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Real-Time Monitoring and Platform Design for Concrete Compactness Using Long Short-Term Memory Networks

Kenan Zhao, Jie Chen, Yanke Shi*, Kai Sun

School of Civil Engineering and Communication, North China University of Water Resources and Electric Power, 450045 Zhengzhou, China

* Correspondence: Yanke Shi (shiyanke@ncwu.edu.cn)

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Abstract: To address the complexities and inaccuracies associated with traditional methods of concrete compactness monitoring, in this paper, a real-time monitoring approach based on long short-term memory (LSTM) networks has been developed. Traditional methods often involve cumbersome data processing and yield large errors, especially in complex environments, in contrast, the proposed method leverages the LSTM network's ability to process time-series data, enhancing accuracy in detecting compactness defects within concrete structures, and the ultrasonic wave velocity through concrete under standard conditions has been set as a baseline value. The platform can visualize the curve of ultrasonic propagation speed in the monitored concrete over time, allowing for a direct comparison with the baseline to assess the extent and location of potential defects. The degree of deviation from the baseline indicates the compactness and defect severity, facilitating more accurate monitoring. Additionally, a user-friendly monitoring platform interface has been designed using Mock Plus, enabling rapid prototyping and optimization for enhanced data visualization and user interaction, this design allows for effective real-time monitoring, data processing, and user engagement. By integrating advanced machine learning techniques with intuitive platform design, the proposed method offers a significant improvement in monitoring concrete compactness, potentially benefiting both research and practical applications in structural health monitoring.

Keywords: Long short-term memory network; Concrete compactness; Ultrasonic wave monitoring; Mock plus; Real-time monitoring platform

1 Introduction

In recent years, with the continuous improvement of construction quality control standards, accurate monitoring of concrete compactness has become increasingly critical. In the construction process, due to small changes in vibration mode, material ratio, and environmental conditions, the concrete compactness will fluctuate, thus affecting the overall quality and performance of the structure. Although traditional non-destructive monitoring methods such as acoustic emission detection and electromagnetic wave detection can provide a certain degree of information about the internal structure of concrete, most of them are tested after the concrete has a certain strength and cannot carry out real-time monitoring of concrete during the pouring process. With the introduction of neural networks into the ranks of concrete non-destructive monitoring, the intelligence and accuracy of the monitoring system have been significantly improved.

At present, many scholars have studied the application of neural networks in concrete structures. Asteris et al. [1] conducted research to implement a hybrid integrated agent machine learning technique to predict the compressive strength of concrete. Through experiments, it is found that the newly constructed HENSM model has higher prediction accuracy than other models. Ju et al. [2] proposed a concrete strength estimation method combining nano-enhanced sensors, piezoelectric impedance technology, LSTM, and an artificial neural network that provides high-precision strength prediction for construction safety and efficiency through real-time monitoring and analysis of multiple factors. De Smedt and De Weerdt [3] can capture more detailed information between activities compared to process model predictions, while being compatible with typical predictive process monitoring objectives with the same constraints. Imran et al. [4] propose two integrated models for accurately predicting the compressive strength of new concrete containing RCA and GGBFS. Compared with traditional concrete strength estimation, the prediction of compressive strength based on machine learning is accurate, robust and precise. Ranjbar and Toufigh [5] proposed two LSTM network architectures for concrete damage assessment based on ultrasonic waves and compared different input configurations and feature extraction methods. The results showed that direct use of time series signals as LSTM model inputs was more effective than manual feature extraction. Gamil et al. [6] used the long short-term memory methods of shallow neural networks and deep neural networks to establish a prediction model based on real-time data from controlled laboratory test sequences. Golafshani and Behnood [7] established a prediction model for the compressive strength of silica concrete by using the biogeography planning algorithm and estimated the optimal mix ratio by using the constrained biogeography optimization algorithm. Joshi et al. [8] predicted the compressive strength of high-performance concrete and fiber-high-strength self-compacted concrete. In the prediction stage of concrete compressive strength, a hybrid algorithm was designed by combining a deep belief network and long short-term memory, the prediction accuracy of the model was improved. Guzmán-Torres et al. [9] obtained a comprehensive data set for concreteXAI involving mechanical testing and non-destructive evaluation through long-term experiments in the laboratory. ConcreteXAI can be seamlessly integrated with deep learning models so that these models can be directly applied to predict or estimate desired properties. Shim and Park [10] proposed an adaptive SSI-LSTM method combined with deep learning technology for real-time assessment of changes in dynamic characteristics of building structures, which solved the problems of accuracy and calculation time in the OMA method and verified its practicability in experiments and response data of high-rise buildings. Kumar et al. [11] proposed long short-term memory (1D-CNN-LSTM) based on one-dimensional convolutional neural networks to predict carbonization depth and compressive strength of concrete. Gu and Liu [12] proposed a detection method based on the YOLOv7 deep learning algorithm. The test results show that the research model can detect all concrete structural defects and has a relatively good detection ability for concrete structural defects under conditions such as rain and dust. Huang et al. [13] proposed a real-time detection method for apparent cracks in concrete DAMS based on the YOLOX deep learning object detection algorithm of a neural network for target detection, which could meet the requirements of efficient, accurate, and real-time crack detection in concrete DAMS. Min et al. [14] and Xu et al. [15] proposed a structural pattern recognition method combining a deep neural network and a long short-term memory algorithm that can effectively analyze and predict the long-term structural response data of cable-supported bridges. Kumar et al. [16] introduced an open source GUI based on random forest to close the gap between prediction effects. The interface helps operators make mix ratio decisions by accurately estimating SCC compressive strength under various test conditions. Al-Selwi et al. [17] analyzed the literature on weight initialization and optimization techniques for improving the performance of NN-LSTM models from 2018 to 2023 through a systematic literature review based on PRISMA, providing directions for improving LSTM networks. Zhang [18] proposed a real-time target detection algorithm for complex construction environments and a behavior recognition algorithm integrating motion capture and spatial-temporal attention according to the research status of target detection and behavior recognition algorithms, and built an efficient quality monitoring system for the concrete construction process by using the above algorithms. Ai et al. [19] proposed an anomaly detection method based on a dynamic prediction model and compared the performance of ARIMA and LSTM models in processing SHM data from immersed tube tunnels. The results show that ARIMA is suitable for short-term prediction, while LSTM is better at long-term trend capture and early warning.

