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Decomposition and Holt-Winters Enhanced by the Whale Optimization Algorithm for Forecasting the Amount of Water Inflow into the Large Dam Reservoirs in Southern Thailand

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Abstract

This study introduces hybrid forecasting models integrating the Whale Optimization Algorithm (WOA) with Holt-Winters (HW) and decomposition methods, applied in both additive and multiplicative models, for time series forecasting. Focusing on monthly water inflow into four dam reservoirs in Southern Thailand, the study compares these hybrid models against classical statistical models, Grid Search for Holt-Winters (Grid-HW) and Classical Decomposition (Classic-D). The analysis comprises two phases: the training dataset phase and the testing dataset phase. In the training phase, WOA demonstrates superior parameter optimization, enhancing both HW and decomposition methods, resulting in lower Mean Absolute Error (MAE) values compared to classical models. In the testing phase, performance metrics such as Root Mean Square Error (RMSE), MAE, and Symmetric Mean Absolute Percentage Error (sMAPE) are employed. The findings reveal that the Whale Optimization Algorithm with Holt-Winters (WOA-HW) and Decomposition (WOA-D) models surpass classical approaches in long-term forecasting accuracy for three dam reservoirs. Over 24 data points, the WOA with Multiplicative Holt-Winters (WOA-HWx) is optimal for Pran Buri dam, the WOA with Additive Decomposition (WOA-D+) for Bang Lang dam, and the WOA with Multiplicative Decomposition (WOA-Dx) for Kaeng Krachan dam. The Box-Jenkins approach, further refined through a Box-Cox transformation employing a natural logarithm, emerged as the superior forecasting model for Rajjaprabha dam. This model satisfied all critical statistical criteria, including normality of residuals (Anderson-Darling: 0.359, p-value: 0.433), homoscedasticity (Levene's test: 1.24, p-value: 0.274), independence (Ljung-Box test: 14.10, p-value: 0.169), and zero mean (t-test: -0.39, p-value: 0.702), establishing its robustness and reliability for forecast analysis.

Keywords*: *dam reservoir; decomposition; forecasting; Holt-Winters; whale optimization algorithm

1. Introduction

The convergence of time series forecasting and metaheuristics has ignited a continuous wave of development over the past three decades. This emerging synergy thrives on the persistent pursuit of optimal solutions through the application of metaheuristics. The early 1990s witnessed the pioneering efforts of Dorigo (1992) with Ant Colony Optimization (ACO) and Kennedy, & Eberhart (1995) with Particle Swarm Optimization. The dawn of the millennium ushered in a new era of algorithmic ingenuity. Geem et al. (2001)

unveiled Harmony Search, and Karaboga (2005) presented the Artificial Bee Colony (ABC) algorithm. While Yang (2009) ignited the field with the Firefly Algorithm. The same year, Yang, & Deb (2009) introduced the Cuckoo Search. Yang (2010) further enriched the landscape with the Bat Algorithm. The subsequent years saw Pan's (2011, 2012) introduction of the Fruit Fly Optimization and Yang's (2012) conception of the Flower Pollination Algorithm. Gandomi, & Alavi (2012) contributed the Krill Herd Algorithm, and Mirjalili et al. (2014) marked a significant milestone with the Grey Wolf Optimizer. The momentum continued with Mirjalili, & Lewis's (2016) Whale Optimization Algorithm (WOA) and Mirjalili's (2016) Dragonfly Algorithm. Finally, Heidari et al. (2019) expanded the toolbox with the Harris Hawks Optimization.

As time series forecasting continues to evolve, the integration of diverse approaches has opened up exciting possibilities. Among these, the Quantum-behaved Particle Swarm Optimization (QPSO) method, introduced by Sun et al. (2004), has sparked particular interest. Its remarkable flexibility has been showcased in various forecasting applications, suggesting its potential to become a valuable tool for tackling complex forecasting challenges. Cheng et al. (2015) harnessed QPSO to develop a daily reservoir runoff forecasting model that integrates Artificial Neural Networks (ANNs). Niu et al. (2018) furthered its reach by utilizing QPSO alongside the Extreme Learning Machine (ELM) to predict hydrologic time series for the Xinfengjiang reservoir in China. Feng et al. (2020) expanded its utility to monthly runoff forecasting by combining it with variational mode decomposition (VMD) and support vector machines (SVMs). Hadavandi et al. (2010) used particle swarm optimization to develop a time series model for gold price forecasting. Kaewpaengjuntra et al. (2010) applied into monthly electricity consumption forecasting in Thailand with a hybrid approach that fused Holt-Winters (HW) exponential smoothing with the Artificial Bee Colony algorithm. Assis et al. (2013) explored the integration of HW with the Ant Colony Optimization algorithm, while Zhang et al. (2019) successfully combined Support Vector Regression (SVR) with the Firefly algorithm for stock price forecasting. Expanding the potential of the Firefly algorithm, Das et al. (2019) applied it alongside various machine learning techniques, including Extreme Learning Machine, Online Sequential Extreme Learning Machine, and Recurrent Back Propagation Neural Network, for stock market forecasting. Jiang et al. (2020) enhanced the capabilities of HW smoothing by employing the Fruit Fly Optimization algorithm for monthly electricity consumption forecasting.

This collaboration continues to evolve. Bas et al. (2021) introduced the Bootstrapped Holt Method with Autoregressive Coefficients based on the Harmony Search Algorithm. Sun et al. (2022) developed a hybrid short-term runoff prediction model utilizing optimal VMD, an enhanced Harris Hawks algorithm, and a Long Short-Term Memory network for forecasting runoff in four distinct study areas: Shigu, Panzhihua, Pingshan, and Zhongjiang. Mauricio, & Ostia (2023) optimized forecasting accuracy by fine-tuning the smoothing coefficients, level, trend, and seasonal parameters of the HW method using Cuckoo Search Algorithm. Most recently, Minsan, & Minsan (2023) innovated by incorporating the additive decomposition model and the Additive HW model into the Whale Optimization Algorithm. In their study conducted in 2023, