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Research papers

Modeling and simulating of reservoir operation using the artificial neural network, support vector regression, deep learning algorithm

Di Zhang[a], Junqiang Lin[a,*], Qidong Peng[a], Dongsheng Wang[b], Tiantian Yang[c], Soroosh Sorooshian[c], Xuefei Liu[a], Jiangbo Zhuang[a]

[a] State Key Laboratory of Simulation and Regulation of Water Cycle in River Basin, China Institute of Water Resources and Hydropower Research, Beijing, China
[b] China Renewable Energy Engineering Institute, Beijing, China
[c] Department of Civil and Environmental Engineering, Center for Hydrometeorology and Remote Sensing [CHRS], University of California-Irvine, Irvine, CA, USA

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ABSTRACT

Reservoirs and dams are vital human-built infrastructures that play essential roles in flood control, hydroelectric power generation, water supply, navigation, and other functions. The realization of those functions requires efficient reservoir operation, and the effective controls on the outflow from a reservoir or dam. Over the last decade, artificial intelligence (AI) techniques have become increasingly popular in the field of streamflow forecasts, reservoir operation planning and scheduling approaches. In this study, three AI models, namely, the backpropagation (BP) neural network, support vector regression (SVR) technique, and long short-term memory (LSTM) model, are employed to simulate reservoir operation at monthly, daily, and hourly time scales, using approximately 30 years of historical reservoir operation records. This study aims to summarize the influence of the parameter settings on model performance and to explore the applicability of the LSTM model to reservoir operation simulation. The results show the following: (1) for the BP neural network and LSTM model, the effects of the number of maximum iterations on model performance should be prioritized; for the SVR model, the simulation performance is directly related to the selection of the kernel function, and sigmoid and RBF kernel functions should be prioritized; (2) the BP neural network and SVR are suitable for the model to learn the operation rules of a reservoir from a small amount of data; and (3) the LSTM model is able to effectively reduce the time consumption and memory storage required by other AI models, and demonstrate good capability in simulating low-flow conditions and the outflow curve for the peak operation period.

1. Introduction

Half of the major global river systems are affected by reservoirs and dams, and human beings manage and utilize water resources through reservoirs for power generation, water supply, navigation, disaster prevention, flood control and mitigation, drought relief (Dynesius and Nilsso, 1994; WCD, 2000; ICOLD, 2011; Lehner et al., 2011; Shang et al., 2018). In recent years, many countries (including China) have also actively adopted reservoir operations to mitigate the adverse effects of reservoirs and maintain the health of river ecosystems. The scientific calculation, simulation and prediction of reservoir storage or release, as well as the development of proper reservoir operation plans are important to achieve all types of reservoir functions and to avoid danger to humans and river ecology (Loucks and Sigvaldason, 1981)..

Starting in the 1980s, with the development of hydrology, hydraulics and river dynamics, conceptual or physical-based models (such as HEC-ResSim, WEAP21, etc.) have been proposed and are widely used in reservoir hydrological process simulation and reservoir operation decisions (Klipsch and Hurst, 2003; Yates et al., 2005). Such models transform the empirical, mechanical, and blind operation patterns of early reservoir operations that were based on historical hydrological statistics, operated by so-called rule curves. Physical-based models provide a more practical physical and mathematical basis for the calculation of controlled releases or storage (See Table 1).

However, the practical application scenarios of reservoir operation are extremely complex and involve multiple time scales and multiflow regimes, often accompanied by occasional emergencies. A reservoir should undertake the medium- and long-term (seasonal and monthly scale) operation task of managing downstream water supply and optimization of economic benefit. Reservoirs should also undertake short-term (daily and hourly scale) operation tasks of managing power grid load, water demand, navigation and stimulation of fish breeding,

* Corresponding author.
E-mail address: linjq@iwhr.com (J. Lin).

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Table 1
Detailed information of the reservoir operation data.

Operation data name	Unit	Resolution	Normal value of accumlated year	Normal value of flood season
Reservoir inflow	m^3/s	Two or four hours	13,368	22,368
Reservoir outflow	m^3/s	Two or four hours	13,269	22,495
water level upstream of the dam	m	Two or four hours	65.06	65.40
water level downstream of the dam	m	Two or four hours	43.49	46.92

disaster prevention, emergency operations during floods, droughts. These various scheduling scenarios illustrate that the actual operation process of a reservoir is rapidly changing and often deviates from the operation plan. These deviations often make it difficult for the physical model based on the operation rule to accurately simulate reservoir operation and predict the reservoir controlled releases (Johnson et al., 1991; Oliveira and Loucks, 1997). In addition, when the physical model needs to be rebuilt with a new scheduling rule, the demand for the professional expertise of the reservoir operator is high, and the calculation time of the model cannot meet the requirements of emergency operation. Reservoir operation is the result of multiple factors with strongly nonlinear interactions, which are influenced by natural conditions, such as precipitation, runoff, agricultural irrigation and human needs, such as industrial production water consumption, power grid peak shaving, flood peak shaving. These complex factors have uncertainty and increase the difficulty of using physical-based models.