In summary, many scholars have studied the monitoring of concrete compactness by various methods, such as acoustic wave propagation and electromagnetic wave measurement [20, 21]. However, in engineering practice, these evaluation methods are not direct and efficient enough. In order to provide a fast and effective evaluation method for concrete performance, this paper proposes a real-time monitoring method for concrete compactness based on a long short-term memory network and designs a monitoring platform for concrete compactness. The concrete compactness evaluation model is obtained through MATLAB training and LSTM neural network training. The concrete compactness evaluation model is used to predict the subsequent vibration quality of concrete. When the predicted results show that the concrete compactness is poor, the defect degree of the poor area is determined, and the location of the poor area is located. Finally, a monitoring platform for concrete compactness was established to monitor the compactness of concrete in the process of vibratory pouring. All data and processes in the monitoring process would be recorded and saved by the monitoring platform. When the vibration of the concrete is insufficient or excessive, the staff can take timely and effective protective and remedial measures according to the compactness monitoring data to ensure that the concrete has good performance in the process of vibration pouring and improve the strength of the concrete.

2 Theory Summary

2.1 Model Algorithm of Long Short-Term Memory Network

The main difference between the LSTM network structure model and other network models is the memory cell structure. The memory cell can store the processed historical information data and has a special input gate mechanism inside, which can predict the structure to a greater extent according to important information. As shown in Figure 1, the direction of information transmission in the memory cell structure is consistent with the direction of the arrow shown in the figure. The forgetting gate, input gate, and output gate are the main components of memory cell structure, and the communication among them can further realize the memory function of the LSTM network. In LSTM neural networks, the initial data of the memory cell structure is usually input in the form of vectors, and these initial data and the data in the forgetting gate are para-multiplied to judge the degree of forgetting and decide whether to store key information in the cell. The long-term memory output of the current moment not only brings together the information stored in the cell but also fuses it with the new input. The output of the short-term memory is the product of the long-term memory and the activation function, multiplied by the output gate element. Then, through a layer of neural network processing, the final output of the next moment is generated.

