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Construction simulation of high arch dams based on fuzzy Bayesian updating algorithm*

Tao GUAN, Deng-hua ZHONG, Bing-yu REN[†‡], Wen-shuai SONG, Zhi-qiang CHU
State Key Laboratory of Hydraulic Engineering Simulation and safety, Tianjin University, Tianjin 300072, China
[†]E-mail: renby@tju.edu.cn

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Abstract: Construction simulation is an effective tool to provide schedule plans for construction schedule management. The simulation parameter is the foundation of construction simulation for high arch dams. However, the updating construction simulation parameters of the commonly used Bayesian algorithm are constant and inconsistent with the construction process. Due to the lack of construction data, the construction data are not sufficient for the Bayesian updating algorithm. Thus, the construction simulation of high arch dams based on fuzzy Bayesian updating algorithm is proposed. The construction parameters for a dynamic site construction situation are collected, and the original data are fuzzed by fuzzy set theory to provide the foundation for a variety of simulation parameters during the simulation process. Moreover, with the Bayesian updating algorithm, the fuzzed simulation parameters are updated and obtained via the selection of the membership degree. Finally, the construction simulation of high arch dams is conducted based on the updated simulation parameters. A case study shows that the updated simulation parameters are more in accordance with the construction parameters in situ than the original parameters, which can provide a foundation for the change of simulation parameters during the simulation process, and the simulation results are agreed with the actual construction situation.

Key words: High arch dams; Construction simulation; Bayesian updating algorithm; Fuzzy set theory; Simulation parameters
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1 Introduction

The construction progress of high arch dams, the most important water retaining structure, is extremely important for the whole project. However, the construction of high arch dams is extremely complicated because of the influence of many random factors, the most important of which include the selection process of dam blocks (sequence placement), the operation situation and machine fault of construction machines, and the weather condition. A reasonable construction schedule is of great benefit for the management of an entire project. Construction simulation is an effective tool to provide a reasonable schedule for construction schedule management in the construction industry. Computerized system simulation is a method that compares and simulates the system's structure, function, and action (Ruan et al., 2001), and construction simulation is an important application of computerized system simulation in the construction industry. It is of great significance in the construction simulation of high arch dams to determine the simulation parameters. The Bayesian updating algorithm is an effective tool for updating information on the basis of continuously collected information. However, because the construction process of high arch dams often lasts several years, actual construction parameters (such as the moving speed of cable cranes, the

‡ Corresponding author
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ORCID: Tao GUAN, https://orcid.org/0000-0001-7789-4442

fault parameters of construction machines, and the available days of every month) change during the construction progress. For the updating process of the Bayesian updating algorithm, the updated result is a point estimation, which cannot change during the simulation. Thus, the Bayesian updating algorithm cannot reflect the change of construction parameters during the construction process. Additionally, the construction intensity is very high, and the construction machines are operated a huge number of times in a short period; however, only typical times can be recorded because of the lack of information collection means. The shortage of site construction data reduces the reliability of the traditional Bayesian updating algorithm. To address these problems, the fuzzy Bayesian updating algorithm is modified by studying the selection process of membership degree. With this algorithm, the simulation parameters can be updated dynamically when taking the shortage of collected information and the development of simulation parameters during the simulation process into consideration.

2 Literature review

For over four decades, construction simulation has been widely applied in the construction industry to analyze and plan construction processes, and many studies have been published. These studies include CYCLONE (Halpin, 1973), SIREN (Kavanagh, 1985), RESQUE (Chang, 1986), COOPS (Liu, 1991), SIMPHONY (Hajjar and Abourizk, 2002), DSVF (Zhang et al., 2012), SD-DES (Alvanchi et al., 2011), AOO (Zhang et al., 2005), and GVSS (Zhong et al., 2004). These studies have greatly increased the site management of construction schedule, and provided the basis for the construction simulation of high arch dams.

However, for many current studies, the simulation parameters are chosen on the basis of experience and construction specifications. Because of the huge differences between different projects, the simulation parameters are not convincing enough, and the simulation parameters cannot adapt to the changes in actual site construction situations. Updating simulation parameters dynamically is an effective way to solve this problem. There have recently been some studies aimed at updating simulation parameters. Razavi and Haas (2012) proposed a hybrid data-fusion method, which could automatically identify and locate the construction materials, equipment, and tools for large industrial construction projects. Chung et al. (2006) presented that Bayesian updating techniques are an effective approach to improve the quality of simulation input and output on the basis of what has already been observed. With the use of actual project progress data, the Bayesian updating techniques greatly improve the quality of projections. Vahdatikhaki and Hammad (2014) proposed an overarching tracking-technology-independent framework on the basis of the integration of new location tracking technologies with a simulation model to continuously fine-tune the simulation model. Gardoni et al. (2007) developed a methodology for forecasting project progress and final time-to-completion. An adaptive Bayesian updating method was used to assess the unknown model parameters on the basis of recorded data and pertinent prior information. Kim and Reinschmidt (2009) introduced a new probabilistic forecasting method called the Bayesian betaS-curve method (BBM) for schedule performance control and risk management of on-going projects. An overview of these studies is shown in Table 1. These studies have greatly improved the accuracy of simulation parameters. For the traditional Bayesian updating algorithm and probabilistic method, the updated result is a point estimation, which cannot change during the simulation. However, because of the complex construction process and construction situations, the construction parameters of high arch dams change during the construction process, which cannot be resolved with the Bayesian updating algorithm. Additionally, the construction intensity of high

Table 1 Overview of simulation parameter update

Reference	Method	Application
Zhong et al., 2004, 2010	Mathematical statistics	High arch dams
Zhang et al., 2013	Bayesian updating algorithm	Underground project
Razavi et al., 2012	Hybrid data-fusion method	Industrial construction project
Vahdatikhaki et al., 2014	Location tracking technologies	Earthmoving projects
Gardoni et al., 2007	Bayesian updating algorithm	Civilian nuclear power plants
Kim and Reinschmidt, 2009	Bayesian betaS-curve method	

arch dams is very high, but only the typical cycle of all the construction machine operation cycles can be recorded because of the lack of information collection means. The shortage of site construction data reduces the reliability of the traditional Bayesian updating algorithm. These defects hinder the utilization of the Bayesian updating algorithm in the construction simulation of high arch dams. To address these problems, this paper proposes a fuzzy Bayesian updating algorithm to realize the dynamic update of the simulation parameters of high arch dams.

