Prediction for Surface Subsidence of Shield Construction in Water-Rich Sand Egg Stratum Based on Edge Intelligence

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Abstract. The refinement and intelligent control of shield tunneling is the development trend of modern tunnel construction technology. In order to better predict and control the surface subsidence caused by shield excavation, this paper takes the shield construction of Luoyang Metro Line 2 from Longmen Station to Longmen Avenue Station as the background, and proposes a method based on edge intelligence for shield construction in water-rich sand egg strata. Methods for predicting land subsidence. First, low latency and faster data processing are achieved by collecting a large amount of data containing dynamic information about geological conditions and surrounding environments during the shield tunneling process; then using the iFogSim simulator to create different configurations; second, establishing support A surface subsidence model based on vector regression was established, and the model was deployed on the edge equipment; finally, the model was evaluated using the monitoring data of surface subsidence of the water-rich sand egg formation in Luoyang area. The research results show that the edge computing-based system has lower latency and higher processing speed than only deploying cloud data centers. After Pearson-related parameter tuning and model comparison training with Linear as the kernel function, the mean square error of the predicted value and the collected value of the surface subsidence is better than the other two kernel functions. The method proposed in this paper can provide real-time prediction service for large-scale surface subsidence prediction caused by shield construction, and is more practical.

Keywords: Surface deformation · Upper soft and lower hard soil layer · Curved shield construction · Mindlin solution · Random medium theory

1 Introduction

In recent years, with the continuous acceleration of urban development and the continuous increase of population, the situation of ground traffic congestion is getting worse and

Z. Xiao et al. (Eds.): ICECI 2022, LNICST 478, pp. 196–212, 2023.
https://doi.org/10.1007/978-3-031-28990-3_14

worse. In order to solve this problem, my country has begun to focus on the development of underground railway transportation, and the subway has played an indispensable role in urban transportation. The construction methods of subway sections generally include open-cut method, cover-cut method, shield method, etc. Among them, shield method has become the most important construction method due to its advantages of safety, reliability and high efficiency, but it is still unavoidable in the construction process. It will affect the surface buildings and surrounding pipelines to a certain extent, causing large surface subsidence [1]. Therefore, the prediction and control of surface deformation is one of the important measures to ensure the safety of tunneling.

At present, many scholars at home and abroad have carried out research on the prediction of surface subsidence caused by shield construction, mainly including theoretical analysis method [2–4], model test method [5, 6], numerical simulation calculation method [7, 8] and other methods. With the advent of the era of "big data", the operation monitoring of shield machines is becoming more and more perfect, and the construction of shield tunnels presents the "three highs" requirements of high-capacity data storage capability, efficient real-time data processing capability and high-strength multi-source heterogeneous adaptability. The recorded measured data not only contains a large amount of information about the operation process of the shield machine, but also contains the interaction mechanism inside the shield machine and the external environment. Through machine learning and other methods to analyze and excavate the hidden between the construction monitoring data. It is of great significance for predicting surface subsidence. Ye et al. [9] used a time-series-based back-propagation neural network (TS-BPNN) to predict soil subsidence in the fast and slow subsidence stages, respectively. Li et al. [10] studied the influence of different machine learning algorithms and model parameter choices on the prediction of land subsidence. Hu et al. [11] established a surface subsidence prediction model based on rough set-support vector regression (RS-SVR) to predict the surface subsidence of the soft and hard uneven strata caused by shield construction. Wang et al. [12] propose a shield tunneling underneath railroad risk evaluation model based on set pair analysis, and the importance of each evaluation index in the model is optimized by rough set theory. The factors of surface settlement caused by shield construction are complex, and although the above methods of predicting settlement have achieved some success, there are still some shortcomings and limitations in practical engineering application.

