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Rockfill dam compaction quality evaluation based on cloud-fuzzy model*

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Abstract: The quality of compaction is key to the safety of dam construction and operation. However, because of incomplete information about the construction process and the unknown relationship between compaction quality and the factors that influence it, traditional evaluation methods such as neural networks and multivariate linear regression models fail to take uncertainty fully into account. This paper proposes a cloud-fuzzy method for assessing compaction quality by considering randomness, fuzziness, and incomplete information. The compaction parameters and material source parameters are the key parameters in the assessment of compaction quality. A five-layer neural-network model of compaction quality assessment is established that considers compacted dry density and its classification membership and probability as the criteria, and the rolling speed, rolling passes, and compacted layer thickness as alternatives. Because of uncertainties in the criteria and alternatives, the cloud-fuzzy method, in which a fuzzy neural network is extended with a cloud model to handle uncertain and fuzzy problems more effectively, is introduced to determine the compaction quality. A case study is presented to evaluate the compaction quality of a hydropower project in China. The results indicate that the cloud-fuzzy model is feasible in relation to precision and makes up for the sole focus on precision by traditional methods. The proposed method provides a triple index for understanding compaction quality, which facilitates assessment of the compaction quality of an entire dam surface.

Key words: Rockfill dam; Cloud model; Uncertainty; Compaction quality evaluation
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1 Introduction

The quality of dam compaction is critical to the stability and durability of the dam itself. Inadequate control of compaction quality can lead to decreased strength and bearing capacity, and increased settlement, volume change, and permeability (Liu et al., 2012).

In the traditional field of transportation engineering, previous studies of the evaluation of compaction quality have focused on correlating compaction quality with soil properties and construction parameters, such as machine drive power (MDP) technology (Komandi, 1999; White et al., 2004), soil stiffness (Kb, a measure of the compaction) (Anderegg et al., 2004, 2006; Kaufmann and Anderegg, 2008), compaction meter value (CMV) (Sandstrom and Pettersson, 2004), and total harmonic distortion (THD) (Mooney and Rinehart, 2007; Rinehart and Mooney, 2008). However, although the aforementioned approaches address the issue of compaction quality control in road construction, they are not immediately applicable to the construction of dams from earth rock because of the different construction materials and quality-control philosophies involved in these two types of construction (Liu et al., 2012).

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There are two main measures for controlling the compaction quality of a rockfill dam. One is the dry density obtained from pit testing. However, it may be unreliable or even misleading to represent the compaction quality of an entire surface from a limited number of spot samples, and the feedback provided in this manner is often too late (Liu et al., 2012). The other type of measure is the compaction parameters of the construction process itself. In the existing study, a method is proposed for monitoring the operational compaction parameters in real time and correlating them with the compactness to control the quality in an earth-rock dam construction project (Zhong et al., 2009, 2011, 2017). Monitoring the compaction quality of the core of a rockfill dam in real time may be effective in improving the efficiency of the surface-compaction quality control, and can allow the compaction parameters to be measured at any location on the surface.

However, because of uncertainties in the material source parameters, the compaction quality cannot be based on the compaction parameters alone (Zhong et al., 2009, 2011). Hence, relationships are established between the compaction parameters and the compaction quality to evaluate the construction quality. Liu et al. (2012) and Liu and Wang (2014) used a multiple regression model to investigate the relationship between compaction itself and the associated compaction parameters. They established a non-linear relationship between the two measures, and proposed methods for evaluating the compaction quality of the entire dam surface. A dual evaluation model that combined dry density and reliability has also been developed by Wang R et al. (2015). They obtained the variability of dry density and its influencing factors via reliability and sensitivity analyses of its parameters, thereby improving the reliability of evaluation. A multilayer forward artificial neural network was used to establish a non-linear relationship between the compaction parameters and the dry density. This involved taking the distribution of material parameters into consideration, thereby allowing the dry density to be fitted anywhere on the dam surface (Wang XL et al., 2015). Hence, the compaction parameters and the distribution of material source parameters were analyzed from a large number of test pit data in the same dam area to obtain relatively credible values of the material parameters. This provided data support to the evaluation of compaction quality while considering material uncertainties, thereby taking account of incomplete information.

There are many factors that affect the quality of dam compaction, and any uncertainty, especially randomness and fuzziness, in those factors complicates its evaluation. On one hand, because of the limited number of samples, randomly selected test data regarding dry density and other material source parameters are bound to contain some uncertainty, especially the characteristic of fuzziness in spatial distributions. Compaction parameters are associated with a construction process that is inherently affected by random operations. On the other hand, the relationship between compaction and its factors is neither linear nor non-linear but a complex one that also presents fuzziness. There are various methods for measuring such uncertainty. For example, the numeral unit spread assessment pedigree (NUSAP) method was used to quantify qualitative uncertainty in the frequency analysis of regional rainfall (Zhu et al., 2015). A fuzzy pattern-recognition method that takes fuzziness into consideration was used to assess groundwater vulnerability (Mao et al., 2006). A cloud model is a cognitive model that can realize a bidirectional cognitive transformation between a qualitative concept and quantitative data based on probability statistics and the theory of fuzzy sets (Wang et al., 2014). Forward and backward cloud transformations are used to make cognitive transformations between the intension and extension of a concept (Wang and Xu, 2012). Combined with randomness and fuzziness, a cloud model forms a mapping between quantification and quality, thereby constituting a breakthrough at the limits of probability, statistics, and fuzzy-set theory (Li et al., 2006).

Hardly any previous studies have attempted to unite fuzziness and randomness to evaluate compaction quality. To solve this problem effectively, in the present study a cloud model is proposed based on fuzzy mathematics and probability statistics, thereby taking both fuzziness and randomness into consideration. This provides the possibility to evaluate dam compaction quality and uncertainty. The approach is no longer focused entirely on accuracy, but rather on depicting the uncertainty relationship.

The present study introduces the theory of artificial intelligence with uncertainty based on a cloud model for the evaluation of the compaction quality of a rockfill dam. A cloud-fuzzy model is established that makes dam construction evaluation conform to a set of objective laws. The compaction parameters and material source parameters are analyzed through data mining based on massive real-time monitoring and testing data regarding compaction quality, and are analyzed with the cloud model. The distribution characteristics of the compaction quality and material source parameters at the testing pit site are obtained and are used to generate material data by means of bootstrap methods. The reliability (i.e. predictive uncertainty) and precision of the cloud-fuzzy model are assessed in comparison with those of an improved back propagation (BP) neural network, a radial basis function (RBF) neural network, and a multivariate linear regression (MLR) model. The cloud-fuzzy model based on artificial intelligence with uncertainty is used to forecast the dry density distribution and make fuzzy evaluations. This approach may overcome the failure of previous methods to consider uncertainty in the evaluation of the surface compaction quality of rockfill dams.