The fuzzy Bayesian updating algorithm combines fuzzy set theory with the Bayesian updating algorithm. Recently, there have been some studies focused on the fuzzy Bayesian updating algorithm. Wu (2004, 2006) applied the fuzzy Bayesian updating method to assume system reliability under a complex environment, and they also provided the computational procedures to evaluate the membership degree of any given Bayes point estimate of reliability. Osoba et al. (2011) proposed that fuzzy rule-based systems can approximate prior and likelihood probabilities in Bayesian inference and thereby approximate posterior probabilities. Yin and Li (2011) proposed a new method on the basis of cut set to describe the fuzziness, deduce the fuzzy operation equations, and generalize Bayes' theory to the fuzzy computation area, specifically the fuzzy sample information in the Bayesian reliability assessment of electronic equipment. Gholizadeh et al. (2012) proposed fuzzy Bayesian system reliability assessment on the basis of a prior two-parameter exponential distribution under the squared error symmetric loss function and precautionary asymmetric loss function. The fuzzy Bayesian updating algorithm provides an important method for system reliability estimation. However, the fuzzy Bayesian updating algorithm has not been utilized for the updating of parameters in the construction industry. The simulation parameter update process of high arch dams is even more complex, because only parts of the site data can be recorded, and the update process of simulation parameters needs to consider the variety of simulation parameters during the simulation process. Moreover, regarding the fuzzy Bayesian updating algorithm, it only can provide the distribution of fuzzy parameters to analyze system reliability. Therefore, to combine the fuzzy Bayesian updating algorithm with construction simulation, the selection process of membership has to be studied.

Thus, in the current studies, the simulation parameter updating algorithm is not appropriate for the construction simulation of high arch dams. This paper proposes a construction simulation for high arch dams based on fuzzy Bayesian updating algorithm. With dynamic actual construction data, the initial condition of the construction simulation is updated. With fuzzy set theory, the original data are fuzzed. Moreover, the fuzzed simulation parameters are updated dynamically with the Bayesian updating algorithm. With this updated information, the construction schedule is developed with the construction simulation system. During simulation, the simulation parameters are chosen on the basis of the characteristics of the simulation parameters and the simulation time. In this way, the construction simulation system can track the dynamic site construction situation and the simulation parameters are more realistic.

3 Research method

To realize the construction simulation of high arch dams based on fuzzy Bayesian updating algorithm, the fuzzy set theory, Bayesian updating algorithm, construction simulation theory, and 4D visualization are adopted in this study. The fuzzy set theory and the Bayesian updating algorithm are combined to establish the fuzzy Bayesian updating algorithm. The construction simulation theory is the main body, which includes the updating of initial condition and simulation parameters, the simulation calculation, and result analysis, whereas 4D visualization provides a tool for the visualization of construction progress and the construction simulation. After simulation calculation, the construction schedule is obtained, which provides guidance for the construction management. The relationship between these theories and algorithms is shown in Fig. 1. For these theories and algorithms, the simulation calculation and 4D visualization have been researched in previous studies (Zhong et al., 2004, 2010, 2017; Kim et al., 2011; Guan et al., 2015), and the fuzzy set theory and the Bayesian updating algorithm are combined to build the fuzzy Bayesian updating algorithm, which is the key issue.

The real-time dynamic construction progress is the initial condition of the simulation system. It includes the construction progress of dam blocks and joint grouting. Based on the collected progress information, the initial condition is built.

Dynamic construction parameters are the bases of simulation parameters. The dynamic construction parameters are fuzzed to overcome the shortage of site construction data and provide the foundation for the variety of simulation parameters during the simulation process. After the parameters are fuzzed, the simulation parameters are updated using the Bayesian updating algorithm.

The simulation system is updated with the initial condition and updated simulation parameters. The construction schedule is simulated based on discrete event simulation (simulation calculation in Fig. 1), and the simulation calculation process is discussed below in detail. After result analysis, the construction schedule is developed. With the execution of the construction schedule, the construction simulation progress and construction parameters are generated.

With 4D visualization technology, the actual construction data and simulation process are displayed in a 4D environment for the interactive query of construction information.

4 Methodology

The construction process of high arch dams is composed of three main procedures: concrete production, concrete transportation, and concrete placement. Thus, the construction system is decomposed into three main subsystems, the concrete production subsystem, concrete transportation subsystem, and concrete placement subsystem (Zhong et al., 2004), and the three subsystems are shown in Fig. 2.

The concrete volume is often millions of cubic meters for a high arch dam, and it is impossible to construct a dam as a whole. The dam is divided into several dam monoliths with cross joints. The cross joints need to be grouted when the temperature and age of the concrete meet the requirements. Additionally, according to the construction ability of the construction machines and the concrete cooling method,

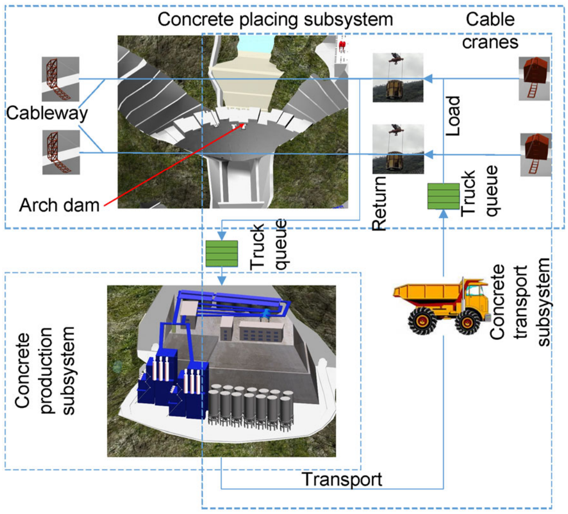

Fig. 2 Construction process of high arch dams

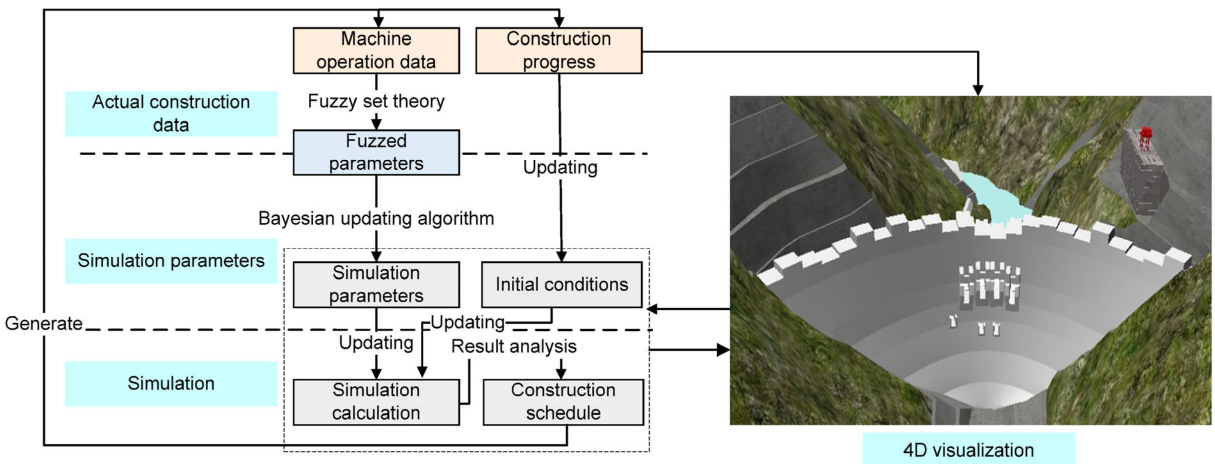

Fig. 1 Construction simulation framework

a dam monolith is composed of many dam blocks in the vertical direction. Because only the dam blocks that meet all constraints could be placed, the dam blocks are not placed continuously, and the placing of high arch dams is not a continuous process.

