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DEFORMATION MONITORING AND ANALYSIS OF DEEP FOUNDATION PIT CONSTRUCTION PERIOD BASED ON INTERNET OF THINGS TECHNOLOGY

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Abstract. In order to solve the problem of low detection accuracy in building structure safety monitoring, the author proposes a deformation monitoring and analysis during deep foundation pit construction based on Internet of Things technology. This method takes a large-scale construction project in a certain city as an example, applies neural network prediction models to deformation monitoring of foundation pits and main structures, and compares and analyzes the predicted results with actual measurement data. The experimental results show that the average MAE value of the predicted values is 0.15mm, and the average RMSE value is 0.17mm. The prediction accuracy of the neural network prediction model is high, which meets the accuracy requirements of deformation monitoring prediction. The use of Internet of Things technology can effectively ensure the safety of large buildings during construction, and has wider application value and prospects in deformation monitoring of future construction projects.

Key words: Neural network, Deformation prediction, Precision analysis, IoT technology

1. Introduction. In recent years, with the continuous development of urbanization and the influx of population, the utilization of urban land resources is no longer limited to flat areas, and the development of underground space has become an important part of urban construction [1,2]. During the long-term operation of building structures, they may be affected by environmental, geological changes, loads, and other factors, which may lead to structural safety hazards such as settlement, deformation, stress reduction, or stress concentration. In severe cases, it can lead to structural damage. With the support of Internet of Things technology, engineering managers can use sensors to collect specific data and use this data to determine the condition of building structures, thereby timely discovering and addressing hidden dangers. With the continuous development of underground space, the construction scale of foundation pit engineering is also constantly increasing. Due to complex geological conditions and possible improper construction techniques, there is a risk of serious accidents such as foundation pit collapse and surrounding building collapse during the construction process of foundation pits. For example, the collapse of the foundation pit of a certain subway line has caused huge social impact and economic losses [3]. Through the investigation of more than 160 excavation accidents, it was found that inadequate monitoring and untimely alarms are important reasons for excavation engineering accidents, so excavation monitoring is becoming increasingly important.

During the construction process of foundation pits (foundation pit enclosure, earthwork excavation, and basement construction), changes in the stress state of the soil inside and outside the pit can cause deformation of the foundation pit enclosure and soil. When the internal force or deformation of the enclosure structure exceeds the allowable limit, it can lead to instability and damage of the foundation pit, resulting in serious construction accidents. In order to timely obtain information on the stress and deformation of the retaining structure and surrounding soil, provide early warning and guidance for foundation pit construction, and monitor the entire construction process [4].

2. Literature Review. During the construction process, the main body of the building experiences significant settlement due to the continuous increase in load [5]. How to ensure the safety of foundation pits and main construction is increasingly becoming a focus of attention. In order to ensure construction safety, monitoring points must be set up in important areas for monitoring. In order to accurately predict

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the trend of changes in foundation pits and building structures, it is crucial to adopt effective prediction methods. Currently, the main prediction methods used include establishing regression models, singular spectrum analysis, empirical mode analysis, and establishing Kalman filtering models. Due to the influence of various factors such as foundation, load, precipitation, construction environment, and personnel on the deformation monitoring data of the foundation pit and main body, the established regression model is not significant and the accuracy of the prediction model is poor [6]. Singular spectrum analysis utilizes monitoring data from multiple periods for time series analysis, in order to obtain trend terms and useful high-frequency signals, achieve time series reconstruction, and then predict and analyze monitoring data. However, due to the many deformation inducing factors of the foundation pit and the main body, it is difficult to decompose and reconstruct useful monitoring information through singular spectrum analysis, resulting in low prediction accuracy. Empirical mode analysis is generally suitable for short-term time series analysis and prediction, while deformation monitoring of foundation pits and building structures is generally a long-term process, so its reliability is low. The Kalman filter prediction model has strong applicability for establishing linear models, but its performance is poor for nonlinear applications. In order to improve the prediction accuracy of deformation monitoring data for foundation pits and main structures, and ensure the safety of engineering operation, it is necessary to study a high-precision and efficient prediction model [7].

