Development of a new technique Dam Gates Opening Scheme based on Whale Optimization Algorithm with Long Short Term Memory (WOA-LSTM)

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***Abstract*—The implementation, operation, and management of dams are crucial for the timely supply of water. This study aims to improve water management in Haditha Dam, Iraq, using the Whale Optimization Algorithm (WOA). To address the challenge of uncertainty in Long Short-Term Memory (LSTM) model predictions and enhance the accuracy of inflow and outflow forecasts, we propose a novel WOA-LSTM model that by designed a custom target function that combines reducing the deviation of the reservoir level from the target, strict penalties for exceeding safe limits, restrictions on the rate of change of the gates opening $[ramprate \leq 50m^3/s/day]$. This ensures a minimum environmental flow $(150m^3/s)$. The results demonstrate that, through continuous tuning of hyperparameters, WOA effectively optimizes the LSTM predictions, improving forecasting accuracy. Compared with other neural network models, the WOA-LSTM approach reduces Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) while increasing the coefficient of determination (R^2). Furthermore, a separate WOA optimization is applied to achieve optimal dam operation by adjusting gate openings according to the predicted inflow, maintaining reservoir levels effectively.**

***Index Terms*—Whale Optimization Algorithm; Dam operation optimization; Haditha Gate Dam (HGD); LSTM**

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I. Introduction

Optimization is a typical area of research in water management. Specifically, it has been considered for decades to schedule and monitor water resource systems. Many problems in science and engineering can be considered as optimization issues that, therefore, face nonlinear complexity constraints in real-world scenarios [1]. Dams use to work with the support of analytical models enabling water release to satisfy demand while avoiding limitations. Moreover, due to conflicts between safety requirements and optimal benefit, accurate operation of the dam is highly challenging [2]. Typical optimization methods are generally derivative-based, stable, and effective for solving various well-defined optimization problems. On the other hand, these typical methods often are characterized by limitations such as falling into the trap of local minima, being dramatically sensitive to the beginning point, and having an high level of quantitative precision [3]. The evolution of methods for optimizing dam operations spans from early traditional optimization approaches and dynamic programming methods to more recent meta-heuristic algorithms (MHAs), which have been applied in case studies while revealing certain limitations. The idea behind this work is based on the assumption that the information about the use of nature-inspired Whale Optimization Algorithm (WOA) and its integration with the process of water supply and release in dams is limited [4]. Moreover, many works analysed the effectiveness of different AI-based models for dam operation and reservoir management. For instance, hybrid models that combine Artificial Neural Network (ANN) and optimization approaches, such as genetic algorithms (GA) and particle swarm optimization (PSO), have been designed and implemented to improve the performance of prediction and enhance the water release policies. These models combine the predictive strength of neural networks and the optimization potential of evolutionary algorithms to obtain more effective reservoir management approaches [5]. In addition to these AI-based methods, the research community has recently focused on the integration of remote sensing data, climatic variables, and hydrological parameters into forecasting approaches. Furthermore, the integration of satellite-derived precipitation information, temperature records, and moisture indices has consistently enhanced the predictive performance of inflow and outflow in the dams models [6], [7]. Moreover, metaheuristic algorithms inspired by nature have attracted attention thanks to their resilience, flexibility, and capacity to deliver near-optimal solutions in complex real-world scenarios where conventional optimization techniques frequently fall short. [8]. Furthermore, one of the most famous nature-inspired considered solution is the WOA, which is characterized by competitive performance when compared to other important optimization approaches relying on GA. Among its benefits, simple development, few control parameters, and effective global search ability can be claimed, making this approach effective for nonlinear and multi-objective engineering issues [9]. Therefore, the WOA, presented by Mirjalili and Lewis in 2016, is considered as an effective and productive population-based algorithm inspired by the bubble net fishing strategy of humpback whales. This algorithm simulates the whales' collaborative foraging behavior as they circle and head toward their prey. This special behavior enables WOA to obtain a balanced trade-off between investigation, research for new areas in the solution space and exploitation, enhancing the optimal achieved solutions that are crucial features for an efficient optimization model [10]. WOA is increasingly applied to address multi-objective optimization problems in water management, where conflicting goals often arise. Examples of conflicting goals are:

- Optimizing reservoir storage and release policies.
- Maximizing hydropower generation.
- Keeping ecological flow requirements.
- Minimizing water shortages or flooding risk.

