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AI-Enabled Prediction and Control of Settlement during Construction of Concrete-Faced Rockfill Dams: Method and Engineering Application

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ABSTRACT: (1) Background: During the construction of the concrete-faced sand-gravel dam with a height of 247 m at the Dashixia Water Conservancy Project in Xinjiang, China, pronounced stage-related changes in dam settlement and marked settlement differences among dam zones were observed. Under these conditions, conventional settlement monitoring and prediction methods were insufficient to support the real-time decision-making required for on-site construction. (2) Methods: To address this practical engineering problem, this study developed an AI-enabled method for settlement prediction and control during construction. Settlement monitoring data collected throughout construction were combined with key dam filling parameters to establish a multi-source dataset for the construction period. On this basis, a settlement prediction model with rolling updates based on random forest regression was established. The model can predict the settlement development trend, support the identification of potential nonuniform settlement zones, and provide references for construction control based on actual construction conditions. (3) Results: The results of field application and quantitative error evaluation show that the predicted settlement is generally consistent with the measured settlement trend. The model effectively captures settlement responses during construction stoppage and the subsequent resumption of filling. (4) Conclusions: The proposed method provides practical quantitative support for optimizing construction organization and improving the precision of settlement risk control.

KEYWORDS: Concrete-faced rockfill dam; settlement during construction; settlement prediction; monitoring data; rolling prediction; construction control

1 Introduction

Concrete-faced rockfill dams (CFRDs) are widely used in hydropower and water conservancy projects. This widespread use is mainly attributable to their generally good structural performance, adaptability to complex topographic and geological conditions, and relatively efficient construction. In recent years, many hydraulic engineering projects have moved toward greater dam heights, larger reservoir capacities, and more challenging site conditions. Against this background, the construction of CFRDs has become more demanding. Higher stress levels, longer construction periods, and more complex loading processes have become increasingly common. As a result, settlement during construction has become a more prominent issue, especially for ultra-high dams. In practice, this issue is closely related to construction safety, structural behavior, and quality control.

During the construction of ultra-high CFRDs, settlement accumulates gradually as layered filling and continuous loading proceed. Previous studies have shown that this process is usually characterized by pronounced stage-dependent behavior, clear spatial differences, and high sensitivity to construction conditions. The settlement response therefore varies with the construction stage [1–3]. When the construction process transitions from rapid filling to a stoppage period and then to resumed filling, both the settlement rate and settlement distribution may vary markedly. It has also been reported that local nonuniform settlement may develop in some dam sections [4]. In many cases, such settlement may affect deformation coordination within the dam body, alter the stress state of the concrete face slab, and thereby influence subsequent construction activities. For this reason, it is important to track settlement development during construction, identify the risk of nonuniform settlement in a timely manner, and adjust the construction arrangements as needed.

At present, settlement control during construction still relies primarily on the interpretation of monitoring data, engineering experience, and analytical or numerical methods based on simplified assumptions. These methods are useful for design checking, safety evaluation, and analysis after construction, but they are not always sufficient for direct on-site construction control in ultra-high CFRDs. Some researchers have pointed out that conventional computational methods often have limited predictive capability [5]. One reason is that settlement during construction is influenced simultaneously by multiple factors, such as material nonlinearity, zoned filling, changes in construction rhythm, and time-dependent deformation. Under these conditions, traditional models may not fully describe settlement evolution under different construction stages and loading paths. Another issue is that, although large amounts of monitoring data are collected on site, these data are still used more often for later analysis than for real-time decision-making. Therefore, the value of monitoring data in construction control has not been fully utilized. As a result, settlement control during construction still relies heavily on engineering judgment in many cases, especially during rapid filling and stage transitions, where early risk identification and timely response remain insufficient [6,7].

In recent years, neural networks and other machine learning methods have been increasingly used for dam deformation and settlement prediction. Neural networks, such as artificial neural networks and long short-term memory models, are useful for describing nonlinear time-dependent relationships, while other machine learning methods, such as support vector regression and random forest regression, can also learn the relationships between monitoring responses and influencing factors from data [8,9]. These methods provide more flexible tools than traditional empirical or simplified analytical models. However, many existing studies still focus mainly on improving prediction accuracy, while the connection between prediction results and control during construction is not always fully discussed. In this study, random forest regression is used as the base machine learning model and is embedded in a rolling update framework. Compared with a standalone prediction model, the proposed method places more emphasis on the combined use of monitoring data, construction parameters, rolling prediction, and site feedback during construction.

This study is based on the Dashixia Water Conservancy Project in Xinjiang, China, where the main dam is an ultra-high CFRD with a height of 247 m, as shown in Fig. 1. In this project, the main concern was not only how settlement developed, but also how the monitoring results could be used more directly during construction. Based on this engineering background, this paper discusses a method for settlement prediction and control during construction. This study focuses on how field settlement monitoring data can be better used during construction and how prediction results can support construction control. In other words, the goal is not only to explain settlement after it has occurred, but also to make the data more useful during the construction process itself.

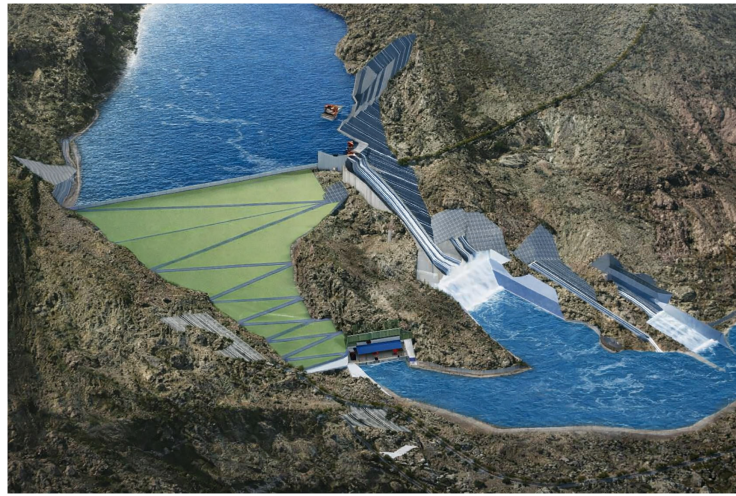


Figure 1: Schematic illustration of the Dashixia project.

