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Average Daily Processing Prediction of Artificial Hydropower Station Based on Machine Learning

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Abstract: More than 20 years ago, China's hydropower undertakings rapid development, hydropower installed capacity has been a breakthrough. With the continuous improvement of hydropower installed capacity, the optimal dispatching of hydropower system is facing great challenges. In this paper, the average daily processing prediction of artificial hydropower station based on machine learning is studied. In this paper, the prediction model based on BPNN neural network is discussed to predict the daily runoff of hydropower station, and the overall system architecture is designed from the aspects of logical structure, physical structure and technical structure. Through THE simulation analysis of the water level of the hydropower station in different time periods, it is verified that the model has good simulation accuracy in the process of water level deduction, which lays a foundation for the optimization of hydropower station operation in the future.

1. Introduction

In the actual operation of power stations, due to the limited level of the existing forecast and the difficulty of the forecast period of runoff to meet the dispatching requirements, the inflow process of the whole dispatching period is often not completely obtained, so it is difficult to directly use the existing deterministic optimal dispatching theory in the actual dispatching of reservoirs [1]. At present, reservoir dispatching often relies on the dispatching chart, which clearly and intuitively describes the output suggestions of power stations in different periods and water levels, and can guide the safe and stable operation of reservoirs. Scheduling figure but unable to give full consideration to the plant to regulate performance, at the same time can't effectively excavate, between comprehensive utilization benefits of cascade reservoirs on the storage performance strong or reservoirs joint operation of cascade reservoirs group, scheduling scheduling results is not satisfactory, and the optimization of scheduling results is far, the economic benefits of the reservoir will suffer [2-3]. Implicit stochastic optimization scheduling based on stochastic scheduling theory can break the limitation of deterministic optimization scheduling and scheduling graph in practical scheduling, and extract optimal scheduling rules by means of fitting learning to guide the actual scheduling of reservoirs. In recent years, with the rapid development of computer technology and artificial intelligence, machine learning methods represented by support vector machine and artificial neural network have been introduced into the extraction of scheduling rules for hydropower stations. However, most of the current research on extraction of scheduling rules is based on a single reservoir, and decision-making factors are often selected based on experience, which fails to fully explore the spatio-temporal relationship between cascade reservoirs. Moreover, traditional machine learning algorithms are prone to problems such as too simple models and insufficient rule learning [4]. Therefore, it is urgent to further deepen the research on the extraction of scheduling rules of cascade hydropower stations, and explore the method that can fully learn the joint optimization scheduling rules of cascade hydropower stations, so as to guide the joint optimization scheduling operation of cascade hydropower stations [5].

Along with the large-scale development and operation of hydropower, the gravity of water conservancy work has been gradually shifted from development and construction to operation management. The joint optimization operation of cascade hydropower stations can make full use of the water resources domination capacity of reservoirs and deeply explore the power generation benefits and comprehensive utilization benefits of cascade reservoirs in the basin, which is of great significance [6-7]. Many experts and scholars at home and abroad have done a lot of research on the optimization of reservoir operation and obtained substantial research results. In addition, with the rapid development of computer technology and artificial intelligence technology, intelligent algorithm and machine learning technology are also used in the research of reservoir hidden stochastic optimization scheduling, promoting the reservoir scheduling toward the direction of fine, information and intelligence. The concept of optimal reservoir operation was first proposed to improve the economic benefits of hydropower stations through non-engineering measures [8]. Subsequently, the optimal operation of reservoirs has become a research hotspot, and various methods have been used in modeling and solving the optimal operation of reservoirs [9]. Linear programming (LP) method is one of the earliest introduced methods, which has simple principle, fixed solution method and can obtain the global optimal solution, and is widely used in the solution of reservoir optimization problems. However, linear programming requires both the objective expression and the constraint expression of the problem to be solved to be linear, so it is often restricted in practical use [10]. Different from linear programming, nonlinear programming (NLP) no longer has linear requirements and is more suitable for the actual reservoir group scheduling problem [11].