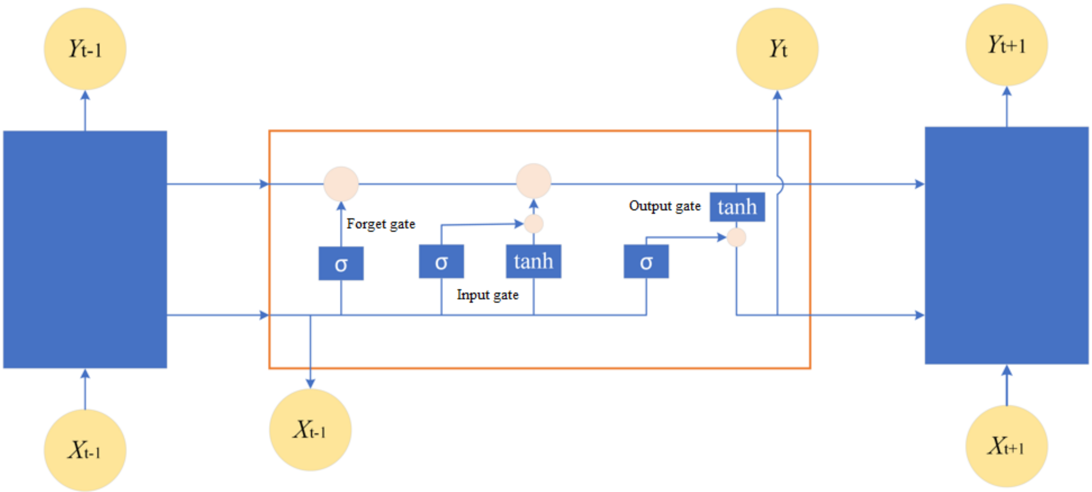

Figure 1. Flow chart of LSTM network structure model

In the LSTM network structure, the state in the memory unit gradually transmits information through the top horizontal line on the graph. With its unique gating mechanism, the LSTM model successfully overcomes the long-term dependence challenge encountered by recurrent neural networks when processing time series data and significantly improves the model's ability to capture long-term information. The horizontal line represents the data from previous historical moments that the current moment can rely on. When new data enters the model, the state of the memory unit filters, evaluates, and updates the information through the multiplication operation algorithm. In the output vector of the neural network layer, the value of each element ranges from 0 to 1, which actually reflects the weight of the corresponding information to be passed. The steps for training a long short-term memory network are shown in Figure 2.

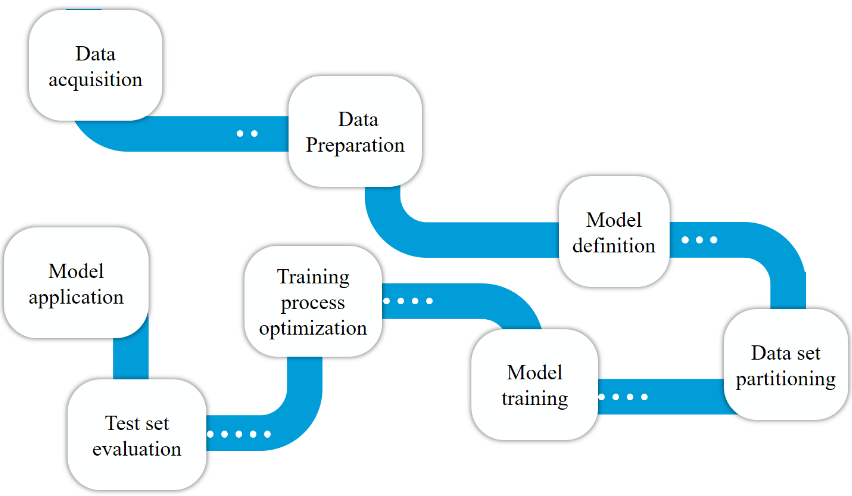

Figure 2. Training steps of long short-term memory network

The selection of LSTM parameters mainly involves the following aspects:

(1) Number of hidden layer units: Determine the capacity and expressiveness of the network.

(2) Input dimension and output dimension: The input dimension corresponds to the number of features in the input data, and the output dimension is the number of predicted results per time step.

(3) Time increment: The length of the sequence affects the time dependence that the model is able to capture.

(4) Learning rate: The step size of the weight is adjusted during optimization. Too high a learning rate may lead to unstable training; too low a learning rate may lead to too slow training.

(5) Batch size: The amount of data used each time the weights are updated. Larger batches can speed up training but may consume more memory.

(6) Discard rate: Used to prevent overfitting.

(7) Optimizer: The selection of a suitable optimization algorithm has great influence on the model training effect.

Regarding the calculation process of LSTM, literature [22] provides a more systematic calculation method. The input value x_t at time t and the output value y_{t-1} at time $t-1$ are taken as the initial data of the network model, and the information b_t in the cell is replaced in real time according to the three-gate structure in the memory cell, as well as the output y_t of the memory cell at that time. Three of the gates work as follows:

The forget gate determines whether the input information and the last time information are forgotten or retained through the sigmoid function. The formula is as follows:

$$f_t = \sigma\left(W \cdot [y_{t-1}, x_t] + b\right) \tag{1}$$

In the formula: y_{t-1} and x_t are the output values of the previous moment and the input value of the current moment, respectively; σ stands for sigmoid activation function; W is the weight of the forgetting door; b is the offset of the forgetting gate.

The input gate is a cell state that is obtained by controlling the addition of new information during training, and the content of the information update is determined by the sigmoid layer. The formula is as follows:

$$\begin{aligned} i_t &= \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \\ K_t &= \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_k\right) \end{aligned} \tag{2}$$

The previous state multiplied by f_t determines the forgotten information, while adding new information for training, the formula is as follows:

$$B_t = f_t \cdot B_{t-1} + i_t \cdot B_t \tag{3}$$

For the output gate in the LSTM model, it first determines the weights of the outputs through the sigmoid activation function and then multiplies these weights with the candidate cell states generated by the tanh function to arrive at the final output value. The formula is as follows:

$$\begin{aligned} O_t &= \sigma\left(W_0 \cdot [y_{t-1}, x_t] + b_0\right) \\ y_t &= O_t \cdot \tanh\left(B_t\right) \end{aligned} \tag{4}$$

In the whole training process, this paper adopts the Adam optimization algorithm. Adam algorithm combines the advantages of AdaGrad algorithm and RMSProp optimization algorithms, comprehensively considers the first-order moment estimation and second-order moment estimation of gradient, and determines different learning rate values according to the results of moment estimation. The expression is as follows:

$$\begin{aligned} m_t &= \beta_1 m_{t-1} + (1-\beta_1)\, g_t \\ v_t &= \beta_2 v_{t-1} + (1-\beta_2)\, g_t^2 \end{aligned} \tag{5}$$

The m_t and v_t in the formula are the first-order moment estimates and second-order moment estimates of the current gradient; g_t is the current gradient value; β_1 and β_2 are the coefficients.

The values of m and t need to be corrected for the deviation, and the corrected Adam method expression is as follows:

$$\theta_{\mathrm{t+1}} = \theta_t - \frac{\eta}{\varepsilon + \sqrt{\hat{v}_t}}\hat{m}_t \tag{6}$$

where,

$$\begin{aligned} \hat{m}_t &= \tfrac{m_t}{1-\beta_1^t} \\ \hat{v}_t &= \tfrac{v_t}{1-\beta_2^t} \end{aligned} \tag{7}$$

2.2 Principle of Early Age Monitoring of Concrete Compactness

In the whole process of concrete, from pouring to reaching the design strength, there is a close relationship and mutual influence between compactness, strength, elastic modulus, and stress wave propagation characteristics. In this process, the elastic modulus of the concrete is constantly changing, and the propagation speed and signal amplitude of the stress wave will also change due to different concrete conditions. The wave equation is as follows:

$$\frac{\partial^2 u}{\partial x^2} = \frac{1}{c_b^2} \frac{\partial^2 u}{\partial t^2} \tag{8}$$

In the formula: $c_b^2 = E/\rho$, E is the elastic modulus of concrete; ρ is the density of concrete; u is the displacement; x is the specific position coordinate. After a certain period of time, the average power P of the reaction spectrum can be expressed as:

$$P = EA^2\omega^2/\left(2c_{\mathrm{b}}\right) = \sqrt{E\rho}A^2\omega^2/2 \tag{9}$$

In the formula: ω is the frequency of the stress wave; A is the signal amplitude, and:

$$A = \left(\frac{1}{\omega}\right)\left(\frac{4P^2}{E\rho}\right)^{\frac{1}{4}} \tag{10}$$

According to formula (7), the signal amplitude A is mainly related to the frequency and power of the signal as well as the elastic modulus and density of the material. With the increase of elastic modulus, the signal amplitude A becomes smaller and smaller, showing an inversely proportional relationship. When the amplitude of the signal is larger, less energy is lost, and the faster the ultrasonic wave propagates.

