Real-time evaluation of compaction quality based on RF-ACGWO with high robustness and generalization ability

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ABSTRACT

The effective evaluation of compaction quality is a key issue for the safety of earth-rock dams. However, existing prediction models of compaction quality are designed to improve prediction accuracy but generally ignore generalizability and robustness, resulting in deviations from practical evaluation results, making these models inapplicable to complex construction environments. To address these problems, a novel real-time evaluation model for construction unit compaction quality based on random forest optimized by adaptive chaos grey wolf algorithm (RF-ACGWO) is proposed in this article. In RF-ACGWO, RF predicts compaction quality, while ACGWO increases efficiency and accuracy for traditional RF parameter selection and improves the generalizability and robustness of the model. Also, meteorological factors at a project site are also considered to affect the model, thereby improving model accuracy. After embedding the proposed method in a Three-Dimensions (3D) rolling monitoring system, real-time evaluation, guidance and feedback on a project site can be obtained. Compared to the conventional evaluation methods, RF-ACGWO achieves the highest accuracy of 0.838, the best generalizability of 0.793 and the most stable robustness when applied to a large-scale, real-life hydraulic engineering project.

Key words: high robustness and generalization ability; real-time evaluation of compaction quality; RF-ACGWO; 3D rolling monitoring system.
INTRODUCTION

Compaction quality control is a research hotspot of safety control for earth-rock dams. During the construction process of earth-rock dam, the dry density is an important metric to measure construction quality. Currently, the primary techniques to detect compaction quality, such as the pit test method, the nuclear densitometer method and the static load test method [Lv, 2017], have their respective disadvantages and detect limited sampling points, making it difficult to comprehensively describe the compaction quality of a construction unit.

Based on these disadvantages, experts have actively explored new evaluation methods to replace traditional compaction quality testing technology. Existing compaction-quality evaluation methods (CQEMs) can be divided into two categories: 1) the real-time monitoring index of compaction quality that is obtained through the analysis and calculation of the acceleration of roller, such as Intelligent Compaction (IC), Compaction Meter Value (CMV), Machine Drive Power (MDP), Resonance Meter Value (RMV), Continuous Compaction Value (CCV) (White, 2008; Xu, 2016), Total Harmonic Distortion Rate index (THD) [Mooney et al., 2007] and Compaction Values (CV) [Liu et al., 2016], which use the common compaction indicators in IC and Continuous Compaction Control (CCC) shown in Table 1; and 2) the rolling times, rolling speed, vibration status and other rolling parameters that are obtained via the real-time monitoring system developed by Zhong et al. [2011], data-driven models, such as Multiple Linear Regression (MLR), Back Propagation Neural Network (BPNN), Support Vector Regression (SVR) and their variants, which were constructed to describe the real-time feedback control of compaction quality, which is a mainstream research direction in the field of compaction quality evaluation. The former analyzes collected data using an accelerometer from a physical perspective, which is interpretable and can characterize the overall compaction effect of the roller accurately. However, considering the difference in the spatial distribution of dam material particles, dam material cannot achieve consistent compaction, even if the work
performed by the roller is on the same dam material [Liu, 2018]. Scholars have noted that most of these indicators are not applicable to the evaluation of compaction quality in the core wall area of earth-rock dams [Wang, 2018a]. Data-driven models can comprehensively consider multiparameter inputs and mine hidden rules. Due to the noise caused via the complex construction environment at the project site and the real-time data being different from the test set in practical applications, the prediction accuracy of the compaction quality evaluation model will be significantly reduced. However, most existing research of data-driven models focused on verifying the applicability and superiority of their proposed models, and ignored the generalizability and robustness of the proposed model, which are important in the practical application of the engineering field. Thus, model generalizability was compared to the accuracy of the data outside the boundary of the hypersphere, while the robustness of the data was tested with the data with noise in this study.

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Study Subject</th>
<th>Author/Institutional</th>
<th>Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>CMV</td>
<td>Vibration acceleration of roller</td>
<td>Geodynamik</td>
<td>Highway rolling</td>
</tr>
<tr>
<td>RMV</td>
<td>Vibration acceleration of roller</td>
<td>Adam and Kopf</td>
<td>Highway rolling</td>
</tr>
<tr>
<td>CCV</td>
<td>Vibration acceleration of roller</td>
<td>Sakai Company</td>
<td>Highway rolling</td>
</tr>
<tr>
<td>THD</td>
<td>Vibration acceleration of roller</td>
<td>Mooney</td>
<td>Highway rolling</td>
</tr>
<tr>
<td>MDP</td>
<td>Roller output power</td>
<td>Caterpillar</td>
<td>Highway rolling</td>
</tr>
<tr>
<td>CV</td>
<td>Vibration acceleration of roller</td>
<td>Liu</td>
<td>Rockfill dam rolling</td>
</tr>
</tbody>
</table>

