Optimization and exploration of reservoir dispatching system based on cloud services

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Abstract. In response to complex water management needs and extreme climate events, this study explores optimizing reservoir dispatch systems via cloud services, utilizing Huawei's cloud platform. High-precision sensors and edge computing facilitate intelligent dispatch decisions. Simulation experiments informed the tuning of sensor accuracy and data collection frequencies, emphasizing system adaptability and decision-making reliability. The goal is to enhance water resource management, disaster response, ecological security, and economic outcomes through ongoing system refinement.

Keywords: cloud service reservoir dispatching, intelligent water resources management, system optimization strategy.

1. Introduction

With the impact of global climate change and human activities, the rational allocation and dispatch of water resources has become increasingly important. Especially in the field of reservoir management, effective dispatching systems play a vital role in ensuring the sustainable utilization of water resources and minimizing disaster risks [1] . In recent years, the rapid development of cloud computing technology has provided new solutions and service models for the optimization of reservoir dispatching systems. Through cloud services, efficient processing, storage and analysis of reservoir dispatch data can be achieved to support more accurate and dynamic dispatch decisions [2] . Therefore, exploring the optimization of reservoir dispatching systems based on cloud services not only has practical significance for improving the intelligent level of reservoir management, but also has a profound impact on promoting the development of water resources management technology. This article aims to discuss in detail the application of cloud service technology in reservoir dispatching systems and its optimization strategies based on the combination of theory and practice , in order to provide scientific reference for the rational utilization and management of water resources.

2. Theoretical overview of cloud service technology and reservoir dispatching system

2.1 Definition and characteristics of cloud services

As shown in Figure 1, cloud services provide dynamic and easily scalable resources through the network. The core lies in using virtualization technology to optimize resource allocation. According to the service method, it can be divided into public cloud and private cloud. Public cloud reduces costs through resource sharing and provides services such as SaaS , PaaS and IaaS to adapt to the needs of different enterprises. SaaS provides network software services, PaaS supports application development, and IaaS enhances IT performance and meets enterprise development. Private cloud meets enterprises with high requirements for data security and privacy and relies on self-built centers and professional teams [3] . Managed cloud combines local deployment and managed management to improve security and experience. The on-demand computing model of cloud services allows users to pay according to actual usage, reducing waste and supporting elastic expansion of business needs.