This work includes three main components. First, monitoring data collected during construction were combined with key construction parameters, including filling elevation, construction rhythm, and stoppage duration, to form a multi-source dataset for settlement analysis during construction. Second, on this basis, a prediction framework with rolling updates was established so that the settlement trend could be updated continuously as construction progressed. Third, the method was validated using typical dam sections and representative elevations from the Dashixia project, and its potential application to construction adjustment and nonuniform settlement risk control was further discussed. The main contribution of this work is that field monitoring data, construction parameters, rolling prediction, and site control are linked within a unified engineering workflow. In this way, monitoring data can be used not only for retrospective interpretation but also for prediction and control during construction.

2 Engineering Issues and Data Basis for Settlement Control during Construction

2.1 Engineering Characteristics of Settlement during Construction

During the construction of ultra-high concrete-faced rockfill dams (CFRDs), dam settlement is a common engineering issue. It develops gradually during layered filling and continuous loading. In practice, this process can be directly reflected in monitoring data. According to the safety monitoring results from the Dashixia Water Conservancy Project in Xinjiang, settlement during construction in this project showed several clear characteristics.

First, the settlement process has pronounced stage-dependent features. Previous studies have shown that settlement usually changes with construction progress [10,11]. During rapid filling, the newly added load often causes a relatively fast increase in settlement. During construction stoppage, filling operations are suspended, and the settlement rate usually slows down. At this stage, deformation is more closely related to creep. After construction resumes and loading is applied again, settlement increases again. When the dam approaches the final elevation, the settlement rate tends to decrease gradually, and the deformation becomes more stable. The monitoring results from the Dashixia project clearly show this pattern. During construction stoppage, the settlement growth rate is much lower than that during rapid filling, while after filling resumes, the slope of the settlement curve becomes steeper again. In other words, stage changes were directly reflected in the monitoring records.

Second, settlement during construction shows clear spatial differences. Previous studies have reported differences among dam sections and elevations, and similar behavior was observed in this project [1,9]. For

example, in Section Right 0 + 125, the settlement values at different elevations differ considerably, as shown in Fig. 2. The maximum cumulative settlement reached 414 mm at elevations of 1631 and 1670 m, indicating marked spatial variability in both the vertical and transverse directions. In practice, this type of nonuniform settlement requires attention. If it is not properly controlled, it may affect the deformation coordination of the dam body and also influence the stress state of the concrete face slab. Therefore, this issue should be closely monitored during site management.

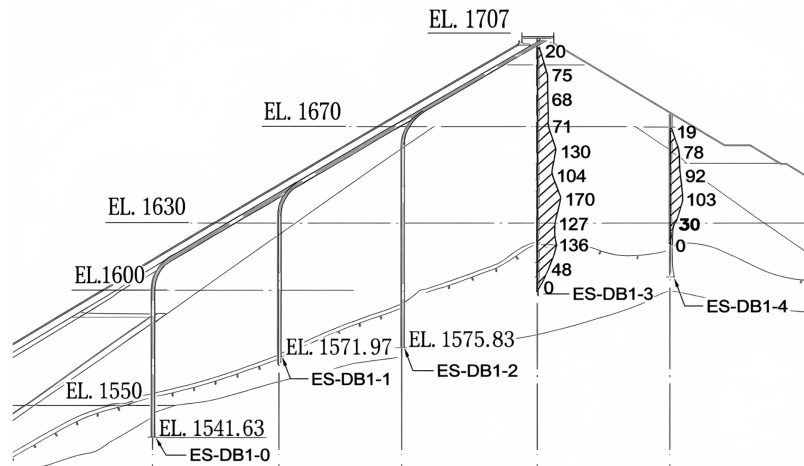


Figure 2: Cumulative settlement recorded by the electromagnetic settlement gauge at Section Right 0 + 125.0 m on the right bank (unit: mm).

Third, settlement during construction is closely related to construction-related parameters. Studies have shown that settlement development is closely associated with filling elevation [12,13]. As the filling height increases, the internal stress level of the dam body also rises, which usually leads to further settlement. In this process, settlement continues to accumulate as filling progresses. At the same time, different construction rhythms can also affect the settlement rate. Therefore, the settlement process does not develop at a constant rate. The settlement–time curves in Fig. 3 show different responses during rapid filling, construction stoppage, and resumed filling. These differences are useful in engineering analysis because they can support stage identification and early assessment of potential settlement risks.

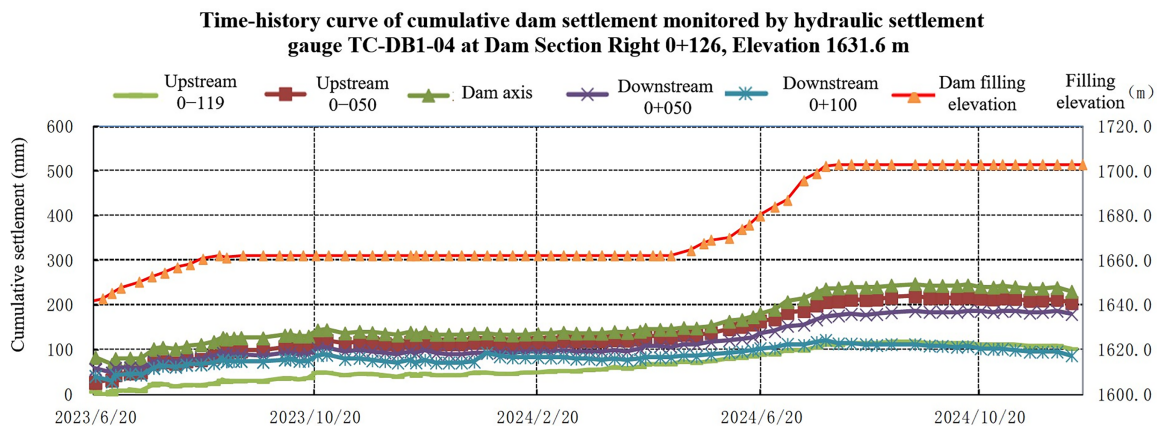


Figure 3: Typical cumulative settlement-time curves recorded by the hydraulic settlement gauge at Section Right 0 + 125.0 m.

Overall, settlement during the construction of ultra-high CFRDs shows three pronounced features: stage dependence, spatial variability, and a close relationship with the filling process. These characteristics can be identified from the monitoring results and provide a direct basis for settlement prediction and control during construction. They also indicate that settlement control cannot rely only on retrospective analysis. For this type of project, the control method should better account for the dynamic changes in settlement under actual construction conditions.