The logic model of construction simulation for high arch dams based on fuzzy Bayesian updating algorithm is shown in Fig. 3. The logic model is a mathematic model set, which contains the initial condition, statue transfer, simulation calculation process, and constraints of construction simulation of high arch dams.

① is the definition of the initial condition, where $H(i, 0)$ and $G(i, 0)$ are the dam elevation and grouting elevation of the ith dam monolith at the start time, and $H_r(i)$ and $G_r(i)$ are the real-time dynamic dam elevation and joint grouting elevation of the ith dam monolith, respectively.

② is the statue transfer formula of construction simulation, where $H(i, t)$ is the dam elevation at time t, $\Delta H(i, t)$ is the placing height during $t-1$ and t, and T is the total simulation period.

③ shows the simulation calculation process, and it is composed of several parts.

③-1 shows the elevation of the maximum dam monolith, where $H_{\max}$ is the maximum elevation of the dam. During simulation, the termination condition of the simulation process is that, the elevation of dam monoliths reaches the maximum elevation of the dam.

③-2 shows the increase of dam elevation, where j is the number of construction machines, M is the number of construction machines, $D(i, j, t)$ is the placement duration of a dam block at time t, $\Gamma(i, t)$ is the concrete temperature field at time t, τ is the temperature field, $V(i)$ is the appearance requirement because of river diversion, $P(i, t)$ is the construction probability of dam blocks, and $\mathrm{Ad}(n)$ is the available day of month n, where n is the month at time t. The increase of dam elevation is a function of placement duration, the temperature filed of dam concrete, and the construction diversion standard.

③-3 shows the placement duration of a dam block, where $q(k, t)$ is the duration of the kth working procedure at time t considering randomness, and K is the total number of construction procedures.

③-4 and ③-5 show the temperature field of dam concrete and the construction diversion standard, respectively, where τ is the temperature field, and γ is the diversion standard.

③-6, ③-7, and ③-8 show the simulation parameter update process on the basis of the fuzzy Bayesian algorithm, where $p_k(\Phi, t)$ is the probability density function, $R(0)$ is the dynamic site construction situation, $\alpha(t)$ is the membership degree, and $\mathrm{RS}(t)$ is the simulation time. The probability density function is determined by the dynamic construction situation

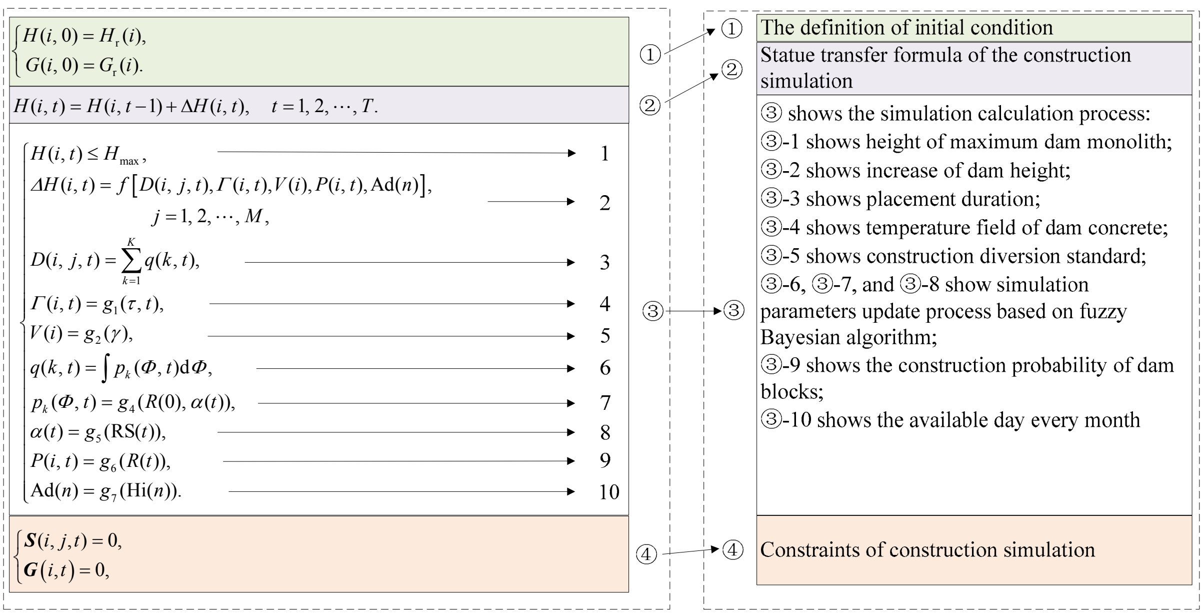

Fig. 3 Simulation logic model

and the membership degree, and the membership degree is obtained on the basis of the dynamic simulation situation.

③-9 shows the construction probability of dam blocks. As there may be several dam blocks satisfying all constraints at the same time, and the selection process of dam blocks is a random process, the construction probability of dam blocks is decided by the dynamic construction situation.

③-10 shows the available day every month. Based on the historical statistics Hi(n), the available working days are obtained according to the construction specifications.

④ shows the constraints of construction simulation, where $\boldsymbol{S}$ is the constraint matrix of dam block selection, including the interval time of dam blocks, the height difference between different dam monoliths, the working range constraints of machines, and the influence of weather conditions; $\boldsymbol{G}$ is the constraint matrix of joint grouting, including the temperature condition and concrete age of different dam monoliths. Only the dam blocks that meet all constraints can be placed. Additionally, the cross joints need to be grouted, when the temperature and age of concrete meet the constraints.