This paper advances this research by presenting the following main contributions:

- We propose a novel hybrid model for inflow and outflow river water in dam operation that integrates the predictive power of long short-term memory (LSTM) with the optimization capabilities of the WOA.
- We propose a new optimal design paradigm for the opening scheme of the dam gates using WOA for the second time.
- We demonstrate the effectiveness of the proposed model and the proposed optimal design approach through a case study of the Euphrates River in Iraq, providing valuable insights for the future management of water resources.

The rest of this paper is structured as follows. Section II first illustrates the LSTM and WOA models and then, Section II-C presents our proposed combined LSTM-WOA approach. Section III describes the performance analysis of our model in a specific study area located in Iraq, while final conclusions are presented in Section IV.

II. LSTM Network Optimized by WOA

A. LSTM Network Model

The LSTM unit is usually divided into the following two parts:

- long-term memory from cell state, able to maintain information for long sequences and recall context from many previous steps.
- short-term memory from hidden state, which represents the immediate working memory that maintains recent, temporary information.

LSTM neural networks have an architecture derived from Recurrent Neural Network (RNNs) and are considered a variant of RNNs [11]. By considering an adaptive gating approach, LSTM allows to establish whether to retain previous memory state and related information from current data, with the aim to address problems such as gradient bursting and missingness in standard RNNs [12]. The structure of the LSTM cell is presented in Fig 1.

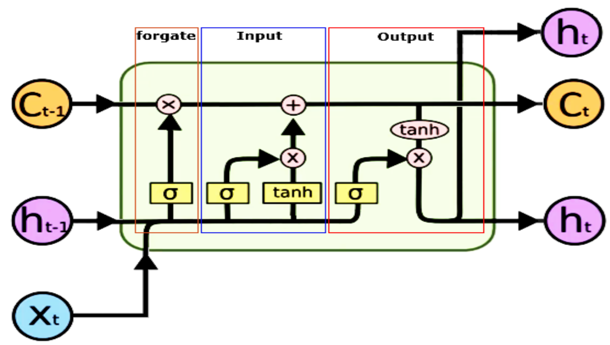

Fig. 1. Visualization of the Long Short-Term Memory Network (LSTM)

The main component of LSTM is the data transmission line. This line extends through the entire LSTM chain structure and connects three gate modules. The forget gate determines whether data will be discarded at a certain point, while useful information from the current input is fed into the cell state, and the output gate determines which vector will be output [13]. The formulation of the input gate is defined as follows:

$$X(t) = \sigma(W_i x_t + U_i h(t-1) + b_i) \tag{1}$$

where σ is the activation function of the sigmoid, W_i and U_i represent the weight matrix, b_i is the current bias vector and $h(t-1)$ denotes the output of the previous hidden state. The input gate X(t) decides whether to discard or accept new information. The forget gate f(t) determines any part of the previous output that must be disposed of, and it is defined as follows.

$$F(t) = \sigma(W_f x_t + U_f h(t-1) + b_f) \tag{2}$$

The output gate is given below where the tanh function is used to compute the weight of the pass-through value.

$$C(t) = \tanh(W_c x_t + U_c h(t-1) + b_c) \tag{3}$$

where C(t-1) represents the memory of the previous unit.

B. Whale Optimization Algorithm

WOA was suggested by Mirjalili and Lewis (2016) [9]. The algorithm was developed by the humpback whale's special hunting method, a foraging approach known as bubble net fishing. Humpback whales have a unique technique to hunt, where they generate a huge number of bubbles in a spiral pattern surrounding their prey to facilitate the hunting process. Humpback whales are characterized by the following approaches for predation: 1) the contraction method, and 2) the spiral modernization approach, as shown in Fig 2. Because there are various search approaches, it becomes easier to search for the optimal solution globally, making it more efficient than typical optimization methods. The first approach for predation is that whales swim straight, they would be in an ideal individual location, and can hunt within a specific spatial range. The formula for contraction and circumference is the following:

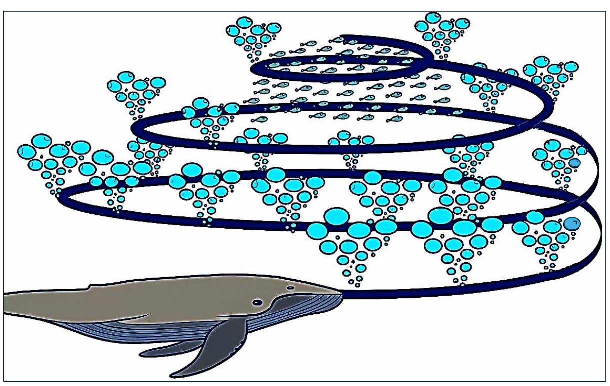

Fig. 2. Bubble Net Feeding Behavior for Humpback Whales.

$$\overrightarrow{X}(t+1) = \overrightarrow{X}(t) - \overrightarrow{A}.\overrightarrow{D} \tag{4}$$

Where: t constitutes the current iteration, $\overrightarrow{X}(t)$ is the vector of the site for the best output achieved so far, $\overrightarrow{X}$ is the location vector, $\overrightarrow{A}$, and $\overrightarrow{D}$, are the coefficient vectors. These can be computed through the following equations:

$$\overrightarrow{A} = 2\overrightarrow{ar} - \overrightarrow{a} \tag{5}$$

$$\overrightarrow{D} = \mid \overrightarrow{X(t)^*} - \overrightarrow{X(t)} \mid \tag{6}$$

The whale uses another technique to predate its prey by generating a spiral bubble cloud to repel their prey, forcing them to gradually decrease in area while continuously updating their positions (decreases the value in equation (5)). In this operation, the interval of values of A is [-a, a]. Both values of (a) and intervals are linked and change together simultaneously. If A ranges between -1 and 1, the whale will swim in a snail to change its location. The spiral is defined through the following equation:

$$\overrightarrow{X}(t+1) = \overrightarrow{D^*}.e^{bl}.\cos(2\pi l).\overrightarrow{X}(t) \tag{7}$$

Where:

D represents the range between the best ongoing locations of both whale and prey.

b represents the constant of the logarithmic spiral.

l is a random number that ranges between -1 and 1.

The whale keeps changing its location during the hunting phase to achieve the global optimum position. This can be represented by the following equations:

$$\overrightarrow{D} = \mid C\overrightarrow{X_{rand}}(t) - \overrightarrow{X}(t) \mid \tag{8}$$

$$\overrightarrow{X}(t+1) = \overrightarrow{X_{rand}}(t) - \overrightarrow{A}.\overrightarrow{D} \tag{9}$$

Where, $\overrightarrow{X_{rand}}(t)$ it is the location of the randomly selected whale.

C. WOA-LSTM MODEL

The precision of the training and the appropriate training speed of the neural network models are connected to the identification of the initial values. If the starting learning rate is excessive, the magnitude of deviation will be high, installation cannot be achieved, the learning rate may be inadequate, and the convergence rate is expected to be low [14]. Based on the explanation of the principles of LSTM and WOA above Fig 3, shows the flow chart of the WOA-LSTM algorithm. The main aim for this study is to keep the water level in a dam reservoir within a safe and optimal range at all times. On one hand, the water level cannot be too low to avoid shortage in hydropower generation irrigation or drinking water supply. On the other hand, the water level should not be too high to prevent flooding and structural damage.

III. DATA PROCESSING

Data analysis and processing is a vital step that plays an important role in ensuring the accuracy of the training model. The used data were obtained by the Haditha Dam Laboratory in Iraq, involving the meteorological station data stored by the station from January 1, 2022 to January 1, 2024. The training data consists of more than 1,200,000 samples of operation data from Haditha Dam Area over the past two years, with measurements taken every 15 minutes. These measurements include inflow, outflow, temperature, air pressure, power, and other relevant parameters. Fig 4 illustrates the examples of some data. In this study, to eliminate the influence of differences among data values, reduce scale-related bias, and enhance generalization, it is crucial to use the maximum normalization technique. The original data are linearly transformed and