2.2 Settlement Monitoring and Data Basis during Construction

This study is based on the Dashixia Water Conservancy Project in Xinjiang, China. The project is a large-scale Class I hydraulic engineering project, and its main retaining structure is a concrete-faced sand-gravel dam with a maximum height of 247 m. In this project, the filling intensity is high, the construction period is long, and the settlement of the dam body is relatively pronounced. Under such conditions, both construction safety and construction management require careful control. For this reason, a comprehensive safety monitoring system was established during construction, which also provided the basic data used in this study [13,14].

2.2.1 Composition of the Settlement Monitoring System during Construction

The safety monitoring system of the Dashixia project was mainly established for two purposes: to ensure the safety of the project area and to address major risks during construction. The system includes several components, namely routine inspection, environmental monitoring, strong-motion monitoring, the deformation monitoring control network, dam safety monitoring, special monitoring of important hydraulic structures, such as spillways and water diversion and power generation systems, and reservoir bank deformation monitoring. Among these components, the dam body, intake section, and spillway gate section are the main monitoring targets during construction. For the present study, deformation monitoring of the dam body is the primary data source [15]. The composition of the safety monitoring system and the key monitoring targets are summarized in Table 1.

Table 1: Composition of the safety monitoring system and key monitoring targets in the Dashixia project.

No.	Monitoring Category	Main Content	Key Monitoring Targets
1	Routine inspection	Structural appearance, construction status	Dam and spillway structures
2	Environmental monitoring	Temperature, water level, etc.	Project area
3	Strong-motion monitoring	Seismic response	Dam and project area
4	Deformation monitoring control network	Displacement and settlement	Dam
5	Dam safety monitoring	Deformation, seepage, etc.	Dam
6	Special monitoring of structures	Structural response	Intake and spillway
7	Reservoir bank deformation monitoring	Slope deformation	Reservoir bank deformation zones

2.2.2 Main Monitoring Items during Construction

To meet the needs of settlement control during construction, a deformation monitoring system that combined internal monitoring and surface monitoring of the dam body was installed. In operation, this

system made it possible to observe settlement responses at different locations and by using different methods. The monitoring instruments mainly used in this study include electromagnetic settlement tubes, hydraulic settlement gauges, vibrating-wire settlement gauges, observation piers, and piezometers. These instruments provided the basic data for analyzing how settlement changed over time and how it varied spatially during construction.

Considering the scale of the project and the characteristics of dam filling, these monitoring instruments were arranged in sufficient numbers and with a reasonable spatial layout. This arrangement allowed settlement differences among dam sections and elevations to be captured more effectively [16]. The project design included 2831 monitoring items, reflecting the large scale of the Dashixia safety monitoring system. For settlement prediction in this study, the main data sources were the dam-body deformation monitoring instruments, especially electromagnetic settlement tubes, hydraulic settlement gauges, vibrating-wire settlement gauges, and surface observation points. The main deformation monitoring instruments related to this study are summarized in Table 2.

Table 2: Main deformation monitoring instruments and supporting sensors during construction.

No.	Monitoring Instrument	Quantity	Role in This Study
1	Electromagnetic settlement tubes	23 sets	Internal settlement monitoring
2	Hydraulic settlement gauges	10 sets	Internal settlement monitoring
3	Vibrating-wire settlement gauges	2 sets	Supplementary settlement monitoring
4	Observation piers	76	Surface deformation monitoring and data verification
5	Piezometers	49	Supporting information for dam safety interpretation

2.2.3 Quality and Reliability of Settlement Data during Construction

For this type of study, the continuity and reliability of monitoring data are essential. During the implementation of the safety monitoring system in the Dashixia project, 2315 monitoring instrument installation subprojects were completed. According to the project records, the overall quality of the monitoring work was well controlled. The acceptance pass rate of the monitoring subprojects reached 100%, the proportion rated excellent reached 99.2%, and the instrument integrity rate reached 98.4%. These figures indicate that the settlement data collected during construction had good continuity and quality.

Based on this monitoring system, settlement data were collected continuously during different construction stages, including rapid filling, construction stoppage, and resumed filling. These records reflect the settlement response under different construction conditions and can be used for subsequent settlement characteristic analysis and prediction model development [17]. For model development, the raw settlement monitoring records were matched with construction process records according to the same update date or filling layer. The construction process records mainly included filling elevation, filling elevation increment, construction rhythm, construction stage, and stoppage duration. The available project documents also confirm that the monitoring system had good coverage and data continuity. For the settlement prediction analysis in this study, the main data sources were dam-body deformation monitoring instruments, including 23 electromagnetic settlement tubes, 10 hydraulic settlement gauges, 2 vibrating-wire settlement gauges, and 76 surface observation piers. Piezometer data were used as supporting information for dam safety interpretation rather than as the main target for settlement prediction. The monitoring records used for modeling covered the main construction stages involved in the case analysis, including rapid filling, construction stoppage, resumed filling, and the later filling stage near the dam crest.

2.2.4 Typical Sections and Layout of Monitoring Lines

To analyze the spatial distribution of settlement during construction, several internal deformation monitoring sections were arranged within the dam body. In this study, Sections Right 0 + 125, 0 + 265, 0 + 375, and 0 + 455 were selected as the main research sections. These sections are located in areas with relatively large dam heights or pronounced settlement responses, so they can better represent settlement behavior in this project.

In addition, the internal settlement monitoring of the dam body followed the principle of extending 10 m into the bedrock and arranging one settlement monitoring unit every 8 m in the elevation direction. With this layout, settlement responses at different depths and in different filling layers could be captured more clearly. The layout of the monitoring lines is shown in Fig. 4.

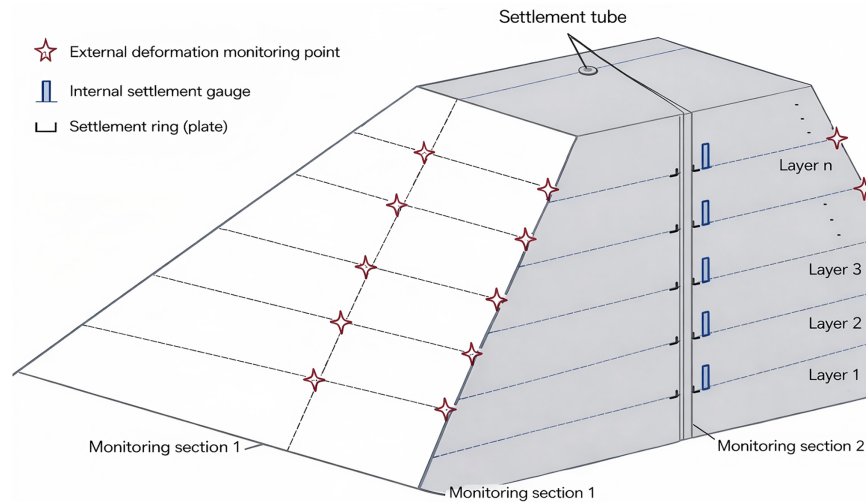


Figure 4: Schematic illustration of the coordinated arrangement of internal and external deformation monitoring points in a layered-construction earth-rock dam.