With the advantages of ultra-high data rate, ultra-low latency and ultra-large-scale access, cloud computing and 5G technology provide solutions for the development of intelligent, safe and green underground space engineering construction combined with edge intelligence, which will effectively respond to the current industrial Many challenges faced by Internet development [13–26]. At present, edge intelligence research at home and abroad has penetrated into key industries and fields such as power, transportation, and mining. For example, Chen et al. [27] design a traffic control algorithm based on label-less learning on the edge cloud;Zhu et al. [28] design a method for vehicle safety control based on internet of vehicles;Hu, et al. [29] design and implement BlinkRadar using UWB Radar for Non-Intrusive Driver Eye-Blink Detection with; Jiang et al. [30] propose a novel user authentication system SmileAuth;Shao et al. [31] proposed A general three-step framework to reduce the inference latency than baseline methods;Zhang et al. [32] design a credit-differentiated edge transaction approval mechanism. Ma et al. [33] proposed a new method to apply edge intelligence to terminal-level identification and diagnosis of transmission line ice thickness. Xie et al. [34] proposed a partial offloading scheme of computing tasks based on the assistance of Reconfigurable Intelligent Surface. Zhang et al. [35] proposed an urban street garbage detection and cleanliness evaluation method based on mobile edge computing and deep learning. Qu et al. [36] combined edge computing technology, mine IoT environment perception technology and data transmission and other related technologies to establish a system architecture based on cloud, edge, and end three-level methane edge monitoring mode.

At present, cloud computing and the Internet of Things have insufficient technical integration in underground space engineering, and there are few successful cases of applying edge intelligence methods to surface prediction caused by shield construction. The edge intelligence method used for surface settlement prediction in shield construction has the following advantages:

(1) The cost is low, and the data of edge intelligence is mainly processed at the near end, so it is used in various links such as network transmission, central computing, central storage and backhaul., can save a lot of server, storage, switching, bandwidth, security, electricity and even physical space and many other costs, so as to achieve low cost.
(2) Low latency, edge intelligence processes data closer to the data source, reducing the bandwidth and delay of data uploading to the cloud platform, and can perform real-time calculation of surface settlement during construction and excavation. When the predicted settlement is too large. It can be remedied in time, but on-site monitoring takes a lot of time, and construction risks cannot be found in time.
(3) The density is high, and the monitoring sections for on-site monitoring often have a distance of 5–15 m. In order to facilitate the calculation and modeling of the numerical model, the side length of the soil unit is generally 2–5 m, and the model based on edge intelligence can be quickly and accurately constructed. The settlement value of any point can be obtained, and the calculated point density in the final output result is much larger than that of field monitoring and numerical model. Therefore, it is of great significance to apply edge intelligence to the surface prediction caused by shield construction.

Based on the shield construction of Luoyang Metro Line 2 from Longmen Station to Longmen Avenue Station as the background, this paper proposes a method for predicting the surface subsidence caused by shield construction of tunnels in water-rich sand egg strata based on edge intelligence. Firstly, by collecting a large amount of data including the dynamic change information of geological conditions and surrounding environment in the process of shield tunneling, and then establishing a surface subsidence model based on rough set-support vector regression, and deploying the model on edge equipment, Finally, the model is evaluated using the monitoring data of surface subsidence of the water-rich sand egg formation in Luoyang area.

There are three main contributions of this paper:

(1) Aiming at the problems of difficult acquisition and processing of surface subsidence data in harsh construction environments, poor prediction quality and high delay in shield construction, a surface subsidence prediction method based on edge intelligence is proposed.
(2) Aiming at the problems of "low value density" in industrial big data, the feature selection method is used to screen the key influencing factors of surface subsidence, and the Pearson correlation coefficient is used to obtain 7 optimal attribute sets.
(3) Comparing and analyzing the calculation results of the support vector machine model using different kernel functions, it is found that the RBF function as a kernel function has better fitting effect and prediction accuracy.

2 The Proposed Method

2.1 Edge Intelligent System Architecture Based on iFogSim

An edge intelligent system architecture based on iFogSim is proposed, as shown in Fig. 1. The surface subsidence data is transmitted to the side layer through the end layer sensor for prediction of the surface subsidence prediction model, and the abnormal situation is returned to the construction party. Subsequently, the edge layer transmits important data and analysis results through the network to the cloud layer server for archiving, storage and supervision, and the cloud layer summarizes and manages the analysis results.