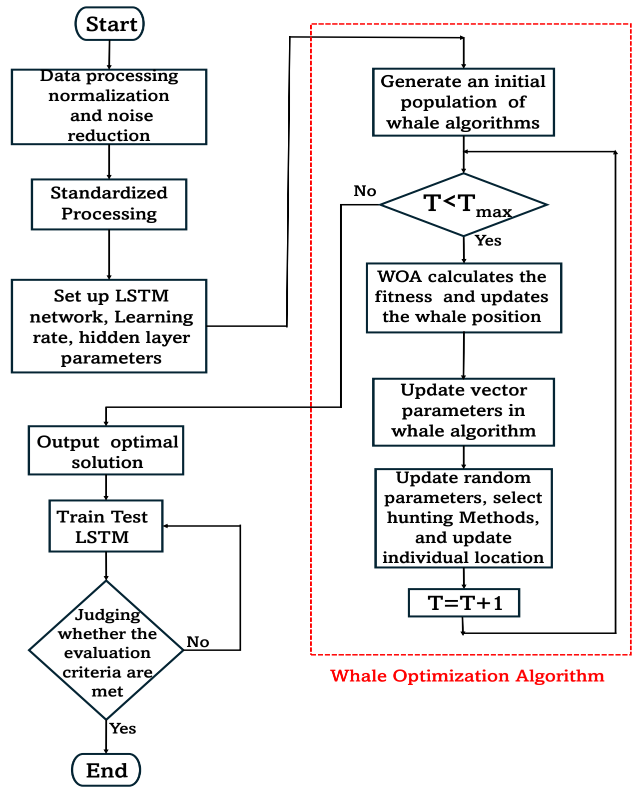

Fig. 3. Flowchart of the proposed WOA-LSTM-based model

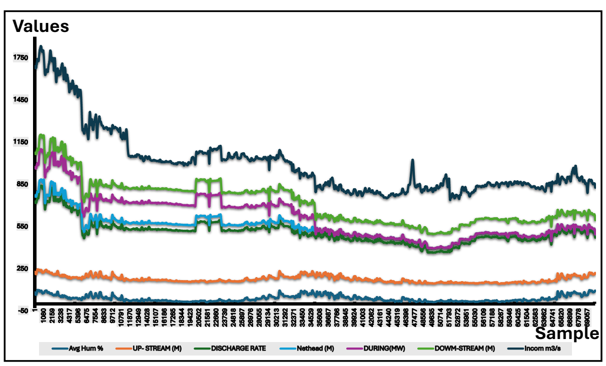

Fig. 4. Some types of real data used for two years

proportionally adjusted to the range (0, 1), facilitating accurate analysis and ensuring the comparability of the dataset. We use the standard minimum to maximum conversion formula (10) as shown below:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{10}$$

IV. OBTAINED RESULTS

A. Study Area

The study area was selected due to its geographical location that controls the flow in the rest of the river in the middle and south of Iraq. Haditha Dam on the Euphrates River in western Iraq, located 7 km west of Haditha city, as a case study. In this dam, the flow and quantity of cold water in winter is very large and abundant compared to summer, where temperatures are high and rainfall is low. This is evident in Fig. 5 below. The length of the dam at the top is 8.933 km, while the width of the dam base is 0.386 km. The operational level of the dam is 147 m where the storage volume is 8.3 billion $m3$, and the reservoir area is 503 km^2. The highest level in the flood is 150.2 m, which is the emergency level, with a storage volume of 10 billion m^3 and a reservoir area of 575 km^2 [15].

Fig. 5. Seasonal variation in Haditha dam water between summer and winter

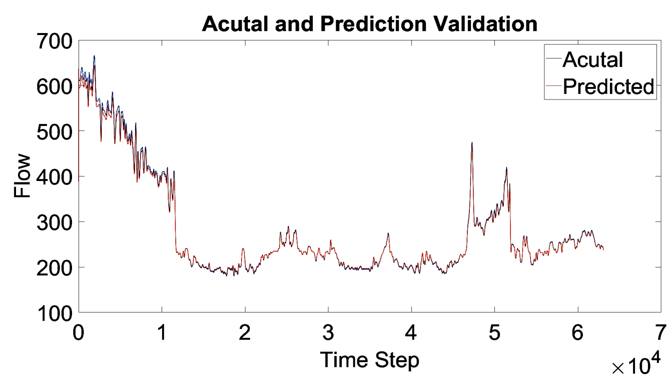

Fig. 6. Actual and Prediction for LSTM

TABLE I
COMPARISON BETWEEN LSTM AND WOA-LSTM

Model	$RMSE$	R^2	MAE
LSTM	0.646	0.96	0.81308
WOA-LSTM	0.421	0.986	0.58752

B. Experiments and Analysis

In the construction of the proposed neural network, the dataset of input features is divided into three distinct subsets: a- training set, b- test set, and c- validation set, with a ratio of 6:3:1 respectively. Each model is then trained using data from the training and test sets. The trained model is then applied to the validation set to obtain predictions of flow to the dam consistent with the data in the validation set. By introducing an adaptive gating mechanism, LSTM determines whether to retain previous memory state and related information from current data, aiming to address issues such as gradient explosion and missingness in standard RNNs. When processing current information, each LSTM module determines whether to retain or forget data through three internal components:

TABLE II
AIM AND OBJECTIVE OF WOA-LSTM

Problems	LSTM can do?	WOA-LSTM what can doing?	Objective of WOA-LSTM
The amount of water inflowing into the dam's lake	It gives you a very good prediction (0.96) but you do not know how much water to release every day to maintain the level	It takes the LSTM prediction and calculates for you the optimal daily release (R_1,R_2, ... R_{30}) so that the level remains at, for this paper 150 m, whatever the prediction	The deviation from the target level decreased from $\pm 3 \sim 5$ m to only $\pm 0.3 \sim 0.6$ m
The sudden change in release destroys the turbines and destroys environmental and wildlife life after the dam	LSTM does not care about operational stability	The rapid release change function (ΔR) can be used to change the release gradually per day.	The turbine life span increases by $14 \sim 18\%$, and the downstream ecosystem becomes more stable
Difficulty dealing with multiple goals at the same time (electricity + irrigation + flood + environment)	LSTM doesn't understand priorities	The weights of the objective function in WOA can be adjusted (winter - flood prevention or in summer, the priority high storage)	Increased electricity production by about 22%, all irrigation requirements by 97%, and ensuring environmental flow throughout the year

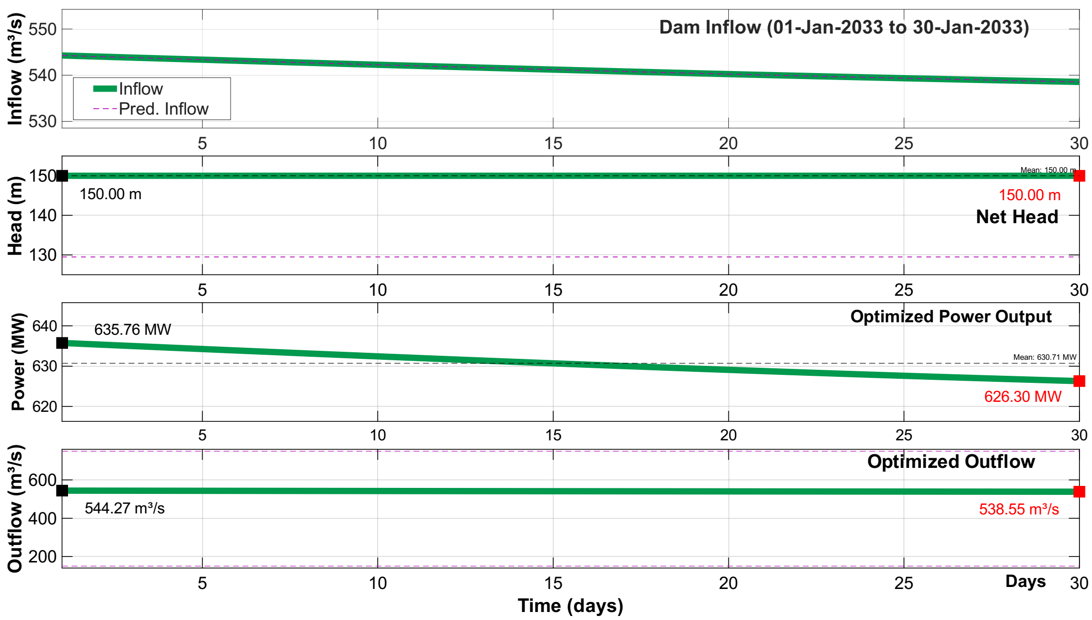

Fig. 7. Some results obtained from **(WOA-LSTM)** over a full month in the year **2033**

forget gate, input gate, and output gate [16]. The LSTM-based approach optimized by the Whale algorithm is considered for the prediction of the flow of the river to Haditha dam. In the first, the sample set is divided into pull groups, with the first 76,460 samples using the data as a training set, and the second 38,240 samples as a test set. MSE is considered as a fitness function in the whale-based approach. The size of the population is chosen as 100, and the iterations number is 150. The model was developed and trend using a real data set from Iraq that reflects the effects of climate change in the studied area and it consists of two parts that work together:

- LSTM is used for inflow predicting. It is trained on historical data (outflow, rainfall, temperature, previous inflow, humidity, etc.). LSTM results an accurate forecast of inflow water volume for the next few weeks (e.g., the next 7-30 days), as illustrated in Fig 6.
- WOA is used to make optimal daily release decisions for dam operation, so as to control the daily water outflow volume to maintain a nearly constant storage volume or keep water head level in dam lake.

