WARSAW UNIVERSITY OF TECHNOLOGY Index 351733
FACULTY OF CIVIL ENGINEERING
COMMITTEE FOR CIVIL AND WATER ENGINEERING
POLISH ACADEMY OF SCIENCES ISSN 1230-2945

DOI: 10.24425/ace.2025.156179

ARCHIVES OF CIVIL ENGINEERING

Vol. LXXI ISSUE 4 2025

pp. 427 – 440

Research paper

Digital twin-based vibration displacement sensing and recognition technology for large engineering structures

Li Gao[1], Shan Chen[2]

Abstract: In recent years, the construction of large-scale engineering structures has involved numerous links in the construction process, including design, construction, supervision, material supply, and so forth. The coordination and cooperation between these links are of paramount importance. The presence of several linkages during the building process raises the possibility of communication breakdowns and information transfer delays, which can negatively affect the project's overall progress and quality. To overcome these obstacles, the study constructed a safety management model for the construction of large engineering structures by introducing digital twin technology. This model was then optimized and improved by using an inverse neural network algorithm based on particle swarm optimization. The outcomes of the improved model were subjected to testing, and the findings demonstrated that the model trained by the research exhibited an exceptionally high degree of accuracy in the test, with a prediction accuracy of 98.2%. Especially in the stress prediction of the cable, by comparing the predicted value of the research model with the actual value, it was found that the prediction accuracy was as high as 99.1%. In addition, the model also showed excellent performance in the eigenvalue system, and the EV value of the model was as high as 0.978. The model was also able to accurately identify the critical components under specific working conditions. From the above results, it can be observed that the research model has reached the expected standard in terms of performance and reliability, and has strong application value in the prediction of structural safety management of large-scale projects.

Keywords: digital twin, particle swarm optimization algorithm, reverse neural network algorithm, large-scale project, shift sensing, identification technology, safety management

[1]DSc., Faculty of Computer and Software Engineering, Huaiyin Institute of Technology, Huai'an, 223003, China, e-mail: ggll201409@126.com, ORCID: 0009-0000-3350-9207
[2]MSc., Software Engineering Department, Shijiazhuang Information Engineering Vocational College, Shijiazhuang, 050000, China, e-mail: 13833469896@163.com, ORCID: 0009-0007-4507-9997

1. Introduction

With the rapid development of science and technology, the safety and stability of large-scale engineering structures such as Bridges and high-rise buildings have attracted increasing attention [1]. In the long-term use of large engineering structures, they will be affected by various external factors, such as earthquake, wind, etc., which may produce vibration and displacement, and then pose a potential threat to the safety of the structure. In order to ensure the safe and stable operation of these large engineering structures, experts and scholars continue to study advanced monitoring and identification technology. For example, Yan and Song proposed an automatic extraction method based on deep learning network to solve the difficult problem of deformation curve extraction of civil engineering structures, realized high-precision identification and extraction, and verified its effectiveness [2]. Eltouny and Liang proposed an unsupervised learning novelty detection framework for damage detection and localization of large structures. The accuracy of structural health diagnosis is as high as 93%, and the accuracy of damage location and detection is as high as 85% respectively [3]. In this context, digital twin technology came into being. As an advanced technology system that integrates multi-dimensional information such as physical information model, sensor update data and operation history, digital twin technology provides unprecedented possibilities for safety monitoring and evaluation of large-scale engineering structures. For example, Momber et al. applied digital twin technology to monitoring and maintenance planning of wind power tower surface protection system for the first time, showing its broad application prospects [4]. Chen and Whyte, for example, developed an innovative method through digital twin technology to reveal the interdependence between systems in large-scale engineering systems and help designers make reasonable decisions when system design changes [5]. However, in the practical application, how to ensure the accuracy and real-time data, how to improve the accuracy and efficiency of the simulation model are urgent problems to be solved. In order to solve these problems, Particle Swarm Optimization Backpropagation (PSO-BP) algorithm based on particle swarm optimization was introduced to improve the digital twin technology. Particle Swarm Optimization (PSO) is an optimization algorithm based on swarm intelligence that can search for optimal solutions in multidimensional space. PSO algorithm is used to optimize the weight and threshold of BP network. PSO-BP algorithm can significantly improve the training speed and generalization ability of neural network, so as to further improve the monitoring and recognition accuracy of digital twin technology. The research is expected to promote the wide application and development of digital twin technology in the field of engineering structure monitoring.