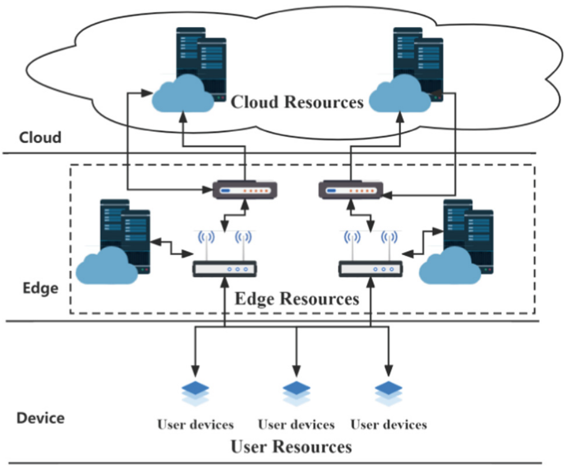

Fig. 1. The edge intelligent system architecture is designed according to the three layers of cloud-edge-device. The edge layer is mainly responsible for the analysis of surface subsidence data, model training and result transmission, and the device layer is mainly responsible for the collection and accumulation of surface subsidence data within the edge of the entire region.

2.2 Round-Trip Time

In computer networks, Round-Trip Time is an important performance indicator.The time required for the entire process from the sender sending data to the sender receiving the acknowledgment signal from the receiver [37], as shown in formula (1):

$$RT_{ij} = (S_i/b_i) + d_i + \left(k_i/n_j\right) + d_i \tag{1}$$

In the formula, S_i is the size of the task, b is the bandwidth, d is the delay, k_i is the number of instructions required to execute the task, and n_j is the number of instructions executed per second.

2.3 Total Execution Cost

The execution cost is also an important performance indicator of the network. The total cost required for task execution, including resource cost and execution cost [37], is shown in formula (2):

$$EC_{ij} = (l_i/n_j) * RC + \left(f_i/b_j\right) * C/b_j \tag{2}$$

$$\mathrm{RC} = \mathrm{R} * (\mathrm{C}/\mathrm{m}) + \mathrm{S} * \mathrm{C}/\mathrm{st}$$

where RC is the resource cost, f_i is the file size, C is the cost of executing the task, R is the RAM of the virtual machine, S is the size of the virtual machine, and st is the amount of storage.

2.4 Pearson Correlation Coefficient

In statistics, the Pearson correlation coefficient (PPMCC or PCCs) is widely used to measure the degree of closeness between two variables, and its value is between −1 and 1. Representation [38].

The Pearson correlation coefficient between two variables is defined as the quotient of the covariance between the two variables and the standard deviation of the two, as shown in Eq. (3):

$$\mathrm{r_{xy}} = \frac{\mathrm{cov(x, y)}}{\sigma \mathrm{x} * \sigma \mathrm{y}} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} (\mathrm{x_i} - \overline{\mathrm{x}})(\mathrm{y_i} - \overline{\mathrm{y}})}{\sqrt{\sum_{\mathrm{i=1}}^{\mathrm{n}} (\mathrm{x_i} - \overline{\mathrm{x}})^2} \sqrt{\sum_{\mathrm{i=1}}^{\mathrm{n}} (\mathrm{y_i} - \overline{\mathrm{y}})^2}} \tag{3}$$

where, x and y are two random variables, respectively, and n is the sample size. If $r = 0$, it means that the two variables are not correlated; if $r < 0$, it means that the two variables are negatively correlated; if $r > 0$, it means that there is a linear correlation between the two variables.

2.5 Support Vector Regression

Support vector regression method is a common machine learning modeling prediction method. Compared with neural networks, which need to train a large amount of sample data, support vector regression is mainly used for the learning of small sample problems, with fast calculation speed and strong prediction ability.

The basic idea is to use a nonlinear mapping function to map the input vector into a feature vector of a high-dimensional space, thereby simplifying the solution of the problem.

For a given training sample

$$D = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}, y_i \in R$$

where x_i, y_i are the input vector and output response, respectively, and n is the number of training samples.

The linear regression model we want to build in a high-dimensional space is

$$f(x) = \omega^T \#(x) + b \tag{4}$$

In the formula, ω and b are the model parameters, #(x) representing the feature vector to be mapped.