The quantitative relationship between the velocity V of ultrasonic wave propagation in concrete and the density of concrete can be described by the following formula:

$$V = \sqrt{\frac{E}{\rho}} \tag{11}$$

In the formula: E is the elastic modulus of concrete; ρ is the density of concrete.

As the density of concrete increases, that is, the porosity decreases, the internal structure of concrete becomes denser and uniform. This change directly affects the elastic modulus E of concrete, causing it to increase significantly. The higher the compactness, the smaller the deformation ability and the larger the elastic modulus of concrete under stress. At the same time, in this case, the density ρ change of concrete is relatively small, because the improvement of density is mainly reflected in the reduction of porosity, and the reduction of porosity has limited impact on the total mass. Therefore, the propagation speed V of ultrasonic wave in concrete will increase significantly with the increase of elastic modulus.

2.3 Prediction Model of Concrete Compactness Based on LSTM

The LSTM network model established in this study consists of an input layer, three hidden layers, and an output layer. At each node of the input layer, three characteristic parameter values of the input sample are respectively the vibration depth of the vibrator, the vibration time of the vibrator, and the vibration frequency of the vibrator. The main factors affecting the model's performance are as follows:

(1) Data quality and quantity: The precision of concrete compactness monitoring depends on high quality and sufficient data. Noise, missing values, or false labels in the data can cause instability in model training and affect the prediction results.

(2) Feature engineering: Inappropriate feature selection or processing can result in models that cannot effectively learn patterns in the data. Suitable feature engineering can improve the prediction ability and model generalization ability of LSTM.

(3) Model parameters and structure: Improper selection of parameters may result in overfitting or underfitting of the model, thus affecting the prediction accuracy. The complexity of the model structure also needs to be appropriately adjusted to balance training efficiency and prediction accuracy.

(4) Training process: It includes the segmentation of training data, the number of training cycles, and the selection of an optimization algorithm.

(5) Environmental factor: The environmental conditions during concrete mixing have significant influence on the compactness.

Due to the lack of control group data, it is difficult to evaluate the advantages of concrete compactness monitoring methods based on long short-term memory networks. In order to solve this problem, this paper uses the spring back instrument method to measure the compactness of the same concrete specimen. Firstly, the defect degree and location of concrete specimens' compactness are predicted by the method based on the long- and short-term memory network mentioned above. After curing the same specimen for 28 days, the elastic meter method is used to detect the concrete compactivity, which will be compared with the predicted results of the LSTM method and the detection results of the elastic meter. The results show that the accuracy of the defect degree of concrete compactivity predicted in this paper is more than 95% compared with the results detected by the position and rebound instrument. Therefore, the method proposed in this paper can be used to monitor the defect degree and defect location of concrete compactivity in real time. The method is simple to operate and greatly improves the structural safety.

3 Concrete Compactness Monitoring Method

3.1 Data Acquisition and Training

The data source of this paper is obtained through experiments. In the experiment, the signal is generated by the waveform generator, and the piezoelectric ceramic end of the piezoelectric sensor is placed in the specified position of the concrete to stimulate the piezoelectric sensor to generate the detection signal. The detection signal is propagated in the concrete and then received by a piezoelectric sensor and its connected data acquisition card. The experimental equipment is shown in Figures 3-6. The purpose of the experiment is to obtain the ultrasonic velocity change data under different conditions by changing the vibration time and the insertion depth of the vibrator. After data preprocessing, normalization, and other operations, neural network training can begin.

The PZT patch of the piezoelectric sensor is fixed on both internal ends of the concrete specimen to be monitored. One end is used as a driver to transmit electrical signals, and the other end is used as a sensor to receive signals. The waveform generator is used to generate a specific voltage signal. When the signal reaches the piezoelectric sensor 1, the driver at the excitation terminal causes the deformation of the surrounding medium due to the inverse piezoelectric effect, which generates a stress wave and propagates in the sample. Subsequently, the stress wave reaches the piezoelectric sensor 2, and under the action of the positive piezoelectric effect, an electrical signal is generated. The piezoelectric sensor 2 is connected to the data acquisition card, and the final transmission waveform and data results are transmitted to the laptop computer for further processing.

Figure 3. Waveform generator

Figure 4. Piezoelectric sensor

Figure 5. Data acquisition card

Figure 6. Laptop computer

Data collection and data preprocessing have been completed. According to Figure 2, the next steps are described in detail:

(1) Model definition: It includes the setting of layer number and structure, activation function, loss function, and hyperparameters of the network.