Overall, the Dashixia monitoring system provided good coverage, data continuity, and engineering representativeness for settlement analysis during construction. For this study, these data supported the identification of settlement characteristics at different construction stages and the subsequent development and validation of the prediction and control method.

3 AI-Enabled Prediction and Control Framework for Settlement during Construction

3.1 Overall Framework

To address settlement problems during the construction of ultra-high concrete-faced rockfill dams (CFRDs), this paper presents a prediction and control framework that can be used in construction management. Previous studies have shown that prediction models are usually more useful when monitoring data are considered together with construction parameters [18,19]. Based on this idea, the present work uses settlement monitoring data, filling process data, and spatial location data as the main inputs to a random forest regression model. The model predicts settlement in the next update period, and the prediction is updated as new monitoring records and construction parameters become available. The updated prediction results are then used to support site control, thereby linking monitoring, prediction, evaluation, and construction adjustment within a single workflow.

In general, the framework in this study consists of four steps. The first step is data preparation. A multi-source dataset is built for settlement during construction, including historical settlement time series, spatial information such as monitoring section and elevation, and construction parameters such as filling elevation, construction rhythm, and stoppage duration. The second step is prediction. Based on these data, a settlement prediction model is established to describe the relationships among settlement development, construction loading, and time. The third step is updating. As construction continues, newly collected monitoring records and construction parameters are added to the dataset, and the prediction results are updated to reflect the latest construction conditions. The final step is application to site control. According to the predicted settlement trend, settlement rate, and spatial difference indicators, corresponding suggestions can be provided for filling rhythm adjustment, stoppage arrangement, and risk control in key sections [20].

For ultra-high CFRD projects, this framework is useful for settlement management during construction. The prediction results are not only used for later analysis, but can also be integrated into the construction process itself. In other words, settlement monitoring is no longer used only to explain what has already occurred. It can also support ongoing construction control and subsequent on-site adjustment. The overall workflow of the framework is shown in Fig. 5.

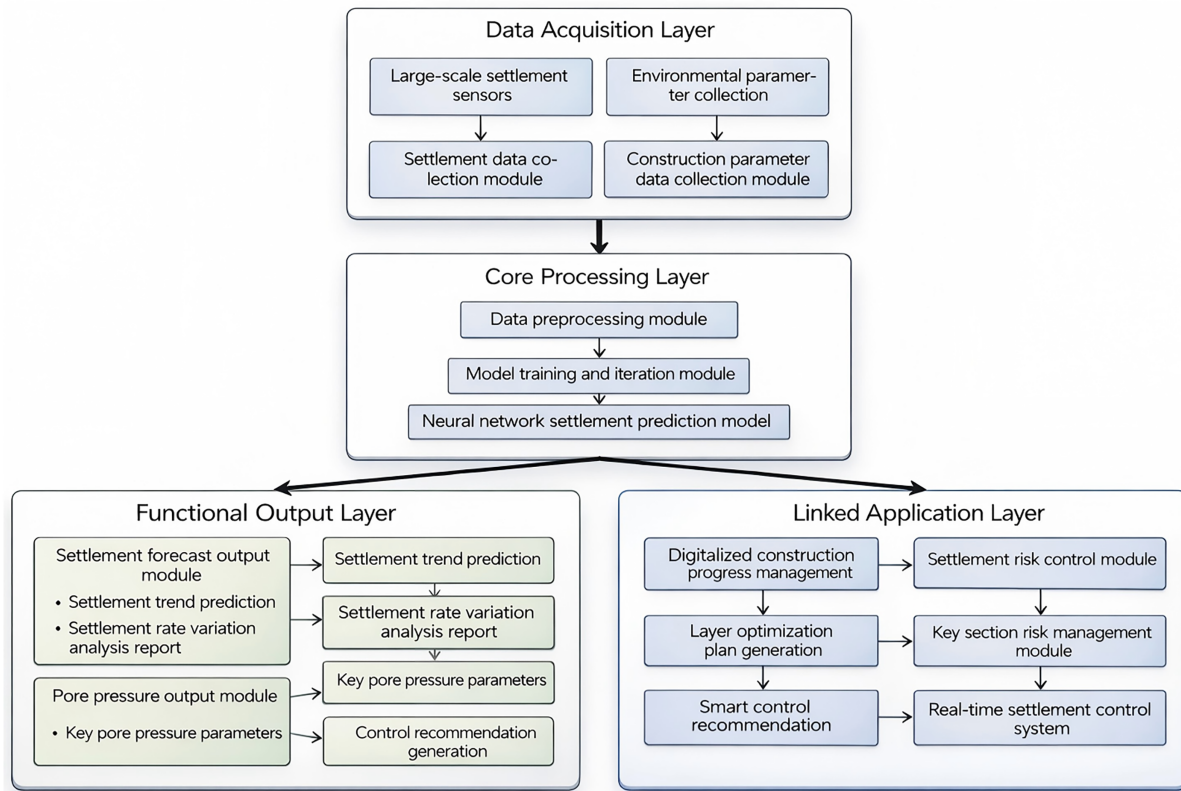


Figure 5: AI-enabled workflow framework for settlement prediction during construction.

3.2 Engineering-Oriented Definition of Inputs and Outputs

In this study, the model inputs and outputs were not defined solely from a computational perspective. Instead, they were determined primarily by data availability at the site and the practical needs of construction management. The emphasis was therefore placed on the engineering applicability and interpretability of the

input and output variables. Previous studies have also shown that predictions are usually more reliable in engineering applications when monitoring data are used together with construction parameters [21,22].

The input data in this study can be grouped into three categories. The first category is the settlement response itself, mainly represented by the historical settlement monitoring time series. These data reflect how the dam body responded in earlier construction stages. The second category is spatial location data, such as the section number and monitoring point elevation. These data are needed because settlement varies among sections and elevations. The third category is construction condition data, including filling elevation, construction rhythm, and stoppage duration. These parameters describe the actual loading process of the dam body and provide the construction context needed to interpret and predict settlement development.