2 Rockfill dam compaction quality evaluation based on cloud-fuzzy model

The framework of the proposed methodology comprises three major parts: obtaining the evaluation parameters, establishing a cloud-fuzzy model, and compaction quality evaluation (Fig. 1). Firstly, from analyzing the results of a real-time compaction quality monitoring system and pit testing, the following are proposed as the input parameters of compaction quality assessment: rolling velocity, thickness, rolling passes, moisture, and gradation. Secondly, a cloud-fuzzy model is established for evaluating the compaction quality by reforming a fuzzy neural network with the cloud model. Finally, a cloud-fuzzy method for compaction quality evaluation is proposed based on the cloud-fuzzy model, and is applied to a case study of rockfill dam compaction quality assessment in a hydropower project in China.

2.1 Cloud-fuzzy model

2.1.1 Cloud model

A cloud model that is based on fuzzy mathematics and probability statistics takes fuzziness and randomness into consideration and realizes a transformation between a qualitative concept and its quantitative expression. In other words, a cloud model is a powerful tool with which to study the transformation between qualitative and quantitative concepts, thereby overcoming the deficiencies of traditional fuzzy and RBF neural networks.

Cloud is defined as follows (Li et al., 2006).

Definition 1: Let $U=\{x\}$ be a universal set described by precise numbers (where x is one type of parameter) and T be the qualitative concept. If there is one number $x \in U$, which is a random realization of the concept T, and the membership $C_T(x)$ of the qualitative concept T is a random number with a stable

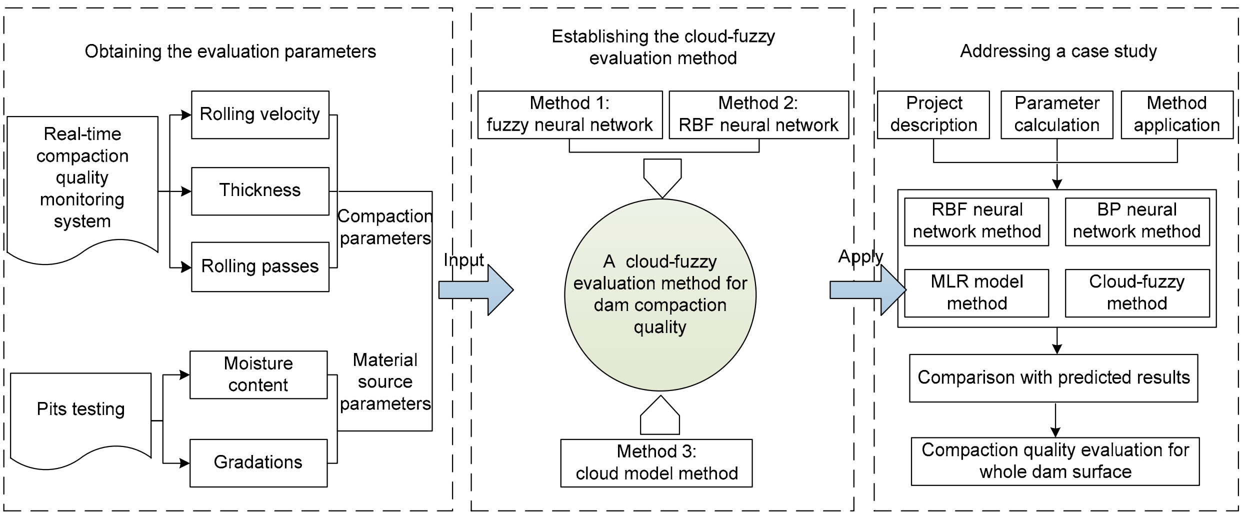

Fig. 1 Framework of proposed methodology

tendency, then the distribution of the membership of concept T in the number field [0, 1] is called the membership cloud $C(X)$, where each X is a cloud drop:

$$C_T(x): U \to [0,1],\ \forall x \in U, x \to C_T(x). \tag{1}$$

A cloud model integrates fuzziness and randomness by using digital characteristics such as the expected value Ex, entropy En, and hyper-entropy He (Li et al., 2006; Wang et al., 2014), whereby

$$C_T(x) = \exp\left[-\frac{(x-\mathrm{Ex})^2}{2\mathrm{En}^2}\right]. \tag{2}$$

Taking the cloud concept of thickness as an example (Fig. 2), in the normal cloud model, the expected value Ex is the most typical sample with which to represent the concept. Corresponding to the center of the mass of the cloud the entropy En is a synthetic measure of the random probability and fuzziness of the qualitative concept. The hyper-entropy He measures the uncertainty of the entropy, which can

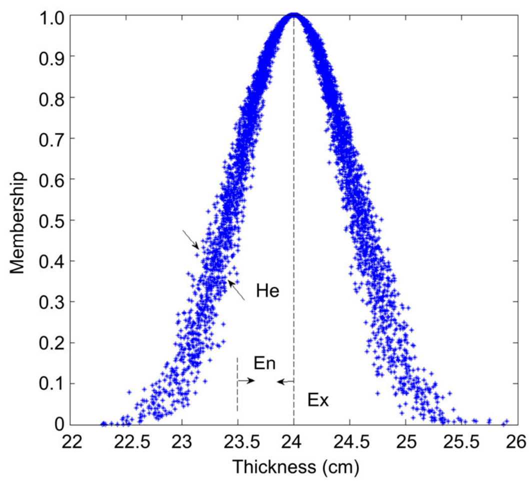

Fig. 2 Cloud concept of thickness (Ex=24 cm, En=0.5085 cm, He=0.0578 cm)

also be considered as the entropy of En. Near the origin of the coordinate with an expected value of zero, a larger value of En corresponds to a greater coverage of cloud drops; the larger the value of He, the more discrete are the cloud drops. It is clear that the expected value reflects the stability of mutation, that the entropy reflects the span of mutation, and that the hyper-entropy reflects the accuracy of mutation; the hyper-entropy He is the degree of uncertainty in the entropy En (Song et al., 2011).

The cloud expectation curves of qualitative knowledge in most natural and social sciences approximately follow normal or semi-normal distributions, which indicate the universality of the normal cloud model (Li et al., 2006). The expectation curve determined by Ex and En can be expressed as

$$y = \exp\left[-\frac{(x-\mathrm{Ex})^2}{2\mathrm{En}^2}\right]. \tag{3}$$

The normal cloud model can be extended to a multi-dimensional normal cloud as follows.