2. Methods and materials

2.1. Vibration displacement sensing and recognition model construction for large-scale engineering based on digital twin

The digital twin is widely applied in many fields, with a greater number of applications in the areas of product design, product production, medical analysis, and engineering construction [6]. However, in the large-scale engineering and construction industry, the application of the digital twin framework system is still in the primary stage. For this reason, it is investigated to improve the vibration displacement sensing and recognition techniques for large engineering structures using the digital twin framework. The digital twin framework consists of a model-driven architecture MDA, a service-driven architecture SDA, and a data-driven architecture DDA [7,8]. Realistic physical model S_{pr} is the basis of digital twin system, which is mostly divided into five parts. The component dimension decomposition item S_{cd}, the component dimension decomposition item S_{co}, the structural dimension decomposition item S_{sd}, the unit dimension decomposition item S_{ed}, and the component dimension decomposition item S_{cc}. The expression of S_{pr} is shown in Equation (2.1).

$$S_{pr} = \begin{pmatrix} S_{cd} & S_{cc} & \cdots & S_{co} \\ S_{ed} & S_{ec} & \cdots & S_{eo} \\ \vdots & \vdots & \ddots & \vdots \\ S_{sd} & S_{sc} & \cdots & S_{so} \end{pmatrix} \tag{2.1}$$

In the architecture of digital twin technology, the twin virtual model B_{ve} is a comprehensive digital representation that consists of four key types of models [9,10]. The first is the geometric model, the second is the physical model, the third is the behavioral model, the fourth is the rule model. The rule model can also be customized and extended to suit different application scenarios and requirements. The mathematical expression of B_{ve} is shown in Equation (2.2).

$$B_{ve} = (B_{vg} + B_{vp} + B_{vb} + B_{vr}) \tag{2.2}$$

In Equation (2.2), B_{vg} denotes the geometric model. B_{vb} denotes the behavioral model. B_{vr} denotes rule model package. In the digital twin system, the role of the comprehensive data center P_{td} is to fully integrate all kinds of data in the digital twin system. The digital twin system's many features, including data processing, storage, transmission, and application, are employed to guarantee the system's effective, secure, and intelligent operation. The expression of P_{td} is shown in Equation (2.3).

$$P_{td} = (P_{tg} + P_{tp} + P_{tk} + P_{tf} + P_{tr}) \tag{2.3}$$

In Equation (2.3), P_{tg} denotes realistic physical data. P_{tp} denotes twin model data. P_{tk} denotes empirical knowledge data. P_{tf} denotes fusion decision data. P_{tr} denotes regression prediction data. The functional application system L_{fa} guides the whole digital twin system for normal operation [11]. From the point of view of service category, functional application system can be divided into two major categories, function-oriented service L_{fi} and application-oriented service L_{fo}. The expression of L_{fa} is shown in Equation (2.4).

$$L_{fa} = (L_{fi} + L_{fo}) \tag{2.4}$$

In the digital twin system, C_{in} can ensure the efficient operation and responsiveness of the digital twin system by constructing an efficient information network. The expression of C_{in} is shown in Equation (2.5).

$$C_{in} = (S_{pr} \cap B_{ve}; S_{pr} \cap B_{td}; B_{ve} \cap P_{td}; S_{pr} \cap L_{fa}; B_{ve} \cap L_{fa}) \tag{2.5}$$

In digital twin technology, the construction of C_{in} involves three core components, i.e., sensing system, network system and communication protocol system [12]. As a cyclic growth process, digital twin requires a closed loop in its logical structure to ensure the integrity and effectiveness of its management model. Therefore, the vibration displacement sensing and identification technology of large-scale engineering based on digital twin is investigated, and a closed-loop management logical framework centered on PAPC is constructed. The study applies vibration displacement sensing and recognition techniques from large-scale engineering to construction safety. Fig. 1 displays the schematic diagram of the digital twin-based construction safety model.

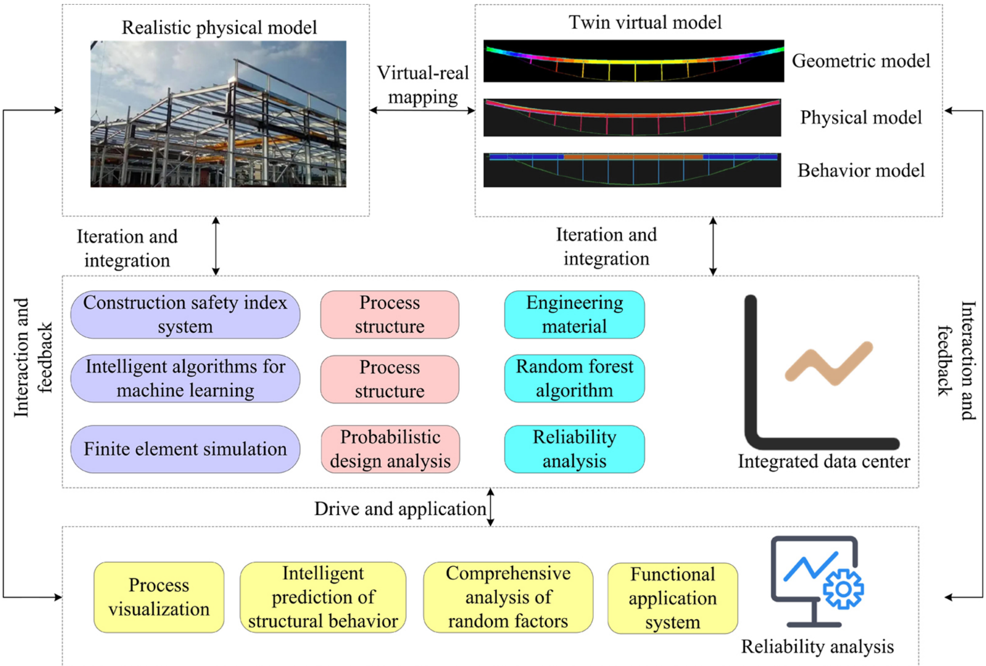


Fig. 1. Construction safety model schematic diagram based on digital twin

The expression of vibration displacement sensing and recognition model for large-scale engineering based on digital twin is shown in Equation (2.6).