The outputs were also defined according to the needs of construction control. The key concern here is not only the settlement value at a specific time, but more importantly, how settlement may develop in the following period (Δt) and what this means for site control. Based on this idea, the outputs mainly include the predicted settlement trend in the next period, changes in the settlement rate, indicators related to spatial differences for assessing the risk of nonuniform settlement, and direct control recommendations for site application, such as filling rhythm adjustment, stoppage arrangement, and coordination among key sections [23].

To facilitate use in construction management, the main inputs, outputs, and suggested update intervals are listed in Table 3.

Table 3: Inputs, outputs, and suggested update intervals for settlement prediction and control during construction.

No.	Category	Content	Recommended Update Frequency
1	Input	Historical settlement monitoring time series	Weekly (or by layer)
2	Input	Spatial location (section, monitoring point elevation)	Fixed
3	Input	Construction parameters (filling elevation, construction rhythm, stoppage duration, etc.)	Summarized daily and checked weekly (or by layer)
4	Output	Settlement trend over the next Δt	Released weekly (or at key stages)
5	Output	Settlement rate and its variation characteristics	Released weekly
6	Output	Spatial variability indicators (representation of nonuniform settlement risk)	Released weekly, with increased frequency when anomalies occur
7	Output	Construction control recommendations (rhythm/stoppage/rolling coordination)	Released together with the prediction results

3.3 Model Structure, Training Procedure, and Hyperparameter Settings

In this study, the settlement prediction model with rolling updates was implemented using random forest regression. Random forest regression was selected because it can describe nonlinear relationships between settlement responses and construction-related variables without requiring a predefined functional form. It is also suitable for engineering datasets containing both spatial information and construction process variables.

For each monitoring point and update step t , the input vector was defined as:

$$\mathbf{x}_{i,t} = [S_{i,t}, \Delta S_{i,t}, r_{i,t}, z_i, c_i, H_t, \Delta H_t, v_t, d_t, g_t]$$

where $S_{i,t}$ represents the cumulative settlement at the current monitoring step, $\Delta S_{i,t} = S_{i,t} - S_{i,t-1}$ represents the recent settlement increment, $r_{i,t} = \Delta S_{i,t} / \Delta t$ represents the recent settlement rate, z_i represents the elevation of the monitoring point, c_i represents the monitoring section code, H_t represents the current filling elevation, ΔH_t represents the filling elevation increment, v_t represents the filling rate, d_t represents the stoppage duration, and g_t represents the construction-stage indicator. The construction-stage indicator was used to distinguish rapid filling, construction stoppage, resumed filling, and the later stage near the final dam height. The output variable was the predicted cumulative settlement in the next update period, expressed as:

$$\hat{S}_{i,t+\Delta t} = f(\mathbf{x}_{i,t})$$

where $f(\cdot)$ denotes the random forest regression model. Based on the predicted cumulative settlement, the settlement increment, settlement rate, and spatial difference indicators were further calculated for use in construction control.

Before model training, the monitoring records and construction records were matched according to the same update date. The dataset was arranged in chronological order, and random shuffling was not performed, so that the training and validation processes remained consistent with actual construction forecasting. In the initial training stage, the earlier monitoring and construction records were used for model training, while the later records were used for validation. This chronological split was adopted instead of random sampling, so that the validation process was consistent with the actual forecasting scenario during construction. During rolling prediction, only the data available before the current prediction period were used for model training. Once new settlement measurements and construction parameters became available, they were added to the dataset, and the model was retrained for the next prediction period.

The main hyperparameters of the random forest regression model were set as follows: the number of regression trees was 100, the maximum tree depth was 8, the minimum number of samples required to split an internal node was 2, the minimum number of samples at a leaf node was 1, bootstrap sampling was used, and the squared error criterion was adopted for node splitting. The random seed was fixed at 42 to ensure reproducibility. Other parameters were kept at their default settings. The same hyperparameter settings were retained during the rolling update process, while the training dataset was continuously expanded with newly collected monitoring and construction data.

The rolling prediction procedure can be summarized as follows:

- Step 1: Collect settlement monitoring data and construction parameters for the current update period.
- Step 2: Construct the input vector for each monitoring point by combining the settlement response, spatial information, and construction process variables.
- Step 3: Train or retrain the random forest regression model using all available records before the current prediction period.
- Step 4: Predict the cumulative settlement for the next update period.
- Step 5: Calculate the settlement increment, settlement rate, and spatial difference indicators from the prediction results.
- Step 6: Use the prediction results to support construction control, and add the subsequently measured settlement response to the dataset for the next rolling update.

3.4 Rolling Update and Closed-Loop Construction Control

During construction, settlement prediction is not used merely to describe the general trend; it should also provide information for site control at the current stage. Previous studies have shown that the settlement response of ultra-high CFRDs changes with the construction stage [24,25]. During rapid filling, construction stoppage, resumed filling, and the later stage near the crest, settlement behavior differs markedly. Therefore, the random forest regression model was embedded in a rolling update procedure, so that the training dataset and prediction results could be updated continuously as construction progressed.

In each update cycle, newly collected settlement monitoring data and the latest construction parameters are added to the existing dataset. The random forest regression model is then retrained using the expanded dataset. After retraining, the model predicts the cumulative settlement for the next update period. The predicted settlement is further used to calculate the settlement increment, settlement rate, and spatial difference indicators for the next stage (Δt). In practice, this step is important because it allows the analysis to follow the actual construction conditions more closely. When the construction stage changes, the settlement response often changes accordingly, and the updated prediction can better reflect this process [26].

For site control, the prediction results in this study were mainly used in three situations. The first situation was construction stoppage. If the predicted settlement rate decreases and the deformation tends to stabilize, this can be used as a reference for judging whether the stoppage plan is reasonable. The second situation was resumed filling or continuous filling. If the prediction shows that settlement may increase more rapidly after reloading, this can provide support for adjusting the filling rhythm and construction management. The third situation was control of nonuniform settlement risk. In this case, the spatial difference indicators can help identify dam sections or elevation ranges where settlement differences may continue to increase. Accordingly, more targeted monitoring and corresponding construction measures can be arranged in advance.

After construction parameters are adjusted, the subsequent settlement response is recorded by the monitoring system and added to the next update cycle. In this way, monitoring data support prediction, prediction results inform construction adjustment, and the subsequent monitoring response provides feedback for the next round of analysis. For this project, this approach is more useful than retrospective interpretation alone, because it allows settlement management during construction to be linked more directly with ongoing site control.

