

- The difference of recognition indexes between training samples and test samples is small, and there is no lack of fitting ability, and the generalization ability is strong.
- The regression learner network has two hidden layers, and the number of nodes is 10 and 4, respectively. The parameter setting with the activation function as identity can meet the inversion needs of the heap damage inducement.
- Inversion calculation of wharf damage incentives needs to establish samples with large data space, while materialization model calculation takes up a lot of computer memory and takes time.

Keywords Heap load · Injury inducement · Inversion analysis · Wharf pile foundation

1 Introduction

Pile foundation is the key component connecting the upper bearing structure and foundation of an overhead vertical wharf and has the stress characteristics of compression, torsion, shear

and bending [1]. Under the action of surcharge incentives, the pile foundation is not only a weak stress member, but also an important 'window' to 'peek' the stress state of the wharf structure and the external damage incentives.

✉ Liangdong Zuo, ld_zuo1984@163.com; Shibao Cao, 254091070@qq.com; Shiliang Zhou, zhsl1972@163.com; Jun Wu, 195575462@qq.com | ¹Hohai College of Chongqing Jiaotong University, Chongqing 400074, China. ²Chongqing Southwest Research Institute for Water Transport Engineering, Chongqing Jiaotong University, Chongqing 400016, China.

As for the safety of pile foundation structure, scholars Li Yuesong et al. [2] and Zeng et al. [3] pointed out that the rear stacking caused the horizontal displacement of soil and the relative dislocation of pile cap components. Wang Yuan et al. [4] studied the structural damage characteristics of the overhead vertical wharf under stacking load.

In the wharf state assessment, the existing research mainly focuses on the health diagnosis and damage identification of the pile foundation itself, rather than tracing the source to cause the unfavorable inducement of the current damage. For example, Zhu [5] established the model of high-piled wharf, the applicability of modal strain energy in damage identification of pile foundation of high-piled wharf is studied by finite element numerical simulation and model test. Alipujiang Jierula [6] made a new damage detection and evaluation method for pile foundations is proposed. This new method is capable of continuously detecting and evaluating the damage of pile foundations in service. Wang [7] developed a new method for pile foundation damage detection based on the curve shape of the curvature mode difference (CMD) before and after damage. Zou [8] adopted a generalized plasticity model for the soil, a plastic damage model for the piles and a nonlinear overburden layer-based seismic input method.

In this paper, the stress data sets of the pile foundation of the overhead vertical wharf under the action of heap load are obtained in batches by means of parametric numerical model calculation. After normalization and dimension reduction of the data sets, the data sets are taken as input samples, and the neural network model is used for inversion calculation, thus realizing the identification of the position and intensity of the inducement of heap load damage, which proves the accuracy and generalization of the inversion method in this paper.

2 Parametric finite element model construction

In this paper, APDL (ANSYS Parametric Design Language) is chosen for modeling. Compared with the materialized model, the parametric model is easier to realize batch modeling and systematic modification and has a powerful data post-processing function.

Table 1 Material selection of the parametric model

Member	Density (kg/m ³)	E (GPa)	μ	Mesh
Piles	2500	32.5	0.17	C3D8R
Cross beam	2500	33.5	0.17	C3D8R
Vertical beam	2500	33.5	0.17	C3D8R

2.1 Constitutive model and material parameters

The linear elastic constitutive model is selected from the parametric models, see Table 1 for material selection.

Select beam188 beam element in ANSYS finite element software to simulate the pile foundation, beam and column of wharf. Shell element simulation of shell181 is adopted for the wharf top panel with plate structure. The riprap bed and rock stratum outside the wharf pile foundation are regarded as linear elastic body, and the spring element of combin14 is used for simulation.

Choose the way of elastic foundation beam to simulate the constraint conditions of loading soil. The riprap bed and foundation rock and soil are regarded as elastic bodies, and the wharf pile foundation is regarded as a beam.

The elastic foundation beam method assumes that the soil around the pile is Winkler elastic foundation, and the soil is equivalent to continuously distributed springs, as shown in Fig. 1.