$$DT_m = (S_{pr} + B_{ve} + P_{td} + L_{fa} + C_{in}) \tag{2.6}$$

Assuming that the construction site of a large engineering structure consists of q members, the actual perceived value A of the mechanics of one of the members q_1 can be set as $A = (x_1, x_2, \ldots, x_n)$. The formula for calculating the average value of A is shown in Equation (2.7).

$$\overline{x} = \frac{\sum_{i=1}^{q} x_i}{q} \tag{2.7}$$

The expression for the weights of each mechanical parameter is shown in Equation (2.8).

$$\omega_i = \frac{\frac{1}{d_i}}{\sum_{i=1}^{q} \left(\frac{1}{d_i} \right)} \tag{2.8}$$

In Equation (2.8), d_i denotes the Euclidean distance from each mechanical parameter to the mean value of the mechanical parameter. Its expression is shown in Equation (2.9).

$$d_i = \|\bar{x} - x_i\| \tag{2.9}$$

The expression for the weighted average of the monitored values of the mechanical parameters of the root tension cable is shown in Equation (2.10).

$$\hat{x} = \sum_{i=1}^{n} \omega_i d_i \tag{2.10}$$

The expression for the overall perceived value of the engineered structure is shown in Equation (2.11).

$$D = \mu + \alpha_c \sigma \tag{2.11}$$

In Equation (2.11), α_c denotes the confidence level of the mechanical parameter analysis. μ denotes the mean of the weighted average of the perceived values of the mechanical parameters of each root member. σ denotes the variance of the weighted average of the perceived values of the mechanical parameters of each root member.

2.2. Construction of intelligent prediction model for large engineering structures based on improved particle swarm optimization algorithm

In this study, the digital twin model is used to provide training samples of real-time structural safety state for deep learning algorithms. In light of the aforementioned samples, the PSO-BP algorithm is employed for the purpose of predicting the safety state, thereby facilitating the dynamic monitoring and early warning of the construction safety of large engineering structures. In the process of structural construction safety prediction, the mapping relationship between design parameters and mechanical parameters is accurately extracted in accordance with the results of digital twin simulation. Deep learning algorithms are then used to analyze the inherent laws between these data to reveal their complex interactions. The expression of the association rule is shown in equation (2.12).

$$f(a_1, a_2, ..., a_m)\, g(b_1, b_2, ..., b_n) \tag{2.12}$$

In Equation (2.12), $f(a_1, a_2, ..., a_m)$ is the set of all parameters of the large engineering structure. $(a_1, a_2, ..., a_m)$ is the random variable of the parameters of the large engineering structure. $g(b_1, b_2, ..., b_n)$ is the set of mechanical parameters of large engineering structures.

$(b_1, b_2, ..., b_n)$ is the random variable of the mechanical parameters of the large engineering structure. To ensure the validity and feasibility of the research model in actual construction, the study further inputs these optimization and maintenance schemes into the digital twin model to verify its practical application effect in safety maintenance. The structure of the digital twin model based on deep learning network is shown in Fig. 2.

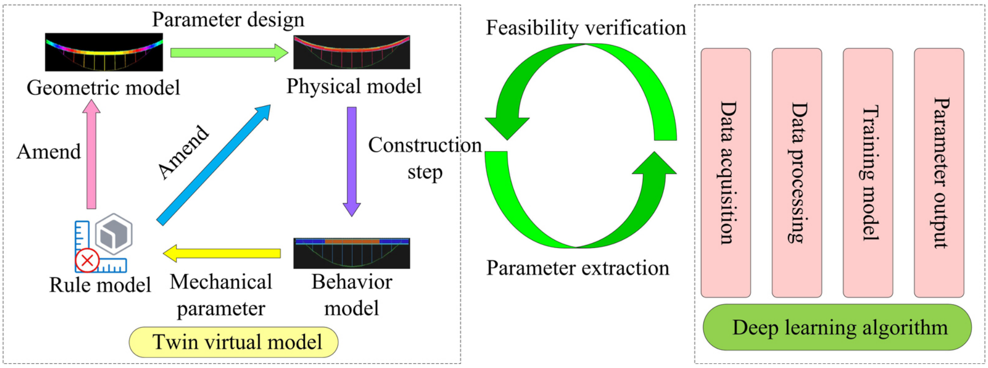


Fig. 2. Diagram of digital twin model based on deep learning network

In neural networks, the transfer function, also known as the activation function, is responsible for determining the output state of each neuron in the network [13]. Among many transfer functions, Sigmoid type function is widely used due to its unique properties and is considered as one of the most classical transfer functions [14,15]. The expression of Sigmoid type function, as shown in Equation (2.13).