(2) Data set partitioning: The first 80% of the data set is divided into the training set, 10% into the validation set, and 10% into the test set.

(3) Model training: Using the data set that has been divided, the parameters of the neural network model are gradually adjusted by optimizing the algorithm.

(4) Training process optimization: By modifying the number of layers and hyperparameters of the network when the model is defined, the model can perform better.

(5) Test set evaluation: Evaluate the performance and generalization ability of the trained model on the data set used independently of the training process.

(6) Model application: The trained LSTM network is deployed on the concrete compactness monitoring platform.

3.2 Determination of Defect Degree of Concrete Compactness

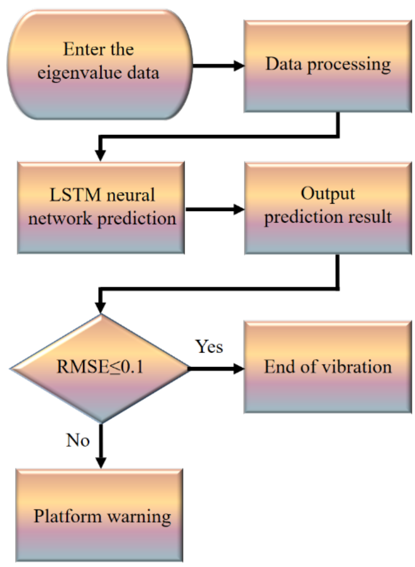

Figure 7. Flow chart of monitoring and control of vibration quality of concrete

In the monitoring and control process of concrete vibration quality, when the sensor monitors the vibration time and insertion depth of the concrete vibrator, the two are input into the trained LSTM model in the monitoring platform as characteristic values for prediction. The processing process follows strict academic norms to ensure the validity and accuracy of the data. The monitoring and control process of concrete vibration quality is shown in Figure 7.

According to this flow chart, the monitoring platform will display the final result. For the concrete compactness that meets the requirements, that is, the RMSE value is within a certain range, the monitoring platform will continue to monitor and collect data to predict the vibration results of the next section of concrete in real time. For prediction results that do not meet the requirements, that is, the RMSE value is outside a certain range, the monitoring platform will immediately trigger the alarm and record the abnormal data value, so that the operator can find and view the abnormal situation and grasp the degree of concrete vibration defects in time.

3.3 Location of Defects in Concrete Compactness

Firstly, the wave velocity monitor is used to determine the range of the ultrasonic wave velocity warning value in standard concrete. Secondly, the vibration time and the insertion depth of the vibrator are input into the monitoring platform. The platform draws the time-wave velocity curve according to the input data and then performs data fitting to obtain the function between the change of time and wave velocity. The position of concrete vibration defects can be located by calculating the end of the platform, and remedial measures can be taken in time. The locating process of concrete vibration defects is shown in Figure 8.

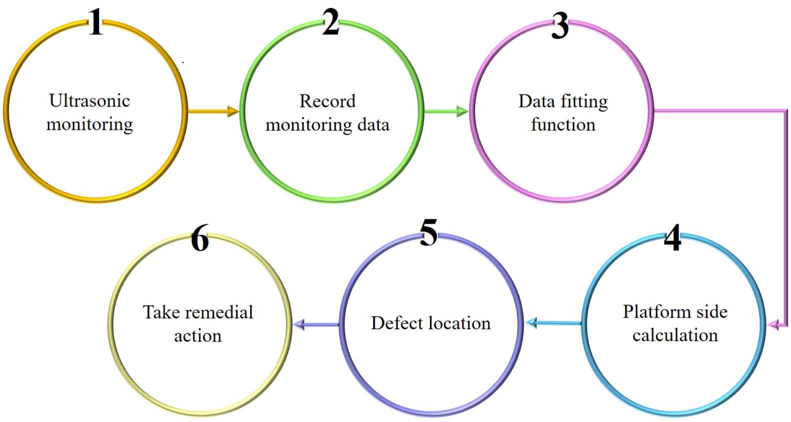

Figure 8. Flow chart of locating vibration defects of concrete

It can be seen from the above flow chart that using an ultrasonic wave velocity monitor to monitor concrete compactness can grasp the defect characteristics of concrete in the vibration process in real time. Workers can take remedial measures to improve the quality and durability of concrete.