The primary objective of this paper is to improve the prediction accuracy and robustness of the proposed model in practical engineering applications by enhancing the generalizability and robustness of the CQEM, which was embedded into a 3D compaction monitoring system to create a visual display that provides actual engineering guidance. To achieve this objective, a novel CQEM based on RF-ACGWO is proposed in this paper. This method was verified at a real construction site, and compared to the evaluation results of the MLR, BPNN and RF algorithms, results show that RF-ACGWO achieves better precision and accuracy, good robustness, and excellent generalizability.
RELATED WORK

As mentioned above, CQEMs can be divided into two categories. Because the former is not applicable to the evaluation of rolling quality in the core wall area of earth-rock dams, this paper uses a data-driven model, which is mainstream in the field of hydraulic engineering, to evaluate compaction quality. The following is a review of the data-driven model proposed in this study.

Overview of compaction quality evaluation algorithms

Commonly used CQEMs primarily include MLR, BPNN, SVR and other data-driven models. As shown in Table 2, the CQEM is compared to other methods. Meehan [2017] used MLR to verify that the consistency between CCC and in situ test data sets is better when the effects of water content are considered. Beainy [2012] developed an intelligent asphalt compaction analyzer based on a neural net-based classifier to classify extracted features into different categories. Liu [2016] developed an MLR data-driven model to verify that the compaction power per unit volume (E) and CMV are significantly correlated with dry density. Wang [2018b] proposed a CQEM based on SVR and a chaos-based firefly algorithm that achieved a high prediction accuracy. Commuri [2011] invented the asphalt intelligent compaction analyzer using an artificial neural network to analyze the compaction quality of hot asphalt mixtures. Those results showed that artificial intelligence can effectively control compaction quality via fitting uncertain construction parameters and the dry density. However, CQEMs, such as the MLR, BPNN and SVR models, ignore model generalizability and robustness when applied at construction sites, and model accuracy must also be improved.

Table 2 Comparison of compaction quality evaluation models

<table>
<thead>
<tr>
<th>Literature</th>
<th>Domain</th>
<th>Model</th>
<th>Input parameter</th>
<th>Indicators</th>
<th>Precision</th>
<th>Robustness/Generation ability</th>
<th>Real-time evaluation</th>
</tr>
</thead>
<tbody>
<tr>
<td>[MEEHAN 2017]</td>
<td>subgrade</td>
<td>MLR</td>
<td>physical parameter + moisture content</td>
<td>CMV, MDP</td>
<td>0.808</td>
<td>not have</td>
<td>NO(ex post evaluation)</td>
</tr>
<tr>
<td>[BEAINY 2012]</td>
<td>subgrade</td>
<td>ANN</td>
<td>Rolling parameter+Material sources parameters</td>
<td>Density</td>
<td>0.791</td>
<td>not have</td>
<td>No(ex post evaluation)</td>
</tr>
</tbody>
</table>
RF has been widely used in many fields, such as hydrology and rainfall prediction. Peters et al. [2007] developed an ecohydrological distribution model based on RF and logistics, and found that the RF prediction error was below that of the logistic model. Wang et al. [2019] developed the superpixel classifier to identify cracks based on five classification algorithms, and a comparison of their performances showed that the RF classifier achieved the best performance. Zhou et al. [2019] developed an intelligent model based on RF to predict risk in deep foundation pits in subway stations. Those results showed that RF prediction performance is better than that of the MLR and BPNN models, and RF can consider parameter uncertainty and exhibits advantages such as good robustness, difficult overfitting, insensitivity to noise, excellent estimation effect and small generalizability error. Thus, the CQEM can be developed based on RF.

However, RF performance is strongly affected via model parameters such as tree number and random feature number [Lin, 2018]. It is also difficult to select parameters based on manual experience; thus, how to choose optimal RF parameters and improve the accuracy, generalizability and robustness of the evaluation model for compaction quality is a key problem that must be solved.

### Overview of optimization algorithms

In recent years, many optimization algorithms have been proposed [Siddique, 2015], including genetic algorithm (GA) [MOHAMMAD, 2014; Fahad, 2021], particle swarm optimization (PSO) [Naresh, 2019], ant colony optimization (ACO) [Altarabsheh, 2018], artificial bee colony optimization (ABCO) [Nhat-Duc, 2018], bacterial foraging algorithm [Venkata, 2018] and whale optimiser algorithm (WOA) [Sultana, 2018]. The hybrid algorithm developed by