The simulation process of high arch dams based on fuzzy Bayesian updating algorithm is built shown in Fig. 4 by instantiating the logic model based on the construction process of high arch dams. It contains the initial condition, status transfer, simulation calculation process, and constraints of the construction simulation of high arch dams. It shows the main process of construction simulation, including the initial condition update, the simulation parameters update, the selection process of cable cranes (the main construction machines), the selection and placing

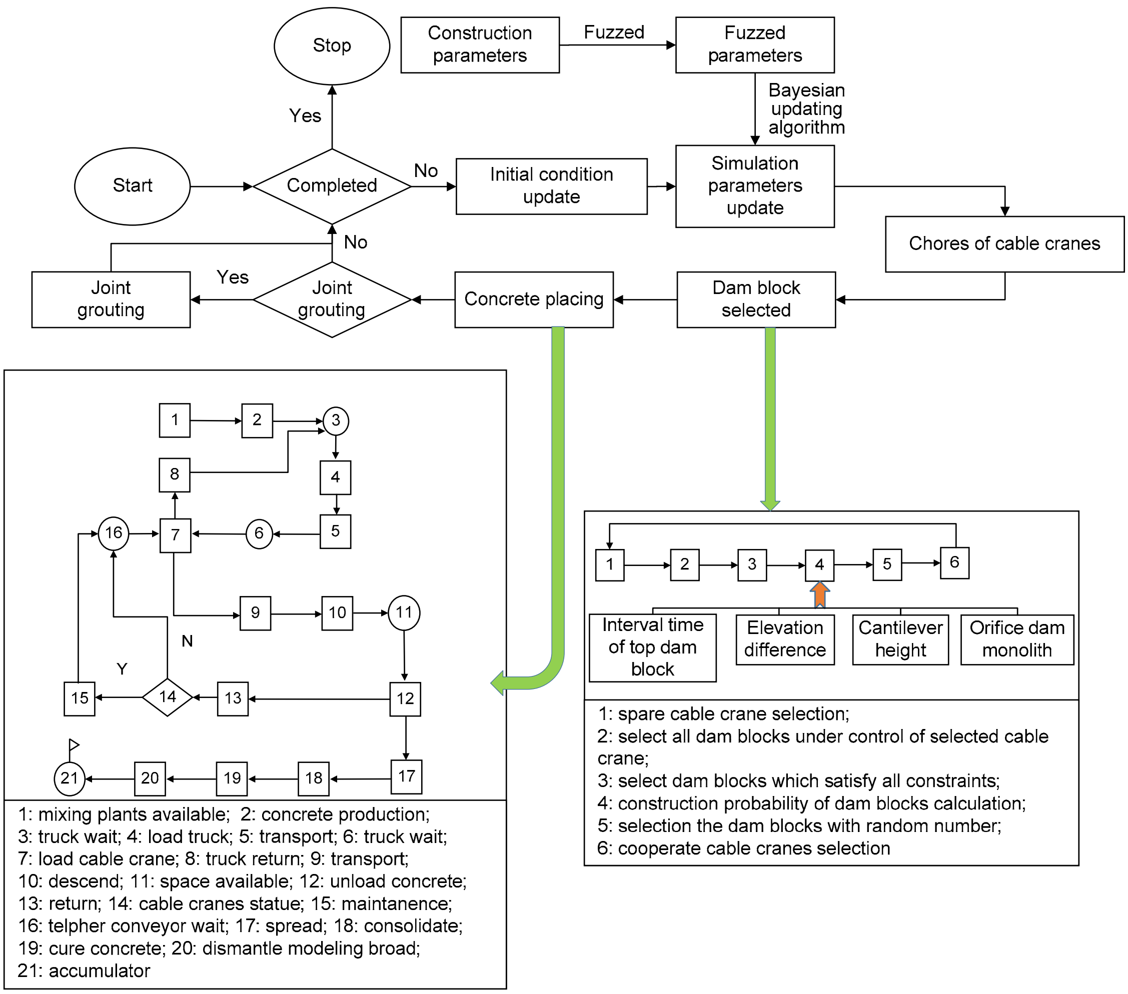

Fig. 4 Simulation process of high arch dams

process of dam blocks, the process of joint grouting, and others.

The real-time dynamic actual construction progress is the initial condition of construction simulation. For construction simulation of high arch dams, the initial condition (also called the dynamic construction progress) includes the following progresses (Guan et al., 2015).

1. Construction progress of dam blocks: This is used to build the dynamic elevation of dam monoliths. In construction site, it includes the name, the start and end elevations, the start and end times, the volume of the dam blocks, and others.

2. Joint grouting progress: This is used to build the dynamic grouting elevation of every cross joints. It contains the name, the start and end elevations, the start and end times of grouting, and the area.

This dynamic construction information is collected in real time by the site managers. This information is input into the simulation system, and the system would build the initial condition automatically.

The main purpose of updating the simulation parameters for high arch dams is to update the simulation parameters dynamically on the basis of the actual site construction information so that the simulation parameters can fit the actual site construction situation, and the update process is shown as ③-6, ③-7, and ③-8 in the logic model. In this study, the simulation parameters to be updated include the cable crane operation parameters, the mechanical fault time (concrete batching plants and cable cranes), the available working days influenced by the weather condition, and the simulation control parameters determined by the dam structure. The first study on computer simulation for concrete dams (Jurecha and Widmann, 1973) mentioned that the simulation process is mainly concerned with the moving process of cable cranes, and other operations are simplified. Thus, the cable crane operation parameters are the most important parameters.

1. Cable crane operation parameters: The cable crane is the only way to transport concrete to the dam, and the number of cable cranes is fixed. Additionally, cable cranes are needed for the transportation of construction machines, metal construction, and concrete formwork (chores of cable cranes), so the operation parameters of cable cranes have a great influence on the simulation result. As shown in Fig. 2, the single cycle of a cable crane could be divided into four parts: loading concrete, transporting concrete, unloading concrete, and return, so a cycle time includes concrete loading time, concrete unloading time, and moving time in the air (including transporting time and return time). Moreover, the moving trajectory is a space trajectory in the horizontal and vertical directions simultaneously, and the moving time is in the larger of the two directions. The cycle time is shown in Eqs. (1)–(3):

$$t_{\mathrm{ch}} = \frac{2D_{\mathrm{h}}}{v_{\mathrm{h}}}, \tag{1}$$

$$t_{\mathrm{cv}} = \frac{2D_{\mathrm{v}}}{v_{\mathrm{v}}}, \tag{2}$$

$$t_{\mathrm{c}} = \max(t_{\mathrm{ch}}, t_{\mathrm{cv}}) + t_{\mathrm{cl}} + t_{\mathrm{cunl}} + \theta, \tag{3}$$

where t_{ch} and t_{cv} are the moving times in the horizontal and vertical directions (two directions in the following content), respectively; D_{h} and D_{v} are the distances in the two directions, respectively, between the concrete supply platform and the dam block; v_{h} and v_{v} are the steady speeds in the two directions, respectively; θ is the variance of the moving time because of the acceleration and deceleration of cable cranes and other factors; t_{c} is the single cycle time; t_{cl} and t_{cunl} are the concrete loading time and concrete unloading time, respectively.

2. Mechanical fault parameters: Mechanical fault is unavoidable in a construction site, and the mechanical fault situation is an uncertain event. If the machine faults, the related work or the entire project would be suspended. The main parameters to describe mechanical fault are the failure time T_{b} and failure time interval T_{int}.

By combining fuzzy set theory and the Bayesian updating algorithm, the fuzzy Bayesian algorithm is built. With the Bayesian updating algorithm, the simulation parameters are updated dynamically, and with fuzzy set theory, the simulation parameters are fuzzed to resolve the shortage of accurate statistical data and provide foundation for the variety of simulation parameters during the simulation process.