$$f(x) = \frac{1}{1+e^{-\beta x}} \tag{2.13}$$

The BPNN algorithm can be fitted with neural units in the output layer. Equation (2.14) displays the formula for its outcome.

$$y_k = \sum_{j=1}^{N_2} \omega_{kj}^2 f\left(\sum_{i=1}^{N_1} \omega_{ji}^1 x_i + b_j\right) \tag{2.14}$$

In Equation (2.14), N_1 is the output neural units contained in the input layer. N_2 is the hidden neural units contained in the hidden layer. ω is the weight value. b is the bias value. BPNN function and error expression as shown in Equation (2.15).

$$E = \frac{1}{2}\sum_{j=1}^{N_3} (\hat{y}_j - y_j)^2 \tag{2.15}$$

In Equation (2.15), N_3 is the neural units in the output layer. $\hat{y}_j$ is the output result of BP. y_j denotes the true values of the BP parameters. The tuning expression of ω is shown in Equation (2.16).

$$\Delta\omega = -\theta \frac{\partial E}{\partial \omega} \tag{2.16}$$

In Equation (2.16) θ is the learning rate. Equation (2.17) displays the neural network model's expression, which is built by the study using the construction features of huge structures as a basis.

$$\begin{array}{c} \text{sample1} \\ \text{sample2} \\ \vdots \\ \text{sample}n \end{array} \begin{array}{c} \rightarrow \\ \rightarrow \\ \\ \rightarrow \end{array} \begin{pmatrix} XL_1 & D_{ucb1} & D_{s1} & D_{c1} & \cdots & IT_{c1} \\ XL_2 & D_{ucb2} & D_{s2} & D_{c2} & \cdots & IT_{c2} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ XL_n & D_{ucbn} & D_{sn} & D_{cn} & \cdots & IT_{cn} \end{pmatrix} \Rightarrow \begin{pmatrix} D_{p1} & S_{c1} & \cdots & W_{b1} \\ D_{p2} & S_{c2} & \cdots & W_{b2} \\ \vdots & \vdots & \ddots & \vdots \\ D_{pn} & S_{cn} & \cdots & W_{bn} \end{pmatrix} \tag{2.17}$$

The expression of the neural network model, which was constructed by the study based on the construction aspects of large structures, is shown in Equation (2.17). By mimicking the movement and flocking behavior of bird flocks during foraging, the PSO algorithm – a global stochastic search algorithm based on group intelligence – was developed. Assume that in the search space, every particle represents a potential solution. Its position is denoted by the position vector symbol X_i, and its velocity is denoted by the velocity vector symbol V_i. Each particle has the ability to memorize its historical best position, which is denoted by the vector symbol P_i. Meanwhile, the whole particle population shares a global best position. This position is selected from the best positions experienced by all the particles in the population and is denoted by the vector symbol P_i. The formula for the updating rule of particle velocity and position, as shown in Equation (2.18).

$$\begin{cases} X_i = (x_{i1}, x_{i2}, ..., x_{in}) \\ V_i = (v_{i1}, v_{i2}, ..., v_{in}) \\ P_i = (p_{i1}, p_{i2}, ..., p_{in}) \\ P_g = (v_{g1}, v_{g2}, ..., v_{gn}) \end{cases} \tag{2.18}$$

In Equation (2.18), n denotes the dimension of the search space and m denotes the number of particle populations.

3. Results

3.1. Construction of intelligent prediction model for large engineering structures based on improved particle swarm optimization algorithm

A mid-plane chord-bearing structure of a large-scale engineering steel roof structure is used as the experimental model for this study. The model has a span of 48 meters, the droop is set to 3.5 meters and is equipped with 9 braces to ensure the stability and load carrying capacity of the structure. Fig. 3 displays the large-scale engineering structural model's unit numbering.

To comprehensively verify the effectiveness of the algorithm, five representative working conditions and three different stages are selected as test objects. The parameter settings of the research algorithm in different working conditions and stages are shown in Table 1.

To confirm the efficacy of the suggested method, the study selects working condition 1 as the test case, and the algorithm is utilized to accurately identify the key components. Through the calculation and analysis of the research algorithm, the judgment results based on a single eigenvalue index are obtained, as shown in Fig. 4.

