Desalination and Water Treatment
www.deswater.com

doi: 10.5004/dwt.2022.28684

271 (2022) 58–64
September

Optimal scheduling and decision-making method of reservoir water treatment based on reinforcement learning and big data

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Received 27 April 2021; Accepted 10 July 2022

ABSTRACT

Water is an inseparable resource for human life, and the stable operation of reservoirs plays an important role in ensuring the quality of life of citizens. Reservoir scheduling is a key step in the process of stabilizing water resources. At present, the construction scale of reservoirs is getting larger and larger, and it is difficult to consider the different conditions and comprehensive factors of power generation and meteorological directions in the traditional reservoir scheduling calculation scheme. The development of big data technology provides a reference for the establishment of data sets for reservoir dispatching methods, and the emergence of reinforcement learning can just be combined with the idea of optimal reservoir dispatching. The historical scheduling methods only make simple single-factor impact analysis based on various influencing factors, and do not carry out joint analysis based on various influencing factors. This paper first analyzes the basic concepts of big data and reinforcement learning, and then analyzes the problem of historical reservoir scheduling methods. Combining big data and reinforcement learning technology, the big data reservoir scheduling platform and the reinforcement Q-learning reservoir scheduling method are designed respectively. The self-learning model of the reservoir obtains the optimal solution in the current scheduling scheme through continuous learning and summarization, and finally realizes the most stable operating state of the reservoir.

Keywords: Water; Reservoir scheduling platform; Reinforcement learning; Big data

1. Introduction

1.1. Reinforcement learning

Reinforcement learning is similar to the SVM algorithm, which belongs to the classification of machine learning. The reinforcement learning department works according to the basic training set, and the key content of its learning is mainly the feedback information received during the interaction process. The goal of reinforcement learning is to continuously optimize through the feedback in the learning process, and to improve its own learning method, and finally achieve the optimal solution of the entire learning process [1]. The entire process is dynamic, similar to the Markov chain. The growth rate of the use of reinforcement learning in the past 5 y is shown in Fig. 1.

There are five key elements in reinforcement learning, of which the agent is the most critical, which is the main body of the entire reinforcement learning. The reward represents the incentive that the reinforcement learning algorithm is currently effective and gets the allocation of the system's agents. The state represents the current situation of the current agent body and can be provided as a parameter to the reinforcement learning algorithm [2]. The environment value simulates real life and provides a container for

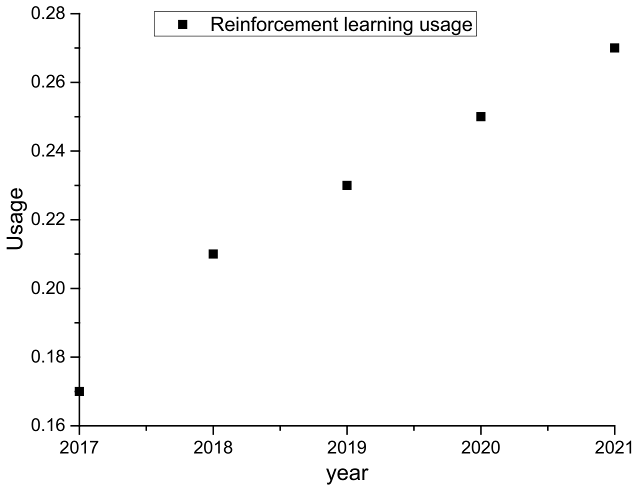

Fig. 1. Reinforcement learning usage growth rate.

the agent's behavior. Behavior represents an action of the agent's learning process training, and one can be selected for training in actual training. The specific classification of reinforcement learning is shown in Table 1.

1.2. Big data

With the rapid development of storage technology, the amount of data exchanged in people's lives has gradually increased, and big data technology has gradually become a key technology for processing large amounts of information. Big data generally refers to providing a reference data set through a large number of aggregations of some aspect of data. This data set enables the aggregator to quickly query and obtain key information according to the rules set by the code, and can also obtain the prediction results of future events through the analysis of historical data. The information that constitutes big data is different from conventional data information, mainly because the amount of information has reached the level of ZB, and this information can continuously generate new information, so that the entire big data technology exists in a dynamic way. The description of the characteristics of big data by research institutions believes that big data should be characterized by high value, various types of data, fast data exchange and increasing data scale. The key connotation of big data is not to store enough data, but to use the stored data to predict future events, thereby providing value to users. At present, big data is mainly used in scientific research data analysis, business data analysis and risk prediction. In the era of cloud storage and artificial intelligence technology development in the future, big data technology will be effectively applied in more fields [3–5].