The unknown variable $\Theta=(\theta_1, \theta_2, \ldots, \theta_k)$ is continuously distributed (it may be the distribution of θ, the failure time T_{b}, the failure time interval T_{int}, and others in this study), and $X_1=(x_1, x_2, \ldots, x_n)$ is the known sample data; the distribution of Θ is updated according to Eqs. (4) and (5) (Liu et al., 2012; Zhang et al., 2013):

$$f(\Theta \mid X_1) = kf(\Theta)L(X_1 \mid \Theta), \tag{4}$$

$$k = \left[\int_{-\infty}^{+\infty} f(\Theta)L(X_1 \mid \Theta)\mathrm{d}\Theta\right]^{-1}. \tag{5}$$

Eqs. (4) and (5) represent the update process of the Bayesian update algorithm, which could be derived with Bayesian theory, where $f(\Theta)$ is the prior distribution of Θ, $f(\Theta|X_1)$ is the posterior distribution of Θ with the sample data known, $L(X_1|\Theta)$ is the likelihood function, which assumes the distribution of Θ, i.e. the distribution of sample data is known, and k is the normalized parameter, with which the cumulative probability of $f(\Theta|X_1)$ is 1. During the process of Bayesian updating, the probability distribution types of the prior distribution and posterior distribution are the same. The normal distribution is analyzed as follows.

Assume that μ and σ^2 are unknown statistical parameters of random variable X, which meets the normal distribution, such that:

$$X \sim N(\mu, \sigma^2). \tag{6}$$

Zhang et al. (2013) derived the Bayesian updating method for a normal distribution with both parameters unknown:

$$\begin{cases} \tau_1 = n_1, \\ \beta_1 = \dfrac{(n_1 - 1)S_1^2}{2}, \\ \hat{\mu}_1 = \overline{x}_1, \\ \hat{\sigma}_1^2 = \dfrac{2\beta_1}{\tau_1 - 1}, \end{cases} \tag{7}$$

$$\begin{cases} \tau_i = \tau_{i-1} + n_i, \\ \beta_i = \beta_{i-1} + \dfrac{\tau_{i-1} n_i (\hat{\mu}_{i-1} - \overline{x}_i)^2}{2\tau_i} + \dfrac{(n_i - 1)S_i^2}{2}, \\ \hat{\mu}_i = \dfrac{\tau_{i-1}\hat{\mu}_{i-1} + n_i \overline{x}_i}{\tau_i}, \\ \hat{\sigma}_i^2 = \dfrac{2\beta_i}{\tau_i - 1}, \end{cases} \tag{8}$$

where τ_i and β_i are the hyper parameters, n_i, S_i^2, and $\overline{x}_i$ are the number, the mean variance, and the average of sample X_i, and $\hat{\mu}_i$ and $\hat{\sigma}_i^2$ are the estimates of average and variance, respectively. Eq. (7) is the first step of Bayesian updating, and Eq. (8) shows the further updating process on the basis of the previous updating process. As these equations have been derived by Zhang et al. (2013), the detailed derivation process is not analyzed in this study.

It can be proved that, the result of the Bayesian updating algorithm is the same as that of the traditional probability statistics method. However, compared with the traditional probability statistics method, the Bayesian updating algorithm is more convenient for updating construction parameters dynamically for a long-term construction process. This is because, the traditional probability statistics method needs to record all sample data to update the construction parameters, but the Bayesian updating algorithm only needs to record the previous updating result and current sample data.

On the basis of the definition of fuzzy set theory and membership degree, we assume that A is the mapping function from set X to [0, 1], i.e. A: $X\rightarrow[0, 1]$, $x\rightarrow A(x)$, where $A(x)$ is the membership degree function of fuzzy set X. X is the parameter that is updated dynamically for simulation in this study. Following the definition of fuzzy set theory, the membership should be between 0 and 1. Moreover, $A_\alpha(x)=\{x: A_\alpha(x)\geq\alpha\}$, $\alpha\in(0, 1]$ is the α-sublevel set. The upper and lower limits are $A-\alpha$ and $A+\alpha$. The definition of the α-sublevel set is shown in Fig. 5 (Ponz-Tienda et al., 2012).

Assuming that $\overline{x}$ and S^2 are the average and mean variance, respectively, of serial data, after being

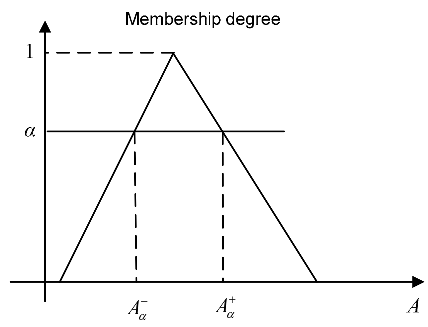

Fig. 5 Definition of the α-sublevel set

fuzzed, the α-sublevel sets of $\bar{x}$ and S^2 are $\bar{x}_\alpha=[\bar{x}_\alpha^-, \bar{x}_\alpha^+]$ and $(S^2)_\alpha=[(S^2)_\alpha^-, (S^2)_\alpha^+]$, respectively. On the basis of the characteristics of a normal distribution, the distributions of the average and variance are t and χ^2, respectively:

$$\frac{\mu-\bar{x}'}{S'/\sqrt{n}} \sim t(n-1), \tag{9}$$

$$\frac{(n-1)(S')^2}{\sigma^2} \sim \chi^2(n-1), \tag{10}$$

where n, $\bar{x}'$, and S' are the number, the mean variance, and the average of the recorded sample. Because when n>30, $t(n-1)$~$N(0, 1)$ and $\chi^2(n-1)$~$N(n-1, 2(n-1))$, to simplify, the membership of the average is the normal distribution.

Thus, the membership degree function is as follows:

$$\alpha=f(\mu)=\exp\left(-\frac{n(\mu-\bar{x}')^2}{2(S')^2}\right), \tag{11}$$

$$\alpha=f\left(\frac{1}{\sigma^2}\right)=\exp\left(-\frac{(n-1)\left(\frac{1}{\sigma^2}-\frac{1}{(S')^2}\right)^2}{4\left(\frac{1}{(S')^2}\right)^2}\right). \tag{12}$$

Thus, for membership degree α, the closed interval $[\bar{x}_\alpha^-, \bar{x}_\alpha^+]$ and $[(S^2)_\alpha^-, (S^2)_\alpha^+]$ could be calculated as follows:

$$\bar{x}_\alpha^-=\bar{x}'-S'\sqrt{\frac{2\ln\alpha}{-n}}, \tag{13}$$

$$\bar{x}_\alpha^+=\bar{x}'+S'\sqrt{\frac{2\ln\alpha}{-n}}, \tag{14}$$

$$\left(\frac{1}{S^2}\right)_\alpha^-=\frac{1}{S'^2}-\frac{1}{S'^2}\sqrt{\frac{-4\ln\alpha}{n-1}}, \tag{15}$$

$$\left(\frac{1}{S^2}\right)_\alpha^+=\frac{1}{S'^2}+\frac{1}{S'^2}\sqrt{\frac{-4\ln\alpha}{n-1}}. \tag{16}$$