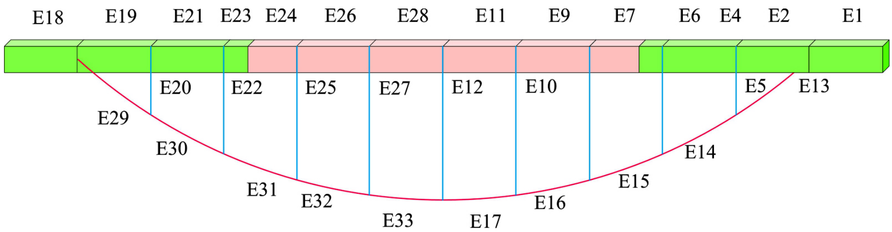
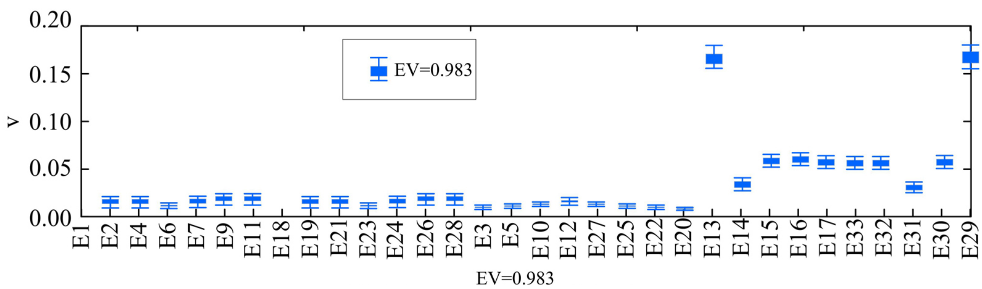


Fig. 3. Schematic diagram of validation example component number

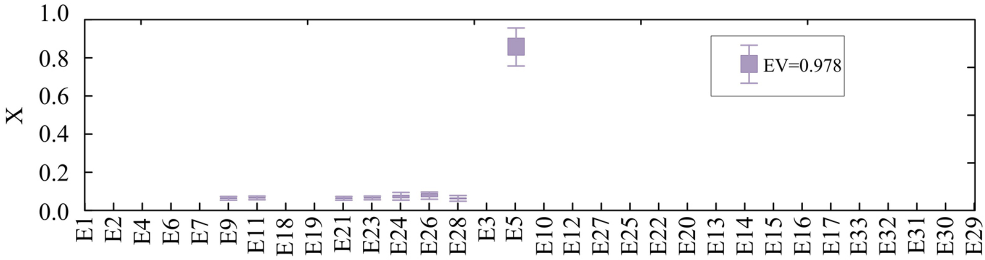
Table 1. Specific settings and parameter tables for different validation conditions and stages

Working condition	**Ground state T phase**	**T1 phase**	**T2 phase**	**Key component distribution**
1	Be self-possessed	Interdistributed loading state	E5 modulus damage 10% corrosion 0.3%	Stay bar
2	Be self-possessed	Interdistributed loading state	E27 modulus damage 10% corrosion 0.3%	Stay bar
3	Be self-possessed	Interdistributed loading state	E28 modulus damage 20% rust 0.5%	Cable + steel beam
4	Be self-possessed	Interdistributed loading state	E9 modulus damage 15% corrosion 0.4%	Steel beam + cable + strut
5	Be self-possessed	Interdistributed loading state	E11 modulus damage 15% corrosion 0.4%	Steel beam + cable + strut

Fig. 4(a) shows the displacement coefficient of variation plot. The maximum value of the displacement coefficient of variation of the research algorithm is 0.178, at which time the corresponding EV value is as high as 0.983. Fig. 4(b) shows the plot of the key coefficient



(a)



EV=0.983

(b)

Fig. 4. The displacement change and ground state key coefficient diagram of the algorithm: (a) Displacement change coefficient diagram, (b) Ground state key coefficient diagram

of the base state. The EV value of the research algorithm is 0.978, and the algorithm is able to accurately identify the critical member E5 unit. In summary, the EV values of both the displacement changes and the base state critical coefficients exceed the threshold value of 0.95.

3.2. Application effect of IPM for large engineering structures based on digital twin

In practical application, data samples are provided by sampling in the digital twin model. In the digital twin model, the mechanical parameters and working conditions of the structure are extracted in real time, and the data is studied as the sample set of deep learning. Among them, 70% samples are selected as training set samples, and 30% samples are selected as test set samples. Data is extracted every 15 seconds, and the extracted data is used as historical experience to train the neural network. The influence of different mechanical parameters and different number of hidden layer neurons on the number of iterations is shown in Fig. 5.

It can be seen from Fig. 5 that when the number of hidden layer nodes is 11, the number of iterations corresponding to vertical displacement is the least; when the number of hidden layer nodes is 11, the number of iterations corresponding to steel beam stress is the least; when the number of hidden layer nodes is 11, the number of iterations corresponding to cable stress is the least. In order to meet the accuracy requirements and model efficiency, the number of nodes corresponding to different mechanical parameters of the neural network is selected as 11, 6 and 10 respectively. Aiming at the actual needs of vibration displacement perception analysis of large engineering structures, the research conducted fitting experiments on the constructed model, and the experimental results were shown in Fig. 6.

As can be seen from Fig. 6, although the fitting effect of the model in the training stage needs to be improved, the predicted fitting effect in the test stage is excellent. In order to verify the application effect of the intelligent prediction model for large engineering structures based on digital twins, the predicted value of the intelligent model of vertical displacement and cable stress was compared with the actual value, as shown in Fig. 7.