1.3. Reservoir scheduling and decision-making

As a country with a large population, my country has always attached great importance to the conservation and use of water resources. Reservoirs that can simultaneously irrigate, supply water, utilize electricity and prevent flooding have been built 50 y ago. The goal of reservoir

Table 1
Reinforcement learning algorithms respectively

Number	Classification
1	Q-learning
2	DDPG
3	Pure planning
4	AlphaZero

scheduling is to adjust inflow and outflow conditions and to change the direction of natural water flow according to the need to increase profits and reduce disasters. The method of regulating the reservoir is the soul of the stable operation of the reservoir. The standard definition of reservoir scheduling is to ensure the effective operation of the reservoir and the safety of the upstream and downstream watersheds, through changes in the water storage conditions of the reservoir, to achieve flood control and profit increase rule changes. Reservoir dispatch is divided into regular dispatch and temporary dispatch, both of which aim to control the operation of the reservoir [6]. In order to dispatch and make decisions on reservoirs and improve the flexibility of reservoirs, some scholars have considered the incorporation of reservoir impact factors from multiple perspectives, and dispatched reservoirs by combining thinking from multiple perspectives. Reference for solutions to improve the dispatch effectiveness and timeliness of current reservoirs.

At present, the dispatching of the reservoir is mostly carried out by dispatching operators. The dispatching of floods and other issues mainly depends on the historical experience of the operators, and the flood control plan also relies on the manual writing of the staff. The whole process has high requirements on the staff. In fact, there are key rules that can be extracted from the historical scheduling experience of the staff. There are many reservoirs in the country, and different reservoir operators have different experience in reservoir operation. Through network technology, the method of reservoir operation can be shared, and finally the data set of reservoir operation can be formed. In the future, the application of big data technology in water conservancy and hydropower is inevitable for the development of the industry. It can realize the improvement of reservoir management capabilities, provide reference for third-party scientific opinions for reservoir operators, reduce the workload of reservoir operators, and improve reservoir flood control and dispatching decision-making capacity [7–9].

2. Current situation of reservoir scheduling

The current dispatching plan of the reservoir is arranged according to the analysis of the impending water entry in the vicinity of the reservoir in the next week. It also involves project overview and reservoir power generation plans. Taking the Three Gorges Dam as an example, its daily water storage depth is 145 m, which can ensure a healthy water level and discharge sand and gravel. In order to ensure the most beneficial power generation of the reservoir, the water level of the reservoir can be effectively controlled within the specified dispatch permit target. And according to the flow of the reservoir and the actual operation state of the current reservoir equipment to reasonably adjust the changes in the power generation of the reservoir. Reservoir operation technical engineers may encounter various difficult problems when conducting reservoir dispatching [10]. Similar to the sudden increase in the water inflow of the reservoir caused by the sudden rainstorm, the dispatch operator cannot predict, and it cannot solve this problem according to the historical operation method. For different dispatching requirements that may arise, the operation technical engineer may be unfamiliar with the dispatching constraints and requirements that need to be understood, while the operation engineer may consult the experience of other reservoirs and adjust the opening and discharge of the reservoir according to the opinions of other experts. The set value of water volume and reservoir inventory water level, and directly give the corresponding adjustment and scheduling method of other parameters. Common parameters involved in reservoir scheduling are shown in Table 2.

In the actual reservoir dispatching, most of the reservoirs have a single dispatching parameter, the consideration is not comprehensive, the dispatching method is not complete and the dispatching cannot be changed according to the actual situation. It has high requirements for manual operation of operators, and fails to realize automatic data analysis and scheduling forecasting methods, and directly gives forecasting methods [11,12]. The electronic monitoring equipment involved in the reservoir includes video, wall stability sensor, water level monitoring sensor, earthquake early warning test, land humidity detector, etc. The attention of the reservoir water level mainly includes the amount of water inflow, the amount of water outflow, the current water storage capacity, the water discharge capacity, and the method of handling stored water in extreme weather. The effect rate analysis of the problems existing in the actual operation of the current reservoir on the operation is shown in Fig. 2.