According to the current codes at home and abroad, the allowable horizontal displacement of the pile on the ground is between 0.6 and 1.0 cm, and the relationship between the soil resistance at any point of the pile body and the lateral displacement of the pile body can be approximately linear.

2.2 Parameterization of heap load

According to the action characteristics of adverse incentives of wharf stowage, the wharf apron is divided as shown in Fig. 2. In order to consider the extreme cases of

Fig. 1 Model of elastic foundation beam

Fig. 2 Heap load distribution

damage incentives, its value will be slightly larger than the value given in the code.

According to the relevant regulations in document [9], for inland container terminals, the determination of stacking load can be divided into three areas, namely the terminal front, the front yard and the rear yard. The load diagram of each area is shown in Fig. 2. According to the actual situation of the inland river overhead vertical wharf, it is determined that the value of uneven front stacking can be set to 10–60 kPa.

The parameterized model of the overhead vertical wharf established according to the above conditions is shown in Fig. 3.

The transverse span of the wharf section is 38 m, and the bent structure is divided into 5 spans with span spacing of 8 m. There are 4 pile foundations under each bent. The lengths of the four pile foundations of the bent are 53.4 m, 51.4 m, 50.4 m and 49.4 m, respectively, all of which are rock-socketed cast-in-place piles. The

Fig. 3 Parametric model of overhead vertical wharf

rock-socketed depth is more than 5 times the pile diameter, the front row is reinforced concrete piles with pile diameter $\varphi = 2.7$ m, and the inner row is three piles with pile diameter $\varphi = 2$. The thickness of soil around the pile is 36 m. The front, back, left and right sections of bedrock adopt displacement constraints perpendicular to the section direction, the bottom adopts consolidation constraint displacement and torque, the side and back of the bank slope adopt displacement constraints perpendicular to the section direction, the back constraint of the bank slope cancels the displacement constraint when the bank slope is thrust loaded after the in situ stress is balanced, and the pile bottom adopts consolidation constraint displacement and torque. All solid elements are used in this model, and C3D8R elements are used in the dumped rockfill layer and foundation rock layer, with the unit size of 2 m.

3 Inversion sample data set construction

In this paper, APDL (ANSYS Parametric Design Language) is chosen for modeling. Compared with materialized model, parameterized model is easier to realize batch modeling and systematic modification, and the process of establishing, modifying, running and result extraction of finite element parameterized model is realized with the instruction of analytic command flow.

In order to realize the batch collection of calculation result data, the subprocess library module in Python program is selected as the parameterization tool.

The parameters of bad incentives for wharf damage were obtained by random sampling and were written into the solution file by command flow, including three processes: calling, applying load and post-processing. Combined with the constructed parametric model, the analysis and calculation of wharf structures under different incentives for damage were realized, and the data of calculation results were obtained. The flow of data collection and sample set construction is shown in Fig. 4.

Fig. 4 Data collection and sample set construction

3.1 Data preprocessing and dimension reduction

For the neural network model, the sensitivity to the input data is very high. If the obtained samples are directly used as the input or verification samples for the inversion of damage incentives, a long iterative calculation step will be generated in the calculation process, and the calculation results are prone to sudden changes and non-convergence. Therefore, the collected data sets should be normalized so that they all fall within the interval $[0, 1]$. Divide the collected data according to different pile foundations, and calculate the range and mean value and then integrate the calculation results into the original data samples to supplement their sample characteristics.

Figure 5 shows the scatter distribution diagram of the original data of pile foundation stress of overhead vertical wharf under the action of stacking load and ship impact. It can be seen from the figure that the magnitude span of data distribution is large, which is not conducive to the sample input of subsequent inversion analysis.

Select the most commonly used linear normalization method, process the collected pile foundation stress samples under the wharf damage inducement and linearly transform the original data, so that the results are mapped to the range of $[0, 1]$, thus realizing the equal scale of the original sample data. The scatter diagram of normalized data samples is shown in Fig. 6.

In this paper, eig () method of linalg module in numpy of python program is used to solve the eigenvalues and eigenvectors of sample space.

Dimension reduction is carried out on the stress data samples of wharf pile foundation under the action of damage inducement, and the data distribution map after dimension reduction is drawn, as shown in Fig. 7.