According to the support vector machine regression principle, the linear regression problem can be transformed into a constrained optimization problem:

$$\min_{\omega, b} \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{m} l_\varepsilon(f(x_i), y_i) \tag{5}$$

where C is the regularization constant and l_ε is the insensitive loss function.

$$l_\varepsilon(z) = \begin{cases} 0 \;\; if \;\; |z| \le \varepsilon \\ |z| - \varepsilon \;\; otherwise \end{cases} \tag{6}$$

Finally, as shown in formula (7), the support vector machine regression function is defined as:

$$f(x) = \sum_{i=1}^{m} \left(\widehat{a_i} - a_i\right) k(x_i, x) + b \tag{7}$$

Among them, a_i and $\widehat{a_i}$ are the non-negative Lagrange multiplier; $k(x_i, x)$ is the kernel function.

The kernel functions used in this paper is shown in Table 1.

Table 1. Kernel functions involved in this paper

Kernel function	Expression	Remark
Linear kernel	$K(x_{i,} x_j) = {x_i}^T x_j$	
Polynomial kernel	$K(x_{i,} x_j) = {x_i}^T {x_j}^d$	$d \geq 1$ is the degree of polynomial
Rbf Kernel	$K(x_{i,} x_j) = \exp\left(\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)$	$\sigma > 0$ is the bandwidth of the Gaussian kernel

2.6 Support Vector Machine Regression Prediction Model

The support vector machine regression prediction model is divided into four parts: data preprocessing, feature selection, model training and validation, evaluation and analysis, as shown in Fig. 2.

The basic principle is: firstly collect and analyze data such as tunnel geometry, shield construction parameters and stratum parameters, and preprocess the data, including: data cleaning, data integration, data transformation and data reduction. The correlation coefficient between the site construction data and the surface subsidence is analyzed by using the correlation coefficient, and the feature selection is carried out in combination with the correlation, and the attribute set is obtained. On this basis, the support vector machine regression model is used to perform regression prediction on the reduced data, and in order to compare the influence of different kernel functions on the PPMC-SVR model, the Linear kernel function, the Poly kernel function and the Rbf kernel function are selected respectively. Training set predictions. At the same time, the SVR model without feature selection is compared and analyzed, so as to analyze the influence of different features and kernel functions on the prediction structure.

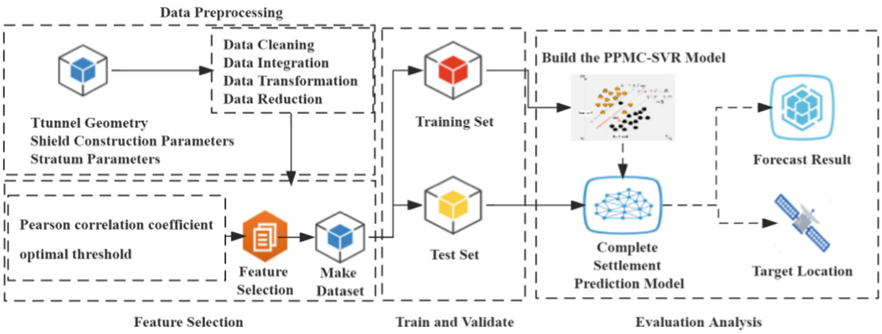

Fig. 2. Support vector machine regression prediction model include four stages: data preprocessing, feature selection, training and validate and evaluation and analysis.

3 Experiments

3.1 Engineering Background

Take the interval between Longmen Station and Longmen Avenue Station of Luoyang Metro Line 2 Project in Henan Province as an example. Starting from Luoyang Longmen Station, it goes down through Tongqu Road, Houzaimen Street, Yiluo Road and ends at Longmen Avenue Station. The interval is mainly located in the municipal Below the road and the planned road block, there are fewer buildings above the section. The total length of the tunnel is 1344.40 m, of which CK22 + 774.804 ~ CK23 + 821.163 is the shield method interval, the length of the shield section is 1046.359 m, the axis is 13.6–17.1 m from the ground, the outer diameter of the lining ring is 6.2 m, and the length of the ring piece is 1.5 m. The terrain of the tunnel excavation route is an alluvial-proluvial plain, and the site stratum is mainly mixed fill, loess-like silty clay, loess-like clayey silt, pebbles, and fine sand, with a thickness of 10–30 m. The groundwater is pore diving, buried at a depth of 10–20 m. The main physical and mechanical properties of each stratum are shown in Table 2.

