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Construction simulation approach of roller-compacted concrete dam based on real-time monitoring*

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Abstract: The parameters of existing roller-compacted concrete (RCC) dam construction simulation are usually fixed based on experience while the actual construction conditions of an RCC dam change during the process of the project. The simulation accuracy of an RCC dam is therefore reduced because the change has not been considered. A new method for RCC dam construction simulations based on real-time monitoring is presented in this paper. First, real-time monitoring technology is used to collect and analyze the actual construction information. Second, meteorological data obtained from the real-time monitoring system are analyzed using the fuzzy average function method, and the weather conditions of the next stage are forecasted. Then the construction schedule simulation model is updated via the Bayesian update method. Results of the analysis are used as the input to the construction simulation parameters, and the construction simulation is performed. A real-world engineering example is presented to compare the simulation results with the actual construction schedule. The results demonstrate that the method can effectively improve the accuracy and real-time performance of construction simulations.

Key words: Roller-compacted concrete (RCC) dam; Construction simulation; Real-time monitoring; Bayesian update; Fuzzy mean generating function
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1 Introduction

Simulation is a rehearsal for the real world (Banks, 2005). Construction simulation is one of the most important methods for the formulation of the construction organization plan and the realization of construction resource allocation. In an actual construction process, if the construction simulation results and actual progress deviate, then the next phase of the actual construction will be full of risk and we lose the guiding role of simulation in the construction process. The simulation parameters of the roller-compacted concrete (RCC) dam are an important part of the simulation system. The accuracy and effectiveness of the input parameters directly affect the credibility of simulation results. However, most RCC dam construction simulation methods are based on the parameters given by experience. The given parameters are assumed to have the mean value or to be a value based on experience. When the variation of the construction simulation parameters cannot be reflected in the simulation model, the simulation results will deviate from the actual construction. Construction simulation based on real-time monitoring takes the changes in the construction parameters into account, dynamically updates the construction simulation model to ensure that the model changes with the actual construction conditions, and improves the

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adaptability of the simulation. Therefore, it is important both in theory and practice to study the construction simulation based on real-time monitoring.

The construction simulation method has been applied to study the construction of an RCC dam for many years (Jurecha and Widmann, 1973). In recent years, the research on the simulation has concentrated mainly on a specific process such as storehouse surface area planning (Dong and Zhao, 2013) and storehouse surface construction simulation (Zhong et al., 2013, 2017). The multi-process coupling has also been developed (Luo, 2009). Simultaneously, with the development of network and information technology, some progress has been made in dynamic simulation (Zhong, 2012). However, due to the shortcoming that the simulation parameters are fixed, the accuracy of the results has been affected by the inaccurate estimation of construction parameters.

Construction quality real-time monitoring is applied to road engineering in its early stages (Anderegg et al., 2006; Hossain et al., 2006; White et al., 2006; Mooney and Rinehart, 2007). It has been successfully applied to hydropower projects, but is used mainly for the rock-fill dam (Cui et al., 2009; Cui, 2010; Zhong et al., 2011). Although some results have been achieved in the field of quality control of concrete dam construction (Zhong et al., 2012a; Liu et al., 2015), studies of construction schedule control based on real-time monitoring technology are lacking.

Construction process simulations based on real-time monitoring information have emerged in recent years. At present, most such simulations are applied to earthwork engineering or rock-fill dam engineering. Song and Eldin (2012) collected real-time data of the site construction which was applied to real-time analysis of the construction schedule. Vahdatikhaki and Hammad (2014) proposed near real-time simulation methods and considered environmental influences to the construction simulation but without any prediction of the impact of rainfall. Lu et al. (2007) introduced a concrete construction decision system based on the trail of vehicle tracking technology, the principle of discrete event simulation, and an optimization algorithm. This system updates the parameters of the simulation using current monitored data. Navon (2005a, 2005b) realized the real-time monitoring of earthwork transportation in highway construction, calculated and analyzed the duration of actual construction, equipment productivity, and the rate of resource degradation in real time using real-time monitored data. Han et al. (2005) analyzed the productivity of earthwork based on GPS (global positioning system) real-time data of the earthwork transportation system and compared the calculated data with the experiential data. Akhavian and Behzadan (2012) updated the simulation model in real time according to the real-time construction data in the site and completed the construction process simulation using the data. The real-time animation model was built by simulations and the 3D dynamic visualization of simulations of the construction process was realized. There were no predictions of simulated parameters for construction process in the future using the site construction data. Akhavian and Behzadan (2013) used *k*-means to analyze the real-time construction information and updated the construction parameters but there was a lack of consideration of the influence of environmental factors. Han et al. (2006) completed the earthwork transportation process model and simulation with online cyclic network simulation technology based on GPS data while updating in real time the earthwork productivity.

We therefore aim to (1) establish a construction simulation model of high roller-compacted concrete dam based on real-time monitoring; (2) use Bayesian update technology, combined with a priori information and sample information, to achieve construction simulation parameter prediction.

2 Construction simulation framework

In this simulation, data are acquired by real-time monitoring. The data are used to adjust and update the simulation boundary and model; then simulation and schedule prediction are based on the current construction features.

We use real-time monitoring technology to collect all types of construction process data. Then a dynamic data analysis method is used to analyze the data to determine the intensity of concrete placing, paving productivity, rolling productivity, quality inspection duration, and predicted daily rainfall. The overall framework for an RCC dam construction simulation is shown in Fig. 1. The implementation steps are as follows: (1) It uses a GPS, a computer network, automatic control, and database technology to monitor the construction process of the RCC dam to acquire real-time data on the dump truck, compactor, quality control, and the storehouse surfaces, in addition to other raw data. (2) Pre-processing is carried out on the dynamic data obtained in step (1) to determine the intensity of concrete placing, paving efficiency, rolling productivity, quality inspection duration, and predicted daily rainfall. The construction time of construction quality inspection data, calculated by different quality inspection points of quality inspection duration, simulates the parameters of the construction quality inspection procedure. The meteorological conditions are the necessary conditions clearly specified in the construction specifications. Therefore, the rainfall data are used to predict the future meteorological conditions. (3) The construction simulation parameters obtained in step (2) are applied in the RCC dam simulation model using Bayesian update and a fuzzy mean generating function. (4) On the basis of step (3), after obtaining the simulation results of the next stage of the construction progress, comparisons are made for the simulation results of the proposed method, traditional methods, and the actual schedule, and then visualize the simulation results. Then these results are used to adjust the construction plan for the next phase to ensure that the next phase of the actual construction schedule will meet the planning requirements. (5) In the next stage of construction, steps (1)–(4) are repeated.

3 Mathematical model

The mathematical model of the construction simulation is the mathematical abstraction of the simulation object evolution process. It is divided into four parts: objective function, state transition equation, constraint condition, and parameter updating method.

