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A RAILWAY ROADBED DEFORMATION MONITORING SYSTEM USING DEEP LEARNING AND AI INTELLIGENT TECHNOLOGY

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Abstract. The author has designed an automated monitoring system for settlement and deformation of high-speed railway subgrade. Firstly, an automated monitoring system is designed based on sensors, data collection and transmission, client tracking and querying, monitoring result processing, automated warning, manual monitoring data analysis, monitoring data analysis and evaluation. Secondly, the system software and hardware are designed, the author calculated and analyzed engineering examples from the perspective of practical applications using artificial neural network methods, obtained corresponding deformation analysis models, and predicted deformation. Finally, the practical application of the system was analyzed for its effectiveness. The experimental results indicate that, the BP artificial neural network method is used to model and predict the Deformation monitoring data. On the premise of 20 learning samples and 4 prediction samples, the Root-mean-square deviation of the prediction is 0.32mm, which shows that the deformation prediction using BP model is feasible and effective in a certain precision range. It has been proven that the application of artificial neural network methods in monitoring and prediction of practical engineering has certain practical significance.

Key words: Artificial neural network; AI intelligence technology; monitoring system

1. Introduction. The infrastructure of high-speed railways presents a typical layered structure. When trains run at high speeds, the wheel rail load of the train directly acts on the track structure and transmits energy, load, deformation, and vibration to the lower layers of the structure. Due to factors such as train speed, lateral bending of steel rails, vertical load deviation, and track irregularity, the dynamic interaction between wheels and rails presents different characteristics. The purpose of continuous wheel rail force detection is to identify wheel defects such as flat scars. When applying the system, it is necessary to replace ordinary fasteners with a force measuring fastener system in sections, which requires a large amount of construction and high cost [1]. The intermittent wheel rail force detection system can identify the peak value of wheel rail force when a train passes, with the aim of statistically analyzing the distribution pattern of a large number of wheel rail force loads. Only a small number of sensors need to be installed to build the system, which is relatively low in cost. This is mainly aimed at analyzing the intermittent wheel rail force monitoring system [2].

For railways, safety and stability are the core, especially for high-speed railway trains with fast speed, high density, and large passenger volume, safety is even more crucial. High speed railway engineering is an important component of railway infrastructure, and its high stability and reliability are important foundations for ensuring the safe and stable operation of high-speed trains, as well as the main premise for ensuring people's comfort and safety in travel [3]. In the trend of gradually expanding the scale of high-speed railway engineering, due to complex geological conditions and other factors, some sections are prone to roadbed settlement and deformation problems, which are closely related to track smoothness and driving safety. However, the current high-speed railway subgrade Deformation monitoring mode is not perfect, which is still dominated by manual monitoring, with large time and cost investment and too large limitations to meet the monitoring needs. Therefore, the author designed an automated monitoring system for high-speed railway roadbed settlement and deformation.

2. References. At present, artificial intelligence technology has developed rapidly and is widely applied in the intelligent transportation industry. Artificial intelligence has solved many thorny problems through particle swarm optimization, genetic algorithm and other means, and effectively promoted the development and progress of intelligent transportation system. The application of artificial intelligence in intelligent trans-

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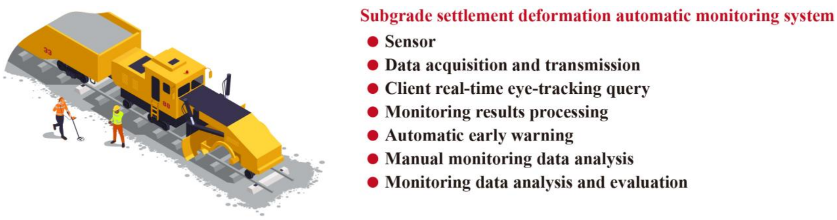

Fig. 3.1: Overall frame of the system

portation systems mainly focuses on two aspects: intelligent travel and traffic control [4]. The research on intelligent transportation systems in countries such as the United States, Japan, and Europe began in the 1990s. After 30 years of vigorous development, a relatively complete structural system has been formed [5,6]. Japan's research on intelligent transportation systems mainly focuses on vehicle electronic toll collection, emergency vehicle management, commercial vehicle management, public transportation management, and traffic information dissemination.