Table 2. main physical and mechanical properties of each stratum

Soil layer	Thickness/m	Cohesion force/kPa	Internal friction angle/(°)	Poisson's ratio μ
Miscellaneous Fill	1.71	5	10	0.33
Silty clay	4.89	22	19	0.29
Sand and gravel layer	18.43	0	36	0.23

3.2 Data Source Description

On-site construction data is divided into three categories: tunnel geometry, shield construction parameters and stratum parameter data. The buried depth and radius of the tunnel are selected as geometrical factors. The main shield construction parameters include: total propulsion, soil bin pressure, cutter head torque, driving time, penetration, synchronous grouting amount, and slag output. The formation parameters include: cohesion, internal friction angle, and gravity γ. According to the needs of the project, combined with the method of sensor detection and manual collection, and all of them are transmitted remotely through the network. In this simulation experiment, we set up 1 cloud and 1 proxy-server in the cloud layer. In order to test the performance of ifogsim in different network topologies, the cloud system simulates and allocates 2, 3, 4, 4, 4, and 4 gateways, the corresponding sensors correspond to 4, 4, 4, 8, 12, and 16, respectively, named as config 1, config 2, config 3, config 4, config 5, and config 6, as shown in Table 3. In order to ensure the accuracy of the experiment, each group of experiments was performed 50 times, and the mean value was taken as the final value.

Table 3. Deployment configuration

User case	config 1	config 2	config 3	config 4	config 5	config 6
numbers of gateway	2	3	4	4	4	4
numbers of sensor	4	4	4	8	12	16

3.3 Test Method

(1) Simulation description

To realize the proposed edge intelligent computing architecture, we choose iFogSim simulation software. iFogSim is an improvement based on the cloud computing framework CloudSim. The physical components of iFogSim include Fog Device, Sensor, and Actuator, which can build multiple data centers, virtual machines, and effectively simulate actual scenarios [39–41].

In the experiment, we established the system architecture of the three-layer surface subsidence prediction model of cloud, edge and end, and designed two application module placement strategies: cloud-only placement strategy Cloud-only, edge placement strategy Edge-ward. Cloud-only placement strategy: All modules of the application are deployed in the data server, and users store and access information through the Internet; Edge placement strategy: The application modules are deployed near the edge of the network, and the processing is completed at the edge layer.

(2) Data preprocessing

The data preprocessing in this paper mainly includes two aspects: processing of outliers and data normalization.

Due to the poor observation conditions of shield construction, abnormal values of measurement data are often caused by factors such as abnormal environment, abnormal signals, and abnormal instruments. The surface subsidence data set contains some outliers, which need to be systematically analyzed and the errors should be eliminated. Because of the small amount of data in this dataset, this paper uses the boxplot method to determine outliers. The boxplot method is a method for finding outliers based on the interquartile range. The specific criterion is to calculate the minimum estimated value, maximum estimated value, first quartile, median and third quartile in the data. If the data exceeds the upper and lower limits, the boxplot will be automatically marked with circles. According to the principle of the boxplot method, this paper determines the outliers of the data set, and draws the boxplots of each parameter, taking the excavation time as the column, and it can be seen that the outliers are represented by red circles, as shown in Fig. 3. For outliers, the mean value is used instead, and the processed data set is combined into a new data set for subsequent modeling.

$$x = \frac{x_i - min(x_i)}{max(x_i) - min(x_i)} \tag{8}$$

Among them, x_i is the data to be normalized, $min(x_i)$ is the minimum value of the sample attribute, and $max(x_i)$ is the maximum value of the sample attribute.