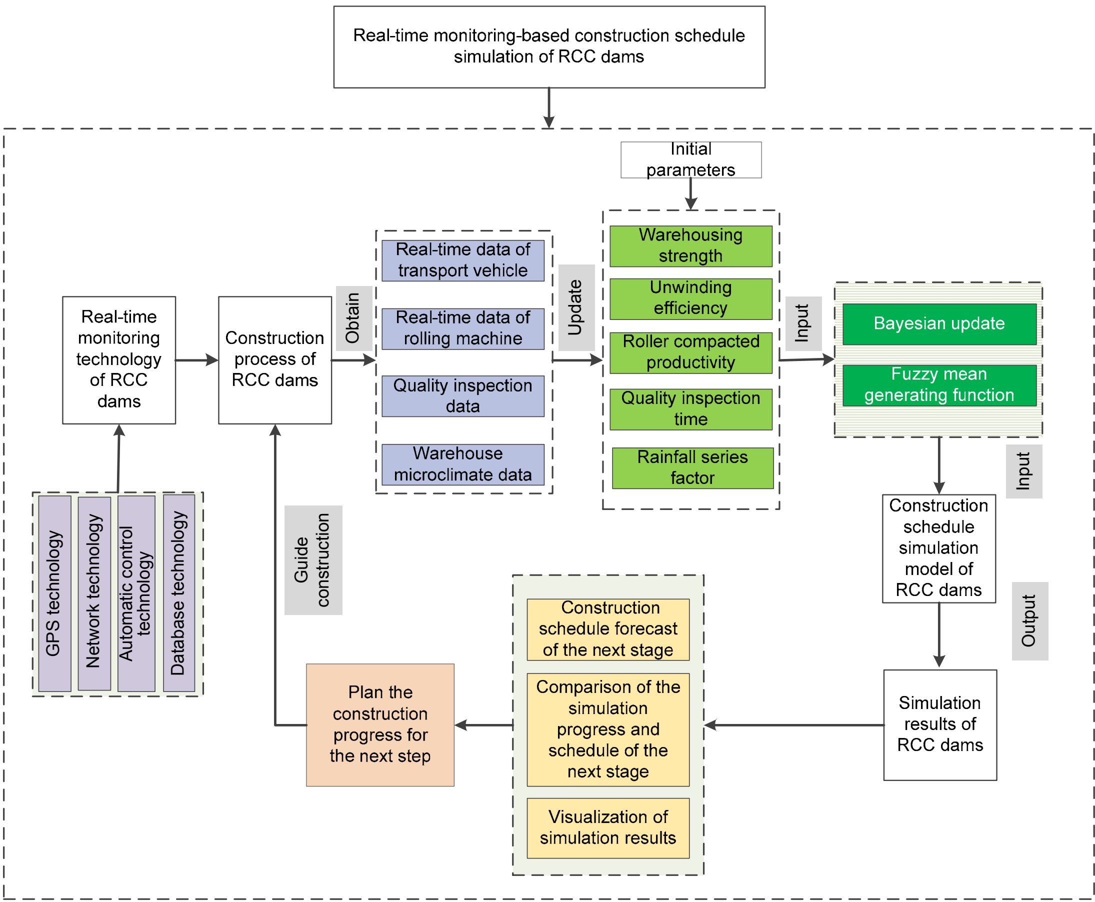


Fig. 1 Framework for an roller-compacted concrete (RCC) dam construction simulation based on real-time monitoring

$$\mathrm{Opt}(T, U), \tag{1}$$

$$\begin{cases} H_{\mathrm{e}}(l) = H_{\mathrm{s}}(l) + \Delta H_l(i), \\ T_{\mathrm{e}}(l) = T_{\mathrm{s}}(l) + \Delta T_l(i), \\ V(l) = V(l) + \Delta V_l(i), \\ T_{\mathrm{C}}(m) = T_{\mathrm{C}}(m) + \Delta T_m(i), \\ V_{\mathrm{C}}(m) = V_{\mathrm{C}}(m) + \alpha \Delta V_m(i), \end{cases} \tag{2}$$

$$T_{\mathrm{s}}(i, j, k) \geq \min(T_{\mathrm{e}}(o, \ldots, \ldots), T_{\mathrm{e}}(p, \ldots, \ldots), T_{\mathrm{e}}(q, \ldots, \ldots)) + T_{\mathrm{b}}(i, j, k), \tag{3}$$

$$\begin{cases} H_{\mathrm{e}}(o, r, j-1) - H_{\mathrm{s}}(i, j, k) \leq H^t_{\max}, \\ H_{\mathrm{e}}(i, j, k) - H_{\mathrm{e}}(o, r, j-1) \leq H^t_{\max}, \end{cases} \tag{4}$$

$$\mathrm{CM} \subset \mathrm{CM}_{\mathrm{b}}(C, E, Q, R), \tag{5}$$

$$\mathrm{RM} = \mathrm{RM}_{\mathrm{B}} \cup \mathrm{RM}_{\mathrm{F}}. \tag{6}$$

Eq. (1) defines the objective function of the construction simulation, where T and U indicate the construction period and utilization factor of the construction equipment, respectively. The construction period and the mechanical utilization rate are optimized.

Eq. (2) defines the dam state transition equations before and after the construction simulation. Specifically, the first equation represents the construction process of dam section l, where $H_{\mathrm{e}}(l)$ and $H_{\mathrm{s}}(l)$ represent the ending and starting elevations of dam section l, respectively, and $\Delta H_l(i)$ represents the pouring thickness of dam section l of pouring warehouses i; the second equation represents the propulsion process of the construction time of dam section l, where $T_{\mathrm{e}}(l)$ and $T_{\mathrm{s}}(l)$ represent the construction ending time and starting time of dam section l, respectively, and $\Delta T_l(i)$ represents the construction period of dam section l of pouring warehouses i, including the waiting period of the warehouse and the actual construction period; the third equation represents the cumulative concrete volume of dam section l, where $V(l)$ represents the volume of pouring concrete of dam section l and $\Delta V_l(i)$ represents the volume of pouring concrete of dam section l of pouring warehouses i; the fourth equation represents the accumulation process of construction duration of machinery m, where $T_{\mathrm{C}}(m)$ represents the construction duration of machinery m and $\Delta T_m(i)$ represents the construction duration of machinery m in pouring warehouses i; the fifth equation represents the cumulative amount of concrete poured by machinery m, where $V_{\mathrm{C}}(m)$ represents the volume of concrete poured by machinery m, $\Delta V_m(i)$ represents the volume of concrete poured by machinery m in pouring warehouses i, and α represents machinery m in the pouring warehouse i project accounting for the proportion of which (m=1, 2, …, M with M the total number of machines).

Eqs. (3)–(5) define the simulation constraints of construction. Specifically, Eq. (3) is the opening constraint, where $T_{\mathrm{s}}(i, j, k)$ represents the starting concrete pouring time of warehouses i ($1 \leq j \leq k \leq N$, N is the total dam number), $T_{\mathrm{e}}(o, \ldots, \ldots)$, $T_{\mathrm{e}}(p, \ldots, \ldots)$, and $T_{\mathrm{e}}(q, \ldots, \ldots)$ represent the completion time of pouring warehouses o, p, and q which have a spatial cross relationship with pouring warehouse i, and $T_{\mathrm{b}}(i, j, k)$ represents the duration of construction preparation of warehouse i. Eq. (4) shows the height difference constraints of dam material transportation, where $H_{\mathrm{s}}(i, j, k)$ and $H_{\mathrm{e}}(i, j, k)$ are the starting and ending elevation heights of pouring warehouses i, respectively, $H_{\mathrm{e}}(o, r, j-1)$ represents the ending elevation height of pouring warehouses r adjacent to pouring warehouses i, and $H^t_{\max}$ denotes the height difference control threshold. Eq. (5) is the construction quality constraints, where CM represents the data set of construction quality and $\mathrm{CM_b}$ represents the standard data set of construction quality, including the detection data set C of rolling control system, the test data set E of upper dam transportation system, the inspection data set Q of construction quality, and the data set R of rainfall information.