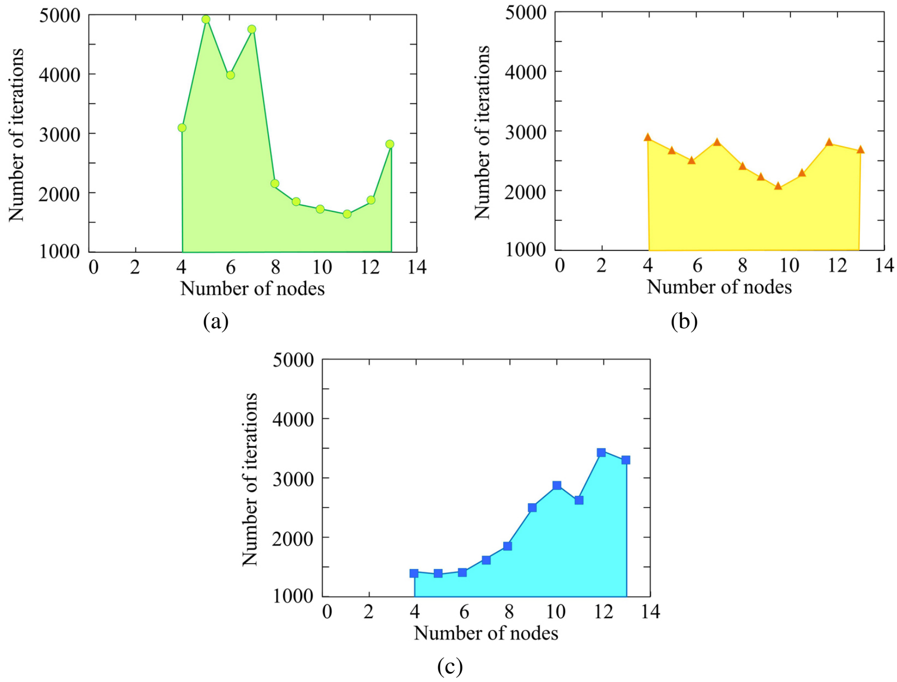


Fig. 5. Schematic diagram of the influence of different mechanical parameters and different number of hidden layer neurons on the number of iterations: (a) The influence of the number hidden layer neurons in vertical displacement on the number of iteration, (b) Diagram of the effect of different hidden layer neurons on the number of iteration under cable stress, (c) The influence of the number of hidden layer neurons on the number of iteration of beam stress

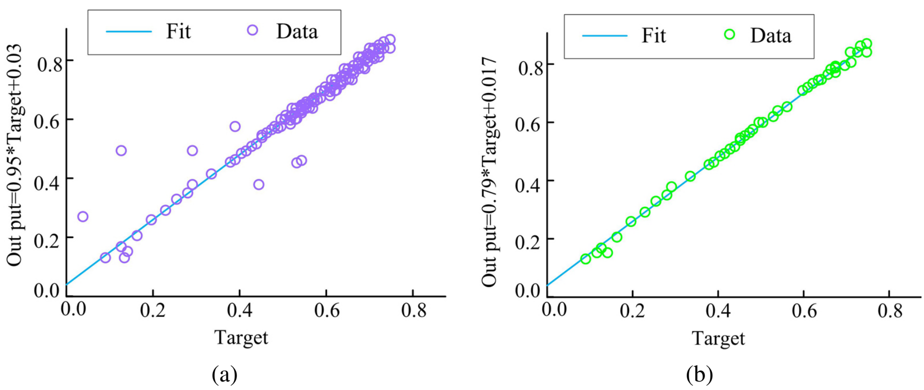
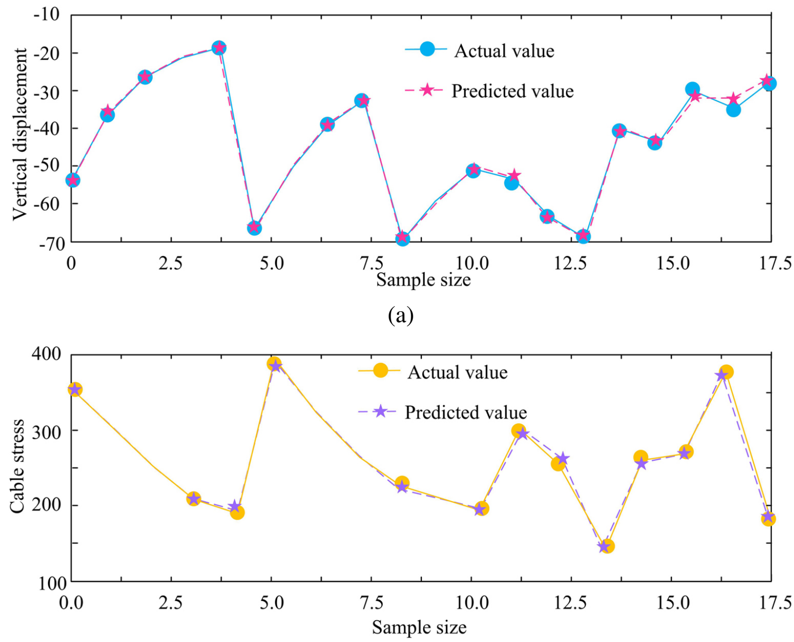


Fig. 6. The study model fits the experimental result graph: (a) Effect fitting during the training phase, (b) Cross-validation phase fitting effect

Fig. 7(a) shows the comparison between the predicted and actual values of the intelligent model for vertical displacement. The model trained by the research demonstrates considerable accuracy in the test, and its PA reaches 98.2%. Fig. 7(b) shows the plot of predicted values versus actual values of the intelligent model for tension cable stress. The prediction accuracy of the research model is 99.1%. It can be concluded that the performance and reliability of the research model meets the expected standards and therefore it can be authorized for practical application and prediction in relevant scenarios.