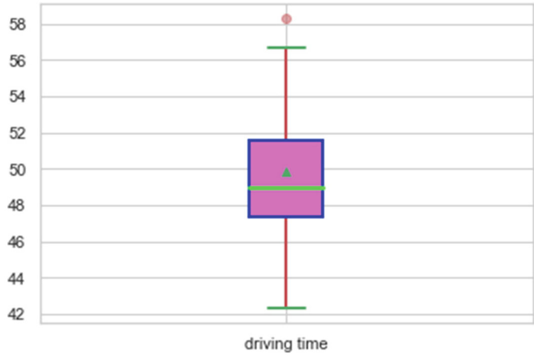

Fig. 3. Boxplot for driving time

In this paper, the characteristic parameters such as internal friction angle, severe γ, total thrust, soil bin pressure, cutter head torque, driving time, penetration, grouting amount, slag amount, settlement amount and other characteristic parameters are calculated by Pearson correlation coefficient. And draw the corresponding heat map to visualize the correlation between different factors, as shown in Fig. 4. Through this heat map, we can see that the settlement has a significant impact on the weight γ, total thrust, soil bin pressure, driving time, cutter head torque, grouting amount, and slag output. At the same time, settlement and penetration, The internal friction angle has a weak correlation. Similarly, we can see that the amount of grouting and the amount of slag are strongly correlated (two variables with a correlation of 0.84 in the figure), so we can only select the variable of grouting amount. The reason why we choose the feature of grouting amount is because The amount of grouting has a strong correlation with the amount of settlement. Similarly, we eliminated other features with little correlation, and finally selected the features for prediction as soil bin pressure, driving time, grouting amount, and settlement amount.

(3) Model training and testing

After correlation analysis, four items including soil bin pressure, excavation time, grouting amount, and settlement amount were selected as part of the input variables, and the corresponding normalized data were re-established as a sample set. The dataset was then divided by ten-fold cross-validation method. The Linear function, the Poly function, and the Rbf function are respectively selected as the kernel function for training to obtain the PPMC-SVR model. Also for comparison, the data set without feature selection is used for modeling, and comparative analysis and trial calculation are performed to analyze different features. And kernel function on the prediction structure.

4 Experimental Results

4.1 Round-Trip Time

Early detection of surface subsidence problems can effectively warn of major construction safety accidents, which requires sensor terminals that collect data, regional edge

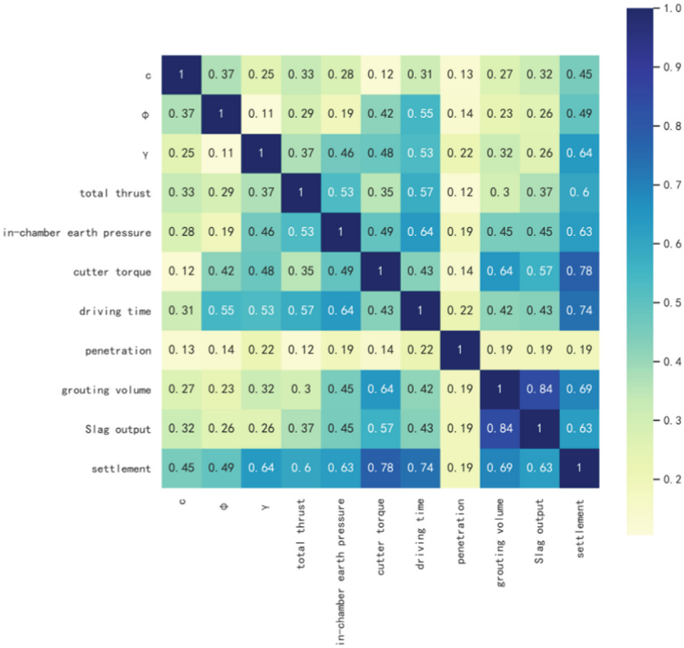

Fig. 4. Heat map for each feature

gateways that carry brain state classification, real-time communication modules between regional edge servers, and effective processing of prediction modules. The time lag in this cycle will seriously compromise the validity of surface subsidence predictions. In Fig. 5. It shows that the Round-Trip Time of the task scheduling algorithm using the Edge-ward placement strategy is significantly reduced compared to the cloud-only placement strategy environment.