Eq. (6) defines the updating method of construction simulation parameters, where RM represents the parameter updating method set, including the Bayesian update method $\mathrm{RM_B}$ and the fuzzy homogenous function $\mathrm{RM_F}$.

3.1 Raw data collection

To obtain the construction simulation parameters in line with the actual conditions of the construction site, we propose a dam construction information acquisition method composed of the differential reference station, monitoring terminal, field control station and control center, applied GPS technology, general packet radio service (GPRS) wireless data transmission technology, computer network technology, and database technology (Fig. 2). Four different methods are used to collect data. Using the GPS technology and the vibration sensor, the compaction construction information, such as the space-time coordinate $P(x, y, z, t)$ and the vibration status Lv are collected in real time (Liu et al., 2015). Using the GPS technology and the loading and unloading sensors, the transportation information of dam construction, such as the position coordinates of vehicle $Q(x, y, z, t)$ and the transport volume V are collected in real time (Cui, 2010). Quality inspection personnel collect construction quality inspection information, including quality inspection time t_q, dry density of concrete ρ_c, and concrete moisture content M_c, with a personal digital assistant (PDA) at the construction site (Liu et al., 2013). The microclimate monitoring station, composed of temperature sensor, humidity sensor, anemometer, and pluviometer, is used mainly to collect construction site temperature T, humidity M, wind speed υ, and rainfall R_f (Zhong et al., 2012b). The resultant construction information is transmitted and stored in the database server of the data center through the GPRS network in real time. The frequency and accuracy of the raw data used in the construction simulation are shown in Table 1.

3.2 Data processing

The real-time monitoring data are the raw data, which reflect the actual construction process of dam construction. Because the data acquisition frequency is inconsistent, the data processing method is used to process the raw data.

3.2.1 Data cleaning

For the cleaning of construction data, Vahdatikhaki and Hammad (2015) monitored the same rigid component of a digger by multiple data collection equipment to ensure the accuracy of the data. An interpolation method was used to fill up the missing values. Zhang et al. (2012) monitored the operation of a crane via multiple data collection and judged whether there existed outliers based on the

Table 1 Precision frequency table of construction simulation raw data

Raw data	Accuracy	Frequency
Temporal and spatial information of roller machine $P(x, y, z, t)$	2–3 cm	1 s
Temporal and spatial information of transport vehicle $Q(x, y, z, t)$	2–3 cm	1 s
Carrier number N	–	Based on the construction schedule
Quality inspection time t_q	–	Based on the construction schedule
Rainfall R_f	0.1 mm	1 min

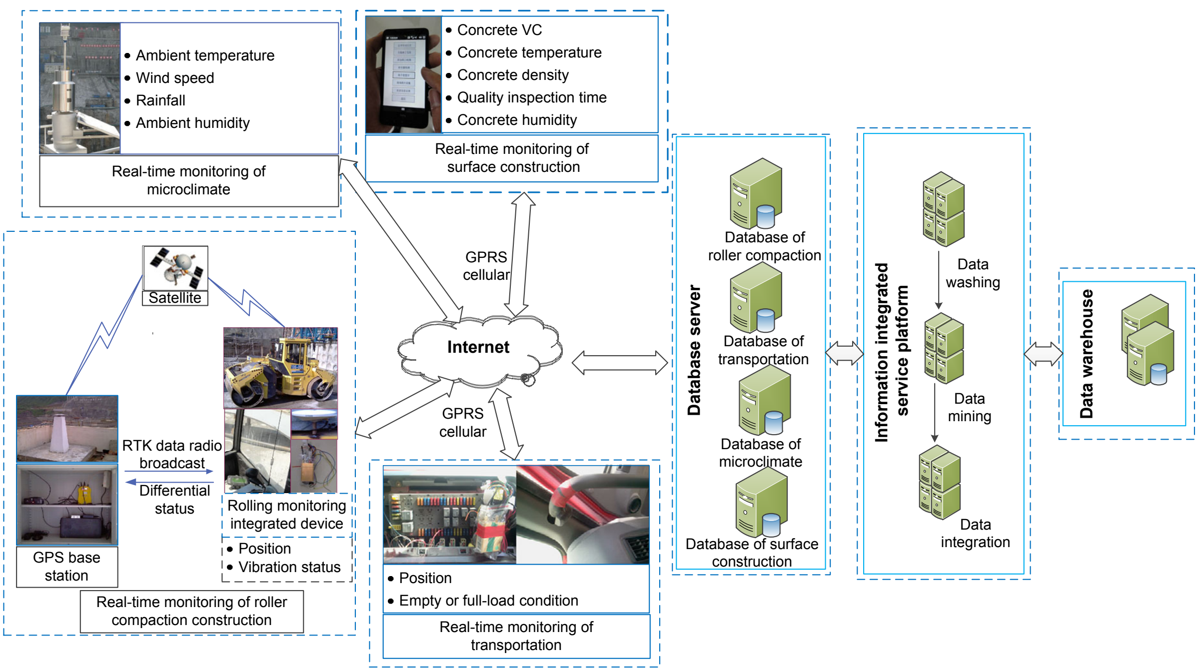


Fig. 2 Framework of real-time data acquisition and processing for an RCC dam construction
RTK: real-time kinematic

geometric constraint conditions and also filled up missing data with interpolation. As we analyzed data which contain spatial data and rainfall data, as well as the spatial data focused on the locations of rolling compaction machines and dump trucks, the processing is comparatively simple. By analyzing raw data, there are constraints on the speed of data changes. In the rolling process, the running distance of a roller in any two seconds cannot be greater than 1 m. The construction information data cleaning problem is transformed into the time series data cleaning problem with speed constraints (Song et al., 2015).

Consider a sequence $X=X_1, X_2, \ldots$, where each X_i is the value of the ith data point and each X_i has a timestamp t_i. Taking all the time series values $x=x_1, x_2, \ldots, x_n$ within time interval $T=[t_1, t_n]$, the time series is detected. If the jth time series value is missing, the time value t_j is added, and $x_j=0$ is taken to ensure the integrity of the time series.

A speed constraint $s=(s_{\min}; s_{\max})$ with window size w is a pair of the minimum speed $s_{\min}$ and the maximum speed $s_{\max}$ over sequence x. For any time t_i and t_j, it requires x_i and x_j to meet the following condition:

$$0 \le t_j - t_i \le w, \quad s_{\min} \le \frac{x_j - x_i}{t_j - t_i} \le s_{\max}. \tag{7}$$

Assuming that the correction value of x_i is x_i', according to the minimum change principle, it requires $\Delta(x_i, x_i')=|x_i, x_i'|$ to be the minimum value.

Taking the spatial information collected by the rolling control information acquisition system as an example, the process of data cleaning is described. The spatial data collected at a certain time period are shown in Table 2.