Definition 2: Let $\boldsymbol{U}$ be a set of n-dimensional ordered vectors $\boldsymbol{U}=\{x_{i1}, x_{i2}, \dots, x_{in}\}$, and A is a fuzzy set of $\boldsymbol{U}$. If there is a stable random number $\mu_A(x_{i1}, x_{i2}, \dots, x_{in})$ corresponding to any element $(x_{i1}, x_{i2}, \dots, x_{in})$, then $\mu_A(x_{i1}, x_{i2}, \dots, x_{in})$ corresponding to any element $(x_{i1}, x_{i2}, \dots, x_{in})$ is defined as the membership $(x_{i1}, x_{i2}, \dots, x_{in})$ of A. The membership μ_A is called an n-cloud, which can also be expressed by n groups of numerical characteristics comprising the expected value (Ex_1, Ex_2, …, Ex_n), the entropy (En_1, En_2, …, En_n), and the hyper-entropy (He_1, He_2, …, He_n). The hyper-expectation curve of the n-dimensional cloud determined by (Ex_1, Ex_2, …, Ex_n) and (En_1, En_2, …, En_n) can be expressed as (Li and Du, 2014)

$$\mu(x_1, x_2, \cdots, x_n) = \exp\left[-\sum_{i=1}^{n}\frac{(x_i-\mathrm{Ex}_i)^2}{2\mathrm{En}_i}\right]. \tag{4}$$

2.1.2 Cloud transform method

Cloud transform is a method for discretizing compaction quality data and transforming them into qualitative concepts. Within the allowable error, using a cloud model to fit the probability density function of the data distribution, any function can be decomposed into cloud stacks. Each cloud represents a discrete and qualitative concept. The transformation error depends on the number of superimposed clouds. The more clouds there are, the smaller the error is. In other words, a cloud transformation can extract a qualitative description in the form of a probability distribution of compaction quality data, leading to the following partitioning (Qin and Wang, 2008):

$$g(x)=\sum_{i=1}^{n}\left(c_i f_i(x)\right)+\xi, \tag{5}$$

$$0<\max\left|g(x)-\sum_{i=1}^{n}\left(c_i f_i(x)\right)\right|<\xi, \tag{6}$$

where $g(x)$ is the data distribution function, c_i is the coefficient of $f_i(x)$: $f_i(x)=\exp\left[-\frac{(x-\mathrm{Ex}_i)^2}{2\mathrm{En}_i^2}\right]$ is the expected function of probability density, n is the number of clouds, and ξ is the defined maximum allowed error (here, we set ξ=0.001).

Because it does not consider the relationship between clouds in the transformation process, the cloud sets so obtained may be coarser. The shorter the distance between clouds, the more similar the described concepts, whereas clouds that are relatively far apart may lead to a conceptual vacuum. Therefore, a comprehensive cloud model is required to promote concepts. The basic method for promoting concepts is soft fusion based on weighting, which can bring clouds closer together.

If there are two adjacent cloud models $C_1(\mathrm{Ex}_1, \mathrm{En}_1, \mathrm{He}_1)$ and $C_2(\mathrm{Ex}_2, \mathrm{En}_2, \mathrm{He}_2)$, where $\mathrm{Ex}_1<\mathrm{Ex}_2$, cloud model $C_3(\mathrm{Ex}_3, \mathrm{En}_3, \mathrm{He}_3)$ can be obtained as follows (Fu et al., 2011):

$$\begin{cases}\mathrm{Ex}_3=(\mathrm{Ex}_1+\mathrm{Ex}_2)/2+(\mathrm{En}_1-\mathrm{En}_2)/4,\\ \mathrm{En}_3=(\mathrm{Ex}_2-\mathrm{Ex}_1)/4+(\mathrm{En}_1+\mathrm{En}_2)/2,\\ \mathrm{He}_3=\max(\mathrm{He}_1,\mathrm{He}_2).\end{cases} \tag{7}$$

To evaluate the effect of concept promotion, the ambiguity degree CD is proposed (Li and Du, 2014). The larger the ambiguity CD, the more discrete the concept, and also the greater the overlap between adjacent cloud concepts. In contrast, the smaller the value of CD, the more convergence between concepts, and also the smaller any adjacent overlap. Furthermore, it is easier for the promoted concepts to reach consensus. For CD∈(0.2, 0.5004], the cloud concept is comparatively mature; for CD∈(0, 0.2], the cloud concept is mature; for CD=0, the cloud concept is very mature and the cloud distribution degenerates into a Gaussian function.

2.1.3 Cloud-fuzzy model

By combining a cloud model with a fuzzy neural network (FNN), a cloud-fuzzy model is established as shown in Fig. 3.

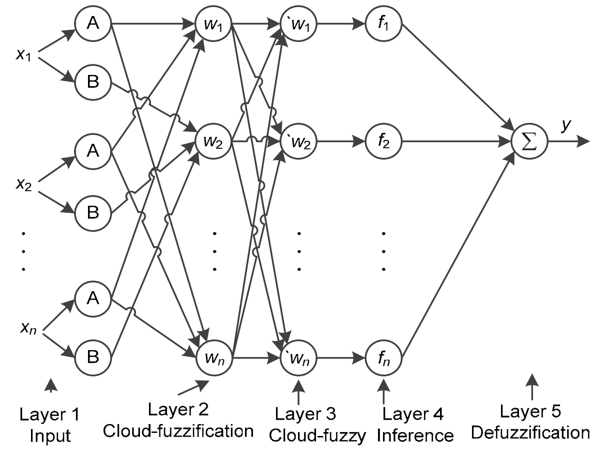

Fig. 3 Cloud-fuzzy model

Each input dimension x_i leads to n_i synthesized cloud models via peak-cloud-transformation and soft fusion. Normal n-dimensional clouds are constructed as neurons of the hidden layer based on the theory of high-dimensional cloud models. Eventually, there will be $n_1 \times n_2 \times \ldots \times n_n$ n-dimensional cloud neurons, each of which is expressed by three groups of numerical characteristics: expected value (Ex_1, Ex_2, …, Ex_n), entropy (En_1, En_2, …, En_n), and hyper-entropy (He_1, He_2, …, He_n).

The cloud neurons can transform the n-dimensional inputs into a group of uncertainties obeying some stable distribution and take the expectation of that group as the final output. For input $\{x_i\}$, the output of the cloud-fuzzy-layer neuron μ_i is

$$\mu_i=\frac{1}{k}\sum_{t=1}^{k}\exp\left[-\sum_{i=1}^{n}\frac{(x_i-\mathrm{Ex}_i)^2}{2\mathrm{En}_j'^2}\right], \tag{8}$$

where En'_j is one of the k n-dimensional random numbers generated with expectation (Ex_1, Ex_2, …, Ex_n) and hyper-entropy (He_1, He_2, …, He_n).

Because certain impossible combinations of high-dimensional clouds may lead to a small output value in the $n_1 \times n_2 \times \ldots \times n_n$ hidden-layer neurons, a threshold value should be set and any output less than that threshold should be set to zero. In addition, the corresponding weight coefficient is not involved in the network training, thereby reducing the ill-condition of the hidden-layer output matrix.

The strength of each rule is normalized by that of layer 3 of the fuzzy inference, and the output of the fuzzy rules is calculated at layer 4.

At the defuzzification layer 5, the output of the training data $x_p=(x_1^p, x_2^p, ..., x_n^p)$ is

$$y=\sum_{i=1}^{h}F_i(\overline{w}_i, f_i), \tag{9}$$

where h is the number of output nodes, and $\overline{w}_i$ and f_i are the weight and value of output node.