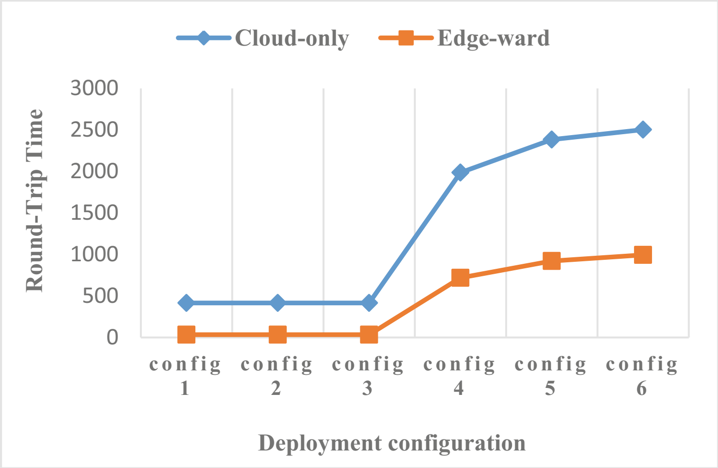

Fig. 5. Round-Trip Time

4.2 Total Execution Cost

As shown in Fig. 6, in the case of cloud-only placement strategy, as the number of sensors connected to the edge server increases, the execution cost of the network also increases significantly, resulting in further degradation of application performance. But if the edge-ward placement strategy is adopted, the network execution cost is greatly reduced.

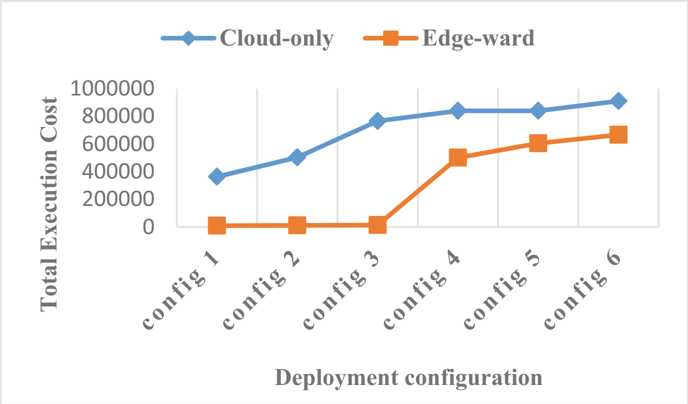

Fig. 6. Total Execution Cost

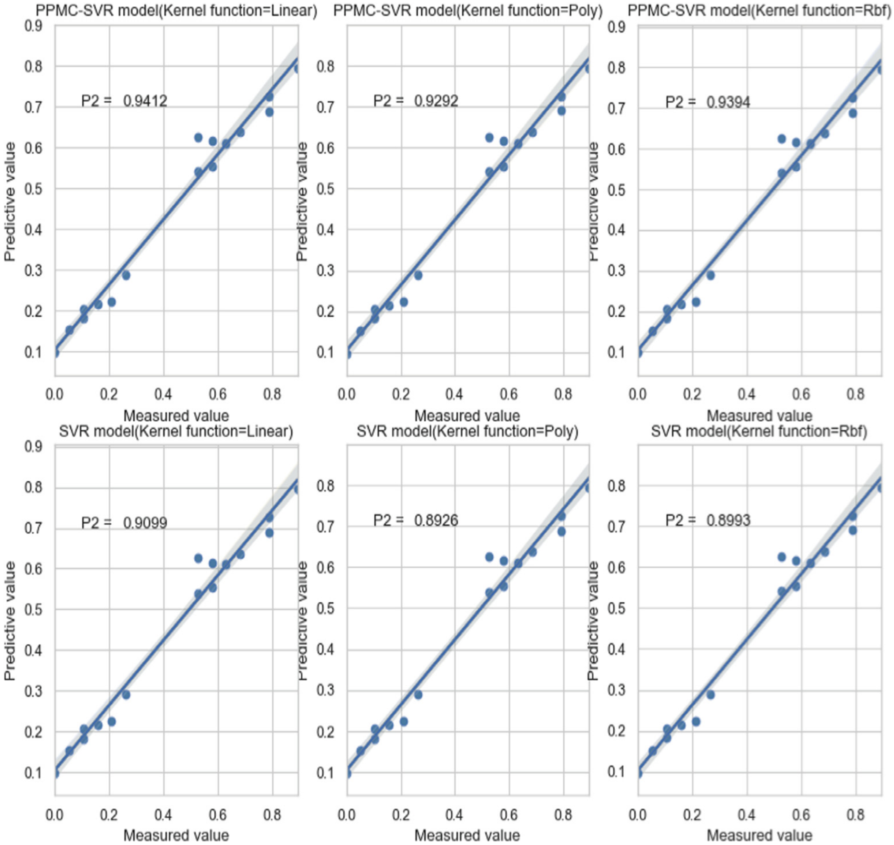

Fig. 7. Comparison of fitting effects of training samples with different kernel function