Moreover, they are the estimates of actual construction parameters expressed with the statistical parameters of recorded data for every month. Combining the Bayesian updating process (Eqs. (7) and (8)) and the α-sublevel set of normal distribution (Eqs. (13)–(16)), the updating process of the fuzzy Bayesian updating algorithm is as follows:

$$\begin{cases}\tau_1=n_1,\\ (\beta_1)_\alpha^+=\dfrac{(n_1-1)(S_1^2)_\alpha^+}{2},\\ (\beta_1)_\alpha^-=\dfrac{(n_1-1)(S_1^2)_\alpha^-}{2},\\ (\hat{\mu}_1)_\alpha^+=(\bar{x}_1)_\alpha^+,\\ (\hat{\mu}_1)_\alpha^-=(\bar{x}_1)_\alpha^-,\\ (\hat{\sigma}_1^2)_\alpha^+=\dfrac{2(\beta_1)_\alpha^+}{\tau_1-1},\\ (\hat{\sigma}_1^2)_\alpha^-=\dfrac{2(\beta_1)_\alpha^-}{\tau_1-1},\end{cases} \tag{17}$$

$$\begin{cases}\tau_i=\tau_{i-1}+n_i,\\ (\beta_i)_\alpha^+=(\beta_{i-1})_\alpha^++\max\limits_\alpha\left(\dfrac{\tau_{i-1}n_i((\hat{\mu}_{i-1})_\alpha-(\bar{x}_i)_\alpha)^2}{2\tau_i}\right)\\ \qquad+\dfrac{(n_i-1)(S_i^2)_\alpha^+}{2},\\ (\beta_i)_\alpha^-=(\beta_{i-1})_\alpha^-+\inf\limits_\alpha\left(\dfrac{\tau_{i-1}n_i((\hat{\mu}_{i-1})_\alpha-(\bar{x}_i)_\alpha)^2}{2\tau_i}\right)\\ \qquad+\dfrac{(n_i-1)(S_i^2)_\alpha^-}{2},\\ (\hat{\mu}_i)_\alpha^+=\dfrac{\tau_{i-1}(\hat{\mu}_{i-1})_\alpha^++n_i(\bar{x}_i)_\alpha^+}{\tau_i},\\ (\hat{\mu}_i)_\alpha^-=\dfrac{\tau_{i-1}(\hat{\mu}_{i-1})_\alpha^-+n_i(\bar{x}_i)_\alpha^-}{\tau_i},\\ (\hat{\sigma}_i^2)_\alpha^+=\dfrac{2(\beta_i)_\alpha^+}{\tau_i-1},\\ (\hat{\sigma}_i^2)_\alpha^-=\dfrac{2(\beta_i)_\alpha^-}{\tau_i-1}.\end{cases} \tag{18}$$

During simulation, on the basis of the characteristics of the parameters, the membership is chosen. For example, the distribution of t_{cl} (loading time of cable cranes) changes with the increase of operators' proficiency. The average of t_{cl}, as well as the variance, decreases when the operators' proficiency increases. Thus, the membership of the average and variance changes from α=1, to the lower limit $A-\alpha$ (where α<1). For the increase of parameters as the construction progresses, the membership should change from α=1, to the upper limit $A+\alpha$ (where α<1). The value selection of α is shown in Fig. 6.

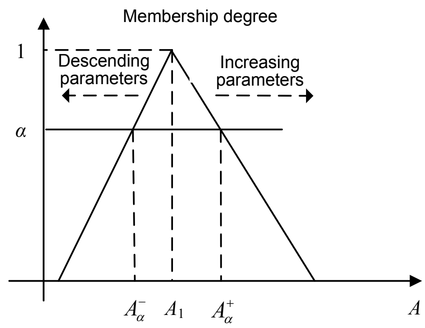

Fig. 6 Value selection of α

During the update process, the actual data are collected for statistics. The simulation parameters are updated as the amount of actual data increases. By using the method above, the simulation system can track the actual site construction situation, and the simulation parameters are more realistic. The normal distribution is analyzed above, and for different types of probability distributions, the updating process can be deduced.

5 Case study

In this study, a high arch dam is analyzed as a case study. It is located in southwest China. The height of the dam is 210 m, and the concrete volume is 3.13×10^6 m^3 with 29 dam monoliths. The main construction machines are two concrete batching plants and four cable cranes. The construction of this dam started in September of the 6th year (2011), and should be finished before October of the 9th year.

As the research purpose is to build the simulation parameters updated based on the fuzzy Bayesian updating algorithm, it mainly includes two parts: the simulation parameter update and the simulation calculation. To verify the effectiveness of the simulation, the case study is divided into two parts: the simulation parameters updated based on the fuzzy Bayesian updating algorithm and the simulation calculation process with the updated simulation parameter.

The simulation parameters vary because the construction process often lasts for several years, so it is very hard to make the simulation parameters close to the real-world construction situation. The purpose of this study is to make the simulation parameters closer than those in the current studies. To verify the effectiveness of the proposed algorithm, we used the actual construction data from seven consecutive months. On the basis of the dynamically collected data, the simulation parameters are updated, and the operation time of cable cranes is studied as a case. On the basis of Eq. (3), the cycle time of the cable cranes includes the moving time max(t_{ch}, t_{cv}), loading time t_{cl}, unloading time t_{cunl}, and variance of the moving time θ, and θ is updated as an example on the basis of the statistical analyses in the following part.

For the first stage (January of the 8th year), there are 161 sets of data, and the average and variance of the samples are 73.4 s and 481.13 s^2, respectively. After being fuzzed, the α-sublevel sets of the average and variance on the basis of Eqs. (13)–(16) are:

$$(\overline{x})_\alpha=[73.4-2.4\sqrt{-\ln\alpha},\; 73.4+2.4\sqrt{-\ln\alpha}], \tag{19}$$

$$(S^2)_\alpha=[481.13/(1+0.11\sqrt{-\ln\alpha}),\; 481.13/(1-0.11\sqrt{-\ln\alpha})]. \tag{20}$$

For the second stage (February of the 8th year), there are 207 sets of data; the average and variance of the samples are 78.03 s and 423.37 s^2, respectively. After being fuzzed, the α-sublevel sets of the average and variance are:

$$(\overline{x})_\alpha=[78.03-2.0\sqrt{-\ln\alpha},\; 78.03+2.0\sqrt{-\ln\alpha}], \tag{21}$$

$$(S^2)_\alpha=[423.37/(1+0.098\sqrt{-\ln\alpha}),\; 423.37/(1-0.098\sqrt{-\ln\alpha})]. \tag{22}$$

The values of 2.4 in Eq. (19) and 2.0 in Eq. (21) are the results of $S'/\sqrt{2/n}$ in Eqs. (13) and (14), respectively.