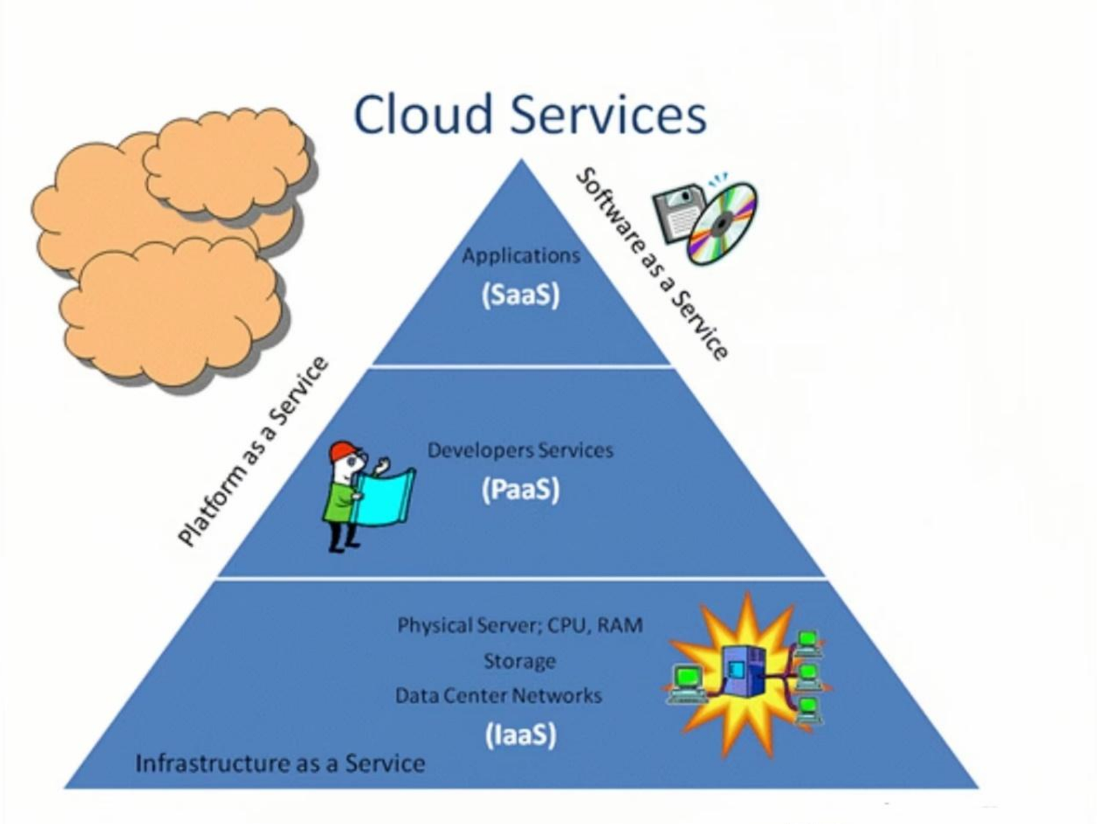

Figure 1 Basic structure of cloud services

2.2 Reservoir operation objectives and principles

Reservoir dispatching in my country is committed to the comprehensive utilization of water resources and maximization of benefits, emphasizing safety first, and achieving coordination between flood control and utilization, and between various water use departments. The dispatching system stores and releases water in a planned manner based on water conditions and forecasts to meet multiple functions such as flood control, power generation, and irrigation [4] . At the same time, following the principle of " one reservoir for multiple benefits, one water for multiple uses", we serve the diverse needs of the national economy with clear priorities and pursue the comprehensive benefits of the reservoir to support the all-round development of the national economy.

2.3 New framework for reservoir dispatching supported by cloud services

Figure 2 is an intelligent reservoir dispatching system centered on the cloud platform. The system integrates three major modules: intelligent water conservancy management, reservoir dispatching and mobile applications. It realizes fast data communication through 4G/5G and uses LoRa technology to ensure low-energy communication of monitoring equipment . . The system covers many aspects such as meteorology, video and environmental monitoring, realizes comprehensive real-time monitoring of reservoir status, improves the intelligence and efficiency of water resources management , and ensures water conservancy safety [5] .

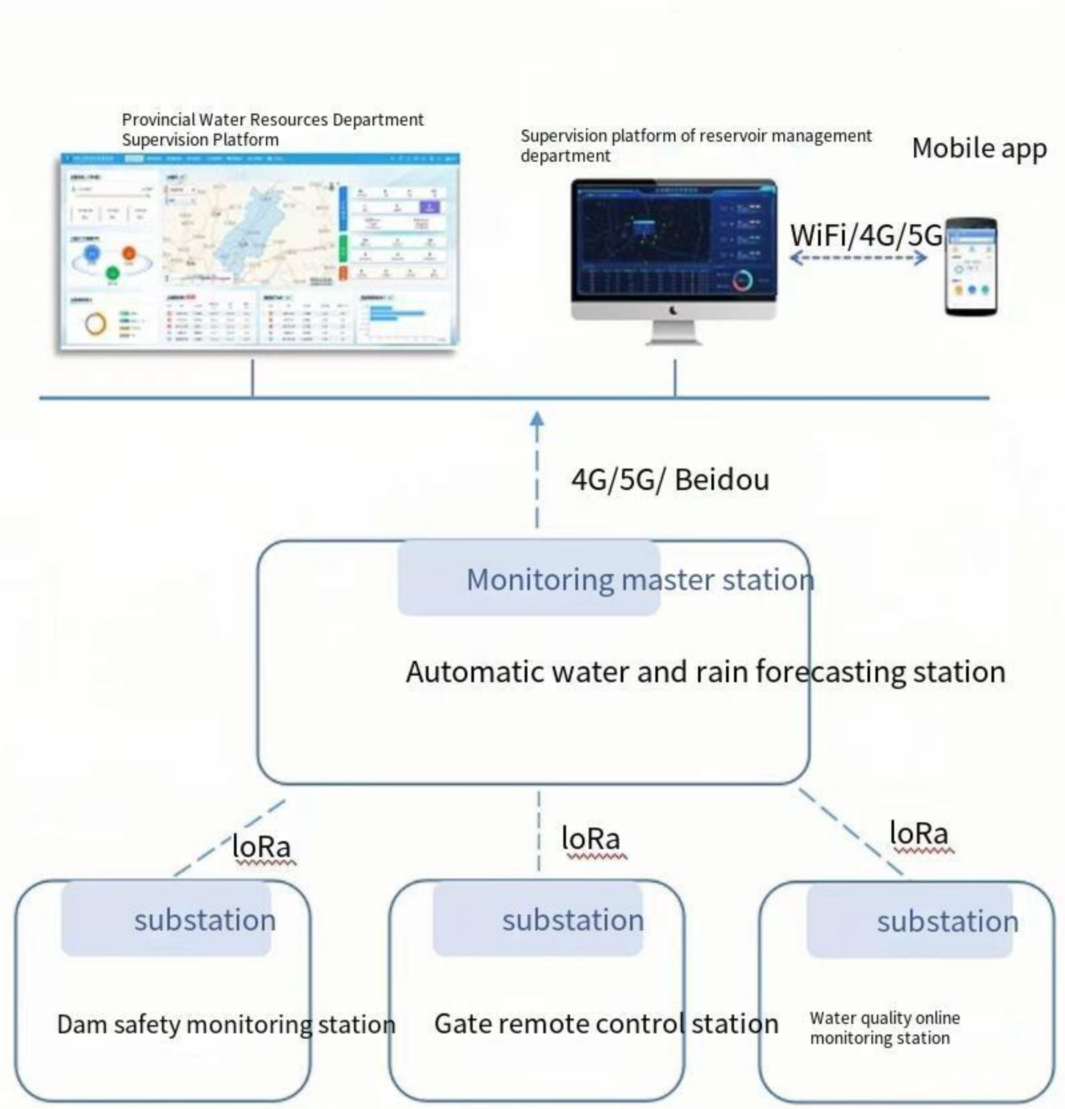

Figure 2 Reservoir intelligent dispatching framework diagram based on cloud services

3. Experimental design

3.1 Experimental goals

The experimental goal is to optimize the water resources management and dispatching strategy of the reservoir by exploring a reservoir dispatching system based on cloud services . Through real-time data collection, analysis and processing, we can improve the intelligent level of reservoir dispatching, enhance the reservoir's ability to respond to natural disasters such as floods or droughts, ensure the effective use of water resources and water ecological security, while reducing energy consumption and improving the economy of reservoir management. benefit.

3.2 Experimental process

3.2.1. Selection of cloud service platform

The experiment selected Huawei Cloud's water agent platform as the core service platform of this reservoir dispatching system. This platform uses advanced artificial intelligence and edge computing technology to focus on computer vision products in the water field , providing comprehensive water quantity and quality monitoring and analysis for river and lake management. The platform integrates high-cost water quantity and quality sensors to alleviate the shortage of human supervision resources, and empowers forecasting and dispatching through AI to cope with the complexity of water conservancy projects and improve the efficiency of dispatching decisions .

3.2.2. Experimental parameter setting and adjustment methods

Regarding the experimental parameter setting and adjustment methods, combined with Huawei Cloud's water agent platform, the primary task is to ensure the accuracy and real-time nature of sensor data. Parameter settings will be optimized around sensor accuracy, data collection frequency and transmission rate. The accuracy of the water sensor can be set to a measurement accuracy of ±0.5%, and the data collection frequency is once every 5 minutes to ensure the timeliness of the data. At the same time, the data transmission rate needs to be configured to meet the needs of real-time monitoring, using a transmission bandwidth of at least 100Mbps. In addition, the learning rate, error tolerance, etc. of the forecast algorithm of the dispatch system need to be dynamically adjusted based on real-time monitoring data and historical data to maintain the accuracy and adaptability of dispatch decisions.

3.2.3. Reservoir dispatch simulation experiment process

After setup, a reservoir dispatch model compatible with Huawei Cloud's intelligent water system was developed, linked to a sensor network that tracks key data such as water levels and rainfall, ensuring real-time synchronization. Tests confirmed sensor precision and stable data transfer. Simulations under varied conditions assessed the strategy's responsiveness and the effectiveness of decisions. The system's adaptability was enhanced by adjusting algorithms and strategies based on the live data feed. Results demonstrated the system's scenario-specific performance and the cloud's robust data handling, informing improvements for operational efficiency and decision-making intelligence.

3.3 Analysis of experimental results

After completing the reservoir operation simulation experiment, the collected data were analyzed in detail. The following is a summary of the experimental results, including the performance of key parameters and the evaluation of the effectiveness of the scheduling strategy.

Table 1 Results of experimental key parameters

parameter	set value	Experimental average	The optimal value	standard deviation
Water sensor accuracy	±0.5%	±0.48%	±0.45%	±0.03%
Data collection frequency	once per minute	once per minute	once per minute	No change
data transfer rate	≥100Mbps	102Mbps	105Mbps	2.5Mbps
Forecast algorithm learning rate	Dynamic Adjustment	0.01	0.005	0.003
error tolerance	Dynamic Adjustment	5%	3%	1%

As can be seen from Table 1, the system shows good performance and stability in most cases. However, further reducing the error will improve the accuracy of the system. In subsequent optimization, these parameters can be continued to be adjusted to further improve system performance.

4. Optimization strategy based on experimental results

4.1 Enhance the adaptive capability of the scheduling system

First, improve the dynamic adaptability of the algorithm. Combined with the adaptive learning rate adjustment mechanism in deep learning, such as the Adam optimizer, the learning rate parameters can be adjusted in real time α . According to the gradient of the loss function L with respect to time t g_t, the learning rate is adaptively updated, as shown in formula (1):

$$\alpha_{t+1}=\frac{\alpha_t}{\sqrt{\hat{v}_t}+\epsilon}\ (1)$$

Among them $\hat{v}_t$ is the exponential moving average of the squared gradient, which ensures that the learning rate can be adjusted sensitively in the face of different scenarios and improves the adaptability of the model in complex hydrological scenarios.