Finally, the parameters can be solved in accordance with the principle of least squares as a Takagi-Sugeno fuzzy model.

2.2 Compaction parameters and material source parameters analysis

The factors that commonly affect the surface compaction quality of a rockfill dam include the filling materials, environment, machines, and construction method. The usual method of compaction evaluation is an example of "control after the event", which is one of the three phases in engineering quality control. The compaction quality is measured by means of the dry density obtained by pit experiments conducted after surface rolling, which is also compared with the compactness at the same pits. Along with pit testing, material parameters such as the moisture content and different size contents (i.e. p=0.074 (the proportion of aggregate diameter less than 0.074 mm) and p=5 (the proportion of aggregate diameter less than 5 mm)) are obtained at the same time. Hence, the factors influencing the compaction quality of the dam surface can be classified as either material source parameters or compaction parameters. Because the material source parameters are obtained via pit testing, it is impossible to obtain their values at every location on the surface. The compaction parameters can be obtained by using the compaction quality real-time monitoring system, which gives complete information. The compaction parameters are collected in real time, and are certain in relation to historical data from the construction process but random in relation to the generation of data regarding the vibration compactor (e.g. the roller speed). As for the material source parameters, they have the characteristics of randomness and fuzziness; this data uncertainty leads to an uncertainty in the compaction quality.

2.2.1 Automatic collection of compaction parameters in real-time

To control the process of rockfill dam construction, Zhong et al. (2009, 2011, 2017) developed technology for the real-time monitoring of rolling velocity, rolling passes, and compacted thickness. This system was designed with thickness and the rate of rolling passes as the main indicators of compaction. Compared with traditional control methods, this system greatly reduces the extent to which human factors interfere in the construction process.

The process of compaction parameters collected is as follows. It begins with obtaining the time-dependent spatial coordinates of the rollers and real-time data about the vibration state via a global position system (GPS) benchmark site, a high-precision positioning and receiving device, and vibration sensors in the construction area. All these data are then sent to a database server through an independent transmission network, and are analyzed in an application server. The results are provided to engineering managers through the same transmission network. The managers regulate the construction process via real-time monitoring of the roller speed, track, rolling passes, and the vibration state. Finally, the compaction is evaluated via a system client that generates maps of the thickness and the rolling-pass ratio.

2.2.2 Material source parameters generation

The parameters of a gravelly soil usually express the different contents of grain gradation and moisture. At the beginning of construction on a hydropower project, the amount of pit testing data is too small to reflect the characteristics of the soil material comprehensively. However, the improved bootstrap method, which is a numerical method that incorporates uncertainty, can be used to overcome this data insufficiency and thereby determine the distribution of the material parameters. Along with the development of construction, the sample data will be replenished, whereupon the statistics obtained using the bootstrap method can reflect the distribution of the material parameters effectively.

The bootstrap method is a resampling strategy that determines a distribution from given observation information alone, with no other assumptions or new observations. It is a numerical method that incorporates uncertainty through digital simulation technology to expand the sample size. This method depends entirely on the sample data themselves without any subjective assumptions, thereby generating sample data that is more objective. The core of the method is the construction of independent samples via resampling; the bootstrap method is therefore an effective way to overcome the finiteness of measured data.

Using moisture content as an example, the sample size is determined by taking a confidence level of 95% and a permissible error of 0.05, whereupon the sample size is determined by

$$N=(z_{\alpha/2})^2\sigma^2/\varepsilon^2, \tag{10}$$

where N is the determined sample size, σ is the population variance of the samples, ε is the permissible error, α is the confidence level, and z_α is the statistic at the confidence level α. Here, N is less than the pit testing sample data size of 1050. Hence, the bootstrap method can be used in this study.

The bootstrap structures the distribution function $F(x)$ through the data $x=(x_1, x_2, \ldots, x_n)$ and samples $x^*=(x_1^*, x_2^*, \ldots, x_n^*)$ in $F(x)$.

2.3 Procedures for evaluation of compaction quality based on cloud-fuzzy method

Based on the cloud-fuzzy model, the detailed process for estimating compaction quality is summarized in Fig. 4.

The procedures are divided as follows:

1. To establish the cloud-fuzzy model, the influence factor of dry density should be analyzed first with a cloud model. The set of compaction data is collected according to the construction procedure. The data include the material parameters of the sampled test pits, such as dry density, moisture content, and gradations (i.e. p=5 and p=0.074), and the compaction parameters associated with the test pits, including roller passes, compacted thickness, and roller velocity, all of which are collected from the real-time monitoring system.

2. Based on the cloud analysis, the structure of the cloud-fuzzy model can be determined. The number of hidden-layer neurons and their arguments, including expected value, entropy, and hyper-entropy, can be calculated.

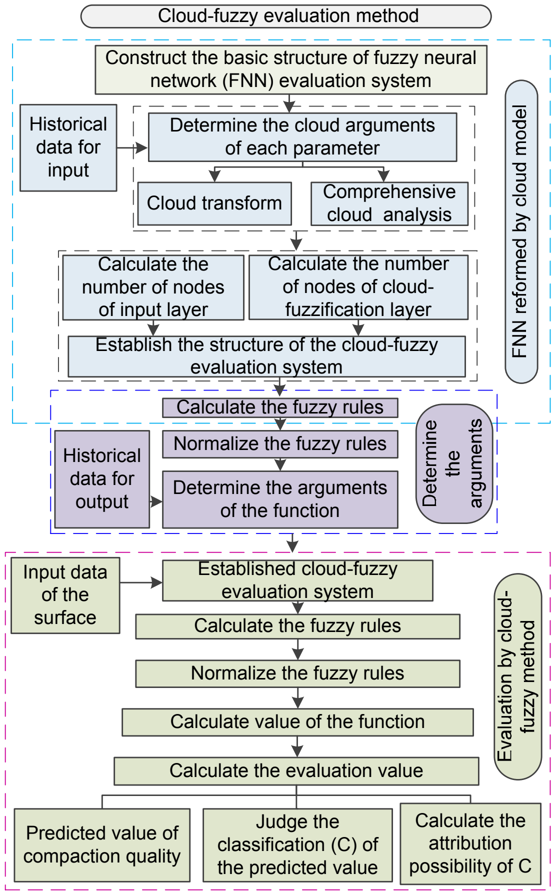

Fig. 4 Detailed procedures for the cloud-fuzzy evaluation of compaction quality

3. Using the historical data, train the cloud-fuzzy model. Firstly, calculate the strength of the rules; normalizing the strength of the rules, calculate the input weights; calculate the output of the rules; then, setting the dry density data as the output, calculate the parameters of the linear transfer function according to the least square method.

4. Using the cloud-fuzzy model, the dry density of each grid in the work area can be calculated on the basis of the known parameter data associated with the grid center point.