4 Concrete Compactness Monitoring Platform Design

4.1 Platform Function Requirement Analysis

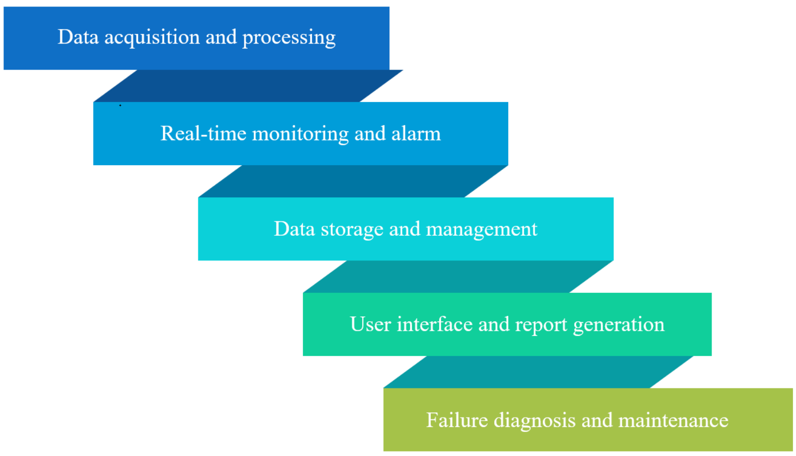

Figure 9. Monitoring platform requirements

The purpose of establishing the concrete compactness monitoring platform is to reflect the health state of the structure in real time by continuously monitoring the change in concrete compactness. Managers are able to respond quickly to any potential problems or anomalies and take timely repair and reinforcement measures to ensure the safety and reliability of the structure. The concrete compactness monitoring platform has the following five main requirements, as shown in Figure 9.

Specifically:

(1) Data acquisition and processing: The platform should be able to connect with various sensors and monitoring equipment to realize real-time acquisition and processing of construction data.

(2) Real-time monitoring and alarm: Provide a real-time monitoring interface to display the current status and trend of concrete compactness. Design an alarm system with preset thresholds, enabling timely alerts when abnormal changes in compactness occur.

(3) Data storage and management: Establish a stable and reliable data storage and management system to store historical data and support data query and retrieval.

(4) User interface and report generation: Design a user-friendly monitoring interface for real-time viewing and historical data analysis. Generate periodic reports for reference and use by decision-makers.

(5) Failure diagnosis and maintenance: Provide system maintenance and technical support to ensure stable platform operation and performance optimization.

4.2 Platform Architecture Design

The architecture design of concrete compactness monitoring platform is not only to realize data collection and monitoring, but more importantly, through efficient data processing, accurate analysis and timely feedback. The modules operate in coordination with each other to help engineering teams and managers ensure the quality and safety of concrete structures. Use Mock Plus software to build the system architecture of the platform shown in Figure 10.

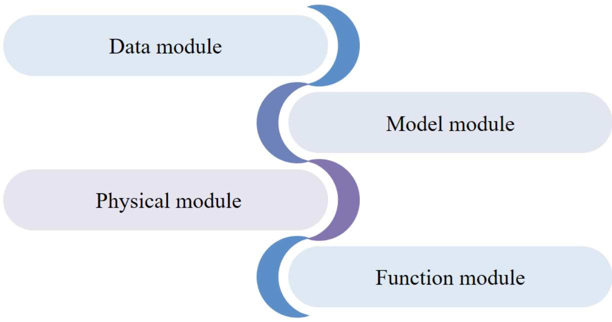

Figure 10. Platform system architecture

Specifically:

(1) Data module: Responsible for data acquisition, storage, and management, including data acquisition systems, databases, and data processing systems.

(2) Model module: The core module of the monitoring platform.

(3) Physical module: Ensure the normal operation of the platform.

(4) Function module: Various ports of the monitoring platform are provided to receive data from different sensors.

4.3 User Interface and Operation

This paper uses mature Mock Plus software to design and create a platform system prototype according to target requirements and function division. During the prototyping process, special attention is paid to the friendliness of the user interface and the fluency of the operation. Through the real-time preview and interaction capabilities provided by Mock Plus software, we can quickly conduct user experience tests and adjust and optimize based on feedback to ensure that the final system design meets user expectations and needs.