4 Engineering Application and Performance Validation

4.1 Project Overview

The Dashixia Water Conservancy Project in Xinjiang, China, is a large-scale Class I hydraulic engineering project. Its main water-retaining structure is a concrete-faced sand-gravel dam with a maximum height of 247 m, making it a representative ultra-high CFRD. Because deformation of rockfill dams is closely related to the mechanical response of rockfill materials and the loading process of the dam body, this project provides a suitable case for examining settlement prediction and control during construction [27].

Based on this engineering case, typical dam sections and representative monitoring elevations were selected to validate the proposed prediction and control method with rolling updates. The selected monitoring data were used to examine whether the proposed method could be applied under actual construction conditions.

4.2 Validation of Settlement Prediction for Typical Sections

To examine how the method performs in engineering applications, several representative sections of the Dashixia project were selected for comparison of predicted and measured settlement values. After considering structural location, data completeness, and construction-stage characteristics, Sections Right 0 + 125 and Right 0 + 265 were chosen as the main study sections for detailed curve comparison. This selection is consistent with the use of representative monitoring data in dam safety monitoring and prediction studies [28].

Within each section, several monitoring points at different elevations were selected. Based on the settlement records and construction parameters collected during construction, the settlement trend in the subsequent stage was predicted using the proposed method with rolling updates. Then, the predicted settlement–time curves were compared with the measured curves at the corresponding locations.

The comparison shows that the predicted curves are generally close to the measured ones in overall trend, particularly during several key construction stages. During rapid filling, construction stoppage, and resumed filling, the prediction results can reflect the main changes in settlement rate and the basic response pattern of stage transition. The method can capture the main settlement trend during construction, although small point-by-point differences from the measured data remain. For quantitative validation, the mean absolute error (MAE) and root mean square error (RMSE) were calculated for representative monitoring points. These two indicators were selected because they directly reflect the absolute deviation between predicted and measured settlement values in millimeters, making them more suitable for field construction control. Because some early-stage settlement values were close to zero, the mean absolute percentage error (MAPE) was not used as the main indicator to avoid unstable percentage errors. A simple persistence baseline was also considered in the interpretation. In this baseline, the settlement value recorded in the previous monitoring period was used as the reference prediction for the next period. This baseline was used as a simple non-AI reference rather than as an additional calibrated prediction model. However, because the monitoring intervals and construction stages varied across monitoring points, the MAE and RMSE of the proposed model were used as the main quantitative indicators in this engineering validation. In addition to the two sections used for detailed curve comparison, other representative monitoring points were also included in the quantitative error evaluation to further examine the robustness of the prediction results. The measured and predicted settlement–time curves are shown in Fig. 6, and the quantitative error results for representative monitoring points are summarized in Table 4.

4.3 Performance Analysis

4.3.1 Consistency in Settlement Development Trends

The quantitative results further support the curve comparison for the typical sections. For the ten representative monitoring points, the MAE ranged from 3.6 to 18.3 mm, and the RMSE ranged from 4.4 to 19.1 mm. The average MAE and RMSE were 8.7 and 10.2 mm, respectively. These results indicate that the proposed model can reproduce the main settlement trend with relatively small absolute errors under field monitoring conditions. Similar agreement between predicted and monitored settlement trends has also been reported in previous studies [29]. In this project, for example, the method can reflect the faster settlement development during continuous filling, such as that observed at the 1541 m elevation of Section Right 0 + 265. It can also show a clear slowdown in settlement rate during construction stoppage, such as that seen at the 1650 m elevation of Section Right 0 + 125. This indicates that the method can capture both the overall settlement trend and the stage-dependent variation during construction.

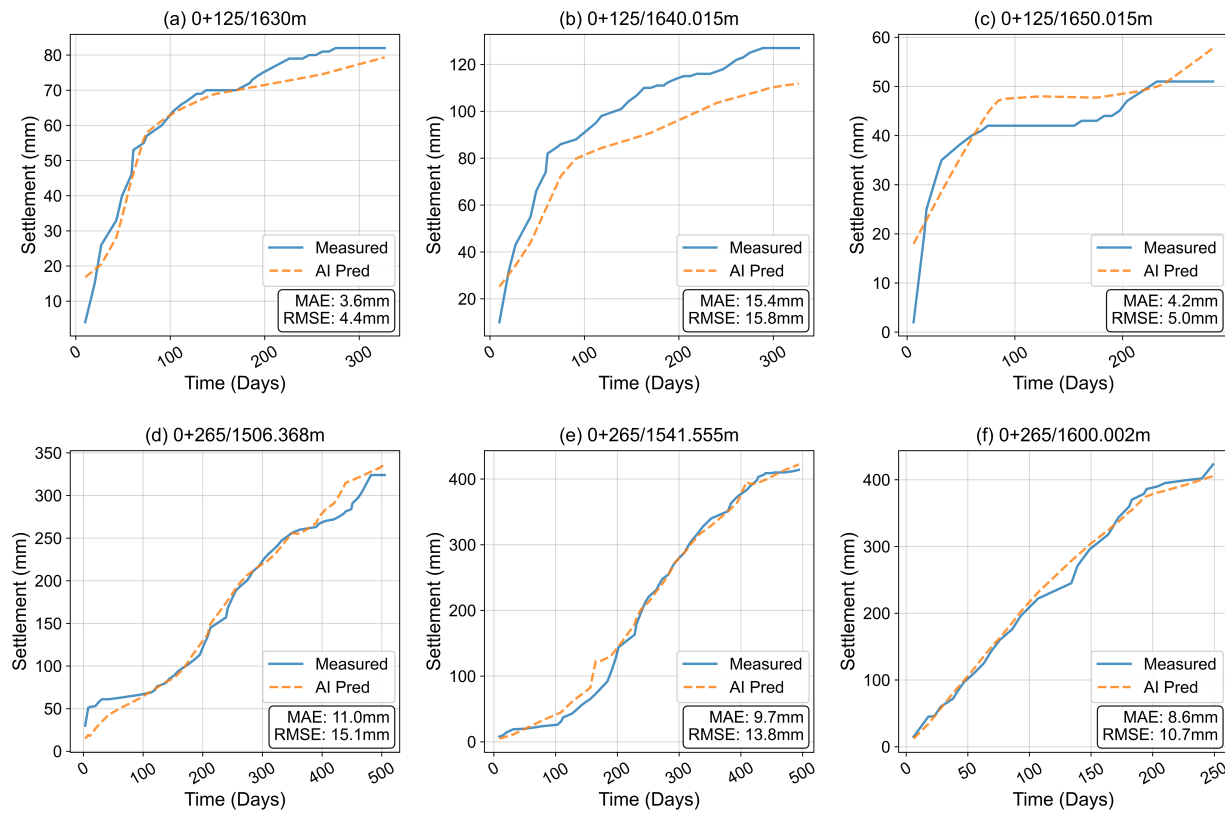


Figure 6: Comparison of measured and AI-predicted settlement–time curves at typical monitoring points. The MAE and RMSE values are shown in each subplot. (a) Section Right 0 + 125, elevation 1630 m; (b) Section Right 0 + 125, Elevation 1640.015 m; (c) Section Right 0 + 125, Elevation 1650.015 m; (d) Section Right 0 + 265, Elevation 1506.368 m; (e) Section Right 0 + 265, Elevation 1541.555 m; (f) Section Right 0 + 265, Elevation 1600.002 m.