Japan's research on intelligent transportation system mainly focuses on vehicle electronic toll collection, emergency vehicle management, commercial vehicle Fahmy, and K. A. S is selecting the most appropriate and best hidden layers and Activation function types for neural networks. Then, define the patient data sent through the Internet of Things protocol. Check the patient's medical sensor data to make appropriate decisions. Then it sends the diagnostic results to the doctor. In this study, artificial intelligence technology will be combined with the Internet of Things [7]. The purpose of Khajehei, H is to use artificial neural networks to predict the rate of orbital geometric degradation. Collected, processed, and prepared positioning geometric measurements, asset information, and maintenance history for five sections of the Swedish railway network to develop an ANN model. We considered the information of the track and used different features of the track section as input variables for the model. By analyzing the performance of the model, we found that artificial neural networks have an acceptable ability to explain the changes in degradation rates at different orbital positions [8]. Gek, D. K creates an intelligent system to determine the quality of predictions. Such a system will become a manual assistant for determining the quality of predictions. If necessary, the system will also be able to indicate necessary adjustments to its prediction method. As part of this work, a software product will be created that will determine the quality of the trade procurement plan created and assist users in adjusting the prediction methods used by the branch if necessary [9].

In recent decades, many domestic and foreign experts and scholars have done a lot of work in performance optimization based on BP algorithm. As a black box method with good data approximation performance, many scholars at home and abroad have studied the use of BP neural networks for deformation prediction. This article designs an automated monitoring system for settlement and deformation of high-speed railway subgrade. Firstly, an automated monitoring system is designed based on sensors, data collection and transmission, client tracking and query, monitoring result processing, automated early warning, manual monitoring data analysis, monitoring data analysis and evaluation.

Secondly, the system software and hardware are designed. Starting from the perspective of practical application, this article calculates and analyzes engineering examples using artificial neural network methods, obtains corresponding deformation analysis models, and predicts deformation, Finally, analyze the practical effectiveness of the system through practical application.

3. System Design.

3.1. Overall System Framework. The overall framework of the high-speed railway roadbed settlement deformation automation monitoring system is shown in Figure 3.1.

3.2. System functional modules.

3.2.1. Sensor module. The sensor module usually converts the response information of various sensor combinations into electrical signals, processes them by transmitting and transmitting data, and converts them into analog signals.-digital [10].

3.2.2. Collection and Transmission of Information. Data transmission and transmission operations include adjusting sensor signals, converting them to analog and digital form, and sending them to an Ethernet-based monitoring station. Designed and developed data collection software DPServer to facilitate data collection and transmission. This application uses a SQL Server database as a medium and can create a frequency of data entry, collection and evaluation. After the configuration is completed, the program automatically analyzes the message and stores it in the database according to the standard.

3.2.3. Client tracking and query module. The client tracking and query module can achieve system visualization functions, which can be divided into two main parts according to its form, namely a real-time tracking platform based on the site; A remote query access platform based on network clients. The on-site real-time tracking platform can be installed on a computer, not only fixed to the on-site monitoring center, but also allows for real-time random inspection and monitoring. This platform can promote users to fully understand the changes in monitoring indicators and limit standards [11]. The client remote query access platform is a key component of this module, which can achieve diversified network clients and real-time query access detection data. Access the interface to query monitoring results, provide warning threshold values by displaying curves, and display temperature and construction content to intuitively understand the monitoring results.

3.2.4. Monitoring result processing module. The function of this module is to automate the generation of data reports and analysis graphics. Users can design standard report templates based on automatic report software according to their own needs, including text, pictures, monitoring data tables and curves. After the template design is completed, Word documents can be automatically generated based on the template content to improve the efficiency of monitoring results report generation [12].

3.2.5. Automatic warning module. Firstly, preliminary warning. During monitoring, any deformation sensor reading exceeding 1.5 times the accuracy value indicates deformation of the roadbed at the measuring point. The system issues a preliminary alarm and promptly notifies the staff to analyze and resolve the issue. Secondly, process monitoring. Continuously observe the settlement status of deformation measurement points, calculate the settlement amount, and observe the deformation trend throughout the entire process. Thirdly, alarm and handling. According to the standard, if the settlement of the roadbed in any area exceeds the limit value of 30mm, a rapid alarm must be given to transmit the location information of the measuring points and the actual situation, so that construction personnel can handle it in a timely manner.

3.2.6. Manual monitoring data analysis module. In order to ensure the efficiency of manual monitoring results analysis, this module transmits the manual monitoring content to an automated platform for unified analysis and processing. Through comprehensive planning and in-depth analysis, seamless integration between manual monitoring data analysis module, automated warning module, and monitoring result processing module is achieved to achieve unified platform management [13].