(1) The login interface of the concrete compactness monitoring platform is shown in Figure 11. It consists of the login method, password, registration, and so on. According to the login information, the company leader or the project user can be selected to log in, and different login personnel have different permissions on the monitoring platform.

(2) The main interface of the concrete compactness monitoring platform is shown in Figure 12. The staff can predict the concrete compactivity by entering the vibrating time of the vibrator and the inserting depth of the vibrator, and the wave speed-time curve will be formed after input. The red line indicates the warning value, and when the

wave-time curve is within the warning value range, it indicates that the concrete compactness is good. When the wave-time curve is not within the range of the warning value, the location of concrete defects, the degree of defects, the number of alarms, and whether the whole process data is saved will be displayed on the right side.

(3) The monitoring platform data recording interface is shown in Figure 13. This interface has a monitoring data table and an alarm record table. The staff can view the historical vibration data of concrete at any time and can also save and export the data.

Figure 11. Monitoring platform login interface

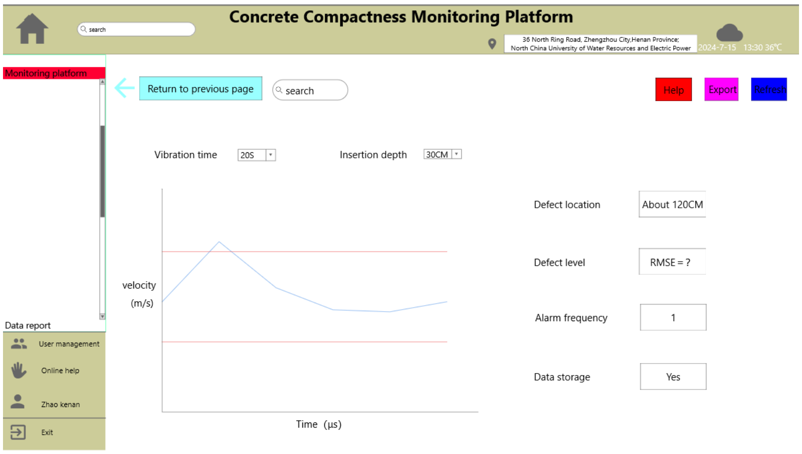

Figure 12. Main interface of the monitoring platform

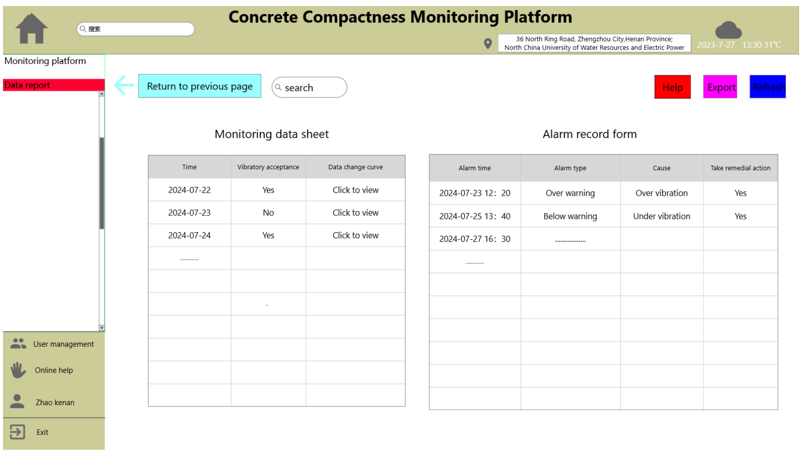

Figure 13. Data recording interface of monitoring platform

5 Conclusions

In this paper, a new concrete compactness monitoring method based on a long short-term memory network is proposed, and a corresponding monitoring platform is designed using Mock Plus. This method can monitor the defect degree and location of concrete compactness more accurately. The application of this method in engineering practice is mainly reflected in the following aspects: First, it can provide real-time feedback for the quality control of the concrete construction process, help engineers timely adjust the construction process, and ensure the long-term stability and safety of the concrete structure. Secondly, using the monitoring platform, the construction site can achieve efficient data collection and analysis, reduce the labor intensity of manual inspection, and improve the management efficiency of project progress.

Future research will focus on the following aspects: First, further optimize the LSTM network model to improve the ability to predict the change of concrete compactness in complex environments. The second is to expand the application range of this method and explore its applicability in different types of building materials and structures. The third is to combine the Internet of Things technology to achieve full automation and remote control of intelligent monitoring systems.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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