The application of neural networks is becoming increasingly widespread, not only in medical, biological, mechanical automation, electronic computers and other fields, but also in the engineering field. Wang, R. S. et al. investigated how precipitation and excavation impact the deformation characteristics of foundation pits. Their findings suggest that as dewatering and excavation proceed, the effect of dewatering on the support structure's deformation diminishes. Instead, the primary factors influencing support structure deformation gradually transition from dewatering to excavation activities within the foundation pit[8]. Jiang, M. et al. conducted an analysis of deep foundation pit excavation techniques, using a specific project as a case study. This analysis encompassed the project's characteristics, key technical measures employed in deep foundation pit construction, and the assessment of safety risk prevention and control measures. The objective was to offer valuable insights for ensuring the construction quality and safety of deep foundation pit engineering projects[9]. ZHANG Shubin et al. believe that deep foundation pit construction technology is one of the core technologies in construction engineering. The application of deep foundation pit construction technology can fundamentally improve the quality of engineering, compact the strength of the foundation, and ensure the good quality of construction projects [10]. XUFei et al. believe that when conducting geotechnical investigations of deep foundation pits, workers should also fully consider factors such as the geological and hydrological environment around the construction area, and try to avoid the adverse effects of these factors on the excavation process during the design process, in order to promote the smooth progress of deep foundation pit excavation and further improve the quality and reliability of construction projects [11].

Therefore, neural networks have unique advantages in processing non-stationary and nonlinear deformation monitoring data, and can better predict the trend of deformation data changes. The author intends to use IoT based technology for deformation monitoring and analysis during the construction period of deep foundation pits.

3. Method.

3.1. Overall design of monitoring system. The Internet of Things technology measures the operating data of bridges, houses and other building structures through sensors, and collects, stores, calculates, integrates and displays structural data with the help of Internet technology. In bridge structure monitoring, sensors that need to be used according to their monitoring content include vibration sensors, cable tension sensors, strain sensors, load sensors, etc. The overall structure of the monitoring system is shown in Figure 1, which includes Narrow Band Internet of Things (NB IoT), Analog to Digital Converter (ADC), Universal Asynchronous Receiver Receiver (UART), and various sensors. NB IoT is a cellular network technology used to achieve the Internet of Things, which has the advantages of low power consumption and low cost. ADC and UART are advanced peripheral interfaces of microcontrollers used to transmit data collected by sensors throughout the entire system. The software system is deployed on the server to process and display the bridge structure safety data collected by the system [12].

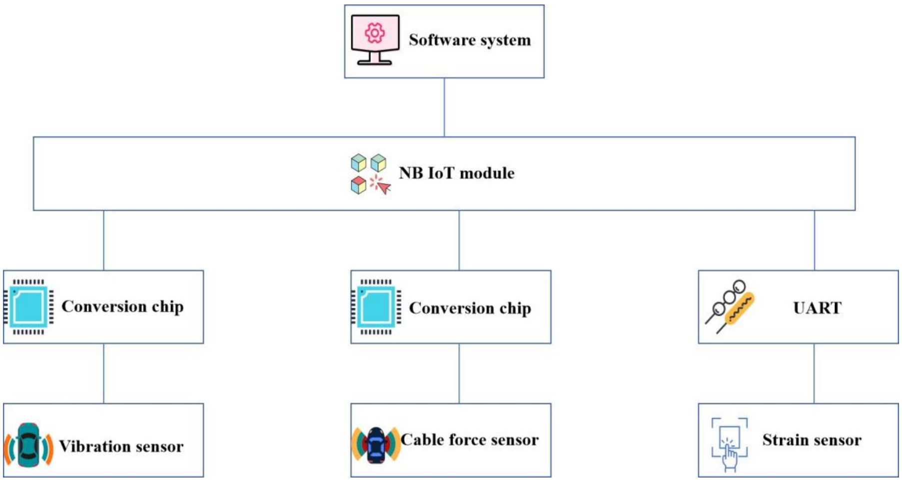

Fig. 3.1: Overall structure diagram of the monitoring system

3.2. Hardware Design of IoT Monitoring System.

(1) Sensor selection. Taking the YBJ-510 strain sensor as an example, in practical application, the sensor can be set at the pile foundation and other parts of the construction site to measure the initial frequency f_0, and then measure the real-time frequency f_i after a certain period of time. According to equation 3.1, the strain $\Delta\epsilon$ of the structure can be calculated.