5. Finally, on the basis of cloud analysis of the dry density of the test pits, the fuzzy assessment F of each grid, which has two indices C_μ and P, can be calculated as follows:

$$C_{\mu}(x)=\max(C_{I\mu},\ C_{II\mu},\ C_{III\mu}), \tag{11}$$

$$P(x)=\begin{cases}1-\phi_I(x), & x\in I,\\ \phi_{II_1}(x), & x\in II,\ x\le \mathrm{Ex}_{II},\\ \phi_{II_2}(2\mathrm{Ex}_{II}-x), & x\in II,\ x>\mathrm{Ex}_{II},\\ \phi_{III}(x), & x\in III,\end{cases} \tag{12}$$

where C_μ is the membership value of the predicted dry density to the qualitative concept $C(I, II, III)$ of dry density, x is the predicted dry density, I, II, and III are the classifications of the dry density, $C_{I\mu}$, $C_{II\mu}$, and $C_{III\mu}$ are the membership of each classification of the predicted dry density, P is the probability that the predicted dry density belongs to the classification of dry density, Ex_{II} is the dry density average of II, II_1 is the left half of II, II_2 is the right half of II, and the function $\phi(x)$ is given by

$$\phi(x)=\frac{1}{\mathrm{En}\sqrt{2\pi}}\int_{-\infty}^{x}\exp\left[-\frac{(x-\mathrm{Ex})^2}{2\mathrm{En}^2}\right]\mathrm{d}x. \tag{13}$$

2.4 Models for comparison

2.4.1 Back propagation neural network

Artificial neural networks (ANNs) are mathematical models that mimic the structure of the human brain, where outputs depend on input signals (Zeng et al., 2017). The BP neural network is one kind of feed-forward neural network with multi-layers. The BP neural network including one or more hidden layers is one of the ANN methods, which have a relative simple structure and thus can be realized easily (Wang et al., 2017).

2.4.2 RBF neural network

An RBF is a real-valued function (Mirinejad and Inanc, 2017). The learning algorithm of this type of neural network requires three parameters: the center of the basis function, and the variance and weights between the hidden and output layers. The mapping from the input layer to the output layer in an RBF neural network is non-linear, whereas the output layer is linear in terms of the adjustable parameter. Therefore, the network weights can be obtained directly as the solutions to linear equations. The learning process of an RBF neural network is fast and may avoid the local-minimum problem.

2.4.3 Multivariate linear regression

MLR analysis is a multivariate statistical technique used to examine the relationship between a single dependent variable and a set of independent variables. The main objectives of MLR are explanation and prediction. Explanation examines the regression coefficients, their magnitude, sign, and statistical inference, for each independent variable. Prediction involves the extent to which the independent variables can predict the dependent variable (Bas et al., 2017).

3 Case study

3.1 Project overview

The cloud-fuzzy method is applied to a case study to evaluate the compaction quality of a dam surface in the hydropower project A located on the Lancang River in Yunnan Province, China based on real-time monitoring data and pit testing data. Hydropower project A is a core rockfill dam (Fig. 5).

It is the first hydropower project to use a real-time monitoring system throughout the entire construction process. Considering the influence of material sources on different dam zones, the dam core was selected as the research target. The moisture content and particle size (<5 mm and <0.074 mm) of the 1050 groups of pit testing data were chosen as the factors influencing dry density. By matching the pit testing data, the compaction parameters of rolling passes, compacting-machinery running speed, and thickness can be obtained.

3.2 Establishing the cloud-fuzzy model

3.2.1 Determining cloud arguments for evaluation factors

To begin with, the frequency distribution of the influencing factors is analyzed, and then the probability density distribution of the factors is fitted by using the heuristic Peck cloud transform method to transform the curve into multiple Gaussian cloud concepts, as shown in Fig. 6.

Taking the rolling velocity as an example, the promoting concepts are low, normal, and high, as shown in Fig. 6. The cloud concepts of moisture content, rolling speed, and soil ingredients are given

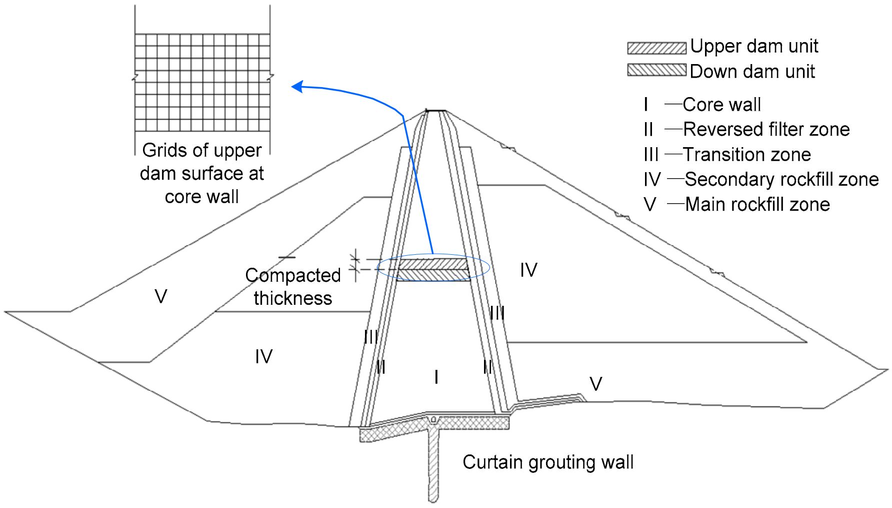

Fig. 5 Details of hydropower project A

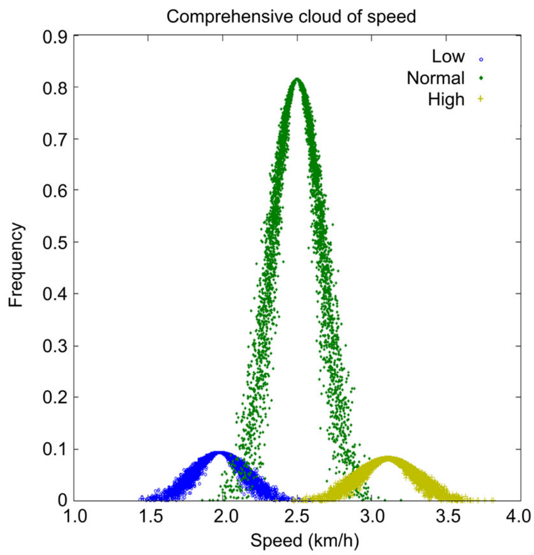

Fig. 6 Promoting concept of velocity

in Table 1. The classification of dry density is also expressed (Table 1). As we can see from the table, the promoting concepts of the factors are comparatively mature and the data can be divided fairly clearly.

3.2.2 Determining function arguments

On the basis of the cloud transform and cloud synthesis method, each factor is divided into three concepts. Hence, the number of neurons in the cloud-fuzzy layer is 3×3×3×3×3, and accordingly there are 243 fuzzy rules. However, there are some combinations with impossible outputs. In such circumstances, those outputs are set to zero according to the threshold ξ=0.001 to improve the robustness of the cloud-fuzzy model.