3.2.7. Monitoring data analysis and evaluation module. The ultimate goal of system monitoring is to identify and evaluate the settlement and deformation status of high-speed railway engineering structures. When evaluating, it is necessary to first construct a high-speed railway roadbed and bridge structure analysis model, and combine the measured data information to modify the calculation model. The modified model is used to accurately analyze and calculate the settlement deformation trend of the structure, in order to facilitate the correct decision-making of high-speed railway operation and maintenance [14]. On this basis, the core function of the system monitoring data analysis and evaluation module is to transform the data information collection results jointly obtained by the bottom modules into evaluation indicators that can effectively reflect the settlement and deformation status, laying a data foundation for correcting the model.

3.3. System Software Design.

3.3.1. System monitoring software. In order to solve the problems of complex types of monitoring equipment and inconsistent data standards, the system monitoring software adopts a three-layer framework mode and provides a unified data interface standard. For different instruments and equipment, it is only

Table 3.1: System monitoring software

Type	Acquisition end software	Server-side software	Client software
Running position	Monitoring on-site data collection instruments	Cloud server computer	Remote client
Function	Control the automatic collection of data, package the results and transmit them to the server	Calculate, analyze, alert, and store monitoring data in response to client query requests	Data Query and Project Configuration

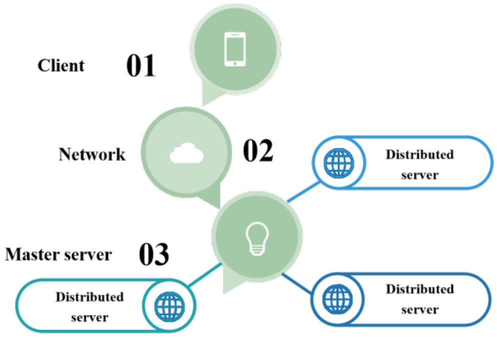

Fig. 3.2: Distributed server framework

necessary to develop targeted acquisition software to ensure that it meets the data interface requirements and can be compatible. The specific system monitoring software is shown in Table 3.1.

3.3.2. Distributed server. The distributed server framework disperses computing resources and broadband pressure across multiple servers to enhance the system's computing power and scalability, meeting the real-time and concurrent requirements of automated monitoring of high-speed railway roadbed settlement and deformation. The distributed server framework is shown in Figure 3.2.

3.3.3. Artificial neural network algorithm. BP neural network algorithm steps:

1. Determine the number of layers o in the neural network, the number of neurons n in the input layer, the number of neurons m in the output layer, and the number of neuron nodes p in the hidden layer [15].
2. Initialization of weights and thresholds.
   Assign random values w_{ij} between (-1,1) to the connection weights w_ij,w_{jk}, and thresholds θ_j,θ_k, where w_{ij} is the connection weight between the input layer and the hidden layer, and w_{jk} is the connection weight between the hidden layer and the output layer. θ_j,θ_k is the threshold $(i = 1, 2, ..., n, j = 1, 2, ..., m)$ for the hidden layer and the output layer, respectively.
3. Given the input mode vector $X_t = x_1, x_2, ..., x_n$ and the output mode vector $Y_t = y_1, y_2, ..., y_m$,(t=1,2... q) q is the logarithm of the input learning sample mode.
4. Calculate the actual output mode vector $C_t = c_1, c_2, ..., c_m$ of the neural network using the following algorithm.
   Firstly, calculate the inputs for each unit in the middle layer using the following formula:

$$S_j = \sum_{i=1}^{n} w_{ij} \times x_i - \theta_j (j = 1, ..., p) \tag{3.1}$$

   Simulate the nonlinear characteristics of biological neurons, take as the independent variable, calculate the excitation function f (x), that is, the output of Interneuron, and generally select Sigmoid function as the excitation function.

$$f(x) = \frac{1}{1 + e^{-\frac{x}{x0}}} \tag{3.2}$$

Obtain the incentive value of $b_j = f(S_J)$, and then transfer it to the output layer to obtain the actual output:

$$L_k = \sum_{j=1}^{m} w_{ij} \times b_j - \theta_k (k = 1, ..., m) \tag{3.3}$$

$$c_k = f(L_k) \tag{3.4}$$

5. Calculate the backpropagation error d_t of each neuron in the output layer from the actual output C_t and the expected output Y_t.
   Among them, d contains m components $d_t^k = (y_k - c_k) \times c_k \times (1 - c_k)(k = 1, ..., m)$
6. Calculate the backpropagation error e_t of the intermediate layer by considering the connection weight w_{jk}, the output b_j of the intermediate layer, and the backpropagation error d_t of the output layer:

$$e_i^j = (\sum_{k=1}^{m} w_{jk} d_t^k) \times b_j \times (1 - b_j)(j = 1, ..., p) \tag{3.5}$$