$$\Delta\epsilon = K(f_i^2 - f_0^2) \tag{3.1}$$

In the formula, K is the calibration coefficient of the strain gauge. For vibration sensors, if the vibration speed is recorded as V, there are:

$$V = U/S_V \tag{3.2}$$

In the formula: U is the measured voltage value; S_V is the speed sensitivity of the sensor. For cable force sensors, the cable force is denoted as T, and the calculation method for T is shown in equation 3.3.

$$T = \frac{4ml^2 f_n^2}{n^2} - \frac{n^2 Eln^2}{I^2} \tag{3.3}$$

In the formula: I is the length of the steel cable; M is the weight per unit length of the steel cable; f_n is the nth frequency of the steel cable; EI is the bending stiffness of the steel cable; π is the pi. $n^2 EIn^2/I^2$ is the correction value of the bending stiffness of the steel cable to the cable force.

(2) The overall structure of the hardware system. After determining the main sensors of the monitoring system, other supporting hardware devices can be selected based on them, including Micro Controller Units (MCUs), power and voltage stabilization modules, and control circuits. The MCU of the system adopts STM32F103ZET6 chip, which integrates a digital to analog converter and can automatically convert voltage signals and digital signals. The chip transmits the data collected by the sensor to the NB IoT module through UART communication, and then transmits the data to the server of the software system through TCP/IP protocol [13,14].

3.3. Software Design of IoT Monitoring System.

(1) The overall structure of the software system. The software system consists of a database, front-end management interface, and server configuration. The database uses SQL Server, and the data Tables include strain threshold Table, vibration threshold Table, deformation threshold Table, cable force threshold table, load data Table, and others. Taking the cable force threshold Table as an example, its fields include cable number

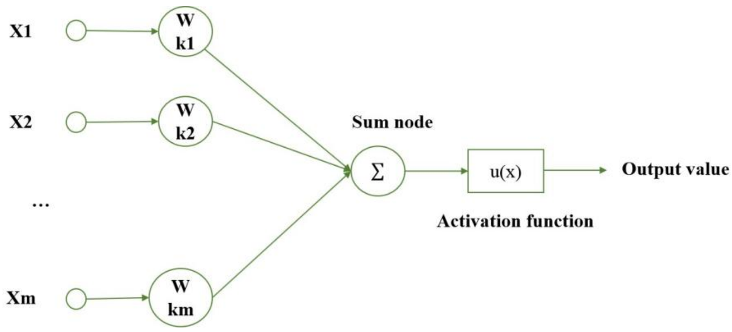

Fig. 3.2: Neuron Model

(Int type), cable length (Float type), unit length cable weight (Float type), cable force unit (Varchar type), cable force threshold (Float type), and input time (Timestamp type). The front-end management interface adopts MVC development mode, the back-end programming language is Java, and the system framework is SpringMVC [15].

(2) Calculation method for monitoring item threshold. The IoT monitoring system has an alarm function. Once the bridge tension, vibration effects, structural deformation, and structural strain monitored by the system exceed the threshold, the system will issue an alarm message. In order to design a reasonable monitoring alarm threshold, a finite element model of the construction site was constructed using Midas/Civil, with load types covering earthquake, vehicle, wind, and personnel activities.

(3) Design results of monitoring item threshold. The monitoring threshold includes cable tension, structural deformation, and structural strain.

3.4. Neural Network Models. Neurons are the fundamental information processing units of neural network models. The model diagram of neurons is shown in Figure 3.2.

The expression for neuron k is:

$$y_k = \varphi(u_K + b_K) \tag{3.4}$$

A neural network composed of multiple basic units of neurons has strong computing power. According to the classification of information flow within the network, it can be divided into feedforward networks and feedback networks [16].

(1) Feedforward network. In feedforward networks, information is first introduced from the outside by the input layer, flowing forward to the hidden layer and then to the output layer, layer by layer forward, so it is very simple to establish a multi-layer feedforward network (see Figure 3.3).