<table>
<thead>
<tr>
<th>Reference</th>
<th>Methodology</th>
<th>Algorithm</th>
<th>Parameters</th>
<th>Evaluation Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>[LIU 2016]</td>
<td>Pavement compaction</td>
<td>MLR</td>
<td>Compactness 0.8</td>
<td>No (ex post evaluation)</td>
</tr>
<tr>
<td>[WANG 2018]</td>
<td>Core wall of earth-rock dam</td>
<td>SVR</td>
<td>Compactness 0.96</td>
<td>No (ex post evaluation)</td>
</tr>
<tr>
<td>[Commuri 2011]</td>
<td>asphalt pavement</td>
<td>ANN</td>
<td>Core densities 0.791</td>
<td>Yes</td>
</tr>
</tbody>
</table>
coupling the data-mining algorithm and the optimization algorithm can significantly improve model performance. Hybrid algorithms can be divided into two categories: algorithm fusion, where various algorithms in the structure of mutual penetration; and algorithm combination, where the algorithm is used in parallel or series [Wang, 2018a]. With the former, many studies integrate artificial intelligence and data-mining algorithms [Smolik, 2017] to improve algorithm performance, such as SVR optimized by particle swarm optimization [Gilan, 2012] or firefly algorithms [Chou, 2015]. With the latter, multiple weak learning machines are used to form a stronger learning machine to improve performance, such as RF [Lin, 2018; Zhou, 2019] and integrated learning methods [Roveri, 2016]. With the help of advanced optimization and data mining algorithms, an evaluation model of compaction quality for a core rockfill dam is developed and can markedly improve the intelligent construction of core rockfill dams.

The Gray Wolf Optimization (GWO) algorithm is a new bionic swarm intelligence algorithm [Mirjalili, 2014]. Studies show that [Adla, 2019; Song, 2015; Mirjalili, 2015], the GWO algorithm is easy to understand, and provides fast convergence, flexibility, good robustness and easy implementation compared to GA, PSO, the simulated annealing, the cuckoo search and the gradient algorithm. GWO is also applicable to different problems because it assumes problems to be black boxes. Pradhan M et al. [2016] used GWO to solve the optimal operation strategy problem of economic load scheduling and showed that the GWO algorithm is a robust and reliable optimization algorithm with potential and effectiveness. Mohanty S et al. [2015] proposed a maximum power point tracking (MPPT) design for a photovoltaic system based on the GWO technique. According to simulation results, this algorithm performed better than perturbed, observed and improved PSO techniques. Mirjalili [2015] used GWO to train a multilayer perceptron and showed that the GWO algorithm can avoid local optima, and provides a higher classification accuracy and function estimation performance.

However, like PSO [Naresh, 2019], ACO [Altarabsheh, 2018], ABCO [Nhat-Duc, 2018], GWO also has certain shortcomings, such as slow convergence rates, a high likelihood of falling into
local optima and an unstable optimization quality. Because of these shortcomings, Jiao [2008] proposed a PSO algorithm with an adaptive inertia weight. With an increasing number of iterations, the inertia weight decreased nonlinearly so that the algorithm could enhance the local search ability by adjusting the weight in the later stage and finally reach its optimal value. Dodson [2015] which expanded the search space into the later stage and achieved good results in solving the benchmark function. To improve the global search capability, Li et al. [2011] combined ACO with a simulated annealing algorithm and proposed an adaptive ant flow-based path selection control mechanism and adaptive adjustment schemes.

Due to the randomness, ergodicity and regularity of chaos motion, chaos can be introduced into optimization variables, thus creating a chaos optimization method [Rachid, 2017]. Cao [2013] used a chaotic sequence to initialize a honeybee source to improve the convergence speed of a colony algorithm and avoid premature maturity of the population. Kohli [2017] introduced chaos theory into the GWO to improve the global convergence speed. Compared to traditional GWO and popular metaheuristic algorithms, results show that chaos GWO achieves better performance than standard GWO under proper chaotic mapping. Therefore, the chaos GWO algorithm was used in this study to optimize the RF parameters.

Based on the literature, this paper used GWO to optimize the RF parameters and then proposed an RF algorithm that is optimized using the adaptive chaos gray wolf algorithm. First, an adaptive scaling factor was used to improve the GWO to provide full search ability and improve its update speed. Chaos theory was then introduced into the late search, which made up for the weak local search in the late stage and avoids the population falling into premature maturity, thus ensuring the generalization accuracy of the optimized results. Then, ACGWO was used to optimize the RF, which showed that traditional RF can adaptively obtain the optimal parameters, resulting in a weak generalizability and improved algorithm robustness. Finally, the model was embedded into a 3D real-time monitoring system to describe the visual dynamic evaluation of the compaction quality of a construction unit.
PROPOSED FRAMEWORK