In recent years, with the development of artificial intelligence (AI) and big data mining technology, data-driven AI models have become important in various fields. This kind of model does not heavily rely on physical meaning, but is good at solving nonlinear simulation and prediction problems that are influenced by multiple complex factors. At present, AI models have been successfully extended to the reservoir operation field. In contrast to physical-based models, AI models have the ability to autonomously learn the various reservoir operation rules from a large amount of hydrological data and the real-time reservoir operation data. Moreover, AI models need low professional requirements from operators and have fast response speeds (Hejazi and Cai, 2009).

Among the many AI models, artificial neural networks (ANN) and support vector machine or regression (SVM or SVR) are the two most typical models in the field of reservoir operation. ANN models benefit from the proposed backpropagation algorithm (BP). The BP solves the training problem of the neural network, which gives the ANN models good nonlinear prediction ability. Many scholars have successfully promoted ANN in the reservoir operation field (Thirumalaiah and Deo, 1998; Jain et al., 1999; Chaves and Chang, 2008). Then, to further improve the accuracy of the ANN model, some scholars coupled the ANN algorithm with other AI algorithms and explored the application of the improved ANN algorithm in reservoir management. For example, Chaves and Chang (2008) improved ANN by combining them with a genetic algorithm and verified the applicability of the improved ANN in reservoir operation simulation. Chen and Chang (2009) combined evolutionary algorithm and ANN and proposed a new evolutionary-ANN algorithm for reservoir inflow prediction.

With increased ANN model research, the limitations of ANN have been highlighted, such as local optimal solutions and gradient disappearance, which limit the application of the model (Yang et al 2017a). At this time, the SVM algorithm invented by Cortes and Vapnik (1995) is better than ANN in many aspects, with fast training speed and global optimal solutions. The SVR algorithm is derived from SVM, which is similar to the SVM algorithm, and it is one of the most widely used AI models in the reservoir operation field (Lin et al., 2006; Hipni et al., 2013;Yang et al., 2017b). Meanwhile, some scholars coupled the SVR algorithm with other AI algorithms and explored the application of the improved SVR algorithm in reservoir management (Khalil et al., 2005; Su et al., 2013; Ji et al., 2014; Aboutalebi et al., 2015). For example, Aboutalebi et al. (2015) coupled the nondominated sorting genetic algorithm and SVR algorithm and applied the coupled model to optimize reservoir operation rules.

In addition to the above two classic AI algorithms, many other AI algorithms have been successfully applied to the reservoir operation field, such as genetic algorithm (GA), adaptive network-based fuzzy inference system (ANFIS), decision tree (DT). Chang and Chang (2001) and Chang et al. (2005) coupled the GA and ANFIS and applied the coupled model to estimate reservoir storage or release. Yang et al. (2016) used the improved DT algorithm, classification and regression tree, to reasonably estimate the storage or release of 9 reservoirs in California.

Although the above AI algorithms have been proved to be applicable to the estimation of reservoir storage or release, those algorithms still have some shortcomings, such as insufficient feature extraction capability and longer time consumption. In recent years, a new type of machine learning method, i.e., deep learning, has gradually become the frontier of computer science and technology and has achieved great success in the fields of computer vision, speech recognition and natural language processing. Deep learning, derived from ANN, is a new field in machine learning research. This algorithm has been proven as an abstract, high-level representation of attribute categories or characteristics through the combination of low-level features and can significantly improve recognition accuracy (Girshick et al., 2014; Lecun et al., 2015). LSTM model is a widely used deep learning model, which is applied to hydrological forecasting because of its ability to solve complex scheduling problems (Zhang et al., 2018). Zaytar and Amrani (2016) and Zhang et al. (2018) applied the LSTM model to forecast weather and urban sewage pipeline overflow, respectively. They obtained satisfactory results and verified the validity of LSTM in the prediction of timing problems. Shi et al. (2015) improved the traditional LSTM model, proposed a convolutional LSTM (ConvLSTM) and used it to build an end-to-end trainable model for the precipitation nowcasting problem on the spatial and temporal scale, and the application of the LSTM model has been extended from a one-dimension temporal sequence to a two-dimension spatial and temporal sequence. Because LSTM is a new type of deep learning model, it has few reports in the field of reservoir operation.

In recent years, research on AI models in the field of reservoir operation has developed rapidly, but there are still many shortcomings. First, at present, AI model research focuses on a specific case problem (often a single time scale or flow regime) and lacks a systematic comparison of the simulation effect of the model with complex operation scenarios (multiscale and multiflow regime). Second, the deep learning model as a popular AI model, has a strong ability to address the time series problem, but whether the model can address the reservoir operation problem effectively and accurately is unknown. Third, the parameter setting is the key technology of AI model building. However, investigations of different parameters among those models and comprehensive comparison studies are rarely reported.

Therefore, in this study, we selected three AI models, (1) a benchmark three-layer backpropagation (BP) neural network, (2) an SVR technique, and (3) the long short-term memory (LSTM) model, and constructed a reservoir operation model with three time scales including hourly, daily, and monthly scale to analyze the sensitivity of applying AI models to reservoir operation. For case study, we choose Gezhouba (GZB) reservoir in China (which had relatively complete, detail and long sequence operation records) to test the simulation performance of three models at various flow regimes, including (1) low flow, (2) intermediate flow, and (3) high flow. In summary, the goals of this study are (1) to summarize the influence of the parameter settings