(2) Feedback network. In a feedback network, all nodes can process information and accept input from external information, as well as output to the outside world. Figure 3.4 shows a feedback network diagram of a single-layer fully connected structure [17].

3.5. Learning process of neural network prediction model. For neural networks, it is crucial to learn and improve their performance from the external environment. Learning is a process that requires external input, adjusting internal parameter structures (such as the number of hidden layer nodes), and adapting to the corresponding environment. The set used to solve learning problems is called a learning algorithm. The following text provides a brief introduction to several learning algorithms [18].

(1) Error correction learning. Assuming that neuron k is the unique node in the output layer of a certain network. The signal vector X(n) is the driver of neuron k, and the parameter n is the discrete time (the time step to adjust the weight of neuron k). The output signal $y_k(n)$ represents the actual output of neuron k, and $d_k(n)$ represents the expected response. This generates an error signal $e_k(n)$.

$$e_k(n) = d_k(n) - y_k(n) \tag{3.5}$$

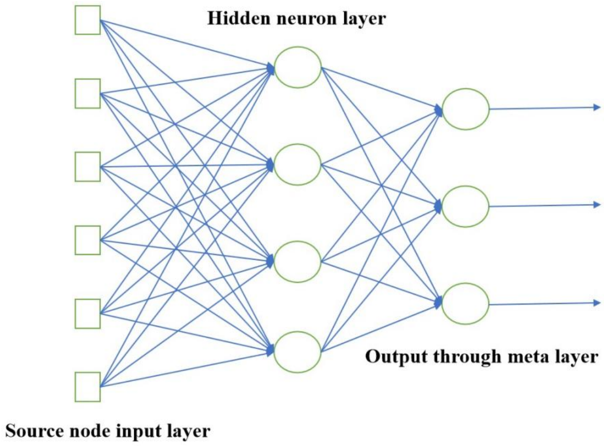

Fig. 3.3: feedforward network model

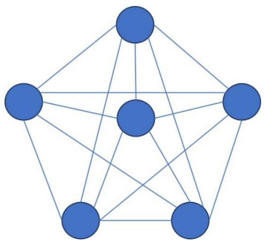

Fig. 3.4: Feedback network model of single-layer fully connected structure

By applying the error signal $e_k(n)$ to the weight of neuron k, the weight of neuron k is adjusted and adjusted until the network reaches a stable state (with almost no change in weight).

(2) Hebb Learning. If two neurons connected at both ends of a synapse are synchronously activated, the strength of that synapse is selectively enhanced; Otherwise, synapses will be selectively weakened or eliminated. The simplest mathematical expression Hebb learns is:

$$\Delta w_{k,j}(n) = \eta y_k(n) - x_k(n) \tag{3.6}$$

In the formula, x_k represents the presynaptic signal, y_k represents the postsynaptic signal, and $\Delta w_{k,j}$ represents the synaptic weight of neuron k, η represents a positive constant that determines the learning rate.

(3) Competitive learning. In competitive learning, output neurons in artificial neural networks compete with each other, with only one output neuron activated. Each input node of the winning neuron releases its weight in a certain proportion. The standard competitive learning rules are defined as:

$$\Delta w_{k,j} = f(x) = \begin{cases} \eta(x_j - w_{k,j}), \text{If neuron k fails to compete} \\ 0, \text{If neuron k fails to compete} \end{cases} \tag{3.7}$$

3.6. Design of neural network prediction model. According to the principles of neural networks, the design of neural networks mainly involves determining the number of neurons and initial parameters of the three-layer network [19].

(1) Number of network layers. The RBF neural networks constructed in this project are all three-layer networks, consisting of input layer, output layer, and hidden layer.

(2) Number of input layer neurons. Based on experience, the number of neurons in the input layer is equal to the dimensionality of the feature vectors of the training samples. Due to the various factors affecting the deformation of foundation pits and main buildings, including air pressure, temperature, precipitation, foundation, and building loads, which are difficult to obtain in practical work, deformation monitoring values are used as input variables and the number of variables is determined.