Table 4: Quantitative evaluation of settlement prediction accuracy at representative monitoring points.

No.	Monitoring Point	MAE (mm)	RMSE (mm)
1	Right 0 + 125/1630 m	3.6	4.4
2	Right 0 + 125/1640.015 m	15.4	15.8
3	Right 0 + 125/1650.015 m	4.2	5.0
4	Right 0 + 265/1506.368 m	11.0	15.1
5	Right 0 + 265/1541.555 m	9.7	13.8
6	Right 0 + 265/1600.002 m	8.6	10.7
7	Right 0 + 375/1567.999 m	4.4	5.2
8	Right 0 + 375/1659.159 m	18.3	19.1
9	Right 0 + 455/1590.549 m	8.1	8.3
10	Right 0 + 455/1633.897 m	3.9	4.7
Average		8.7	10.2

4.3.2 Capability to Identify Construction Stages

Settlement during construction changes markedly with the construction stage. Studies have also pointed out that settlement behavior is stage-dependent [10,24]. From the application results in this project, under the

rolling update process, the method can distinguish the transition from relatively rapid development during filling to slower creep during stoppage, and it can also reflect the renewed increase in settlement after resumed filling. For field control, this result helps identify the current construction stage and adjust the stoppage duration and filling rhythm more reasonably.

4.3.3 Identification of Nonuniform Settlement Risk

By comparing prediction results from different sections and elevations, it is also possible to evaluate how spatial differences in settlement may develop. The prediction results show not only changes in settlement magnitude, but also differences in settlement rate among different locations. In this study, locations with relatively large predicted settlement increments or increasing spatial differences were regarded as potential nonuniform settlement zones, rather than being directly classified as unsafe zones. This use of monitoring-based indicators for early warning, rather than direct safety classifications, is consistent with the general role of data-driven monitoring models in dam safety analysis [30].

For the monitoring points used in the spatial comparison, the prediction errors remained within an acceptable range for construction-stage analysis. Except for the relatively larger error at Section Right 0 + 375/1659.159 m, most monitoring points showed MAE values below 12 mm and RMSE values below 16 mm. This indicates that the model can provide a stable basis for comparing settlement responses among different sections and elevations.

In actual construction, these potential risk zones were used as reference areas for enhanced monitoring and construction control. The validation was carried out by checking whether the subsequent measured settlement continued to show greater deformation or greater spatial differences in the same sections or elevations. If the later monitoring data confirmed a stable trend, the corresponding section was kept under normal observation; if the settlement difference continued to increase, the monitoring frequency and local control measures were strengthened. The comparison of settlement differences among different sections and elevations is shown in Fig. 7.

4.4 Example of Application in Construction Decision-Making

In the Dashixia project, the predicted settlement results were used as technical references for construction planning and settlement control, rather than as automatic control commands. Previous studies have shown that monitoring-based prediction results can support engineering interpretation and decision-making in dam safety management [26,30]. In this project, the prediction outputs were mainly reviewed together with measured settlement records, filling progress, and on-site construction conditions. The main purpose was to provide clearer references for judging stoppage arrangements, filling rhythm adjustment, and local risk control.

One typical application was during a construction stoppage. If the predicted settlement rate decreased and the measured settlement also showed a stable trend in the following monitoring period, the dam body was considered to have entered a relatively stable adjustment stage. This provided a reference for maintaining the planned stoppage period or preparing for resumed filling. If the prediction still showed obvious settlement development, or if subsequent monitoring did not confirm stabilization, continued observation before resumed filling was recommended.

Another application was during resumed filling or continuous filling. When the prediction indicated renewed settlement growth after reloading, the filling rhythm and construction organization were evaluated in combination with the latest monitoring results. When the prediction indicated increasing spatial differences among sections or elevations, the corresponding dam zones were treated as key observation areas. In

these zones, monitoring was strengthened, and local construction measures, such as filling coordination, rolling control, and construction rhythm adjustment, were considered according to on-site conditions.