Fig. 1 shows the overall research framework of the CQEM based on RF-ACGWO and a 3D rolling real-time monitoring system, which primarily includes the following five components. First, because RF is not easily overfit and has good generalizability due to the law of large numbers, RF was used as the basic algorithm for compaction quality evaluation. Second, the adaptive scaling factor and chaos theory were used to improve GWO. The scaling factor changes with the number of iterations, which addresses the shortcoming that the original algorithm cannot provide full search ability due to the linear scaling factor. A chaos fine search strategy was used to mitigate premature populations. Third, ACGWO was used to optimize the RF parameters, which overcame the shortcomings of unimproved accuracy and low efficiency in the traditional RF parameter selection and improved the generalizability, robustness and accuracy of RF. Then, a CQEM based on the RF-ACGWO algorithm was constructed based on the measured data of a project site, and the optimization performance of the developed model was analyzed and evaluated via an error analysis evaluation index, such as the mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), relative absolute error (RAE) and relative root mean square error (RRSE), which verified that the improved algorithm has high accuracy, excellent generalizability and good robustness. Finally, the model was embedded into a real 3D rolling real-time monitoring system to create a visualization and provide real-time feedback control of compaction quality.
Figure 1 Research framework of compaction-quality evaluation method based on RF-ACGWO

Random forest compaction quality model

To evaluate the compaction quality of the core wall area of an earth-rock dam, the RF proposed by Breiman [2001] was used to predict dry density in this study. The law of large numbers guarantees that the RF will not produce overfitting as the number of decision trees increases. Many studies [Wang, 2019; Zhou, 2019] have shown that RF does not easily overfit data; provides good outlier processing, low generalizability error, and excellent prediction results; and generally insensitive to multivariate collinearity. These characteristics are why RF is known to be one of the best algorithms available today. It is worth noting that if feature number (Mtry) is too small, the result of the classifier will be overfit, increasing the error of the prediction classification and decreasing accuracy. If Mtry is too large, the RF construction time will be too long, and the running speed will be slow. If the tree number (Ntree) is too small, the randomness
of RF will decrease due to insufficient training; if Ntree is too large, the computational complexity of the model will increase, and the classification accuracy of the tree will decrease, yielding high randomness. However, the RF algorithm cannot adaptively determine optimal \( M_{try} \) and \( N_{ree} \). To ensure generalizability and model precision, an optimization algorithm must be introduced to optimize the RF parameters.

**Grey wolf optimization algorithm improved by adaptive chaos**

The GWO optimization algorithm that was proposed by Mirjalili et al. [2014] in 2014 was used in this study. The GWO algorithm searches for the optimal parameters of RF via simulating the hierarchy and predation strategy of natural gray wolves, which can be divided into random scattered search, target approach, encirclement and attack. GWO has been widely used due to its fast convergence, fewer adjustment parameters and superior performance in solving function optimization problems. According to an analysis of the GWO algorithm, GWO locates the position of prey via the optimal solution, the suboptimal solution and the third-optimal solution. Thus, this method makes the algorithm more explicit in directivity and achieves fast convergence speeds during early iterations. Conversely, the algorithm is unstable during optimization and falls into local optima easily in the later stage due to few samples.

A linear scale factor also cannot describe the convergence process properly because the GWO behaves nonlinearly during convergence. In the early stage of evolution, we can expand the search range and update the genes of the individuals by increasing the scale factor. In the later stage, the convergence will speed up after reducing it. Also, to prevent the gene structures of advanced individuals from being damaged, the scale factor of the individual that has better fitness values should be reduced. Correspondingly, the scale factor of individuals that have poor fitness values should be increased to help poor individuals improve their gene structures. Thus, a scale factor formula based on a sinusoidal function was proposed, as equation (1) shows:
\[ a = \begin{cases} \sin\left( \frac{t \times \pi}{\max} + \frac{\pi}{2} \right) + 1 - \frac{F_i - \bar{F}}{F_{\max} - \bar{F}} , & F_i \geq \bar{F} \\
\sin\left( \frac{t \times \pi}{\max} + \frac{\pi}{2} \right) + 1 , & F_i < \bar{F} \end{cases} \]  

where \( t \) is the current number of iterations, \( \max \) is the maximum number of iterations, \( F_{\max} \) is the optimal fitness value of the current population, \( F_i \) is the fitness value of the base vector used when generating the \( i \)-th individual and \( \bar{F} \) is the average fitness value of the current population.

Similar to the adaptive scaling factor, the chaos fine search strategy was also used to improve GWO’s search efficiency and mitigate it from falling into local optima. The internal randomness of chaotic motion leads to GWO’s high sensitivity to initial values and thus allows the algorithm to traverse the entire space without repeats within a specified range. In this study, a logistic mapping chaotic system model was used to map chaotic variables to the value interval of optimization variables and then used chaotic variables for optimization [Sivakumar, 2000]. To verify the effectiveness and efficiency of ACGWO, the benchmark function was used in this study. The test results of nine benchmark functions are shown in Table 3:

<table>
<thead>
<tr>
<th>function ( n )</th>
<th>exact value ( f(0,0) = 0 )</th>
<th>Average of search results</th>
<th>variance of search result</th>
<th>Number of iterations</th>
</tr>
</thead>
<tbody>
<tr>
<td>( f_1 )</td>
<td>( f(0,0) = 0 )</td>
<td>1.44447( \times )10(^{-14} )</td>
<td>3.42537( \times )10(^{-28} )</td>
<td>54</td>
</tr>
<tr>
<td>( f_2 )</td>
<td>( f(0, -1) = 3 )</td>
<td>3.000028925</td>
<td>2.7596( \times )10(^{-10} )</td>
<td>175</td>
</tr>
<tr>
<td>( f_3 )</td>
<td>( f(1,1) = 0 )</td>
<td>0.000160554</td>
<td>3.62308( \times )10(^{-08} )</td>
<td>50</td>
</tr>
<tr>
<td>( f_4 )</td>
<td>( f\left(\frac{0, \ldots, 0}{n=30}\right) = 0 )</td>
<td>4.06658( \times )10(^{-12} )</td>
<td>6.07318( \times )10(^{-23} )</td>
<td>200</td>
</tr>
<tr>
<td>( f_5 )</td>
<td>( f(0.0898, -0.7126) ) and ( f(-0.0898, 0.7126) = -1.0316 )</td>
<td>-1.031112905</td>
<td>1.30941( \times )10(^{07} )</td>
<td>17</td>
</tr>
<tr>
<td>( f_6 )</td>
<td>( f\left(\frac{1, \ldots, 1}{n=30}\right) = 0 )</td>
<td>1.13699( \times )10(^{05} )</td>
<td>1.52369( \times )10(^{10} )</td>
<td>235</td>
</tr>
<tr>
<td>( f_7 )</td>
<td>( f\left(\frac{0, \ldots, 0}{n=30}\right) = 0 )</td>
<td>3.9591( \times )10(^{08} )</td>
<td>1.31736( \times )10(^{15} )</td>
<td>162</td>
</tr>
<tr>
<td>( f_8 )</td>
<td>( f\left(\frac{0, \ldots, 0}{n=2}\right) = 0 )</td>
<td>2.30735( \times )10(^{92} )</td>
<td>1.2349( \times )10(^{182} )</td>
<td>150</td>
</tr>
<tr>
<td>( f_9 )</td>
<td>( f(x) = -0.397887, at x = (\pi, 12.275), (\pi, 2.275) ) and ( (9.4247, 2.475) )</td>
<td>0.397990277</td>
<td>1.82832( \times )10(^{08} )</td>
<td>157</td>
</tr>
</tbody>
</table>
As shown in Table 3, the results of these nine functions were independently run 30 times in ACGWO. The average number of iterations of all benchmark functions were below 250, during which each model achieved excellent optimization results. The search error was below 1×e-6. ACGWO thus demonstrates excellent performance in accuracy, stability and convergence speed, and the proposed optimization algorithm was used to optimize the RF parameters.

**Compaction prediction model based on RF-ACGWO**

The basic idea of applying RF-ACGWO is to replace the $Mtry$ and $Ntree$ with the position of the wolf. First, the adaptive scaling factor was used to control the update of parameters and position to improve GWO’s convergence speed. Second, a chaos fine search strategy was introduced in the later search stage of the algorithm. When the algorithm found the optimal solution, a smaller search space was reconstructed, and gray wolf individuals were randomly generated in the new search area to replace gray wolf individuals with poor performance. Finally, the optimal solution was obtained, which kept the search process from falling into local optima and guaranteed the generalizability of the model. Last, the position of the wolf was randomly initialized, and the MSE was used as the fitness value: the smaller the MSE was, the closer the solution was to the target. Then, the position of the wolf was updated, and the RF was trained. The RF model after training was used for prediction, and the pseudocode for the RF-ACGWO algorithm is shown in Table 4.

**Table 4 The pseudo-code of the RF-ACGWO algorithm**

<table>
<thead>
<tr>
<th>Line</th>
<th>Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>Initialize related parameters of RF-ACGWO algorithm, such as number of wolves ($N_w$), maximum number of iterations ($Max$), $Mtry$, $Ntree$, upper and lower bounds of the parameter value, etc.</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>Initializes the Alpha, Beta, and Delta wolf positions and target functions</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>$l=0$</td>
</tr>
<tr>
<td>4</td>
<td>while $l&lt;$Max</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>for $i=1$ : $N_w$</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Return back the search agents that go beyond the boundaries of the search space</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>The fitness function value was calculated, and MSE of RF model prediction result was considered to be the optimization objective function value;</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>if Compare the target function values with the Alpha, Beta, and Delta wolf target function values</td>
<td></td>
</tr>
</tbody>
</table>


10: Update the optimal position;
11: end if
12: end for i
13: Formula (2) was used to calculate the adaptive step size;
14: for i=1: Nw
15: for j=1:dim
16: Surround the optimal parameters and update the position;
17: end for j
18: end for i
19: The optimal individual is searched by chaos
20: l=l+1;
21: Convergence_curve(l)=Alpha_score;
22: end for l
23: Output optimal parameters of RF;
24: Train with the optimal parameters Ntree and Mtry to obtain the final prediction result;

