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Editorial

Safety Monitoring and Management of Reservoir and Dams

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1. Introduction to the Special Issue

Water conservancy projects have the functions of flood control, power generation, water supply, and irrigation, and play a vital role in the survival and development of human society. Reservoir dams are widely distributed, with large spatial differences in the total number and many types of dams. The complexity of their actual operation is far beyond the imagination of engineers and scientists. For hydraulic structures with aging structures, complex environments, and abnormal conditions, the above characteristics are more prominent. Therefore, it is difficult for engineers and scientists to fully understand the safety characteristics of hydraulic structures.

Dams are the most important infrastructure in water conservancy and hydropower projects. Although they bring great benefits, they also have a series of safety problems. Dam failure will bring serious social and economic consequences downstream, causing huge personal and property losses [1]. Dam deformation, cracks, and leakage seriously affect their safe operation. In addition, the fluctuation of the reservoir water level will change the geological environment of the bank slope, resulting in the change of the matrix suction of the unsaturated soil with the water content of the slope and the distribution of water in the slope, thus leading to hydrodynamic landslides in the reservoir area [2]. The safety monitoring model of the dam based on prototype monitoring data is an important means to evaluate the safety of dam operation [3].

This Special Issue of *Water* aims to further understand the structural state of hydraulic structures by applying various safety monitoring facilities, data processing methods, and evaluation methods, combined with geotechnical tests, non-destructive testing, numerical simulation, intelligent algorithms, and other technologies. It is of great significance to improve the safety of water conservancy projects and the development level of human society. Since the announcement of the solicitation of papers in December 2021, 19 original papers have been accepted and published through a rigorous peer review process [1–19], which can be divided into five categories, including the study of data-driven structural safety monitoring model, the study of the mechanism of dam and reservoir slope deformation and seepage, the study of dam vibration characteristics, structural safety performance testing, and the study of hydropower and its economic benefits. To better understand this Special Issue, we provide a summary of the published papers below.

2. Overview of the Contributions of the Special Issue

In terms of the safety monitoring data-driven model, Fang et al. [4] adopted the normal distribution function and Rayleigh distribution function as the lag function of the reservoir water volume and rainfall, respectively. The grey wolf algorithm is used to solve the lag days, and the partial least squares method is used to solve the regression coefficient of the statistical model. Then, the statistical model is used to separate the reservoir water (main water) and rainfall infiltration (external water) of the measuring weir. Peng et al. [5] proposed a dam deformation monitoring model based on the Light

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Gradient Boosting tree (LGB) and Bayesian optimization (BO) algorithm to process massive monitoring data. At the same time, this method can explain the difference in contribution between different input variables to select the factors that have a more significant impact on the modeling. Wang et al. [3] used the modified linear unit function as the activation function, and the Bayesian optimization algorithm to determine the model parameters. Based on LSTM (long short-term memory) network and bidirectional LSTM network, a dam deformation prediction model for Danjiangkou Hydropower Station was established. Zhang et al. [6] proposed an LSTM optimized concrete dam deformation monitoring model based on Empirical Mode Decomposition (EMD) combined with wavelet threshold denoising and Sparrow Search Algorithm (SSA), which can effectively mine the relationship in the measured deformation data and reduce the impact of high-frequency components on the dam prediction accuracy. Hua et al. [1] developed a prediction model of uplift pressure based on a Convolution Neural Network (CNN) and Gated Recent Unit (GRU). The model includes the feature extractability of the CNN model and the learnability of the GRU model for time-series-related data, which can accurately predict the variation trend of dam uplift pressure and improve the accuracy of dam disaster prediction. Wang et al. [7] added the prediction of Autoregressive Integral Moving Average (ARIMA) to the original data and proposed a prediction model based on LSTM and ARIMA, which estimates the slope displacement using the slope deformation data obtained from interferometric synthetic aperture radar. Given the problems of low prediction accuracy and long prediction time in the current debris flow research, Xu et al. [8] first adopted the Fast Multi-Principal Component Extraction (FMPCE) algorithm to select six debris flow impact factors, such as rainfall, slope, gully bed slope, relative height difference, soil water content, and pore water pressure. Based on the Broad Learning (BL) algorithm, the debris flow prediction model based on FMPCE and optimized BL is established with the debris flow inducing factor as the input and the debris flow probability as the output. The model is optimized by using matrix random approximate Singular Value Decomposition (SVD), and a debris flow disaster prediction model is established.