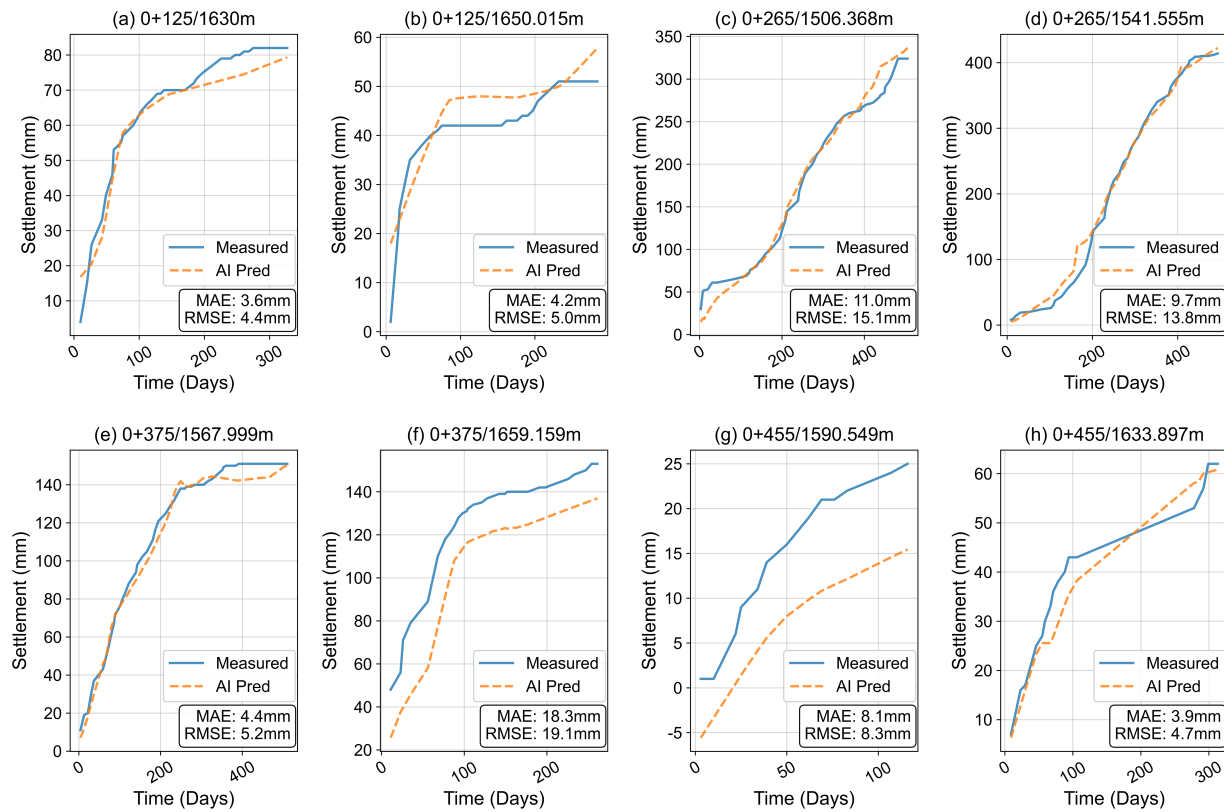


Figure 7: Comparison of settlement differences across different sections and elevations. The MAE and RMSE values are shown in each subplot to quantify the prediction error at each monitoring point. (a) Section Right 0 + 125, Elevation 1630 m; (b) Section Right 0 + 125, Elevation 1650.015 m; (c) Section Right 0 + 265, Elevation 1506.368 m; (d) Section Right 0 + 265, Elevation 1541.555 m; (e) Section Right 0 + 375, Elevation 1567.999 m; (f) Section Right 0 + 375, Elevation 1659.159 m; (g) Section Right 0 + 455, Elevation 1590.549 m; (h) Section Right 0 + 455, Elevation 1633.897 m.

The engineering feedback was mainly obtained through subsequent monitoring. After a prediction result was used as a construction control reference, the later measured settlement response was compared with the predicted trend in the next update cycle. If the measured trend was consistent with the predicted stable or increasing tendency, the prediction result was considered a useful reference for the current construction stage. If the measured response deviated from the prediction, the new monitoring data were added to the dataset and the model was updated before the next decision reference was given. In this way, the practical usefulness of the method was checked through a monitoring–prediction–feedback process. For this project, settlement control was therefore not based only on experience or retrospective interpretation of monitoring data. Instead, it became a process supported by both field monitoring records and rolling analysis results.

5 Discussion

This study was carried out to address a practical problem in the Dashixia project, namely, how to use monitoring data and construction information more directly for settlement analysis and site control during

construction. From the results of this study, one finding is evident: whether this type of method performs effectively depends heavily on the monitoring system and the completeness of construction records.

In actual engineering applications, the method requires continuous settlement monitoring data and relatively complete records of construction parameters. Previous studies have also shown that data quality has a strong influence on prediction performance [21,26]. In the Dashixia project, owing to the relatively good coverage of the monitoring system and the relatively complete construction records, the analysis with rolling updates could be carried out under favorable data conditions. Under such conditions, monitoring, prediction, and on-site decision-making can be more closely linked. However, this may not always be the case in other projects. If the monitoring data are discontinuous, if the monitoring points are not properly arranged, or if the construction records are incomplete, then the method may become less stable and less useful for actual control.

The limitations of this study should also be noted. The present validation is based on only one ultra-high concrete-faced sand-gravel dam project. Therefore, while the results demonstrate the engineering feasibility of the proposed method under the construction conditions of the Dashixia project, they do not fully demonstrate the robustness of the method across different dam types, geological settings, filling materials, or construction processes. The model parameters and settlement response characteristics obtained in this study should not be applied directly to other projects without project-specific verification and recalibration. The proposed method is more suitable for high or ultra-high CFRDs with staged filling, continuous settlement monitoring, and relatively complete construction records. For other dam types, different material zoning, complex geological disturbances, or construction processes with long stoppage periods and abnormal loading, additional training data and independent validation are still required. Therefore, this work constitutes an engineering case study based on a single real project, and further applications in different projects are needed to evaluate the general robustness of the method.

The value of this method is not limited to settlement prediction itself. In actual construction, settlement trend and spatial difference information can also be considered together with other indicators, such as compaction conditions, the number of rolling passes, and filling quality. In this sense, settlement data are not only useful for deformation analysis, but can also support broader construction quality control and construction planning. Previous studies have also shown that settlement development is related to the structural safety and later service performance of CFRDs, including the stress and cracking problems of the face slab [27–29]. From this perspective, the method proposed in this study can also be seen as a possible link between deformation monitoring, quality control, and construction management.

Overall, this study shows that for ultra-high CFRDs, settlement management during construction need not be limited to retrospective interpretation. By combining monitoring data, construction parameters, rolling prediction, and site feedback, settlement analysis can play a more direct role in ongoing construction control. This point is especially relevant in projects where settlement changes markedly with construction stages and is closely related to construction planning.

6 Conclusions

Based on the construction practice of the Dashixia Water Conservancy Project in Xinjiang, this study examined the settlement behavior of an ultra-high concrete-faced rockfill dam during construction and discussed a corresponding prediction and control method. The main conclusions are as follows:

(1) Settlement during construction shows pronounced stage characteristics. In this project, settlement usually developed faster during continuous filling, slowed during construction stoppage, increased again after resumed filling, and then gradually stabilized when the dam approached the final height.

(2) By combining whole-process settlement monitoring records with key construction parameters, a construction-stage dataset was organized for subsequent analysis. This dataset made it possible to describe settlement development under different construction conditions and also provided a basis for prediction.

(3) With the rolling update process, the settlement trend during construction could be tracked dynamically. For the ten representative monitoring points, the average MAE and RMSE were 8.7 and 10.2 mm, respectively, showing that the predicted trends were generally close to the measured settlement trends.

(4) The method could reflect stage transitions and help identify sections or elevations where nonuniform settlement risk might become more pronounced. For construction application, this can provide a more direct reference for stoppage planning, filling rhythm adjustment, and local risk control.

(5) From the application results of this project, the method is useful mainly because it makes settlement monitoring results easier to use in ongoing construction management. In this sense, it helps connect monitoring records, prediction analysis, and on-site decision-making more closely during construction. However, the present validation is still limited to one ultra-high CFRD project, and further verification is needed before the method is applied to different dam types or substantially different construction conditions.

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