(3) Determination of the number of neurons in the output layer. Given the task at hand, which involves predicting deformation data for both the foundation pit and the main building structure, the output layer of the neural network comprises a single neuron. To address the inherent uncertainty in the output values, the output layer employs the Pureline function as its activation function.

(4) Number of hidden layer neurons. While there isn't a definitive algorithm for determining the number of neurons, it's widely recognized that the number of hidden neurons significantly impacts the performance of neural networks. Through iterative experimentation, researchers have derived a reference empirical formula:

$$m = \sqrt{n+k} + a \tag{3.8}$$

The formula incorporates several parameters: m represents the number of hidden layer neurons, n signifies the number of input layer neurons, k denotes the number of output layer neurons, and a is a constant ranging from 1 to 10. By varying the value of a, researchers can analyze the network learning error and ascertain an appropriate number of hidden layer neurons for optimal performance.

(5) Selection of error accuracy. The error accuracy needs to be determined through training. The initial value for this project is 10^{-4}, and adjustments will be made based on the convergence of the neural network.

(6) Selection of learning rate. Selecting an appropriate learning rate is paramount in training neural networks. The learning rate directly influences the magnitude of weight adjustments: higher learning rates result in larger weight changes. If the learning rate is small, the convergence rate of the network will also be affected. Typically, a learning rate of 1 is chosen to strike a balance between convergence speed and computational performance.

(7) Selection of learning frequency. The number of learning sessions needs to be determined based on specific circumstances. Generally, a larger number of learning iterations result in higher prediction accuracy.

3.7. Test preparation. This project is located in the central area of a certain city, with convenient transportation. The project is equipped with two levels of basement and a pile raft foundation. The excavation depth of the foundation pit is 10.0m, which belongs to a large-scale deep foundation pit project. The overall design scheme of the project adopts a sequential approach of drilling and grouting pile row, triaxial cement soil mixing pile waterproof curtain, and a diagonal brace combined with angle brace support system. The safety level of foundation pit support is Level 2. Monitor the displacement and settlement of the top of the foundation pit retaining piles and the settlement of surrounding roads during the construction process of the foundation pit. Among them, there are 48 monitoring points on the top of the retaining piles and 20 monitoring points on the settlement of surrounding roads. The main buildings of the project are two high-rise buildings, A1 # and A2 #, with 59 floors and a height of 303m, in zone A. Based on the structure, foundation, and load characteristics of the building, and in combination with relevant regulatory requirements, 24 observation points are set up for Building A1 # and Building A2 # [20].

4. Results and Discussion.

4.1. Analysis of experimental prediction data. According to the design of the network, the neural network structure for this experiment was determined. The cumulative changes of the first 40 monitoring points of foundation pit settlement CW6, CW15, CW22, CW36, and CW41 were selected as training samples for the network and trained separately to predict the settlement deformation for the next 10 times. In addition, the first 40 monitoring points of main settlement A107, A118, A201, A212, and A222 were selected to predict the settlement deformation for the next 10 times.

(1) Training results of point CW6. Compare and analyze the actual measured values of point CW6 with the predicted values of the neural network, as shown in Figure 4.1.

From the CW6 settlement change curve in Figure 4.1, it can be seen that the trend between the two is consistent, indicating a good prediction effect. In order to more intuitively reflect the comparison between

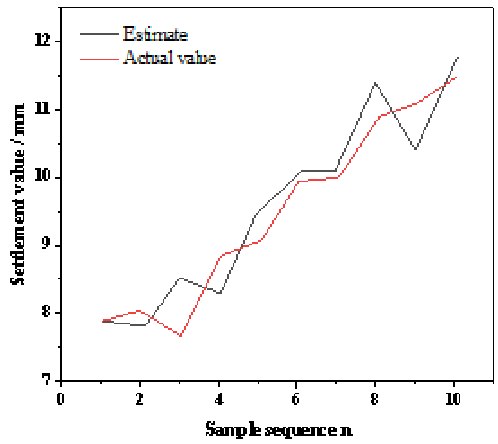

Fig. 4.1: Time series of predicted and actual measured settlement values at monitoring point CW6