Output: Prediction results of dry density

IMPLEMENTATION AND RESULTS

Implementation

The CQEM based on RF-ACGWO was run on the MATLAB R201b platform. The implementation is built upon the RF algorithm toolbox available for the MATLAB platform that contains internal modeling and prediction code for RF, which facilitates the development and implementation of various methods. As a prototype, the proposed method was tested on a 64-bit Microsoft Windows 7 Enterprise computer that included the following hardware configuration: Intel(R) core(TM) i7-4712hq cpu@2.30ghz, 16.0gb of ram, NVIDIA Quadro K1100M GPU(graphics processor). Results show that the proposed model is applicable to practical engineering problems and can achieve high accuracy, excellent generalizability and good robustness.

Field trials

Combined with the monitoring data of a large-scale high earth-rock dam hydropower station in southwestern China, the scale ranks the highest among the same type of dams in the world. The model developed in this paper was used to evaluate the compaction quality of the construction
unit in the core wall area of an earth-rock dam in real time, which verified the applicability of the model in a real engineering project. The consistency, representativeness and superiority of the model are verified by analyzing the accuracy, generalizability and robustness of the model and comparing those metrics to those of other models.

A total of 104 groups of core wall construction data from early November 2016 to the end of March 2017 were selected as research objects. The compaction quality evaluation index data were obtained by rolling real-time monitoring system, pit test and weather station for earth-rock dams. Model accuracy was validated via a fivefold cross-validation, and the test of generalizability was described via the precision of the data outside the bounds of the hypersphere, while the robustness was tested via the noise-added data.

**Parameter selection**

The data of a hydropower station during the early period of construction were used to develop the model. Rolling parameters, particle 5 and moisture content have been shown to have a strong correlation with compaction quality in many studies [Liu, 2016; Wang, 2018a; Meehan, 2017; BEAINY, 2012]. To verify that the new material source characteristic parameters, including inhomogeneity coefficient (Cu) and curvature coefficient (Cc); and meteorological factors, including temperature and humidity H, have a correlation with dry density, this paper performed Pearson correlation (R) analysis for the newly added parameters, and the results showed that the newly added parameters Cc and H are strongly correlated with dry density and significantly correlated at the 0.01 level; therefore, these two additional parameters can help establish the model and improve its accuracy and robustness.

**Results**

Existing methods typically use cross-validation to analyze the evaluation results of the model. Studies [Wang, 2013] have shown that fivefold cross validation is more applicable and valid; therefore, this paper used the fivefold cross validation method to validate the error of the model. First, the initial data of RF-ACGWO were set up. Then, the rolling times, moisture content,
particle 5, Cc and humidity were selected as influencing parameters to pass as inputs to RF-ACGWO; these parameters were fitted with the output variable. Then, the error analysis of the solution results was performed using fivefold cross validation, which calculated the correlation coefficient R, RMSE, MAE, RAE, RRSE and other precision characterization parameters. Finally, these operations were run five times, and the mean of the results was used as the estimation of the accuracy of RF-ACGWO.
Figure 2: The line diagram of dry density measured value and RF-ACGWO solution result under five-fold cross-validation

A line diagram that compares the measured dry density value and the solution result of RF-ACGWO under fivefold cross validation is shown in Fig. 2. Via correlation analysis, the R is found to be 0.83881, which indicates a significant linear correlation. The F test shows that the significance is 0.000, which is lower than the significance level of 0.01; thus, the RF-ACGWO prediction model can be used for compaction quality prediction via testing. The average absolute error is 0.007, and the average MSE is 1.24E-04, which is lower than the average value of 1E-04. The accuracy of the solution is thus higher than 99%, and the fitting degree of the model is excellent.

Comparison of generalization ability

Relevant research on the date-driven evaluation model of compaction quality has effectively promoted the real-time control of compaction quality. To verify the advantages of the CQEM based on RF-ACGWO, RF [Lin, 2018], BPNN [Lv, 2017; BEAINY, 2012; Meehan, 2017] and MLR [MEEHAN, 2017; Liu, 2016] were used to evaluate the compaction quality of the study area, and the results were compared to those of RF-ACGWO.