In order to solve the above problems, the following three steps can be performed: (1) Collect the historical data of various reservoir operations in the world, establish a reservoir operation data set and a corresponding giant database, which contains various types of hydrological data, mainly from various global reservoirs. Reservoir operation methods when faced with various reservoir scheduling problems, such as flood discharge volume, inbound and outbound flow, and daily water storage. (2) Establish a big data analysis platform, and obtain scenario information similar to the current scheduling demand through the analysis and comparison of the current scheduling demand data and the historical data, and can directly obtain the effective and feasible scheduling plan. (3) Establish a scheduling scheme based on the enhanced Q-learning method in machine learning, take the global reservoir scheduling historical database as the training database, and combine the database content and the Q-learning method to establish a scheduling self-training model. Generate schemes that can be used for reservoir scheduling according to requirements, and automatically optimize and select the optimal scheme, thereby reducing the workload of reservoir scheduling staff and improving the scientific nature of reservoir scheduling [13–15].

Table 2
Parameters involved in reservoir scheduling

Number	Index
1	Unit meets
2	Inbound traffic
3	Water level fluctuation
4	Drain capacity

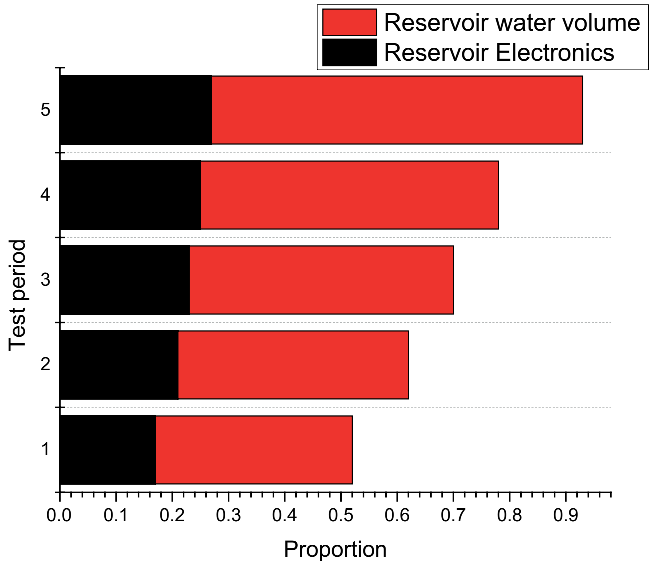

Fig. 2. Importance ratio of each factor in the actual operation of the reservoir.

3. Optimal scheduling and decision-making method of reservoir based on reinforcement learning and big data

3.1. Based on big data acquisition scheduling and decision-making methods

The main goal of reservoir regulation is to complete the dam storage safety. Due to the limitations of the author's own research conditions, only the dispatch of independent reservoirs is considered this time. Although China has built large-scale facilities such as the Gezhouba Dam and the Three Gorges reservoir, the intelligent method of reservoir dispatching is still relatively lacking. With the development of data science, the traditional method of reservoir manipulating paper records is no longer applicable [16]. In the theory of big data, scholars believe that effective big data is the general term for the part of the data that is used. The use of big data in reservoir scheduling can provide operators with informative decisions. According to the characteristics of reservoir data, the characteristics of big data can be divided into three types.

First of all, reservoir big data has the characteristics of rapid growth. At present, due to the arrangement of various electronic sensor monitoring equipment in various reservoirs in my country, the inlet and outlet of the reservoir are also in a real-time monitoring state, and the resulting data volume is huge. The amount of data also shows different growth characteristics, such as the growth rate of surveillance video and electronic hardware devices is gradually slowing down, while the amount of data generated by software development is accelerating. Secondly, the reservoir big data capacity has increased. At present, the rapid development of data science and technology, the database has also developed from a traditional relational type to a non-relational type. Various cache and non-relational databases have been able to directly receive different types of data for storage. According to the statistics of relevant institutions, the monitoring data of all reservoir sites in my country are currently approaching the ZB level. Finally, there are different types of reservoir big data [17]. For example, some reservoir data belong to office documents such as video images or engineering drawings, while some reservoir data are material data and project report data of fluid mode. These data constitute the basic characteristics of reservoir big data. This paper designs a reservoir scheduling analysis and decision-making platform based on big data technology. The software configuration of the reservoir big data system is shown in Table 3.