As the sample size of every month is larger than 30, the statistical parameters of the sample cycle could represent the statistical parameters of the whole month. With Eqs. (17) and (18), the simulation parameters from January to July of the 8th year are updated. The updating process, with a membership degree of 1, is shown in Table 2 and Fig. 7.

To compare the difference in real data versus the updated fuzzy Bayesian updating result with the difference in real data versus the unchanged parameters, the unchanged parameter is chosen as the updated result of the first stage. Fig. 8 shows the comparison result. In Fig. 8, Average (UP) is the difference in the average between the updated parameters and the real parameters, where Average (UC) is the difference in the average between the unchanged parameters and the real parameters. The definitions of Variance (UP) and Variance (UC) are the same. Every corner expresses the comparison result of every month. For most months, compared with the difference between updated parameters and real parameters, the difference between unchanged parameters and real parameters is larger. All these abovementioned data show that, by updating, the simulation parameters can track the dynamic site construction situation, and the simulation parameters are closer to the real-world construction situation than the unchanged parameters.

Fig. 9 is the comparison of the different membership degrees of the first month. With the traditional Bayesian updating algorithm, only point

Table 2 Update process of θ

Serial	Number	$\bar{x}$ (s)	S^2 (s^2)	$\hat{\mu}$ (s)
1	161	73.40	481.13	73.40
2	207	78.03	423.37	76.00
3	189	67.65	416.24	73.17
4	232	83.20	437.14	76.12
5	198	82.40	408.29	77.38
6	221	87.02	466.94	79.14
7	227	79.57	478.62	79.21

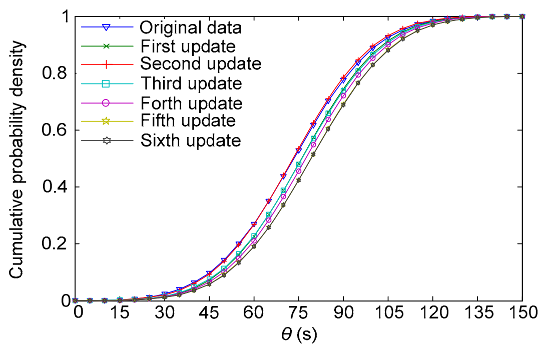

Fig. 7 Updating process of θ

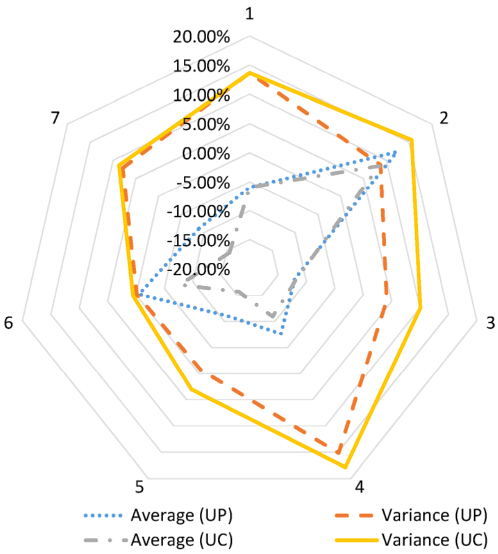

Fig. 8 Comparison between updated parameters and unchanged parameters

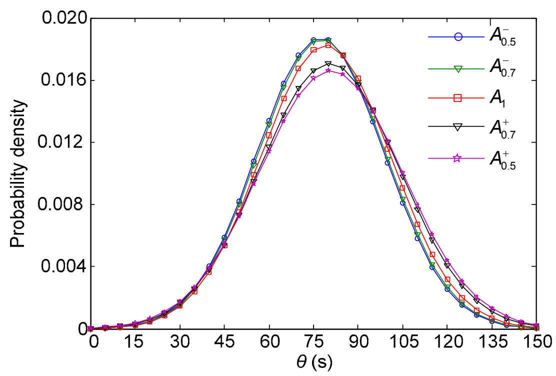

Fig. 9 Comparison between different membership degrees

estimation of the simulation parameters is obtained. Compared with the traditional Bayesian updating algorithm, the fuzzy Bayesian updating algorithm can provide a wider range of estimation parameters. The construction efficiency of different machines varies with the process of high arch dams. For the traditional Bayesian updating algorithm, the simulation parameters are constant, which could not reflect the variety of construction efficiency. With the proposed method, the simulation parameters can change with the selection of membership to adapt to the changes of simulation parameters during the simulation process.

The construction of a dam is a field exploration work, which is influenced by the weather condition. The available working days are shown in Table 3. In this study, the distribution of unavailable days is a straight-line distribution, and the simulation control parameters are shown in Table 4.

The capacity of a cable crane is 9.6 m^3, and the steady transportation speed is 7.5 m/s in the horizontal direction and 3 m/s in the vertical direction. For other operation parameters, they are expressed in Table 5. t_{cl} and t_{cunl} are the loading time and unloading time of cable cranes, T_{int} (cable crane) is the failure time interval of cable cranes, T_b (cable crane) is the failure time of cable cranes, T_{int} (concrete batching plant) is the failure time interval of concrete batching plants, and T_b (concrete batching plant) is the failure time of concrete batching plants.

The simulation system is built with the 4D computer aided design (CAD) model (Guan et al., 2015) based on the logic model and the simulation process. On the basis of the dynamic updated parameters, the simulation system could develop a construction schedule according to the simulation process and ③ in the simulation logic with the simulation system. Two working conditions are studied on the basis of the initial conditions (① in the logic model and the initial condition update in the simulation process) in January (Condition 1) and July (Condition 2) of the 8th year. The initial appearance of Conditions 1 and 2 is shown in Figs. 10 and 11. Figs. 12 and 13 show the simulation process on Sept. 15th of the 8th year and Mar. 3rd of the 9th year for Condition 1, respectively. For a typical completion time, the

Table 3 Available working days every month

Month	Available day (d)	Unavailable day (d)	Available hour (h)
1	28	3	20
2	23	5/6	20
3	27	4	20
4	26	4	20
5	27	4	20
6	25	5	20
7	27	4	20
8	26	5	20
9	24	6	20
10	27	4	20
11	27	3	20
12	28	3	20

Table 4 Simulation control parameters

Simulation control parameter	Value
Cantilever height (m)	60
Height difference between adjacent dam monoliths (m)	12
The biggest height difference in the dam (m)	30