To verify the generalizability of the model proposed in this study, the boundary data of the hypersphere were used for verification, and the generalizability of the model was quantified with the accuracy index to characterize its ability to adapt to the new data. The hypersphere was constructed with input parameter vectors, and part of the data near the center and sphere was used as the test set, while the remainder was used as the training set. These methods ensure that the intersection of the training and test sets was zero, and the test set was located at the periphery. The test set constructed via this method can be used as the test data of generalizability and can be expressed as shown in equation (2):

\[ x_i \in \{x_i| x_i \in S_{r1}\} - \{x_i| x_i \in S_{r2}\} + \{x_i| x_i \in S_{r3}\} \]  

(2)

where \( S_{r1}, S_{r2} \) and \( S_{r3} \) are, respectively, the hypersphere that is constructed with input
parameters, the hypersphere near the sphere and the hypersphere near the center of the sphere. As shown in equation (2), the sphere and center data in the hypersphere constructed with input parameters were considered to be the test set to test model generalizability. Because the test data exceeded the hypersphere coverage of the training data, the accuracy of the test set (i.e., $R$, $MAE$, $RMSE$, $RAE$, $RRSE$) can describe the generalizability of different models. The residual results of different models (predicted value minus real value) are shown in Fig. 3(a). Fig. 3(b) compares the generalization performances of different models. The residual fluctuation and the predicted value fluctuation of the compaction quality of the RF-ACGWO model are below those of other models. The $R$ of the RF-ACGWO model is 0.793, which indicates that the model is applicable for new data. The $R$ of the RF model is 0.707, indicating that the generalization error is small. However, the correlations of the MLR and BPNN models are 0.343 and 0.284, respectively, indicating that the generalizabilities of the BPNN and MLR models are poor. Additionally, by comparing the MSE, RMSE, RAE, RRSE and other indicators, the RF-ACGWO model still achieves the best performance. Therefore, the RF-ACGWO model can be used to establish a CQEM for earth-rock dams in terms of generalizability.

![Figure 3](image)

**Figure 3** Comparison of generalization ability of different models

**Comparison of robustness**

In this study, the robustness of the proposed RF-ACGWO model was tested by adding noise
data. Typically, the robustness of the model can be represented via the decrease in accuracy when the noise data are continuously enhanced. The random noise value generated via a normal distribution was added to the existing training data set, and its variance was adjusted to control the size of the noise. The decrease in the accuracy of the test model with the increase in noise intensity demonstrates the model’s ability to manage noise.

The construction environment of core-wall rockfill dams is complex, leading to noise in the compaction information of the construction unit. Therefore, the stronger the anti-noise ability of the model is, the better it is to analyze the spatial compaction quality distribution. Fig. 4 shows how the R of different models decreases with increasing noise intensity.

![Figure 4](image)

**Figure 4** The curve of noise variance intensity with the accuracy of different models

As shown in Fig. 4, the anti-jamming ability of the BPNN model with regard to noise data is the worst. With increasing noise intensity, the accuracy of the RF decreases rapidly. Concurrently, although the RF and MLR models are better than the BPNN model in resisting noise, they also have a significant downward trend. Particularly for the MLR model, when the noise intensity is 1.5, the accuracy of the model exhibits a considerable decline. However, the accuracy of the RF-ACGWO model presented in this study decreases slowly with increasing noise, and there is no rapid decline, which indicates that the model proposed in this study exhibits strong anti-noise performance. Therefore, regarding robustness, the RF-ACGWO model can be used to establish the compaction quality dynamic evaluation model of earth-rockfill dams.
comparison of accuracy

By analyzing the MSE, RMSE, MAE, RAE and RRSE, the performances of the four types of CQEMs are discussed. Considering the correlation between the predicted and measured values from the overall perspective, a comparative analysis of the mean and Standard Deviation (SD) can be performed. The error analysis results are shown in Fig. 5(a). Finally, the measured values of dry density and the predicted results of the evaluation models are shown more intuitively as means of four Y-line diagrams (four Y-axes in one diagram to represent the evaluation values of different models, as shown in Fig. 5(b)).
From these test results, the following conclusions can be drawn. As shown in Fig. 5(a), the average values of the results of the four evaluation models are nearly identical to the measured values. Additionally, the statistical analysis of the model results shows that 78% of the RF-ACGWO and BPNN results; 87.5% of the RF-ACGWO and RF results; and 90.4% of the RF-ACGWO and MLR results have an error below 1%. These results show that RF-ACGWO is highly consistent with RF, BPNN and MLR.

RF-ACGWO has an $R$ of 0.8388 and an $F$-test of 0.000 under a significance level of 0.01, which indicates that there is a significant correlation between the evaluation and the measured value, and is greater than that of RF, BPNN and MLR. The MSE (1.24E-04), MAE (0.007), RAE (2.37E-07) and RRSE (2.43E-06) of RF-ACGWO are below those of BPNN and MLR; thus, RF-ACGWO’s accuracy is higher than that of RF, BPNN and MLR. The average of RF-ACGWO is also closer to the average of the measured values. These results show that the generalization error of the model based on RF-ACGWO is the smallest and the accuracy is the
highest. These results are representative and indicate that RF-ACGWO can replace the BPNN and MLR models to evaluate compaction quality.