In this paper, the downstream cascade reservoir is taken as the research object, focusing on the fine modeling and efficient solution of the mid - and long-term generation optimal dispatch of cascade hydropower station and the generation dispatch rule extraction of cascade hydropower station.

2. Reservoir Level Prediction Model Based on BP Neural Network

2.1. Model Building

The structure of BP neural network is: topology structure of neural network with 3 or more layers, including input layer, hidden layer and output layer, which is a parallel and multi-layer feedforward network [12].

After setting the basic parameters such as the number of neurons in the hidden layer, target error, learning rate and maximum training times, and normalizing the input data, the KTH component xnk of the NTH input variable enters the input layer of the BP neural network. The product of xnk, the weight wnh between the input layer and the hidden layer of the neural network, and the threshold θ between the input layer and the hidden layer of the neural network are accumulated into the hidden layer of the BP neural network, and the output hn of the hidden layer is obtained after the calculation of the transfer function f(x) of the BP neural network [13-14].

$$h_n = f_s(\sum_{i=1}^{N} w_{nk} u_{nk} + \theta_n) \tag{1}$$

The output of hidden layer accumulates the product of weight wh and threshold θh between the output layer and hidden layer, and then passes into the output layer of BP neural network to obtain the output signal yk.

$$y_k = f_s(\sum_{h=1}^{H} w_n h_n + \theta_h) \tag{2}$$

The error E is calculated according to the predicted output signal yk and the corresponding expected output ok generated in the process of neural network training. Contrast error and setting error values, if is greater than the setting threshold, the error back propagation to the hidden layer and its gradient, update the weights and thresholds, and a calculation is made return toward, until the error is less than expected or maximum number of iterations, get the final training network, get the final output of neural network [15-16].

In this study, the BP neural network with three layers is selected to establish the prediction model. The newff function was used to create the model, the model activation function was chosen tansig, the transfer function from the input layer to the output layer was chosen purelin, and the sim function was used to simulate the network. The number of neurons in the hidden layer was set to 5, the momentum term coefficient η=0.01, and the learning rate μ=0.01. The maximum training times is 1000, and the minimum error of training target output is 0.00001. In general, when the ratio of training set and test set is greater than 7/3, the data can ensure a certain accuracy. The initial weights and thresholds are the default values of the system, and the display frequency S=25, that is, the training process is displayed every 25 runs, and other parameters are the initial values.

The purpose of this study is to predict the change process of the water level in front of the dam in the future by knowing the current initial water level, the inflow flow, output and the gate opening in a certain period of time in the future. The specific length of the forecast time period depends on the predictable time range of future incoming traffic. The incoming flow Qsi of the secondary power station depends on the outgoing flow Qzo of the upstream primary power station. Therefore, it is necessary to conduct trial calculation on the input data and determine the neural network water level prediction model with the highest accuracy according to the results.

Because there is a certain hydraulic relationship between the selected influencing factors and the predictors, the results will be the most accurate if all the selected influencing factors are input for training. In order to find the appropriate input mode, this study selected two schemes to judge the influence of input factors on the simulation results. However, due to the delay of water flow, we delayed processing multiple input parameter data and compared the simulation results with the original input parameter data. The output parameter is the second-level upstream water level Zsu. The two working conditions are as follows:

Table 1. Error analysis of models trained with different input parameters

	MAE	RMSE	NSE	Number of training	Running time (s)
Input parameter 1	0.4236	0.6832	0.2752	152	15
Input parameter 2	0.1893	0.2415	0.8634	648	30

As can be seen from Table 1, compared with input parameter 2, the operating conditions are respectively at a higher level, indicating a high degree of fit between the measured and predicted values simulated by the model. Therefore, input data is selected as input parameter 2 in this research model.