According to the construction site control standard, we can see that the rolling speed is limited as $s=(s_{\min}; s_{\max})=(0; 2)$ where $w=2$. Given that the timestamps of the space coordinates are $t_1, t_2, \ldots, t_{10}$, the corresponding spatial coordinates are $\{(x_1, y_1, z_1), (x_2, y_2, z_2), \ldots, (x_{10}, y_{10}, z_{10})\}$. Because the data variation is constrained to the roller speed, the coordinates are converted into a roller speed that is $\{v_1, v_2, \ldots, v_{10}\}$. Thus, the data change rate between v_7 and v_8 is $\frac{2.701-0.851}{3-1}=0.925<2$. Then the missing space coordinates (233.85, 12.635, 1105.0315) are obtained by the interpolation method from finding the existence of missing values by detecting the timestamps. Similarly, the data change rate between v_8 and v_9 is $\frac{1004.777-1.351}{4-3}=1003.426>2$. Thus, v_9 is the abnormal value and should be deleted, and then the new spatial coordinates (236.25, 12.66, 1105.0295) are obtained by interpolation. The new data are listed in Table 3.

Table 2 Spatial data collected at a certain time period before data cleaning

Time	x (m)	y (m)	z (m)	v (m/s)
2011/3/15 11:24:55	227.5	12.58	1105.034	0.808
2011/3/15 11:24:56	228.3	12.83	1105.038	0.838
2011/3/15 11:24:57	229.2	12.59	1105.040	0.931
2011/3/15 11:24:58	230.0	12.86	1105.035	0.844
2011/3/15 11:24:59	230.8	12.61	1105.035	0.838
2011/3/15 11:25:00	231.7	12.88	1105.032	0.939
2011/3/15 11:25:01	232.5	12.59	1105.036	0.851
2011/3/15 11:25:03	235.2	12.68	1105.027	2.701
2011/3/15 11:25:04	236.1	12.83	100.250	1004.777
2011/3/15 11:25:05	237.3	12.62	1105.032	1004.783

Table 3 Spatial data collected at a certain time period after data cleaning

Time	x (m)	y (m)	z (m)	v (m/s)
2011/3/15 11:24:55	227.50	12.580	1105.0340	0.808
2011/3/15 11:24:56	228.30	12.830	1105.0380	0.838
2011/3/15 11:24:57	229.20	12.590	1105.0400	0.931
2011/3/15 11:24:58	230.00	12.860	1105.0350	0.844
2011/3/15 11:24:59	230.80	12.610	1105.0350	0.838
2011/3/15 11:25:00	231.70	12.880	1105.0320	0.939
2011/3/15 11:25:01	232.50	12.590	1105.0360	0.851
2011/3/15 11:25:02	**233.85**	**12.635**	**1105.0315**	**1.351**
2011/3/15 11:25:03	235.20	12.680	1105.0270	1.351
2011/3/15 11:25:04	**236.25**	**12.660**	**1105.0295**	**1.050**
2011/3/15 11:25:05	237.30	12.620	1105.0320	1.050

Bold values indicate that the data were obtained after data cleaning

3.2.2 Data analysis

In traditional construction simulation, Zhou and Zhao (2008) selected the pouring strength, efficiency of concrete spreading, and productivity of the rolling machine as the construction simulation parameters; Chang et al. (2013) chose the construction quality inspection time as a simulation parameter. On the basis of the above research, taking into account the feasibility of real-time information collection at the construction site, we selected pouring strength, efficiency of concrete spreading, productivity of the rolling machine, and construction quality inspection time as the simulation parameters. The RCC construction specifications stipulate that the construction should be forced to stop when the rainfall is at a certain point, which has great influence on the construction site organization. Taking into account this situation, rainfall in the dam area is chosen as a constraint condition.

1. Analysis of the intensity of concrete placing and paving productivity

The current state of the machine, including the position, speed, and direction, is determined by the automatic acquisition of the monitoring data. Taking transport vehicle warehousing as an example, 'geo-fencing' technology (Reclus and Drouard, 2010) based on mechanical positioning data can be used for dynamic analysis and real-time calculation of the actual intensity of concrete placing (P_{a}) and paving productivity (P_{b}):

$$P_{\mathrm{a}}=\sum_{i=1}^{m}\frac{N_iV_i}{\Delta t}, \tag{8}$$

$$P_{\mathrm{b}}=\sum_{l=1}^{n}\frac{3600V_l}{t_{\mathrm{e}l}-t_{\mathrm{s}l}}, \tag{9}$$

where N_i is the carrier number of the ith vehicle in the pouring period Δt, V_i (m^3) is the rated carrying capacity of the ith vehicle, Δt (h) is the concrete pouring time, m is the number of vehicles used for transport, $t_{\mathrm{s}l}$ (s) is the moment at which transport vehicle l enters the storehouse surfaces, $t_{\mathrm{e}l}$ (s) is the moment at which transport vehicle l exits the storehouse surfaces, V_l (m^3) is the rated carrying capacity of transport vehicle l, and n $\left(n=\sum_{k=1}^{m}N_k\right)$ is the number of vehicles entering the storehouse surface.

2. Analysis of rolling productivity

The most critical operating procedure in the construction of RCC dams is storehouse surface rolling, which is directly related to the quality and progress of the whole project. In the operating system, the rolling productivity P_{c} is an important index to control the construction schedule. In this study, the following method is used to analyze the rolling productivity.

Although the driving process of the rolling machine in the storehouse surfaces is inevitably influenced by the driver, the machine itself and the construction environment have a strong regularity in terms of the specific time, specific storage area, and specific construction. According to its operating rules, based on the real-time monitoring system, the position coordinates of the two points $P(x_1, y_1, z_1, t_1)$ and $P(x_2, y_2, z_2, t_2)$ of one track and their corresponding time t_1 and t_2 can be extracted. Based on the extracted data, the length of the compacted section l and the roller speed v can be obtained:

$$\begin{cases} l=S\left(P_1,P_2\right)=\sqrt{\left(x_1-x_2\right)^2+\left(y_1-y_2\right)^2+\left(z_1-z_2\right)^2}, \\ v=\dfrac{l}{\Delta T}=\dfrac{S\left(P_1,P_2\right)}{t_2-t_1}, \end{cases} \tag{10}$$

where $S(P_1, P_2)$ (m) is the distance between P_1 and P_2 and ΔT (s) is the time interval.

Finally, the roller productivity is calculated using the following equation:

$$P_{\mathrm{c}}=\frac{3600(z-c)lhK_{\mathrm{t}}}{(l/v+t_0)N_{\mathrm{R}}}, \tag{11}$$

where z (m) is the width of the roller wheel, c (m) is the lap width of the rolled strip, h (m) is the thickness of the paving layer, l (m) is the length of the compacted section, v (m/s) is the speed of the roller, t_0 (s) is the turning and shifting time of the roller, N_{R} is the rolling pass number, and K_{t} is the time factor.

3. Quality inspection duration analysis

The quality inspection process of the storehouse surface with a nuclear density meter is presented as follows: after the completion of storehouse construction, the on-site inspection personnel use a nuclear moisture density meter to measure the density of the compacted surface (i.e. the quality inspection procedure). After the completion of a point, the detection data, detection time, detection position, and other information are sent to the total control center database using a handheld PDA until all test points have been analyzed. Therefore, the real-time monitoring data analysis module can calculate the duration of inspection procedure of the storehouse based on the data of the detection time in the database, as shown below:

$$T_{\mathrm{q}} = \frac{t_{\mathrm{eq}} - t_{\mathrm{sq}}}{3600}, \tag{12}$$

where T_{q} (h) is the duration of construction quality inspection, t_{eq} (s) is the detection time of the first point, and t_{sq} (s) is the detection time of the last point.