3.3 Evaluation by the cloud-fuzzy method

3.3.1 Comparative analysis

For comparison, as well as training and testing the cloud-fuzzy neural network, we also trained and tested a BP neural network, an RBF neural network, and an MLR model using the same data. We set 800 groups as training data and 250 groups as testing data among the 1050 groups of data. Table 2 gives the absolute testing errors of the four types of model, and Table 3 gives the relative errors. It can be seen from Tables 2 and 3 that the RBF neural network has the smallest maximum error and sum of squared errors, followed by the improved BP neural network. Although the maximum error and the sum of square errors of the cloud-fuzzy model are larger than those of the RBF and improved BP models, it has an obvious advantage over the MLR model and no apparent disadvantage.

3.3.2 Rationality analysis of the cloud-fuzzy models

Fig. 7 (p.299) allows comparisons between the results predicted by the four models and the real measured values.

Clearly, the distribution of results predicted by the RBF neural network with the smallest sum of square errors has a flat elliptical structure, and the

Table 1 Promoting concepts

Factor	Concept	Expectation	Entropy	Hyper-entropy	Ambiguity degree	Percentage (%)
Thickness (cm)	Thin	18.51	0.75	0.085	0.383	23.26
	Normal	24.00	0.51	0.058	0.383	75.53
	Thick	30.43	0.40	0.090	0.099	1.21
Moisture content (%)	Low	10.75	0.37	0.051	0.416	9.03
	Normal	12.50	0.63	0.089	0.429	75.08
	High	14.57	0.59	0.084	0.429	15.89
Rolling velocity (km/h)	Low	1.98	0.17	0.027	0.485	9.38
	Normal	2.50	0.17	0.027	0.485	81.55
	High	3.11	0.19	0.028	0.445	8.17
Particle size less than 5 mm (%)	Low	33.93	0.86	0.11	0.379	27.13
	Normal	38.39	1.54	0.19	0.379	50.80
	High	46.46	2.27	0.23	0.308	22.07
Particle size less than 0.074 mm (%)	Low	27.13	1.98	0.24	0.363	16.84
	Normal	33.80	1.39	0.22	0.477	68.59
	High	37.77	1.14	0.18	0.477	14.57
Dry density (g/cm^3)	I	1.79	0.007	0.0009	0.347	46.38
	II	1.83	0.013	0.0016	0.347	29.33
	III	1.93	0.022	0.0009	0.121	24.29

Table 2 Absolute error comparison

Model	Maximum absolute error (g/cm^3)	Minimum absolute error (g/cm^3)	Average absolute error (g/cm^3)	Error sum of square
Improved BP neural network	0.1014	0	0.0263	0.2734
RBF neural network	0.0943	0	0.0241	0.2384
Cloud-fuzzy model	0.1073	0	0.0283	0.3272
MLR model	0.2438	0	0.0618	1.3750

Table 3 Relative error comparison

Model	Maximum relative error (%)	Minimum relative error (%)	Average relative error (%)
Improved BP neural network	5.46	0	1.43
RBF neural network	5.14	0	1.31
Cloud-fuzzy model	5.78	0	1.53
MLR model	11.52	0	3.33

predicted values tend to the average dry density of the samples. The errors are the largest for the smallest and largest values of dry density, which is not consistent with the actual results. Compared with the results of the RBF model, those predicted by the improved BP model are more scattered and form two regions on either side of the average but still gather near the mean. The results predicted by the cloud-fuzzy model are even more scattered at larger values of dry density, but most values still lie in the range from −0.05 to +0.05. The results predicted by the MLR model are the worst, with the predicted data being the most scattered and gathering into three regions that the main region crosses the +0.05–−0.05 envelope. Only a few data are close to the line of original values, which shows that it is not a simple linear relationship. There is a slight improvement for the accuracy of the cloud-fuzzy method at the smaller end (<1.8 g/cm^3) and the larger end (>1.9 g/cm^3) compared with RBF between the factors and the compaction quality.