Second, adjust the adaptive threshold of error tolerance. By setting the error feedback adjustment mechanism, when the system prediction error e_t exceeds the current error tolerance T_t, the threshold is automatically adjusted to adapt to changes in the current environment, such as formula (2):

$$T_{t+1}=T_t\times\left(1+k\times\left|e_t\right|\right)\ (2)$$

Here k is the adjustment coefficient, which is determined through experimental data analysis to ensure that the system can maintain stable prediction performance in the face of increased uncertainty. Finally, a reinforcement learning algorithm is implemented to further optimize the scheduling strategy. Utilize Q-learning or Deep Q Networks (DQN) in reinforcement learning to iteratively update the policy π to maximize expected returns according to the environment state S_t and rewards R_t, as shown in formula (3):

$$Q\left(S_t,A_t\right)\leftarrow Q\left(S_t,A_t\right)+\beta\times\left(R_{t+1}+\gamma\times\max_a Q\left(S_{t+1},a\right)-Q\left(S_t,A_t\right)\right)(3)$$

where is A_t the action taken in the state , β is the learning rate, and γ is the discount factor. S_t This approach allows the system to autonomously adjust its strategy based on real-time feedback, thereby optimizing the decision-making process under changing environmental conditions.

4.2 Improve the resource scheduling efficiency of the system

The key to improving system resource scheduling efficiency is to optimize resource allocation and utilization. To this end, the task scheduling optimization algorithm will first be implemented. The optimization model based on the genetic algorithm (GA) can find the optimal solution by simulating the mechanism of natural selection, such as formula (4):

$$P_{n+1}=GA\left(P_n,C,M\right)\ (4)$$

Among them, P_{n+1} represents the new generation population, P_n which is the current population, C represents the crossover operation, and M represents the mutation operation. Through iterative evolution, the optimal resource allocation strategy is searched.

Secondly, a scheduling strategy based on event triggering is introduced. When a key parameter is detected to exceed a preset threshold, the system automatically triggers a mechanism to reallocate resources. Formula (5) can be expressed as:

$$Trigger(e)=\begin{cases}1 & \text{if metric } (e)>\text{ Threshold}\\ 0 & \text{otherwise}\end{cases}\quad(5)$$

Among them, $Trigger(e)$ is the trigger function of event e, $\text{metric }(e)$ is the monitored event-related parameter, and Threshold is the set threshold.

Finally, the allocation can be dynamically adjusted according to resource utilization. Formula (6) is expressed as:

$$R_{t+1}=R_t+\alpha\cdot\left(E_t-U_t\right)\ (6)$$

Here, R_{t+1} it represents the resource allocation amount in the next time period, R_t which is the current period, α which is the adjustment coefficient, E_t which is the target efficiency, but the current resource utilization rate. U_t

4.3 Ensure the safety and reliability of scheduling decisions

In order to ensure the safety and reliability of scheduling decisions, we must first introduce a fault-tolerant mechanism and design a fault-tolerant control strategy to deal with potential system errors and exceptions. The specific method is to apply redundant design, formula (7) is:

$$S_{\text{redundant}} = f\left(S_{\text{primary}}, S_{\text{backup}}\right) \quad (7)$$

Here, $S_{\text{redundant}}$ the redundant system state is represented, S_{primary} which is the primary system state, but the backup system state. S_{backup} When the main system fails, the backup system can take over control to ensure continuous operation.

Secondly, perform multi-level verification of data to ensure that scheduling decisions are based on accurate and reliable data. Verification formula (8) can be expressed as:

$$V(d) = \begin{cases} 1 & \text{if } v_1(d) \wedge v_2(d) \wedge \ldots \wedge v_n(d) \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

Among them, $V(d)$ is the data verification result, $v_1(d)$ and $v_n(d)$ is the verification function at different levels.

Finally, the risk assessment model is used to predict the potential risks of decision-making, and the model is formula (9):

$$R_i = \sum_{j=1}^{n} w_j \cdot x_{ij} \quad (9)$$

Among them, R_i represents the risk value of the w_j i- th decision, is the weight of risk factor j, and x_{ij} is the performance of decision i on risk factor j. Risk assessment helps predict and reduce possible negative impacts.

5. Conclusion

The study verified the performance of the reservoir dispatching system under cloud services through a series of simulation experiments , and formulated specific optimization strategies to address the shortcomings of the system. Future work will focus on improving the system's adaptability in complex environments, enhancing the safety and reliability of scheduling decisions, and further improving resource scheduling efficiency. With the advancement and continuous optimization of technology, this system will serve water resources management more accurately and contribute to meeting increasingly severe water resources challenges.

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