2.2. Design of Prediction System

The daily runoff prediction system of hydropower station is mainly based on the combined prediction model based on neural network and other prediction models to measure and report the 6-hour, 12-hour and 24-hour runoff, and complete the release of the forecast results. It is an important part of the automatic water situation measurement and report system. The latter mainly provides telemetry station data acquisition and reception processing, real-time flood forecast simulation and correction, database and data maintenance and water condition forecast services for the daily runoff prediction system. According to the requirements of system functions, the application layer of the whole system is divided into relatively independent functions according to functions. The function allocation of each subsystem is relatively independent and coordinated in parallel. The methods of data exchange buffer and operation notification are used to connect each subsystem to each other, which is conducive to ensuring the relevance and integrity of the whole system

To make each subsystem more efficient and independent to achieve their own unique functions.

The logic structure of daily runoff prediction system of hydropower station is divided into three levels: human-computer interaction layer, system application layer and system support layer. The interactive prediction program is used to realize the information interaction between users and the daily runoff prediction system, and the prediction results are corrected by users in real time in the human-computer interaction layer. The application layer of the system includes functional modules such as pre-processing of forecast data, real-time flood forecast, real-time flood correction, flood simulation forecast and forecast result management. The information support layer includes forecast comprehensive database and model database.

The system uses spring, struts2, hibernate and other three lightweight framework integration way to develop system programs, SSH is a java Web application development framework, usually used programming language is object-oriented language java, provides a basic environment for the system modular, structured development. This framework mainly includes presentation layer, business logic layer, data persistence layer and domain module layer. Each layer is responsible for data foreground display, business logic processing, data access and storage, data object and other technical support.

The system supports multi-level structured software development, in which Struts2 supports the separation of MVC, supports the front Jsp page and the back servlet technology, is responsible for the business logic processing, view display and control adjustment and other functions, through its own with the custom tag to quickly show the page information, improve the development efficiency. The Hibernate framework is responsible for providing support for the data access persistence layer. The system can respond to the user's Request sent from the front page in a timely manner, and the struts-config.xml configuration file is responsible for specifying the service processing process to the Action [17-18].

Spring is a lightweight open source framework and container that enables inversion of control and dependency injection, establishes dependencies between objects, integrates with other frameworks, supports AOP for facet programming, simplifies complex enterprise business processes, and supports remote invocation of services using interface programming. It establishes a unified service interface for system invocation, implements integration with Hibernate persistent DAO, and manages Javabeans and transactions in a unified way.

Hibernate, as a widely used ORM framework, can establish the mapping relationship between entity objects and database tables. It reduces the workload of repeated SQL writing by encapsulating JDBC; it can provide complete data output through the view layer, freeing the data processing work of the view and controller, and improving the component reusability and development efficiency through the data persistence work.

3. The Simulation Results

In this paper, first of all need to deal with abnormal data in the raw data, including by monitoring system failure or water level measurement error caused by the abnormal data to eliminate and interpolation of missing data in time series, due to the abnormal data and missing data for a short period of time the proportion of total water level time series data, in this paper, based on the data before and after the water level change trend, The linear interpolation method was used to modify and supplement the data.

In this paper, the time series data information of water level of hydropower station is known by Spss software, and the water level in the future period is simulated. BP neural network model for the validation of hydropower station water simulation precision of the time series, this article selects several typical time values in the model simulation results and the actual monitoring comparison and verification, BP neural network model for visual display of the fitting effect of water, this article has carried on the water level simulation of multiple sets of sequence diagrams show.

4. Simulation Experiment Analysis

Table 2. Comparison of water level observed on the first day with BPNN simulated values

	13:00	14:00	15:00	16:00	17:00
Observations value	1007.95	1008.04	1008.25	1008.30	1008.32
Simulation value	1007.52	1007.98	1008.13	1008.24	1008.25

As shown in Table 2, the comparison of water level values from 13:00 to 15:00 on the first day shows that there is little difference between the observed value and the simulated value.