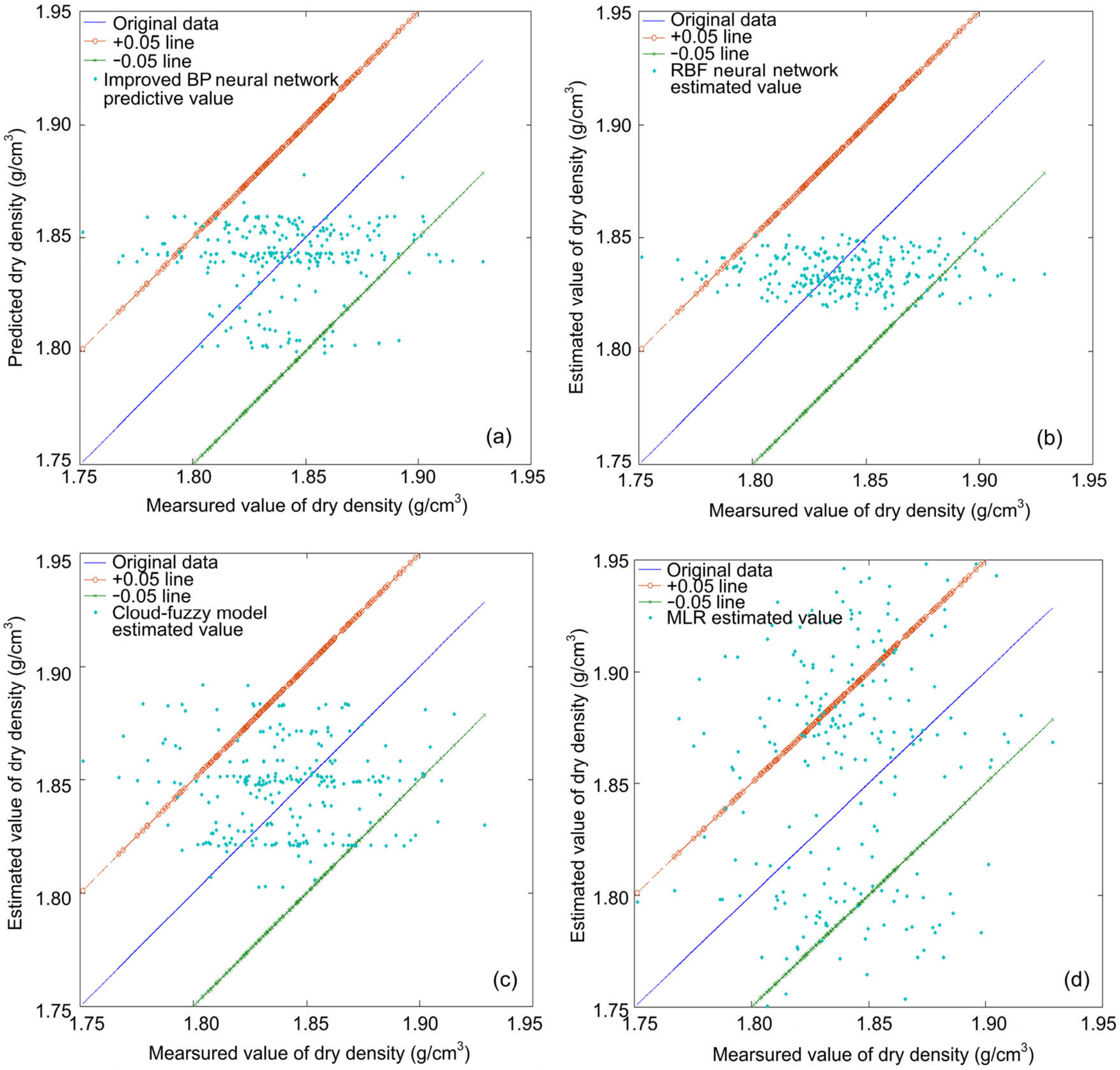

Fig. 7 Measured value and estimated value of different models

The prediction errors of the four models are shown in Fig. 8, where it can be seen that the error distributions of the cloud-fuzzy model are qualitatively similar to those of the improved BP and RBF models and quantitatively of the same order of magnitude.

The errors of groups 101–150 of the testing data are shown in Fig. 9. The relationship between the absolute errors can be seen clearly. The RBF testing error is not always the smallest, and neither is the cloud-fuzzy error always larger than the RBF one, but the MLR error is generally the highest.

The improved BP neural network, RBF neural network, and MLR model are based on limited samples to determine the relationship between influencing factors and construction quality, but the cloud-fuzzy model is based on overall sample distribution. The improved BP neural network, RBF neural network, and MLR model are deterministic models to describe the relationship between the influencing factors and the construction quality, but the cloud-fuzzy model is an uncertain model. The relationship between influencing factors and construction quality is not a simple linear one. MLR is a linear model, while the improved BP neural network, RBF neural network, and cloud-fuzzy model are non-linear models. To evaluate the performance of the models, we should not only pay attention to their accuracy, but also pay attention to uncertainty. Therefore, the cloud-fuzzy model is effective for evaluating the quality of compaction.

3.2.3 Compaction quality evaluation of whole dam surface

By analyzing the real-time monitoring data in relation to the dam core area, the No. EL711.7_3 surface is chosen as an example. It is divided into grids (2 m×2 m) according to the desired level of accuracy and the attribute values of the factors are obtained for each grid, as shown in Fig. 10.

Therefore, the dry density for any grid of No. EL711.7_3 can be estimated using a cloud-fuzzy model (Fig. 11). The predicted values and those actually measured from test pit samples after the work surface was finished are given in Table 4.

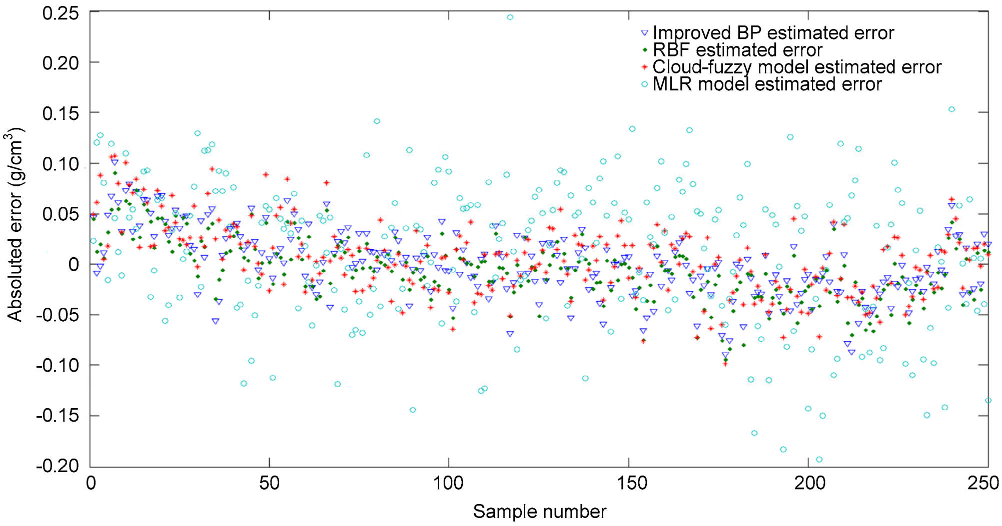

Fig. 8 Errors of the predictions

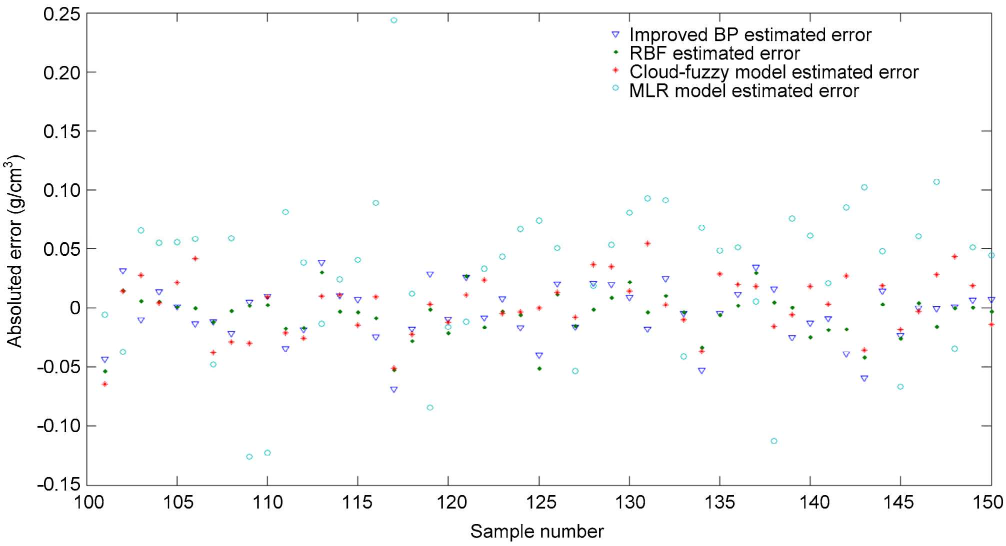

Fig. 9 Partial errors of the predictions

Table 4 Comparison of actual values and prediction values

Name of test pit	Actual value (g/cm^3)	Prediction value (g/cm^3)	Absolute error (g/cm^3)	Relative error (%)
EL711.7_3-01	1.873	1.880	0.007	0.4
EL711.7_3-02	1.836	1.823	−0.013	0.7
EL711.7_3-03	1.832	1.821	−0.011	0.6
EL711.7_3-04	1.860	1.845	−0.015	0.8

Taking the 15th column as an example, because each calculation may involve a different time, the assessment results are averaged over 10 calculations and are presented in Table 5. Most of the values of dry density belong to $C(II)$, which is the general level, with the others belonging to $C(III)$, meaning a high dry density. It can also be seen that the close values of membership C_μ may result in a large difference in the probability P, because the dry density values are on the opposite sides of the expected value Ex. Hence, $C(I)$ should be avoided in the construction process. The higher the value of P for the dry density, the greater the possibility of over-rolling. Thus, $C(III)$ should also be treated carefully.