(b)

Fig. 7. The comparison between the predicted value and the actual value of the model vertical displacement and cable stress: (a) Intelligent algorithm of vertical displacement predicted value compared with the actual value, (b) Comparison of the predicted value and the actual value of the cable stress by intelligent algorithm

4. Discussion and conclusions

4.1. Discussion

With the increasing number of large engineering structures such as bridges and high-rise buildings, their safety and stability have become the focus of attention in the engineering field. When engineering structures are subjected to external factors such as earthquakes and wind, they will vibrate and displace, which poses a serious threat to the safety of the structures [16,17]. To increase the safety of engineering structures, it is crucial to conduct research on vibration displacement sensing and detection methods for large engineering structures based on digital twin [18, 19]. In the research process, by comparing the predicted value of the intelligent model and the actual value of the vertical displacement and the cable stress, it can be seen that the prediction accuracy of the vertical displacement is 98.2%, and the prediction accuracy of the cable stress is as high as 99.1%. This result verifies the validity and accuracy of the research model, and also indicates the great potential of digital twin technology in the field of engineering structure monitoring, which is similar to the results obtained by Dong team in the study of real-time fatigue life prediction method of bridge crane structure based on digital twin [20]. When the structure is affected by external factors, its vibration displacement is effectively controlled, and there is no obvious safety hazard. This indicates that through digital twin technology, the health status of the structure can be monitored in real time, and countermeasures can be formulated in advance to ensure the safe operation of the structure. This result is consistent with the conclusion of Mosltt et al.'s digital twin study on compensating crane lifting planning at sea [21]. Through Monte Carlo sampling method, it is found that the vertical displacement safety index samples are mainly distributed in the range of –8 to 16, and there is a close correlation between the vertical displacement safety index and the prestress. This finding is consistent with the results obtained by Chen's team in the federal analysis digital twin study using Bayesian methods, which once again verifies the accuracy and reliability of the research model [22].

4.2. Conclusions

For the perception, analysis, prediction and control of safety problems in the construction stage, an effective solution is urgently needed. Based on the concept of digital twin, this paper deeply explores the management methods of construction safety problems of large engineering structures, and constructs a set of intelligent management system of large engineering structures based on digital twin. Through the actual case verification, the method not only shows high feasibility and significant advantages, but also the trained algorithm shows high accuracy in the test, and can accurately predict the mechanical parameters of the structure, providing a strong basis for safety evaluation. Looking forward to the future, it is necessary to continue to deepen the research on digital twin technology in the field of large engineering structures to promote its wide application in construction safety assessment, structural optimization design, etc., so as to further improve the overall management level of large engineering structures construction process and ensure project quality and safety.

Acknowledgements

The research is supported by: Jiangsu Province industry-university-research cooperation project, Research and development of a smart constitute site safety management system, (NO. BY20221107).

References

[1] O. Hakimi, H. Liu, and O. Abudayyeh, "Digital twin-enabled smart facility management: A bibliometric review", *Frontiers of Engineering Management*, vol. 11, no. 1, pp. 32–49, 2024, doi: 10.1007/s42524-023-0254-4.

[2] X. Yan and X. Song, "Large-scale civil engineering structure deformation monitoring research based on image recognition", *Traitement du Signal*, vol. 40, no. 2, pp. 501–509, 2023, doi: 10.18280/ts.400209.

[3] K.A. Eltouny and X. Liang, "Large-scale structural health monitoring using composite recurrent neural networks and grid environments", *Computer-Aided Civil and Infrastructure Engineering*, vol. 38, no. 3, pp. 271–287, 2023, doi: 10.1111/mice.12845.

[4] A. Momber, T. Mller, D. Langenkmper, T. Nattkemper, and D. Brün, "A digital twin concept for the prescriptive maintenance of protective coating systems on wind turbine structures", *Wind Engineering*, vol. 46, no. 3, pp. 949–971, 2021, doi: 10.1177/0309524X211060550.

[5] L. Chen and J. Whyte, "Understanding design change propagation in complex engineering systems using a digital twin and design structure matrix", *Engineering Construction & Architectural Management*, vol. 29, no. 8, pp. 2950–2975, 2022, doi: 10.1108/ECAM-08-2020-0615.

[6] A. Rakic, S. Zivanovic, and Z. Dimic, "Digital twin control of multi-axis wood CNC machining center based on LinuxCNC", *Bioresources*, vol. 16, no. 1, pp. 1115–1130, 2021, doi: 10.15376/biores.16.1.1115-1130.