In order to match the reservoir big data hardware requirements, the reservoir big data hardware configuration is shown in Table 4.

The arrival of the era of big data has revolutionized the industrial structure of society. More than in the past, society values and relies on the holistic use of information. The essence of big data is the aggregation of complex data. Its basic mode of operation is the collection and processing of information. Of course, the way big data technology collects and processes information is different from general data processing technology. The data collected through big data technology can be organized into valuable information in the hands of professionals, and the analysis and organization of the collected data can also greatly improve the decision-making ability of managers. The role of big data in organizational management, decision-making and operation determines its practical value, and this value will continue to deepen and innovate. The minimum computing level of big data can reach 1,000 × TB = PB level, which shows the large amount of data. Big data is a huge amount of information material. Another way of saying it is the data that cannot be captured, managed and processed within a specified time using general software tools. Processing, this model has more powerful decision-making, insight and process optimization capabilities. At the same time, big data has a high growth rate. Its characteristics are reflected in many aspects: a huge amount of data, a large number of sources and channels are carried out at the same time; there are many types of data; the speed of flow is faster than the speed of acquiring data information; the information density is relatively low, and the various information data in big data It may not have value, and we must mine its value in a corresponding way [18–21]. By comparing the efficiency of the big data reservoir dispatching platform designed in this paper with the efficiency of the original manual analysis method, it is found that the application of big data technology to reservoir dispatching can greatly improve the efficiency of reservoir dispatching. The specific conditions are shown in Figs. 3 and 4.

Table 3
Software configuration required by reservoir big data

Software	Configure
Development language	Python
Configuration software	Kingview
Database	HBASE, Redis, Oracle
Operating system	Ubuntu

Table 4
Hardware configuration required by reservoir big data

Device name	Configure	System
Show server	I7-8750 h, 32 g	CentOS
Storage server	I7-8750 h, 64 g	CentOS
Training server	I7-8750 h, 32 g	CentOS

3.2. Scheduling and decision-making methods based on reinforcement learning

Reservoir scheduling and decision-making are also divided into optimization and simulation. Simulation dispatch mainly uses mathematical symbols to replace various variables in reservoir dispatch, such as water inflow, outflow, power generation and discharge. The method of placing the simulated variables in a computer program for simulation is called system reproduction simulation. The best way to simulate reservoir scheduling is to use a visualization method to display, and the process involves reinforcement learning algorithm. In this paper, the Q-learning method is used to simulate the calculation of reservoir scheduling. Inputs to a simulated schedule can include revenue, flood forecasts, water level trends, and flows. There is great uncertainty in the reservoir scheduling method, but after using Q reinforcement learning, a general and flexible simulation scheme that is more suitable for the reservoir scheduling method can be found in the continuously optimized path [22,23].

Machine learning algorithms mainly include three different methods: reinforcement learning, supervised and unsupervised. Reinforcement learning theory is mainly developed based on parameter perturbation adaptation and animal learning methods. Reinforcement learning is more suitable for scenarios that require continuous judgment and selection, and develop optimal solutions through continuous selection. Before reinforcement learning, the same type of algorithm includes dynamic library programming and value iteration. The value iteration scheme is used in the Q-learning method of reinforcement learning, which iterates a special Q function [24–26].