Fig. 10 Initial appearance of Condition 1

Fig. 11 Initial appearance of Condition 2

Table 5 Machine operation parameters

Item	t_{cl}	t_{cunl}	T_{int} (cable crane)	T_b (cable crane)	T_{int} (concrete batching plant)	T_b (concrete batching plant)	T_b (concrete batching plant)
Distribution	Normal	Normal	Normal	Normal	Normal	Normal	Normal
Average	50 s	50 s	20 d	5 h	30 d	2 d	2 d
Standard deviation	10 s	5 s	2 d	0.2 h	2 d	5 h	5 h

construction intensities of the two conditions and the actual construction situation are shown in Fig. 14. The fractional errors between the actual construction intensity and the two conditions are shown in Fig. 15, and the correlation between the actual construction intensity and the two conditions are shown in Table 6. For most months, the simulation result of Condition 2 is closer than that of Condition 1, and the correlation between actual construction intensity and Condition 1 is less than that between actual construction intensity and Condition 2, which means that with the updated parameters, the simulation result is closer to the actual construction situation. The fractional error is large in the last two months because the construction

Fig. 12 Simulated appearance on Sept. 15th of the 8th year

Fig. 13 Simulated appearance on Mar. 3rd of the 9th year

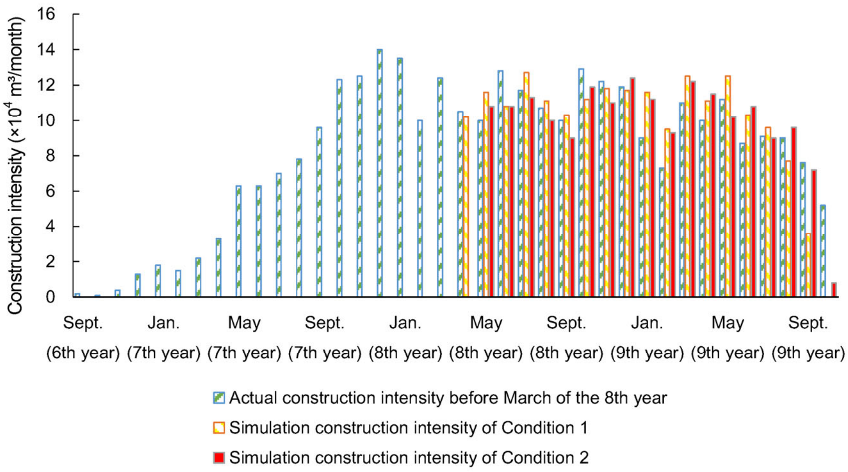

Fig. 14 Construction intensities of the two conditions

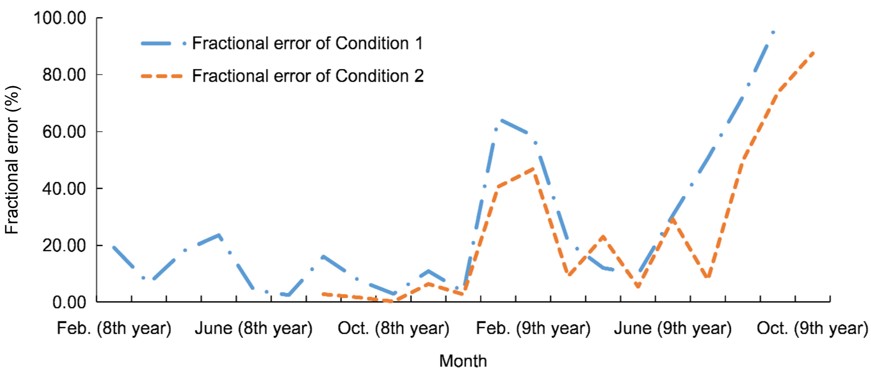

Fig. 15 Fractional errors of the two conditions

Table 6 Correlation between actual construction intensity and the two conditions

Item	Actual construction	Condition 1	Condition 2
Actual construction	1.00	0.72	0.73
Condition 1	0.72	1.00	0.92
Condition 2	0.73	0.92	1.00

simulation is finished, and the concrete to be placed is limited in the last two months. For Condition 1, the concrete to be placed in the penultimate month (September of the 9th year) is only 1.2×10^3 m^3, and for Condition 2, the concrete to be placed is only 6.5×10^3 m^3 in the last month (October of the 9th year). Thus, the difference is great in the last two months.

6 Conclusions

To address the problems that simulation parameters could not track the actual construction site situation and the fuzzy Bayesian updating algorithm has not been applied in the construction industry, the fuzzy Bayesian updating algorithm, which combines fuzzy set theory with the Bayesian updating method, is proposed to update simulation parameters. The Bayesian updating method could realize the dynamic update of simulation parameters on the basis of site construction situations, and the fuzzy set theory could fuzz the original data to overcome the lack of sufficient data. Additionally with the fuzzy Bayesian updating algorithm the simulation parameters could change during simulation, which could describe the change of construction parameters during the construction process. The case study shows that compared with the unchanged parameters, the updated parameters could track the dynamic site construction situation. Moreover, the reliability of the simulation parameters is increased, because the origin of the simulation parameters is the actual construction site, and the simulation parameters suit the given project, which could provide a foundation for more accurate simulation results. The simulation result shows that with the continuously updated simulation parameters, the simulation results are closer to the actual site construction situation.

The dynamic updating of construction parameters in this study has some limitations; with the development of computer and internet technology, digital hydropower projects will be used more frequently in project management. However, the system in this paper is a standalone version and has limitations in terms of reliance on remote control. Therefore, the dynamic construction schedule analysis system for high arch dams requires further research in the internet environment to adapt to new demands and challenges.

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中文概要

题　目：基于模糊贝叶斯更新的高拱坝施工进度仿真

目　的：针对当前高拱坝施工进度仿真研究中施工仿真参数难以实现对现场施工状态的有效跟踪的现状，研究施工仿真参数实时更新方法，以提高施工仿真参数及仿真计算结果的准确度。

创新点： 1. 通过贝叶斯更新方法，建立施工仿真参数实时更新方法；2. 基于模糊集理论，并通过对隶属度的取值，实现对仿真计算过程中施工仿真参数变化的有效模拟。

方　法： 1. 通过对高拱坝施工过程的分析（图 1），建立高拱坝施工进度仿真的模型（图 2 和 3）；2. 基于贝叶斯更新方法，建立高拱坝施工仿真参数实时更新方法（公式（4）~（8））；3. 基于模糊集理论，实现仿真过程中施工仿真参数实时更新；4. 将模糊集理论与贝叶斯更新整合，建立模糊贝叶斯更新方法，实现施工仿真参数实时更新（公式（17）和（18））；5. 将实时更新的施工仿真参数应用到施工进度仿真中，实现施工进度的仿真分析。

结　论： 1. 采用贝叶斯更新方法，减小了施工仿真参数与实际参数之间偏差程度；2. 采用模糊贝叶斯更新方法，通过不断更新施工仿真参数，使得仿真计算结果与实际施工状态更为接近。

关键词： 高拱坝；施工仿真；贝叶斯更新方法；模糊集理论；施工仿真参数