The basic sample data set of damage inducement inversion obtained by parameterized numerical model is

normalized and dimensionalized, and the obtained sample features are calculated as x , the behavior of x is expressed as the number of samples, and the number of columns represents the number of features. The parameters of injury incentive action corresponding to samples are defined as target vector y , and the number of behaviors of y represents the number of injury incentive parameters, which is expressed as $y = [\text{injury incentive type, injury incentive action position and injury incentive intensity}]$. According to the above method, x and y are defined, respectively, and they are one-to-one corresponding to form matrix data set $[X, y]$.

Fig. 6 Normalized scatter plot

Fig. 5 Stress scatter diagram of wharf pile foundation

Fig. 7 Stress scatter diagram of dimension reduction processing

Table 2 Inversion sample splitting

Position	Training sets	Test sets
1	1900	615
2	1890	620
3	1860	630
4	1850	635
Total	7500	2500

Table 3 Parameter of neural network

Parameter	Hunting zone
Solver	{'lbfgs','sgd','adam'}
Activation	{'identity','logistic','tanh','relu'}
Hidden layer	{1, 2, 3}
Implicit node	{1, 2, 3, ..., 100}
Alpha	(0.001–10)

Table 4 Optimization parameters of neural network

Parameter	Learner type	
	Classification	Regression
Solver	Adam	Adam
Hidden layer	1	2
Number of nodes	[5]	[10, 4]
Activation	Relu	Identity
Convergence error	0.001	0.001
Alpha	0.01	0.8
Maximum iterations	550	550

4 Neural network model training

4.1 Data preprocessing and dimension reduction

According to the random sampling method, the inverse analysis data set of stacking action is divided according to the training set and the test set before analysis and calculation. Considering that there is no big difference in the distribution probability of stacking load in the four regions, the number of samples in the four regions is basically the same. Training set accounts for 75%, and test set accounts for 25%. So there are 7500-fold and no hold-out set. Sample splitting is shown in Table 2.

The sample set is brought into the neural network model for training and analysis, in which the position parameter depends on the training of classification

Fig. 8 Loss curve of classifier

learner and the intensity parameter depends on the training of regression learner. The initial parameter settings are shown in Table 3.

The optimization parameters of neural network are determined by Gridsearch method, and the key parameters of two kinds of learners are searched by sklearn, a learning library of python software, and Grid Search, a search tool. The classification learner takes accuracy as the search criterion, and the regression learner takes fitness as the search criterion. After searching, the established neural network model is verified by cross-validation. The calculation results are shown in Table 4.

4.2 Inversion result analysis

4.2.1 Position identification

The identification of the action position of the pile damage inducement belongs to the classification identification problem, and the cross-entropy is taken as the loss index of the model classification learner, and the loss curve calculated by the model is shown in Fig. 8.

The cross-entropy loss curve of classifier shows a downward trend with the increase in iterative calculation times. The loss curve of 0–30 iterations drops rapidly, the decline rate of 30–50 iterations slows down, and the decline rate of 50–80 iterations accelerates again. When the iteration times reach 109 times, the model converges and the calculation is completed.

There are four different positions in the data set of heap damage inducement, and the statistics of calculation results are shown in Table 5. Among them, precision indicates the accuracy of the model for position recognition, and the optimal value is 1; F1 represents the harmonic average of sample recall quantity and accuracy,

Table 5 Location recognition results

Position	Classification				Regression			
	Sample	Precision	F1	Hamming loss	Sample	Precision	F1	Hamming loss
1	1900	0.997	0.999	0.001	615	0.989	0.988	0.002
2	1890	0.989	0.987	0.002	620	0.988	0.979	0.002
3	1860	0.988	0.993	0.002	630	0.989	0.993	0.002
4	1850	0.996	0.991	0.001	635	0.996	0.988	0.001
Total	7500	0.993	0.993	0.001	2500	0.991	0.987	0.002

Fig. 9 Loss curve of regression

and the optimal value is 1; Hamming loss represents the difference between the calculated value of the model and the true value, and the optimal value is 0.