In Table 6, the dry density assessment matching C is presented for the entire dam surface. As we can see, at least 90% of the surface area meets the specification requirements, which indicates that the compaction quality was controlled nearly perfectly. This result can give timely feedback to help the relevant personnel control and improve quality.

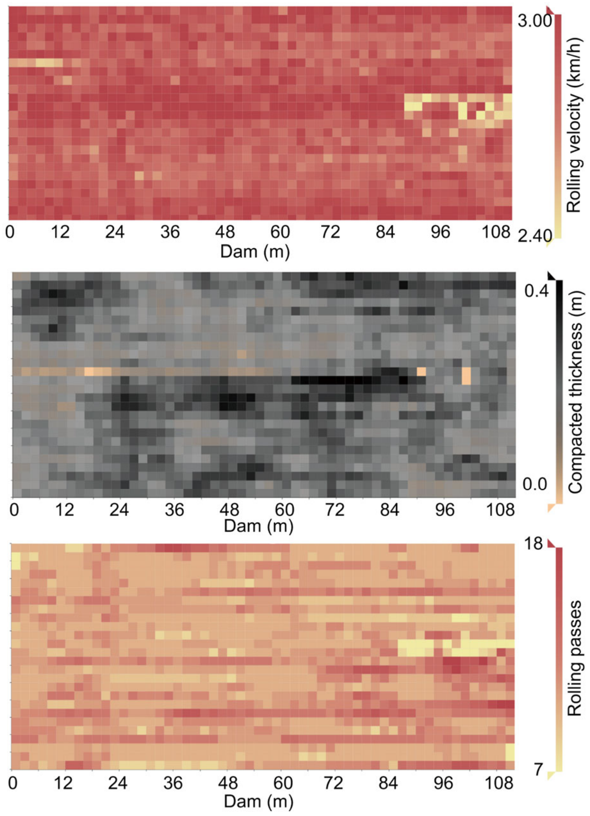

Fig. 10 Surface division and compaction parameters statistical analysis

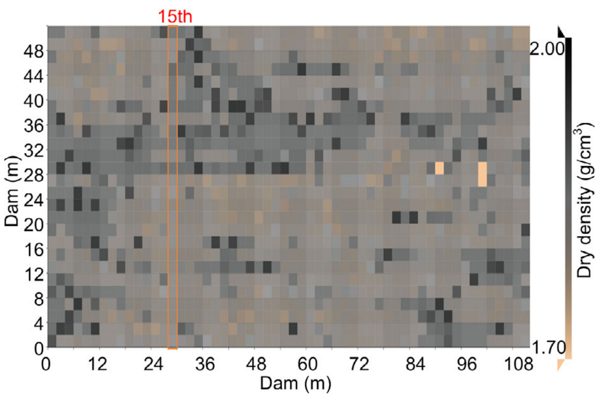

Fig. 11 Dry density prediction of whole dam surface

Table 5 Assessment of the 15th column grid of the dam surface

Dry density (g/cm^3)	C	C_μ	P
1.828	II_1	0.988	0.437
1.823	II_1	0.879	0.306
1.810	II_1	0.324	0.067
1.819	II_1	0.689	0.194
1.819	II_1	0.689	0.194
1.823	II_1	0.879	0.306
1.811	II_1	0.344	0.072
1.805	II_1	0.167	0.029
1.857	II_2	0.124	0.020
1.822	II_1	0.815	0.261
1.826	II_1	0.960	0.387
1.805	II_1	0.167	0.029
1.844	II_2	0.577	0.147
1.823	II_1	0.879	0.306
1.882	III	0.094	0.015
1.823	II_1	0.879	0.306
1.884	III	0.113	0.018
1.882	III	0.093	0.015
1.822	II_1	0.815	0.261
1.826	II_1	0.960	0.387
1.805	II_1	0.167	0.029
1.844	II_2	0.577	0.147
1.823	II_1	0.879	0.306
1.882	III	0.094	0.015
1.823	II_1	0.879	0.306
1.884	III	0.113	0.018
1.882	III	0.093	0.015

Table 6 Percentage of each class for whole surface

C	Percentage (%)
I	8.79
II	59.62
III	31.59

4 Conclusions

In this paper, a cloud-fuzzy evaluation method was proposed and established by considering artificial intelligence with uncertainty and fusing a cloud model with a fuzzy neural network. Based on real-time monitoring data and pit testing data, compared with an improved BP model, an RBF model, and an MLR model, the present cloud-fuzzy method was verified not only as feasible in relation to precision but also in its ability to express uncertainty relationships.

The present cloud-fuzzy model takes into account the uncertain relationship between compaction and its factors. It can express the randomness and fuzziness of compaction, and can compensate for the sole focus on precision by traditional approaches. The present model brings compaction evaluation more into line with objective rules.

In the process of evaluating the compaction of the entire surface of a core rockfill dam, a triple-indicator method was proposed for evaluating the compaction quality. Not only can this provide the value of dry density at any grid, it can also give membership and the probability of dry density belonging to a particular classification. The cloud-fuzzy evaluation method can be used to calculate relatively accurate distributions of dry density, make fuzzy linguistic assessments, and realize a triple evaluation of compaction.

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中文概要

题　目：基于云-模糊模型的堆石坝施工质量评估

目　的：施工质量对于大坝建设期及运行期的安全至关重要。由于施工过程中的信息不完备及碾压质量与影响因素之间的关系并不是完全确定等原因，传统的评估方法很少考虑不确定性对施工质量的影响。本文旨在探讨考虑不确定性影响的碾压质量评估方法，改善施工质量评估的可信性。

创新点：1. 通过研究模糊神经网络与径向基神经网络，结合云模型建立云-模糊模型；2. 建立施工质量三指标体系评价方法。

方　法：1. 通过碾压质量实时监控系统和现场试坑试验获取参数数据；2. 通过云分析，建立云-模糊模型；3. 对比不同的模型，验证云-模糊模型的可行性；4. 利用验证的云-模糊模型对大坝施工仓面进行压实干密度预测；5. 计算评价体系的三指标，对施工质量进行评估。

结　论：1. 云-模糊模型不但能在精度上满足预测要求，而且能够综合考虑施工质量与影响因素之间的不确定性关系；2. 云-模糊评价方法弥补了传统评价方法仅追求精度的单一性，使得施工质量评价更符合客观规律；3. 提出的施工质量三指标评价体系充实了传统的评价方法，能够更客观地指导实际工程建设。

关键词：堆石坝；云模型；不确定性；施工质量评价