Q-learning is a kind of reinforcement learning algorithm, and the algorithm characteristics of the optimal solution obtained by it are just in line with the characteristics required for reservoir scheduling. The specific equations used by the

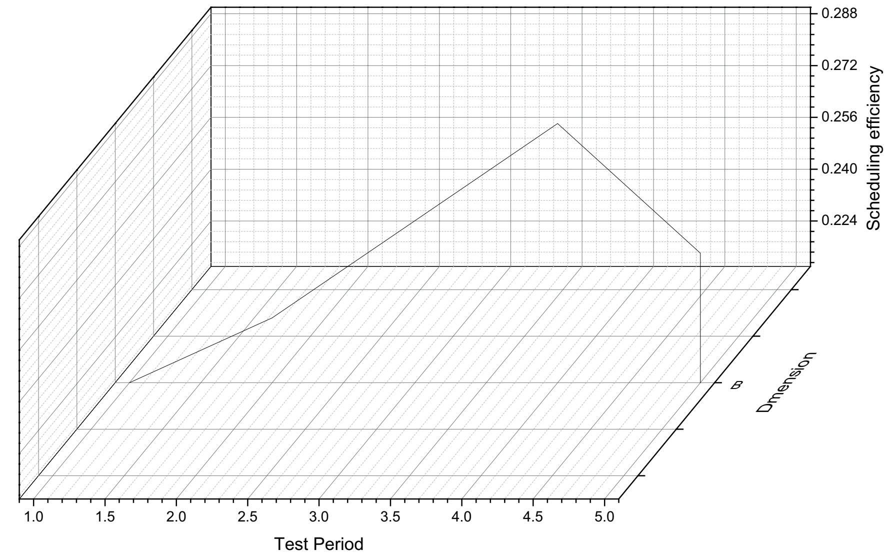

Fig. 3. Efficiency of manual analysis method for reservoir dispatching.

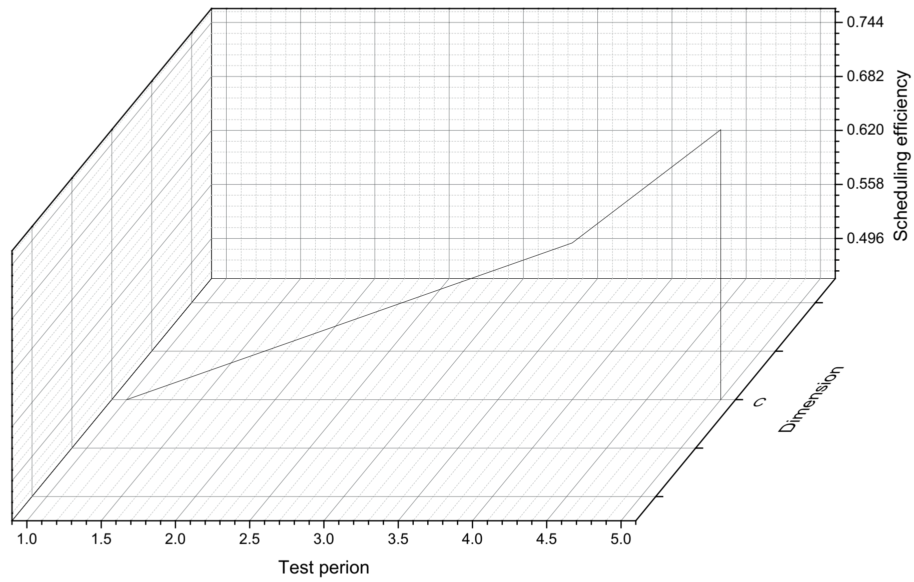

Fig. 4. Efficiency of big data reservoir dispatching platform.

Q-learning algorithm for reservoir scheduling are shown in Eqs. (1) and (2):

$$Q_{\text{target}} = R + \gamma \max Q(S',a) \tag{1}$$

$$Q_{\text{target}} - Q(S,A) \tag{2}$$

The parameters represent the storage capacity, discharge capacity, and power generation capacity of the reservoir, respectively. Since Q-learning does not need to interact with the reservoir scheduling model, it only needs to iterate a specific function. Through 4 different parameters, the learning process of the reservoir scheduling method can be iterated. The specific equations are shown in Eqs. (3) and (4):

$$Q_{k+1}(S_1,A_1) = Q_k(S_1,A_1) + \alpha\left[R_2 + \gamma \max_a Q_k(S_2,a_2) - Q_k(S_1,A_1)\right] \tag{3}$$

$$Q_{k+1}(S_2,A_2) = Q_k(S_2,A_2) + \alpha\left[R_3 + \gamma \max_a Q_k(S_3,a_3) - Q_k(S_2,A_2)\right] \tag{4}$$