4.3 Comparison of Effects with Different Kernel Functions

In order to compare and analyze the performance of the PPMC-SVR model and the SVR model, this paper uses three kernel functions to model the PPMC-SVR model and the SVR model respectively, and compares the R2 of the training samples.

The results are shown in Fig. 7. From the fitting results of the training set, the horizontal comparison of similar models shows that the correlation between variables is higher and the error is smaller when Linear is selected as the kernel function. There is a better fitting effect.

It can be seen from Table 4 that the prediction errors of the PPMC-SVR model and the SVR model with Linear as the kernel function are 8.42% and 6.05%, respectively, which are smaller than the other two kernel functions; When comparing longitudinally with different kernel functions, the prediction errors of the PPMC-SVR model are smaller than those of the SVR model. In summary, the PPMC-SVR model with Linear as the kernel function is not only the fitting effect on the training samples, but also the generalization of the test samples. The ability is better than the other models.

Table 4. Prediction Error Comparison of Test Samples Using Different Kernel Functions

NO	model	Linear		Rbf		Poly	
		relative error	mean relative error	relative error	mean Relative error	relative error	mean relative error
1	PPMC-SVR	3.16	8.42	1.71	7.455	35.24	33.59
2		13.68		18.86		38.51	
3		13.18		−0.43		29.85	
4		3.66		− 8.82		30.77	
1	SVR	− 0.75	6.05	3.18	8.02	37.05	33.32
2		11.01		22.6		31.34	
3		12.22		0.41		40.36	
4		− 0.22		− 5.91		24.53	

5 Conclusions

"Safety first, prevention first" is the consistent policy of tunnel construction. Therefore, the timely and accurate prediction of surface subsidence has practical significance. In this paper, a surface subsidence prediction method based on edge intelligent environment is proposed, and various simulation results and performance indicators are evaluated through simulation experiments. The simulation results show that the method is feasible in the specific system framework of the three-layer surface subsidence prediction model of cloud, edge and end. Under the same kernel function, the performance of the PPMC-SVR model is better than that of the SVR model. The values are basically the same, the designed PPMC-SVR prediction model can accurately predict the surface subsidence, and the research results can provide reference for the prediction of the surface subsidence of the shield construction similar to the water-rich sand egg formation.

In future research, there is still much room for improvement, which can be summarized as follows:

(1) The problem of the experimental platform, the experiment in this paper is implemented on the iFogSim platform, and there is a certain error with the actual production environment.
(2) Dataset scenarios and quality issues. Data collection is not perfect, and there is a lack of post-consolidation and sub-consolidation settlement data, resulting in unpredictable long-term settlement.

Acknowledgment. This work was supported in part by the Scientific research projects funded by the Department of education of Hunan Province (No. 21C0628, No. 20C1472 and No. 22C0497), the Huaihua University Double First-Class initiative Applied Characteristic Discipline of Control Science and Engineering (No. ZNKZN2021–10), the National Natural Science Foundation of China (No. 62172182), the Hunan Provincial Natural Science Foundation of China (No. 2020JJ4490), the Project of Hunan Provincial Social Science Foundation (NO. 21JD046), the Huaihua University Project (No. HHUY2019–25), the Philosophy and Social Science Achievement Evaluation Committee of Huaihua (No. HSP2022YB40) and the Science and Technology Innovation 2030 Special Project Sub-Topics (No. 2018AAA0102100).

Data Availability. The data used to support the findings of this study are included within the article.

Conflicts of Interest. The authors declare that there are no conflicts of interest regarding the publication of this paper.

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