4. Analysis of the influence of the microclimate

The microclimate of the dam area has a strong influence on the construction of the RCC. Special weather impacts the working efficiency of the construction machinery, and excessive rainfall and high winds can lead to construction stagnation. The accuracy of the weather forecast must be improved to facilitate a timely understanding of the meteorological conditions of rainfall and air temperature and proper planning of the construction schedule during the construction period.

The microclimate monitoring device collects microclimate data and sends the data to the database every minute. A fuzzy mean generating function method is used to update the parameters in the construction simulation. The fuzzy mean generating function (FMGF) takes the data collected within 1 h as a data bit and the data collected within 24 h as a data column. This requires the analysis of microclimate data to meet the requirements of real-time updating of the simulation parameters. Taking rainfall as an example, because the system uploads rainfall data every minute, the total amount of rainfall within 1 h is shown as follows:

$$\mathrm{RF} = \sum R_{\mathrm{f}}, \tag{13}$$

where RF (mm) is the total rainfall within 1 h and R_{f} (mm) is the rainfall data collected from the real-time data microclimate monitoring device.

3.3 Simulation parameter updating

3.3.1 Real-time updating of the construction efficiency parameters

Bayesian update technology provides a systematic method for subjective estimation of data and effective integration of real data. Based on the actual data acquired from the real-time construction information monitoring system, Bayesian updating technology can effectively improve the input and output accuracies of the simulation model.

Assume that the initial probability density function of input parameter x_i of the simulation model is $f'(x_i)$ (according to the past experience and analysis, known as the prior density function). When actual observational data are acquired, they can be used to modify and update the initial hypothesis according to Bayes' theorem; then the posterior distribution $f''(x_i)$ can be obtained. The expression is shown below (Straub and Papaioannou, 2015):

$$f''(x_i) = k_{\mathrm{s}} L(x_i) f'(x_i), \tag{14}$$

where $L(x_i)$ is a likelihood function and k_{s} is a standard constant whose expression is

$$k_{\mathrm{s}} = \left[\int_{-\infty}^{\infty} L(x_i) f'(x_i) \mathrm{d}x_i \right]^{-1}, \tag{15}$$

where x_i represents the intensity of concrete placing ($\mathrm{m^3/h}$), the paving productivity ($\mathrm{m^3/h}$), rolling productivity ($\mathrm{m^2/h}$), or quality inspection duration (h) (i=1, 2, 3).

According to the central limit theorem, the construction efficiency of each process E obeys the normal distribution, i.e. $e \sim \mathrm{N}(\mu_e, \sigma_e^2)$. However, the mean μ_e and variance σ_e^2 of the normal distribution are unknown. Therefore, the overall distribution $p(e; \boldsymbol{\theta})$ contains two unknown parameters, where $\boldsymbol{\theta}=\{\mu_e, \sigma_e^2\}^{\mathrm{T}}$.

According to the posterior distribution $(\sigma_e^2|t)$ using the posterior expectation estimation, the variance σ_e^2 and mean μ_e of each process duration can be updated with Eqs. (16) and (17) as follows (Zhang et al., 2014):

$$\hat{\sigma}_e^2 = \frac{\beta_1}{\alpha_1 - 1} = \frac{\dfrac{\tau_0 n(\mu_0 - \overline{t_1})^2}{2(\tau_0 + n)} + \dfrac{\sum_{i=1}^{n}(t_{1i} - \overline{t_1})^2}{2} + \beta_0}{\alpha_0 + \dfrac{n}{2} - 1}, \tag{16}$$

$$\hat{\mu}_e = \mu_1 = \frac{\tau_0 \mu_0 + n\overline{t_1}}{\tau_0 + n}, \tag{17}$$

where α_0, β_0, μ_0, τ_0 are hyper-parameters of conjugate prior distribution $f(t|\alpha_0, \beta_0, \mu_0, \tau_0)$, μ_0 $\left(\mu_0 = \frac{1}{n}\sum_{i=1}^{n} t_i\right)$

is the mean of a priori data, $\tau_0=n$, $\alpha_0=(n-1)/2$, $\beta_0=\sum_{i=1}^{n}(t_{1i}-\bar{t})^2/2$, and $f(t|\alpha_0, \beta_0, \mu_0, \tau_0)$ is a normal-inverse-Gamma distribution (Gelman et al., 2004). Its posterior distribution is $f(t|\alpha_1, \beta_1, \mu_1, \tau_1)$, where n is the sample size of the first stage, $\bar{t}_1$ is the sample mean of the first stage, and t_{1i} is the ith component of the sample of the first stage, where $i<n$.

3.3.2 Real-time updating of weather data

Using the FMGF model (Wei and Cao, 1993), the short-term meteorological event sequence is predicted; this provides the basis for the long-term placement of the dam. To make the application of the average function more extensive and improve the fitting precision, Wei and Cao (1993) extended the mean generating function to the fuzzy set and formed the FMGF:

$$\begin{gathered}\bar{X}_l(i)=\frac{1}{n_l}\sum_{j=0}^{n_l-1}\hat{\mu}_A(i+jl)X(i+jl),\\ i=1,\ 2,\ \ldots,\ l,\ 1\le l\le M,\end{gathered} \tag{18}$$

where M=INT(N/2), n_l=INT(N/l), N is the sample size, and $\hat{\mu}_A(i)$ is a membership function for the periodic time series $X(t)$,

$$\hat{\mu}_A(i)=\begin{cases} r\mathrm{e}^{-\beta(N-i)}\sin\left[\dfrac{2\pi}{l}(N-i)\right], & i<N,\\ 1, & i\ge N.\end{cases}$$

According to the meteorological historical data structure, the meteorological original time series is $X^0(t)$, t=1, 2, …, N. To achieve the effect of a high-pass filter, the first- and second-order differences of the original sequence are calculated to obtain $X^1(t)$ and $X^2(t)$, respectively.

The FMGFs of the sequences $X^0(t)$, $X^1(t)$, and $X^2(t)$ are obtained, and three sets of FMGF extension sequences $f_l^0(t)$, $f_l^1(t)$, and $f_l^2(t)$ are created by periodic extension. To fit the upward and downward trends in the original sequence, the cumulative continuation sequence is further established.

Finally, a double-score criterion is used to select the 4×M extended sequence. Assuming that K predictions are eventually introduced, the sequence prediction model is defined according to

$$\hat{X}(t)=a_0+\sum_{i=1}^{K}a_i f_i(t), \tag{19}$$

where a_i represents the coefficient of the ith epitaxial FMGF sequence and a_0 represents the value of $x(t)$ when no fuzzy mean-generating function is introduced.