7. Correct the weight w_{jk} and threshold θ_k from the middle layer to the output layer based on the output layer backpropagation error d_t :

$$w_{jk}(n + 1) = w_j k(n) + \alpha \times d_t^k \times b_j \tag{3.6}$$

$$\theta_k(n + 1) = \theta_k(n) + \alpha \times d_t^k \tag{3.7}$$

   In the equation, $\alpha \epsilon (0, 1)$ is the Learning rate.
8. Learn new samples, re iterate the above process t=t+1, and re enter step 3) until the global Error function E of the network is less than the preset amount, that is, the network converges, or reaches the upper limit of the number of learning times to end the iterative calculation, that is

$$E = \frac{1}{2} \sum_{t=1}^{q} \sum_{k=1}^{m} (y_t^k - c_t^k)^2 \tag{3.8}$$

3.3.4. BP model and its application in Deformation monitoring. A Inter-city rail is a passenger dedicated high-speed railway with a speed of 350km/h, which is an overpass project under the high-speed railway, the whole planned line is 459.45m, the site is on soft soil foundation and the groundwater level is high, so the settlement requirements are very strict[16].

In order to ensure that there is no serious impact of roadbed settlement and deformation during construction, a high-precision automated monitoring system needs to be installed to monitor the affected road sections in real-time throughout the entire process, in order to apply the high-speed railway roadbed settlement and deformation automatic monitoring system designed by the author. The monitoring has a total length of 290.11m, covering the roadbed section, with 42 measurement points arranged. Sensors are installed on the shoulder and cantilever plate of the bridge, and safety protection buckets are designed for them. In addition, install automated collection units, collection software, computers, wireless transmitters, and conduct automated monitoring every 10 minutes, transmit measurement results to the monitoring center through message transmission. This high-speed railway engineering project uses the author's design system to collect, analyze data, and provide alarms[17].

Considering that the factors affecting the settlement change of observation points in Deformation monitoring are complex and difficult to determine, the BP neural network algorithm in the time domain is used here, that is, only historical observation data input is used for prediction, without considering the characteristic quantity input of other factors.

Since the 23 layer network can realize the mapping of Continuous function with arbitrary precision, the simplest 3-layer neural network design is adopted here, and the Matlab neural network toolbox is used to realize the BP algorithm and apply it to the actual Deformation monitoring analysis and prediction. The specific model implementation is as follows:

1) Selection of sample data. Considering the full utilization of data and the reproducibility of network training learning, the observed data is divided into learning samples and prediction samples, and the rolling sample collection method is used to determine the learning and prediction samples. Assuming the input parameter of the BP model is 4 and the output parameter is 1, 20 learning samples and 4 prediction samples can be obtained based on the sample data.
2) Selection of excitation function. The excitation function of the intermediate layer adopts a logarithmic s-shaped transfer function, while the intermediate layer to the output layer is a linear function.
3) Selection of initial parameters. The optimal range of hidden layer nodes is determined based on the empirical formula:

$$m = \sqrt{l+n} + a \tag{3.9}$$

In the formula, l and n are the number of input and output nodes, and a is a constant between 1-10. The optimal hidden layer node is determined by the above formula, and then the specific number is obtained through repeated experiments.

In addition, the selection of Learning rate α should not be too large or too small, which determines the Rate of convergence of the network and the final network error. This time, a variety of Learning rate are selected for calculation, and the best Learning rate is determined according to the results.
4) Objective function of training network. The global error E for selecting the objective function of the training network:

$$E = \frac{1}{2}\sum_{t=1}^{q}\sum_{k=1}^{m}(y_t^k - c_t^k)^2 \tag{3.10}$$

That is, the sum of squares of the difference between the actual output value of the network and the expected output value, until it converges to a certain error standard, otherwise the parameter modification will continue [18].

Use the above parameters to realize and calculate the Learning rate α in Matlab. The selection of includes 0.01, 0.05, 0.1, 0.5, 0.8, 0.95 values. The number of neuron nodes in the middle hidden layer ranges from [5,12]. The combination of different Learning rate and the number of hidden layer nodes is calculated and tested, and the network Mean squared error is obtained respectively as shown in Figure 3.3.