[7] J. Lee, et al., "Integration of digital twin and deep learning in cyber-physical systems: Towards smart manufacturing", *IET Collaborative Intelligent Manufacturing*, vol. 2, no. 1, pp. 34–36, 2020, doi: 10.1049/iet-cim.2020.0009.

[8] Y.R. Wang, Y.D. Wang, W.Z. Ren, and Z.Q. Jiang, "Knowledge driven multiview bill of material reconfiguration for complex products in the digital twin workshop", *The International Journal of Advanced Manufacturing Technology*, vol. 130, no. 7, pp. 3469–3480, 2024, doi: 10.1007/s00170-023-12885-x.

[9] V. Buljak, G. Cocchetti, A. Cornaggia, T. Garbowski, G. Maier, and G. Novati, "Materials mechanical characterizations and structural diagnoses by inverse analyses", in *Handbook of Damage Mechanics*. Springer, 2015, pp. 619–642, doi: 10.1007/978-1-4614-5589-9_33.

[10] T. Garbowski, A. Cornaggia, M. Zaborowicz, and S.Sowa, "Computer-aided structural diagnosis of bridges using combinations of static and dynamic tests: A preliminary investigation", *Materials*, vol. 16, no. 24, art. no. 7512, 2023, doi: 10.3390/ma16247512.

[11] Q. Liu, L. Tang, T. Wu, and Q. Chen, "Deep reinforcement learning for resource demand prediction and virtual function network migration in digital twin network", *IEEE Internet of Things Journal*, vol. 10, no. 21, pp. 19102–19116, 2023, doi: 10.1109/JIOT.2023.3281678.

[12] S. Si-Mohammed, A. Bardou, T. Begin, et al., "NS+NDT: Smart integration of network simulation in network digital twin, application to IoT networks", *Future Generation Computer Systems*, vol. 157, no. 3, pp. 124–144, 2024, doi: 10.1016/j.future.2024.03.038.

[13] P. Preethi and H.R. Mamatha, "Region-based convolutional neural network for segmenting text in epigraphical images", *Artificial Intelligence and Applications*, vol. 1, no. 2, pp. 103–111, 2023, doi: 10.47852/bonviewAIA2202293.

[14] Z.L. Chai, C.L. Zhou, R. Guo, et al., "Research on the model of scale removal under slurry impact based on BP neural network", *JOM*, vol. 76, no. 1, pp. 445–451, 2024, doi: 10.1007/s11837-023-06206-6.

[15] G.R. Hecht and E.M. Botta, "Particle swarm optimization-based co-state initialization for low-thrust minimum-fuel trajectory optimization", *Acta Astronautica*, vol. 211, pp. 416–430, 2023, doi: 10.1016/j.actaastro.2023.06.021.

[16] J.H. Lin, B.F. Zhang, T. Zhang, and X.W. Chen, "Structure-engineering the stability, electronic, optical and photocatalytic properties of hexagonal C2P2 monolayers", *Physical Chemistry Chemical Physics: PCCP*, vol. 25, no. 21, pp. 15052–15061, 2023, doi: 10.1039/D3CP00484H.

[17] L. Wang, Z. Wang, L. Chu, Z. Huang, M. Yang, and G. Wang, "Electronic structure modulation and morphological engineering of trifunctional NixCoyP electrode for ultrastable overall water splitting at 1 Acm^2 and efficient biomass oxidation valorization", *International Journal of Hydrogen Energy*, vol. 64, pp. 830–841, 2024, doi: 10.1016/j.ijhydene.2024.03.305.

[18] F. Xiang, Y.D. Zhou, Z. Zhang, et al., "Digital twin-driven green material optimal selection and evolution in product iterative design", *Advanced Manufacturing*, vol. 11, pp. 647–662, 2023, doi: 10.1007/s40436-023-00450-4.

[19] K.N. Anyfantis, "An abstract approach toward the structural digital twin of ship hulls: A numerical study applied to a box girder geometry", *Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment*, vol. 235, no. 3, pp. 718–736, 2021, doi: 10.1177/1475090221989188.

[20] Q. Dong, B. He, Q. Qi, and G. Xu, "Real-time prediction method of fatigue life of bridge crane structure based on digital twin", *Fatigue & Fracture of Engineering Materials & Structures*, vol. 44, no. 9, pp. 2280–2306, 2021, doi: 10.1111/ffe.13489.

[21] G.A. Mosltt, D. Padovani, and M. Hansen, "A digital twin for lift planning with offshore heave compensated cranes", *Journal of Offshore Mechanics and Arctic Engineering*, vol. 143, no. 3, 2020, doi: 10.1115/1.4048881.

[22] D. Chen, D. Wang, Y. Zhu, and Z. Han, "Digital twin for federated analytics using a bayesian approach", *IEEE Internet of Things Journal*, vol. 8, no. 22, pp. 16301–16312, 2021.

Received: 2024-07-04, Revised: 2024-08-26