3.3.3 Updating the construction simulation boundary conditions

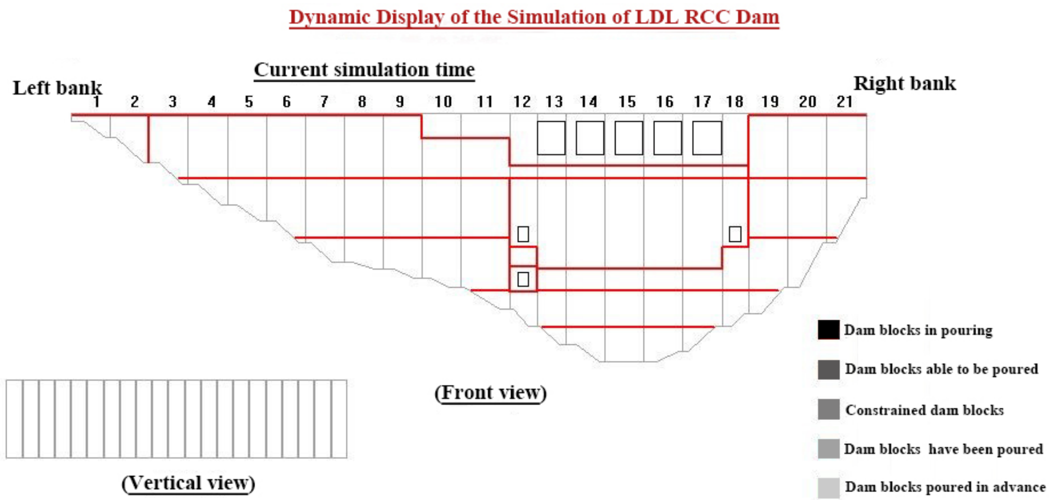
A simulation based on real-time monitoring is conducted to provide support and service for the progress forecast and scheduling. Therefore, the simulation must update the parameters of the model and obtain and update the current state of the system simulation boundary conditions in real time. The comprehensive information system of the project contains many types of construction information, such as recent resource scheduling and the next phase of the construction tasks. The information is updated quickly and reflects the real situation of the engineering construction and provides the necessary prerequisites for acquisition and real-time updating of simulation boundary conditions.

3.4 Implementation

We adopt the discrete event simulation method to develop the simulation software with C++ independently. The updating of the simulation model is realized by updating the simulation parameters. When the simulation program receives the command to start the simulation, it reads the raw data from the database. Then the initial simulation parameters are calculated using the formula given in this study. The initial simulation parameters are automatically put into the Bayesian network to obtain the simulation parameters. Then the simulation model is carried out. The above processes are automatically completed. The construction simulation interface is shown in Fig. 3.

4 Case study

An RCC dam in southwest China is selected as a case study to demonstrate the validity of the research. The maximum dam height is 140 m. The dam is divided into 28 sections. It uses two grades of RCC on the upstream face and abnormal concrete to control



Information on each dam section

Type/Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Status																					
Cumulative increase	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Concrete (10000M³)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Fig. 3 Construction simulation interface

seepage. In addition to the intake section, the dam is constructed using RCC around the bottom hole and above the surface of the weir.

The construction simulation is divided into four stages. In the actual construction process, the construction simulation can be carried out according to the needs of the construction site. After the simulation, the simulation results such as elevation of each section and the maximum area of storehouse surface, are stored in the web database which can be displayed in real time. The real-time progress control system will read the simulation results in the web database and display it in real time, as shown in Fig. 4.

At the beginning of the simulation, because the construction of the dam has not yet started, the real-time monitoring system failed to capture real-time monitoring data. The simulation input model cannot be updated.

Therefore, the simulation parameters of the whole process simulation of the pre-construction process are used as the initial input parameters and the simulation results are shown in Tables 4 and 5.

After the construction of the first stage, real-time monitoring data regarding the real construction process are used to update the simulation input model, and the updated model is used to simulate the next stage.

Fig. 4 Visualization of construction schedule simulation results

A regression model is established based on the rainfall data of the Ludila (LDL) project. Taking the rainfall information of June, July, and August as the regression samples and using the fuzzy average function model, the forecasting factors are selected using the double-score criterion, and the regression model is established. Finally, through the regression model, rainfall information for September is forecasted and verified. The regression model is given in Eq. (20), and the regression coefficient and FMGF can be observed in Table 6.

$$\hat{X}(t)=a_0+\sum_{i=1}^{9}a_i f_i(t). \tag{20}$$

Table 4 Dam sections in different construction stages

Serial number	Stage I	Stage II	Stage III	Stage IV
1	Sections 13–16	Sections 13–16	Sections 12–17	Sections 4–9
2	Sections 7–11	Sections 4–9	Sections 18–20	Sections 10 and 11
3	Section 12	Section 12	Sections 2 and 3	
4	Sections 17–19	Sections 18–20		

Table 5 Comparisons between simulation results and actual construction results

Stage	Section	Time (d)		Maximum area (m^2)		Maximum intensity of concrete placing (m^3/h)		Filling volume (m^3)	Filling elevation (m)
		Simulation	Actual	Simulation	Actual	Simulation	Actual		
I	1	62	137	6700	5300	410	386	10.72	1110
	2	44	87	5690	4300	396	375	11.51	1150
	3	35	65	540	420	57	45	7.93	1128
	4	76	132	4900	4150	375	350	16.61	1153
II	1	28	31	6680	6530	350	335	9.81	1125
	2	123	170	10000	8700	495	467	13.89	1190
	3	35	35	610	593	97	90	1.45	1142
	4	117	177	5300	4950	325	280	8.57	1191
III	1	243	276	4200	3850	250	235	39.9	1192
	2	114	104	2100	2970	175	140	3.88	1225.5
	3	43	51	560	560	83	80	0.91	1225.5
IV	1	59	56	2550	2707	167	180	5.49	1222
	2	150	156	2500	2340	165	146	7.24	1213

Table 6 Regression coefficient

Regression coefficient	Value	FMGF	Regression coefficient	Value	FMGF
a_0	−2.5333	–	a_5	0.2975	$f_{32}^{(0)}(t)$
a_1	0.4450	$f_{44}^{(0)}(t)$	a_6	0.1586	$f_{41}^{(0)}(t)$
a_2	0.3695	$f_{35}^{(0)}(t)$	a_7	0.1893	$f_{37}^{(0)}(t)$
a_3	0.5332	$f_{46}^{(0)}(t)$	a_8	0.2663	$f_{20}^{(0)}(t)$
a_4	0.1281	$f_{45}^{(2)}(t)$	a_9	0.2007	$f_{31}^{(0)}(t)$

FMGF: fuzzy mean generating function; $f_{44}^{(0)}(t)$ is an epitaxial FMGF sequence whose original sequence period is 44 d; $f_{45}^{(2)}(t)$ is an epitaxial FMGF sequence whose two-order differential sequence period is 45 d

The regression model was used to forecast the rainfall in September. The maximum fitting error is 5.72 mm between the forecast value and the actual value, the mean error is 1.63 mm, and the correlation coefficient is 0.874. The comparisons of the measured and fitted values are shown in Fig. 5, demonstrating that the verification results are satisfactory.

Roller productivity (m^3/h), the main input parameter of the simulation model, is used to illustrate the whole Bayesian updating process. The sample size of the roller productivity data is 160. The average value is 41.79 m^3/h, the standard deviation is 11, the median is 40.45 m^3/h, and the minimum and maximum values are 20.51 and 70.97 m^3/h, respectively. The Kolmogorov-Smirnov (K-S) and Phillips-Perron (P-P) tests are conducted. The results indicate that the best-fitting distribution is a normal distribution with a mean value of 41.79 m^3/h and a standard deviation of 11. The distributions of the first and second updates are shown in Fig. 6.