In terms of mechanism research on deformation and seepage of the dam and reservoir slope, Yang et al. [9] proposed an analytical method to calculate the leakage of clay core wall based on Darcy's law and stable seepage theory. Through reasonable assumptions, the authors proposed the calculation formula of seepage flux of underground water level at different positions below and above the reservoir bottom. An engineering example shows that the analysis method has high accuracy and efficiency. Ma et al. [10] analyzed the characteristics and development trends of blasting rockfill dams in detail by collecting data on main blasting rockfill dam projects. At the same time, the design requirements of an impermeable body in the initial stage and reinforcement stage are systematically reviewed. The discrete element method is used to analyze the structural characteristics of the blasting dam and the effectiveness of the phreatic line height after reinforcement. The study shows that a proper construction schedule and flexible impervious materials are the key guarantees for the safety of the dam body. When the dam body is deformed and stable, secondary treatment of an impermeable water body should be considered to improve the safety of the dam body. Jin et al. [11] carried out horizontal seepage tests on four representative alluvium gradations using a large high-pressure scouring test device. The results show that the overload pressure can significantly improve the internal stability of the samples with continuous grading or high fines content. In contrast, in the case of low gap grading or fine grain content, because the stress is mainly borne by the coarse skeleton, its internal stability has no obvious improvement under overload pressure. Ma et al. [12] took a concrete face rockfill dam in Ningxia as an example, established a three-dimensional finite element analysis model of dam deformation based on the Duncan-Chang E-B model, and carried out a sensitivity analysis on the model parameters of the main rockfill zone, the secondary rockfill zone, and the reservoir bottom backfill zone. The study showed that when using the Duncan-Chang E-B model to analyze the deformation of a concrete face rockfill dam, Kb, Rf, and K should be focused. Hou et al. [13] used the finite element simulation analysis method to inverse the upstream surface temperature boundary conditions and concrete thermal parameters and simulated and analyzed the temperature evolution process of the arch dam during long-term operation. The distribution characteristics of the design reservoir water temperature and actual reservoir water temperature are compared, and the difference in temperature field during the storage and operation of the arch dam under design and actual conditions is studied. The study shows that under the design conditions, the temperature of the dam body rises slowly after closed grouting, and then tends to be stable. Under actual conditions, the temperature rises 7.1~9.2 °C after closed grouting, reaches the highest temperature in about 8~12 years, and falls back to the stable temperature in 40~80 years. Zhang et al. [14] studied the influence of channel characteristics on wave propagation and hydrodynamic pressure distribution on dam surface by numerical method, analyzed the mechanism of affecting wave height, and established a wave height prediction model considering channel characteristics. The results show that the water depth and the bend angle of the river channel have a positive effect on the energy attenuation carried by the landslide surge. The width of the water level mainly affects the propagation of pulse waves in the far field. The channel characteristics have an impact on the dynamic pressure value on the dam surface but have a small impact on the dynamic pressure distribution on the dam surface. The distance between the dam site and the landslide site has a great influence on the distribution of dynamic pressure of the dam body. Lu et al. [2] simulated the relationship between resistivity, volume temperature, water content, and temperature of landslide soil. The model is verified by the indoor landslide model test and Baijiabao field test, and the influence of reservoir water level on landslide water content is studied. The test results show that the water content of landslide soil increases with the rise in the reservoir water level. In addition, the measured results are well matched with the inversion results based on the resistivity data by using the high-density electrical method combined with the established resistivity, volume water content, and temperature relationship model, indicating that the proposed method is reliable and feasible in the monitoring of hydrodynamic landslides.

In the research of dam vibration characteristics, Guo et al. [15] proposed a modal threshold identification method for high arch dam flood discharge structures based on an improved wavelet threshold Empirical Mode Decomposition (EMD) and Random Decrement Technology (RDT) algorithm. Based on the measured vibration response data of the dam, the wavelet threshold is used to filter most high-frequency white noise and reduce the boundary accumulation effect of EMD decomposition. After EMD decomposition, De-trend Fluctuation Analysis (DFA) is used to filter white noise and low-frequency flow noise. The natural frequency and damping ratio of the structural system are obtained by using the improved RDT algorithm. Cheng et al. [16] used the seismic monitoring data of the Pacoima arch dam to identify its structural modal parameters. At the same time, they summarized different excitation, seismic input, and modal identification methods, analyzed the reasons for the differences in these identification results, pointed out some problems in the current concrete dam modal identification, and provided valuable guidance for the selection of appropriate identification methods and the evaluation of system identification results in practical engineering applications.

In terms of structural safety performance detection, Xu et al. [17] proposed a crack image detection model based on an attention mechanism (Faster-RCNN based on attention, AF-RCNN), which assigns different weights to the suggestion frame around the crack target to accurately detect the position of the crack target. The algorithm achieves 81.07% mapping on the expanded dam crack data set, which is 8.39% higher than the original Faster-RCNN algorithm. Compared with other traditional dam crack detection algorithm models, the detection accuracy was significantly improved. Zhang et al. [18] proposed an Injection AC electric Field Method (IAC-FM) to detect the orthogonal cracks in the piston rod of the hydraulic cylinder of the gate hoist. By injecting AC axially into the steel bar, an alternating magnetic field is generated inside the steel bar, and the longitudinal and transverse cracks can be detected at the same time. The magnetic field behavior near the crack is analyzed by using three-dimensional finite element software. At the same time, an experimental device is established and a verification experiment is carried out. The influence of the working frequency and scanning path is also studied, which provides great potential for the detection of the hydraulic cylinder in service of the gate hoist.

In addition, this Special Issue has also made achievements in the research of hydropower and its economic benefits. Wang et al. [19] first used EEMD decomposition to obtain relatively stable component signals, and then used the ADAM optimization algorithm to optimize the parameters of the GRU neural network. The relatively stable component signals obtained from EEMD components are sent to the optimized GRU model for training and prediction. Finally, the prediction results of hydropower generation are obtained by accumulating the prediction results of each component. The results show that the model is more effective in predicting the time series of hydropower generation and can quantitatively estimate the economic benefits of hydropower generation.

3. Conclusions

The guest editor assumes that the papers published in this Special Issue will arouse the interest of researchers and practitioners in the safety monitoring and management of reservoirs and dams, and will help to determine further research routes. We also hope that readers will find the materials in this Special Issue interesting and enlightening when exploring the fields of safety monitoring models, hydraulic structure deformation, seepage, vibration characteristics, structural safety performance testing, and economic benefits of hydropower generation. The research results and methods introduced in this Special Issue, including the data-driven model and mechanism research on the deformation and seepage of dams and slopes, the vibration characteristics of dams, structural performance testing, and the economic research on hydropower generation, are helpful for relevant scholars and project managers to analyze and manage the safety behavior of the main hydraulic structures of reservoirs and dams and reservoir slopes, and have great research significance and technical contributions.

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