For the position recognition under the inducement of heap load damage, the average value of training sample is 0.993, and that of test sample is 0.991, both of which reach a high level. F1 performance, the average value of training samples is 0.993, and the average value of test samples is 0.987, which can also reach the level close to the optimal value of 1; In terms of Hamming loss, the average values of training samples and test samples are 0.001 and 0.002, respectively, which are close to the optimal value of 0.

4.2.2 Intensity identification

The identification of the intensity of surcharge damage incentive belongs to the content of regression learning, and the variance is taken as the model loss index of regression learner, and the calculated loss curve is shown in Fig. 9.

Compared with the intersection entropy loss curve in classification learning, the variance loss curve in regression learning has a larger decline ratio, which shows that the convergence speed of this analysis and calculation is faster. In the process of 0–200 iterations, the decline rate of variance loss curve keeps a large decline, but the number of iterations of convergence of the model calculation is 451, which is obviously higher than that of classification and recognition. This is mainly due to the greater difference in sample space of intensity recognition.

For intensity identification, the calculation results of its training set and test set are shown in Table 6.

Among them, R^2 represents the fitting degree of identifying the size of the inducement of heap load damage, and the optimal value is 1; MSE is the mean square deviation, which indicates the square expectation of the error between the calculated value and the real value of the pile-load damage inducement, and the optimal value is 0; MAE is the average absolute error, which represents the absolute value of the average error between the calculated value and the real value of the cause of heap load damage, and the optimal value is 0.

The mean value of R^2 of the fitness for identifying the size of the inducement of heap load damage is 0.992, which is very close to the optimal value of 1, so it can be considered that it has achieved a good identification

Table 6 Intensity recognition results

Position	Classification				Regression			
	Sample	R^2	MSE	MAE	Sample	R^2	MSE	MAE
1	1900	0.991	1.301	0.910	615	0.988	1.230	0.868
2	1890	0.986	1.312	0.901	620	0.981	1.410	0.914
3	1860	0.997	1.013	0.859	630	0.998	1.109	0.837
4	1850	0.995	1.118	0.919	635	0.996	1.113	0.820
Total	7500	0.992	1.186	0.897	2500	0.991	1.216	0.859

Fig. 10 Comparison chart of 20 random samples

effect. The mean values of MSE and MAE are 1.201 and 0.878, respectively, which are far from the optimal value of 0.

Randomly select 20 predicted values from the calculation results, and compare them with the real values, which can more intuitively compare the advantages and disadvantages of the identification results of the size of the heap damage inducement. The comparison curve is shown in Fig. 10.

Among the 20 randomly selected samples, the difference between the predicted value and the sample value is very small, and the change trend of the two values is basically consistent. From the above calculation results, it can be seen that the inversion model constructed in this paper has a good performance in the calculation of the pile-load damage incentives, can accurately identify the location and size of damage and has a strong generalization ability, which can meet the needs of the inversion analysis of the pile-load damage incentives.

5 Conclusion

1. The analysis of 10,000 samples of pile foundation stress caused by surcharge damage shows that the average accuracy of position recognition is 0.991, and the average value of R^2 of size recognition is 0.992, which all show good performance. The difference of recognition indexes between training samples and test samples is small, and there is no lack of fitting ability, and the generalization ability is strong.
2. In the neural network model constructed in this paper, Adam is used for iteration, the classification learner network is set to 5 nodes in one hidden layer, and the activation function is relu; the regression learner network has two hidden layers, and the number of nodes is 10 and 4, respectively. The parameter setting with

the activation function as identity can meet the inversion needs of the heap damage inducement.

3. Inversion calculation of wharf damage incentives needs to establish samples with large data space, while materialization model calculation takes up a lot of computer memory and takes time. Therefore, in this paper, parametric modeling is adopted, and MANSYS module is called by Python's subprocess module for batch calculation, which can obtain inversion calculation samples more efficiently and in batch.
4. The establishment of parametric model in this paper is based on the analysis of wharf structure under the action of adverse damage inducement, which can be extended to the analysis of similar frame structures. In the future, it is necessary to do further in-depth research on the setting of the interface between structure and foundation.

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Declarations

Conflict of interest We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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