It can be seen from the figure that when the Learning rate is high, the result of selecting any number of nodes is not very good, and some models with 12 nodes, for example, even have a divergent trend in the later stage.

Considering that the Mean squared error of the network is the smallest, better two groups of combinations are obtained (α=0.1, hidden layer nodes 5) (α=0.01, the number of hidden layer nodes 7) were predicted for four periods, and the prediction results were analyzed to determine the optimal combination, as shown in Figure 3.4.

It can be seen from the figure that when the Learning rate is 0.1, basically the number of most neuron nodes can get good simulation results, but for some nodes 6, 7 and 12, there is a trend of gradually deviating from the sample in the later stage. It can be predicted that when the Learning rate is 0.01 and 0.05 respectively, the simulation effect of learning samples is relatively good, and there is little difference between the two. It can be clearly seen from the prediction results that, α the prediction results of 0.01 hidden layer nodes are significantly better than those of other groups, except for the large prediction deviation in the first stage. The specific predicted values are shown in Table 3.2.

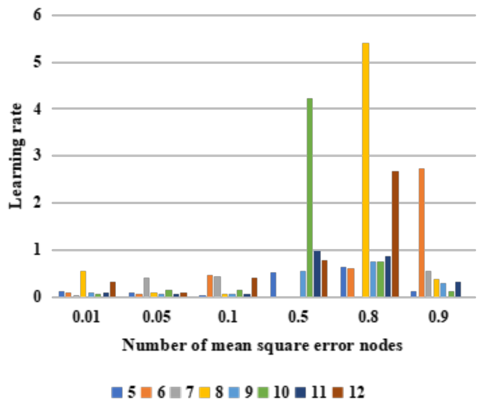

Fig. 3.3: BP model calculates the test network mean variance results

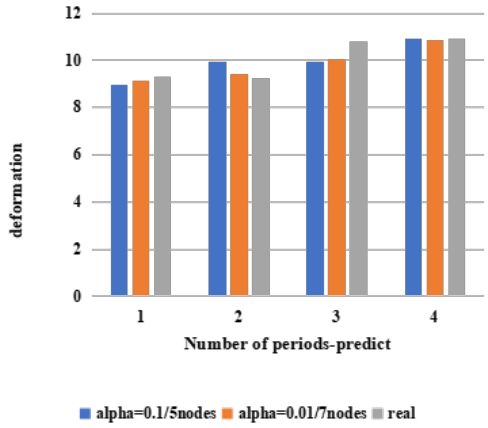

Fig. 3.4: Combined prediction and simulation results of the two groups

Note: Combination 1, i.e α=0.1, with 5 hidden layer nodes; Combination 2, i.e α= 0.01, with 7 hidden layer nodes.

To sum up, it is recommended that when the number of nodes in the hidden layer of the network is 7 and the network Learning rate is set to 0.01, the minimum Mean squared error of the network is 0.05, and the prediction effect of the trained prediction model is good and the prediction accuracy is high.

4. Conclusion. In summary, in order to effectively solve the problem of settlement and deformation of high-speed railway subgrade, the author has designed an automated monitoring system. The system is based on the settlement automatic acquisition instrument as the sensor, configured with automatic monitoring software, and realized fully automatic operation with the aid of computer control to realize the visualization and real-time goal of settlement Deformation monitoring. Artificial neural network systems have high fault tolerance and adaptability, which are suitable for solving the ambiguity and uncertainty problems involved in deformation prediction. This time, the BP artificial neural network method is used to model and predict the Deformation monitoring data, on the premise of 20 learning samples and 4 prediction samples, the Root-mean-square deviation of prediction is 0.32mm, which shows that under a certain precision range, the deformation prediction using BP model is feasible and effective. The determination of learning rate and the number of hidden layer neuron nodes in the BP artificial neural network method plays a key role in the process of network

Table 3.2: Comparison of two groups (units: mm)

Forecast period	Observed value	Combination 1 Predicted value	Combination 1 Absolute error	Combination 2 Predicted value	Combination 2 Absolute error
1	9	9.247	0.247	9.077	0.077
2	10	9.249	0.751	9.465	0.535
3	10	10.816	0.816	10.076	0.076
4	11	10.910	0.090	10.864	0.136
RMS	-	0.66	-	0.32	-

modeling and learning, which directly affects the Rate of convergence and modeling accuracy of the network. In addition, the BP artificial neural network model still has many shortcomings of its own, and needs to be improved and perfected.

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