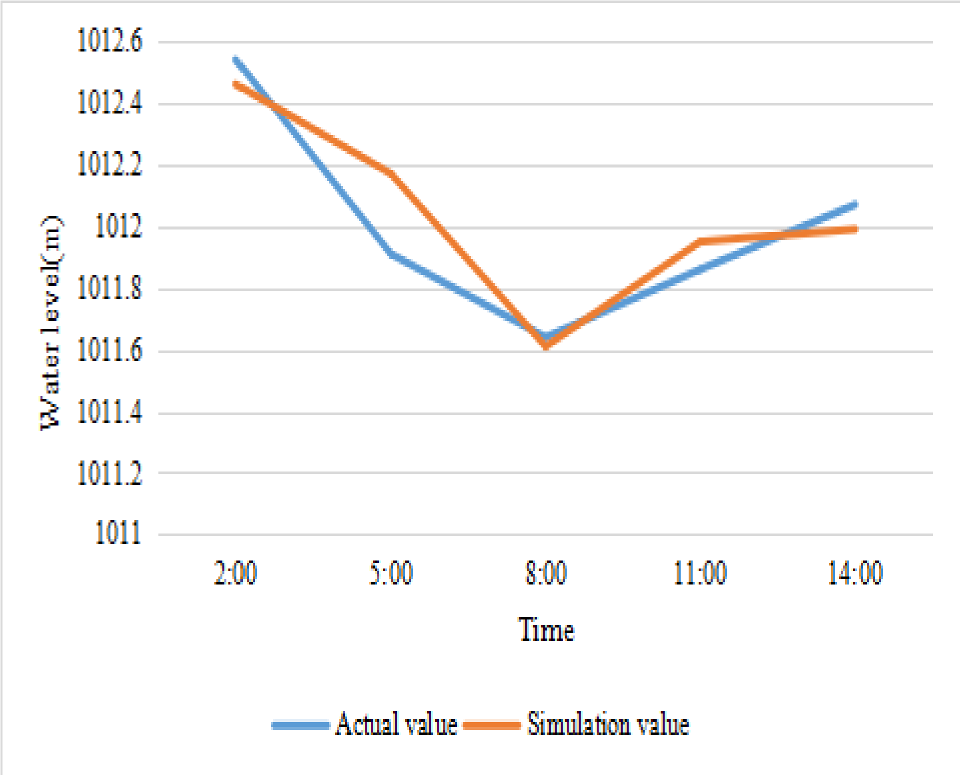

Figure 1. Comparison between observed and simulated water level values

As shown in FIG. 1, is the comparison of water level from 2:00 to 14:00 on the second day. It can be seen from the figure that its absolute error is larger than that on the first day.

Table 3. Results of comparison between observed and simulated water level on the third day

	0	1:00	2:00	3:00	4:00
Observations value	1012.64	1012.72	1013.05	1012.75	1012.79
Simulation value	1012.59	1012.53	1012.87	1012.57	1012.46

As shown in Table 3, it is the comparison of water level from 0 to 4 o 'clock on the third day.

As shown in FIG. 2, comparison of water level values from 13:00 on the fourth day to 1:00 on the next day is shown.

To sum up, the simulated value of the upstream water level of hydropower station based on the BPNN model is very close to the actual observed value, and the absolute error value is about 0.5m. Moreover, the simulated trend of the water level value of the BPNN model is basically the same as the actual observed value. According to the simulation results of the BPNN model constructed in this paper, the short-term water level simulation of hydropower station based on BPNN model has good calculation accuracy. In addition, since BPNN model is based on the real water level monitoring data in the past years to simulate the future water level, in the actual scheduling decision, all are known quantities, the whole simulation model is driven by data, and has high accuracy, which has great practical value.