After the data volume of the reservoir increases, in order to realize the intelligent dispatch of the reservoir, it is necessary to select a method that can intelligently analyze and learn the reservoir data. The Q-learning in reinforcement learning can find out the dispatching rules existing in the reservoir dispatching process through training, find out the hidden search method in the data set, and finally realize the Q-learning intelligent dispatching. The optimal design of reservoir dispatching can obtain effective data sets of dispatching methods, and establish the relationship between the stable water level, power generation, and water inlet and outlet conditions of the reservoir, so as to arrange reservoir dispatching [27,28]. Through a questionnaire survey of reservoir operation engineers who have used the Q reinforcement learning algorithm, it is found that the Q reinforcement learning method can effectively adapt to the needs of reservoir scheduling. The details are shown in Table 5.

The reservoir scheduling scheme based on the Q-learning method can realize the correlation between the reservoir water level, the reservoir flow and the power generation. Through the investigation of the overall efficiency of the application of the Q-learning method to the reservoir scheduling, it is found that its efficiency has been greatly improved compared with the original scheme. Through the investigation of reservoirs that use Q-learning algorithm to optimize dispatch, it is found that the specific situation of efficiency improvement is shown in Fig. 5.

A questionnaire survey was distributed to some operating enterprises that adopted the reservoir learning method, and it was found that the reservoirs using the enhanced Q-learning method were higher than the same type of reservoirs in the direction of flood control, water flow arrangement, and reservoir profit operation efficiency. In addition, the dispatching rules in the power generation direction of the enterprises that use Q reinforcement learning have also achieved a significant improvement in efficiency compared to the enterprises that have not adopted them.

Table 5
Q-learning and reservoir scheduling matching

Number	Q-learning characteristic	Reservoir scheduling
1	Award	Power generation
2	Environmental value	Water storage
3	State	Water level control

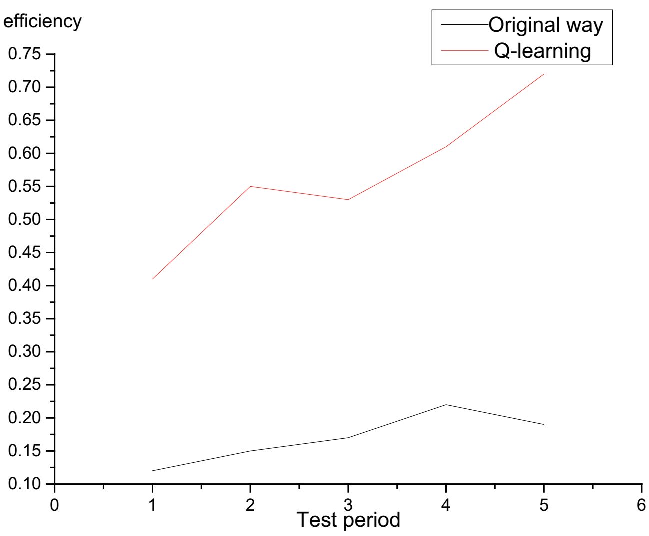

Fig. 5. Reservoir dispatch efficiency using Q-learning algorithm to optimize dispatch.

4. Conclusion

At present, various reservoirs have problems such as too fast change in flow rate, unpredictable flood period, unclear flood source analysis, unclear source and output basin analysis, and untimely analysis of gate opening and discharge. The development of big data technology provides a reference for the establishment of data sets for reservoir dispatching methods, and the emergence of reinforcement learning can just be combined with the idea of optimal reservoir dispatching. After analyzing the theory of reinforcement learning in big data, this paper sorts out the shortcomings of the previous reservoir scheduling methods. According to the current more active reinforcement learning technology, simulates the flood control scheduling scheme of the reservoir, and combines Q-learning for data training to build a reservoir that can be used for reservoirs. In addition, based on big data, this paper designs a reservoir scheduling and decision-making platform that can continuously accumulate data. Through the continuous preservation and analysis of historical reservoir scheduling information, the learning ability of the big data platform is improved, and ultimately the workload of reservoir scheduling analysts is reduced workload.

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