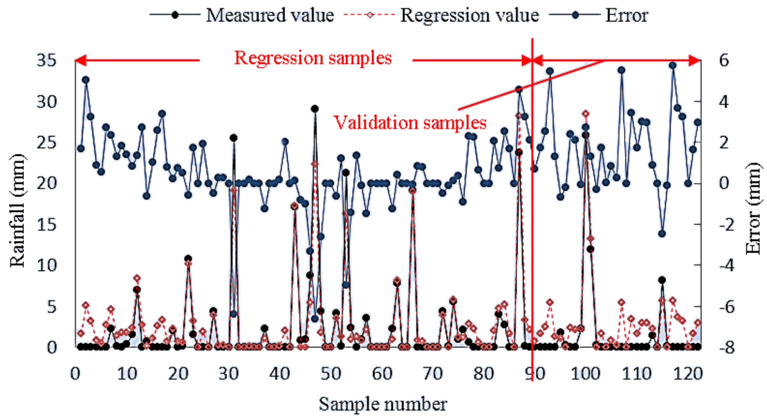


Fig. 5 Rainfall fitting forecast results

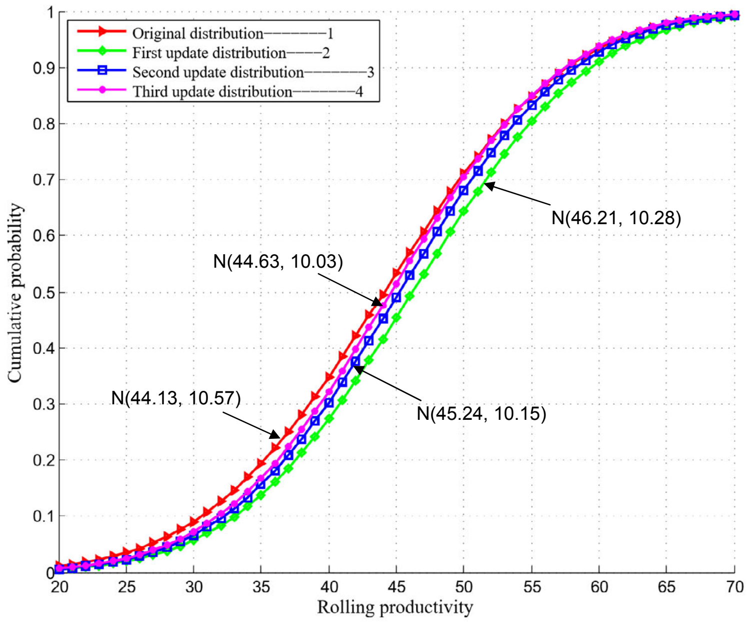


Fig. 6 Comparison chart of roller productivity distribution

In the initial simulation model, the roller productivity fits the normal distribution whose mean value is 55.0 m^3/h and standard deviation is 3, as indicated in Table 7. In addition, the other input parameters of the simulation model, such as the storehouse construction intensity, paving efficiency, and quality inspection duration, can be dynamically updated using Bayesian techniques.

Table 7 Comparisons of roller productivity

Distribution type	Initial empirical distribution	Actual data fitting distribution
Distribution	Normal distribution	Normal distribution
Mean value	55.00	41.79
Variance	3.00	11.00

After completion of stage I, the simulation parameters of stage II such as the intensity of concrete placing, paving productivity, rolling productivity, quality inspection duration, and rainfall influence factors can be obtained by analyzing the raw data acquired by the real-time monitoring system. When the simulation of stage II starts, the simulation parameters will be calculated on the basis of the raw data. A Bayesian updating technique and an FMGF model are used to calculate simulation parameters of stage II. The simulation program automatically puts parameters into the simulation model and obtains the simulation results. Stages III and IV repeat the above steps, and the simulation results of different stages are shown in Tables 4 and 5. Fig. 7 shows the simulation results of each stage and the comparison between the simulation results and the actual construction schedule. Table 8 shows the actual construction schedule of the RCC dam.

Table 5 and Fig. 7 show that the simulation results for the first stage, in terms of both the overall progress and sub-schedule, are very different from the actual construction results. The simulation construction period is 61 d while the actual construction period is 137 d, i.e. a difference of 76 d. The actual construction schedule of different sections lags behind the construction simulation results. The actual construction time of section 2 is completely behind the simulation time. The reason for the above hysteresis is that on the one hand, the input parameters of the simulation model are based on experience, but on the other hand, because the dam has just started, it cannot completely determine the key construction process. In the second stage of simulation, the simulation results are close to the actual construction results. The total duration of the simulation is 181 d, when the total actual construction period is 183 d. However, there is a great gap between the simulation

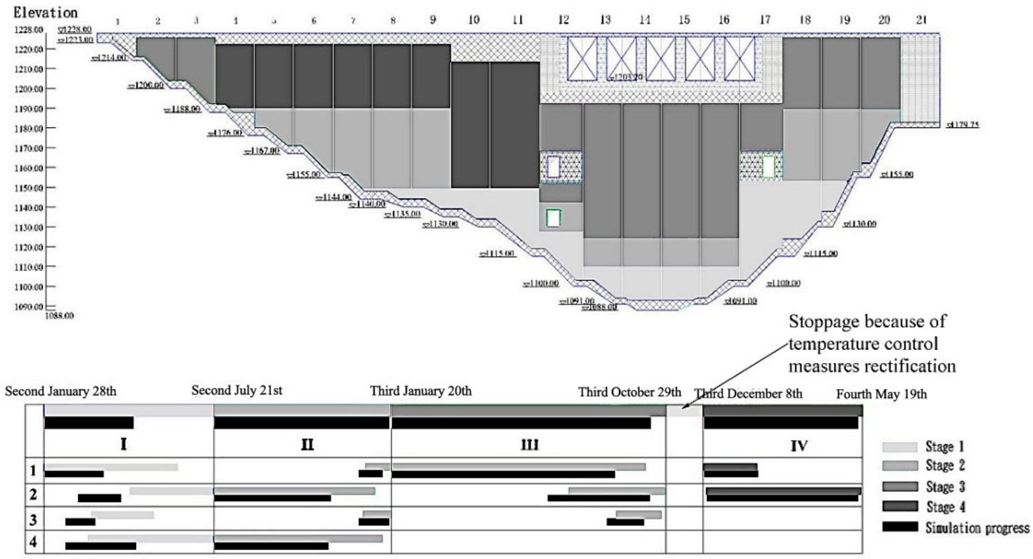


Fig. 7 Comparison between simulation results and actual results

Table 8 Actual construction schedule of the dam

Construction stage	Dam section	Time	Filling volume ($\times10^4$ m^3)	Filling elevation (m)
I	1	2011.1.28–2011.6.13	10.72	1110
	2	2011.4.23–2011.7.18	11.51	1150
	3	2011.3.17–2011.5.20	7.93	1128
	4	2011.3.12–2011.7.21	16.61	1153
II	1	2011.12.20–2012.1.19	9.81	1125
	2	2011.7.21–2012.1.6	13.89	1190
	3	2011.12.17–2012.1.20	1.45	1142
	4	2011.7.21–2012.1.13	8.57	1191
III	1	2012.1.7–2012.10.9	39.90	1192
	2	2012.7.18–2012.10.29	3.88	1225.5
	3	2012.9.5–2012.10.25	0.91	1225.5
IV	1	2012.12.8–2013.1.31	5.49	1222
	2	2012.12.15–2013.5.19	7.24	1213

results and actual construction in the sub-schedule. The differences are 47 d and 60 d in sections 2 and 4, respectively. The reasons for the above results are arranging the construction process rationally and prioritizing the key processes to be completed successfully. In the third stage, the total construction period is 283 d, the construction simulation result is 269 d, a gap larger than that for the second stage. However, the maximum sub-schedule is 33 d which is less than the second. The main reason is that the total duration is affected by flood control, while the sub-schedule is closer and closer with the updating of simulation parameters. In the fourth stage, the total construction period is 162 d, and the construction simulation result is 158 d. The sub-schedule differences are 3 d and 6 d. It can be seen that without the influence of external factors, the simulation results including overall progress and sub-schedule approached closer and closer to the reality.