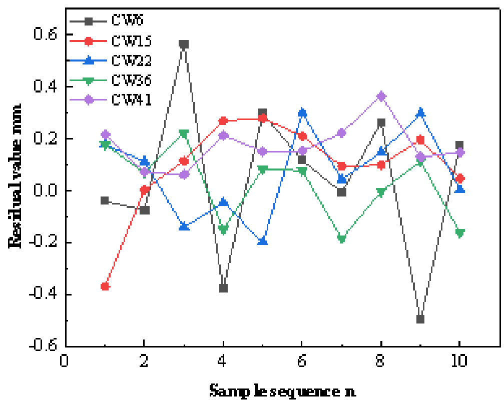

Fig. 4.2: Residual sequence diagram of foundation pit slope top settlement predicted by neural network

the actual and predicted values of the settlement at the top of the foundation pit slope, residual time series diagrams of monitoring points CW6, CW15, CW22, CW36, and CW41 were drawn. As shown in Figure 4.2.

In order to more intuitively reflect the prediction effect of building main body settlement, draw residual time series diagrams of neural network prediction values and observation values of monitoring points A107, A118, A201, A212, and A222 (as shown in Figure 4.3).

By analyzing the residual time series of the 5 monitoring points in the foundation pit and the 5 monitoring points for the main settlement, it can be seen that the residual values are all within 0.45mm, and the residual values are all around the 0 axis. After calculation, the maximum residual value is 0.43mm of the monitoring point CW6 Phase 3.

In order to further analyze the reliability and accuracy of neural network deformation prediction technology, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were introduced. The test analysis results are shown in Table 4.1.

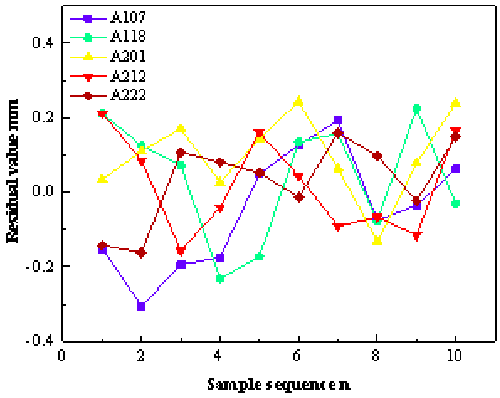

Fig. 4.3: Residual sequence diagram of main body settlement predicted by neural network

Table 4.1: Statistics of neural network prediction accuracy

Monitoring points	MAE/mm	RMSE/mm
CW6	0.21	0.29
CW15	0.16	0.19
CW22	0.14	0.16
CW36	0.10	0.12
CW41	0.16	0.18
A107	0.13	0.15
A118	0.13	0.15
A201	0.11	0.13
A212	0.11	0.12
A222	0.08	0.10

According to Table 4.1, the MAE and RMSE values predicted by the IoT neural network prediction model are all within 0.20mm and 0.30mm, with an average MAE of 0.15mm and an average RMSE of 0.17mm. The error value meets the accuracy requirements for measurement prediction. Which further demonstrates that the prediction model based on the Internet of Things neural network has good prediction accuracy, can effectively ensure the safety of high-rise buildings during construction and operation, and has more extensive application value and prospects in future prediction of foundation pit deformation and main body settlement deformation.

5. Conclusion. The author proposes a deformation monitoring and analysis method for deep foundation pit construction based on Internet of Things technology. Using an Internet of Things neural network prediction model, the deformation monitoring data of the main body and foundation pit of a super high-rise building in a certain city are predicted and analyzed. The predicted data from 5 monitoring points of the selected foundation pit and 5 monitoring points of the main settlement are analyzed. The results show that the average MAE value is 0.15 mm and the average RMSE value is 0.17 mm. The Internet of Things neural network has high prediction accuracy and can be well applied to predict deformation data of buildings and foundation pits, effectively ensuring the safety of high-rise buildings during construction and operation. It has a wider application value and prospects in future foundation pit deformation prediction.

6. Fund project. Enterprise entrusted Project approval unit: Jiangsu Provincial Institute of Geological Exploration and Technology Project name: Research on the key technology of early warning of super-large and super-deep subway foundation pit".

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