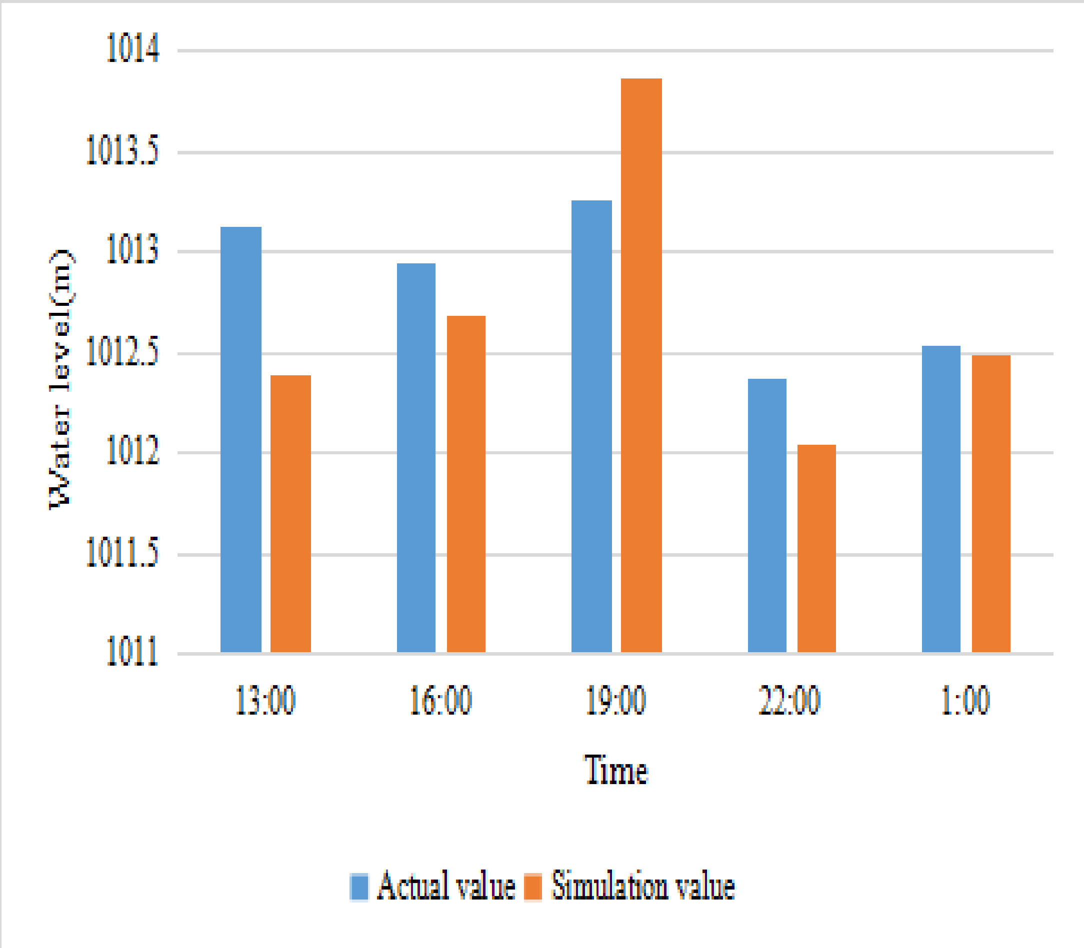

Figure 2. Comparison of observed and simulated water level values on the fourth day

5. Conclusion

Due to the characteristics of topography in China, the spatial and temporal distribution of water energy resources is not uniform, mainly enriched in the southwest of China. With the continuous improvement of hydropower installed capacity, the optimal operation of hydropower system is faced with great challenges and difficulties. The runoff forecast provides input information for the optimal operation of hydropower stations. The runoff forecast method with high accuracy can provide guarantee for the optimal operation of hydropower stations, so as to guide the safe and stable operation of hydropower stations. In THIS paper, BP NEURAL network is used to construct a water level prediction model, which can achieve high precision water level prediction in front of sluice gate, and is suitable for short-term water level prediction in front of hydropower station. Are still many deficiencies, the following can be further in the direction of the research institute adopts spatial accuracy of data accuracy is not enough, the higher the precision of elevation model data, simulate the more close to the actual situation, and because of the lack of Bridges, culverts and block block water parameters such as buildings, not import them into a three-dimensional model, As a result, the channel model cannot reach the highest level, which needs further study.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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