This study has used the mathematical model of this method to carry out the simulation which updated the parameters and the traditional simulation. Specific calculation results are shown in Fig. 8. We can learn from the landscape contrast between different simulation methods and the actual construction schedule that: at the beginning of the simulation, the construction period simulated by the method of this study and the traditional method are all 61 d because the simulation models and parameters are the same, while the actual construction period is 143 d. However, in the second stage, the construction period simulated by the proposed method is 181 d. The construction period simulated by the traditional simulation method is 176 d. The differences between the results of these two methods and the actual construction period are 2 d and 7 d, respectively. In the third stage, the construction period simulated by the proposed method is 269 d. The construction period simulated by the traditional simulation method is 245 d. The differences between the results and the actual construction period are 14 d and 38 d. In the fourth stage, the construction period simulated by the proposed method is 158 d. The construction period simulated by the traditional simulation method is 132 d. Differences between the results and the actual construction period are 4 d and 30 d. Therefore, deviation will occur with both the above methods. However, it can be seen that the deviation of the traditional method is greater than the method which has applied parameter updating in the second, third, and fourth stages. This is because the update of parameters can better reflect the actual conditions of the construction site. It can be found by longitudinal contrast of the second, third, and fourth stages that: the simulation results of the proposed method gradually approach the actual construction period, and the traditional simulation method will cause more and more deviation with the progress of construction because its parameters cannot be updated.

Our method and the traditional simulation method use the same platform. Simulation platform parameters are shown in Table 9, and the time consumptions of simulation in different stages are shown in Table 10.

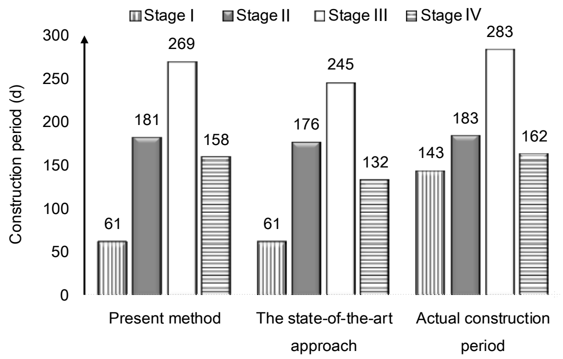


Fig. 8 Results contrast graph of different simulation methods

Table 9 Simulation platform parameters

Configuration type	Parameters
Hardware configuration	CPU: Intel (R) Core (TM) I7 2.40 GHz; Memory: 16.0 GB; SSD: 512 GB
Software configuration	Win 7.0 x64 system; net Framework 4.0; Access 2010

Table 10 Time consumptions of simulation in different stages

Stage	Time consumption (s)	
	Traditional method	Proposed method
I	485	485
II	1298	763
III	934	527
IV	761	356

5 Conclusions

In this paper, a new method for RCC dam construction simulations based on real-time monitoring has been presented. In traditional construction simulation methods, the parameters and boundary conditions were determined based on the average value of the mechanical construction efficiency or according to experts' experience. The proposed simulation method uses real-time positioning and data acquisition technologies to collect real-time data of the construction process. The obtained data were analyzed to obtain the parameters, including the intensity of concrete placing, paving productivity, rolling productivity, quality inspection duration, and rainfall influence factors. These parameters are simulation parameters and must be updated for the simulation model. The proposed method can avoid the situation, in which the simulation model cannot reflect the changes in the construction conditions over time and effectively compensates for the defects of the existing construction simulation methods. The feasibility and practicability of this method have been verified by application to the LDL project. Through comparisons of the results of actual construction and our study, the following conclusions were obtained:

1. Real-time monitoring technology has been used to obtain the actual construction data in real time and to provide a solid database for the construction simulation.

2. The data dynamic analysis technique was used to analyze the mass data collected by the real-time monitoring technology, and the simulation parameters were obtained.

3. With the use of Bayesian updating technology, the construction simulation parameters were updated in real time to ensure that the simulation parameters have a better fit with the actual situation.

4. Based on the meteorological data, the fuzzy mean generating function method was used to predict the weather, and the time series of the corresponding data was produced as a construction simulation parameter.

At present, the construction of RCC dams is increasing, and the construction simulation method based on real-time monitoring of RCC dams should be developed further. This method can be used for the establishment of a more intelligent real-time data acquisition and processing mechanism and can even be used to create an online integrated model and simulation platform, which is better for construction schedule control management services.

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中文概要

题　目：基于实时监控的碾压混凝土坝施工仿真

目　的： 碾压混凝土坝施工过程中施工仿真参数会随着施工现场环境变化而变化。本文探讨实时监控方法获取的施工信息对施工进度仿真的影响，研究碾压混凝土坝施工仿真参数自适应更新方法，提高施工仿真的精度。

创新点： 1. 通过碾压混凝土坝施工信息实时获取技术，分析计算碾压混凝土坝施工仿真参数；2. 利用贝叶斯更新技术对施工仿真参数进行更新；3. 利用模糊均生函数对坝区短期降雨量进行预测；4. 建立基于实时监控的碾压混凝土坝施工仿真模型，对碾压混凝土坝施工过程进行仿真并与实际施工进度对比。

方　法： 1. 通过实地采集，获取碾压混凝土坝施工过程中实时施工信息（图 2）；2. 通过理论推导，构建施工仿真参数先验分布均值和方差与后验分布均值和方差之间的关系，得到施工仿真参数更新方案（公式(16)和(17)）；3. 通过理论推导，利用已知坝区降雨量数据预测未来短期内的降雨情况（图 5）；4. 通过仿真模拟，得到施工仿真参数更新后的仿真成果并将其与实际施工进行对比，验证本方法的有效性和准确性。

结　论： 1. 施工仿真参数的准确性对碾压混凝土坝施工仿真结果准确性有很大影响；2. 可以利用贝叶斯更新技术对施工仿真中的仿真参数进行更新，利用模糊均生函数对坝区短时期内降雨量进行预测；3. 运用基于实时监控的碾压混凝土坝施工仿真方法对碾压混凝土坝施工过程进行仿真，仿真结果与实际施工进度之间的偏差明显减少，仿真准确性明显提高。

关键词： 碾压混凝土坝；施工仿真；实时监控；贝叶斯更新；模糊均生函数