According to Fig. 5(a) and the four Y-line graphs in Fig. 5(b), the distribution of the solution results produced by RF-ACGWO is most similar to the measured results. Although the SD of BPNN considering the uncertain fitting relationship is closest to the measured value, BPNN’s accuracy is lowest because it easily falls into a local minimum and has other disadvantages. Although the error of MSE and MAE of MLR are small, and fluctuations in distribution are most similar to the measured values, the MLR ignores the nonlinear influence of the parameters, which results in the largest difference in SD. As shown in Fig. 5(b), the RF-ACGWO model of the "black box" operation considers the uncertainty of the material source parameters, and its solution results have the minimum MSE (1.24E-04) and the best fitting distribution with the measured values. Therefore, the evaluation result of CQEM based on RF-ACGWO is more accurate and superior with regard to consistency, representativeness and superiority.

Thus, compared to MLR, BPNN and RF, RF-ACGWO is a "black box" fitting evaluation model that can consider the uncertain fitting relationship between parameters and dry density, and the uncertainties of source material parameters. Concurrently, the results of this study exhibit the smallest generalization error and best anti-noise ability. By comparing the evaluation results with those of the RF, BPNN and MLR evaluation methods, results show that the RF-ACGWO algorithm exhibits a high precision accuracy, excellent generalizability and good robustness.

**PRACTICAL APPLICATION**

By comparing and analyzing the accuracy, generalizability and robustness of several models, the CQEM based on RF-ACGWO is shown to achieve excellent performance with regard to these metrics. Therefore, the RF-ACGWO model can be used in practical applications to intelligently evaluate the quality of the construction unit. There are two primary application modes of the model. First, when embedded in the 3D rolling real-time monitoring system [Zhong, 2011; Wang 2018a], the rolling parameters, material source parameters and
meteorological elements can be acquired in real time via the 3D rolling real-time monitoring system, material source acquisition system and small weather stations, respectively. Then, the parameters are input into the intelligent evaluation model in real time to describe the intelligent evaluation of compaction quality. The other is the intelligent evaluation of the compaction quality after the construction unit is completed.

Figure 6 The interface of intelligent evaluation of the compaction quality

Considering a construction unit of the core wall of a project, the construction unit is located at a height of 2696 m, and its size is 80 m × 50 m. The element is divided into 1000 grids by a 2 m × 2 m grid. During compaction of the construction unit, the RF-ACGWO model was used to evaluate the compaction quality of the construction unit in real time. Concurrently, the evaluation results and rolling parameters were shown on the system interface in real time to provide feedback and guidance for onsite workers, as shown in Fig. 6.
Figure 7 Intelligent evaluation of rolling construction quality on dam construction unit

After the compaction of the construction unit was finished, the model could generate a 3D compaction graph report, as shown in Fig. 7, which shows that the minimum dry density of the construction unit is 2.1819, the maximum is 2.24026 and the average is 2.223. According to the requirements of dam material design and construction parameters of this project, the rate of reaching the standard for dry density (i.e., dry density $\geq 2.18 \, \text{g/cm}^3$) in the core wall area is not below 97%. As shown in Fig. 7, the dry density of the construction unit reaches the standard. The rate is 100%, which is higher than the 97% required in the filling compaction control standard. Therefore, the compaction quality of the construction unit is qualified.

CONCLUSION

This paper proposed a CQEM based on RF-ACGWO. According to various results, the following conclusions can be drawn:

(1) To evaluate the compaction quality of earth-rock dams, an algorithm that uses a random forest optimized by adaptive chaos gray wolf intelligence was proposed to improve model prediction accuracy and robustness, which is not applicable to the complex construction environments of most real engineering projects. RF without overfitting was used to ensure model generalizability and robustness, and an adaptive scaling factor and chaos theory were
used to provide full search ability and keep the group from falling into GWO prematurity. ACGWO was used to overcome the shortcomings of RF but cannot determine optimal parameters adaptively; thus, the accuracy of ACGWO must be improved.

(2) A compacting quality evaluation model based on RF-ACGWO was developed. First, the original dataset of compaction quality evaluation indices was constructed based on parameters obtained by the rolling real-time monitoring system, field test and small weather station. Second, the input parameter set of the CQEM was obtained via correlation analysis to ensure that the prediction accuracy would not be disturbed via irrelevant factors. Cc and H were added to the input parameters to improve model precision and robustness. Finally, after parameter optimization and modeling, the RF-ACGWO model was used to predict the construction unit. The accuracy, generalizability and robustness of the RF-ACGWO, MLR, RF and BPNN were compared and analyzed using a fivefold cross validation method, prediction of the data outside the hypersphere boundary and data with noise. The model proposed in this paper was verified to be representative, achieve better performance, higher generalizability and better robustness.

(3) Regarding the engineering applications of CQEM based on RF-ACGWO, the RF-ACGWO compaction quality evaluation model was embedded into a 3D rolling real-time monitoring system, which guarantees that the rate of reaching the standard for dry density is more than 97%. The results of this experiment show that the model proposed in this study can directly evaluate compaction quality in real time with high precision and can provide a visual evaluation of the compaction quality of an entire construction unit after compaction.
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