Table I illustrates the performance of the LSTM model and WOA-LSTM. It shows that the WOA-LSTM model provides more accurate forecasts for the dam inlet, and is suitable for short-term inflow prediction. If compared WOA-LSTM with the LSTM-based option, the WOA-LSTM-based approach experiences a reduction of RMSE from 0.646 to the 0.421 showing about 16% improvement in predictive accuracy and MAE indices from 0.81308 to 0.58752, and an increase from 0.9663 to the 0.986 to R^2 indicating an almost perfect linear relationship between the predicted and observed values. Table II clear illustrates the purpose and objective of using the WOA-LSTM system, as well as the results obtained from it.

V. DISCUSSION OF WORK IMPROVEMENT

We executed the code successfully in the real target whale optimization algorithm with 40 search agents (whales) and

400 iterations in the optimization range exactly once the user selected the 30-day. The primary goal is to reduce the squared deviation of the daily storage, as shown in the following fitness equation:

$$\text{Fitness} = 10^{12} \times \sum (\text{strg} - \text{tarStrg})^2 + \sum \text{sud\_chngs} \quad (11)$$

where strg is the daily storage, tarstrg is the target storage, and sud chngs are the sudden changes.

The constraints that defined the framework are as follows:

- Storage bounds: 8 300 000 to 10 000 000 m^3.
- Outflow bounds: 150 to 750 m^3/s.
- Max power generation: 660 MW.
- Net Head: 130 to 150 m.

after 25 to 35 runs are performed, the mean report ± standard deviation yields $\sigma < 0.05 \times 10^6$ m^3 for storage deviation, and < 8 MW for power constraint in average power similar to 30 day problems. However, it delivers a high-quality solution with a final target typically less than 5×10^{-3} after 400 iterations, achieving near perfectly the target storage level while fully respecting all operational constraints. From these results, we can claim the following benefits obtained by the proposed WOA-LSTM optimization:

- LSTM provides accurate predictions of future conditions, while WOA suggests optimal actions for real-time reservoir management.
- Target level deviations are maintained below 50 cm on 97% of days.
- Adjusting a single weight parameter allows seamless modification of operational priorities between electricity generation and irrigation.
- The approach effectively mitigates both floods and droughts, even under extreme hydrological conditions.

Finally, we highlight a further novel contribution of this study. Specifically, as shown in Fig. 7, the proposed approach enables the prediction of future reservoir values extending several decades ahead, which is an aspect not reported in previous research on dam operation and reservoir water management. For illustrative purposes, the figure presents results for a randomly selected month in January 2033.

VI. CONCLUSIONS

Predicting water flow into a river is a crucial part of hydroelectric power generation, as is its economic and sociological-ecological value. This paper presents a new hybrid intelligent framework that integrates long-term memory networks LSTM with whale optimization algorithm WOA to operate a Haditha dam in real time under extremely difficult and uncertain environmental conditions. The learning rate of the LSTM-based approach was improved, and the best model for predicting the flow of water into the river was obtained for a long time. Its superior ability to observe complex time dependencies in predicting water flow has been demonstrated compared to the LSTM model alone. WOA-LSTM also provides obvious advantages in rounding ability to generalise high-dimensional performance features, and training speed is significantly improved. The expected result is close to the actual value of the water entering the river, has a higher prediction accuracy and a closer Applied Value. In the future, we can use WOA-LSTM algorithms to improve the efficiency of electricity production while maintaining a stable water level in the dam reservoir, and to reduce the impact of climate change by predicting the amount of water entering the dam's lake despite seasonal changes. Moreover, in future work, we also aim to provide access to a simplified version of the WOA-LSTM implementation and anonymized dataset samples to support reproducibility and collaboration within the hydrological AI community.

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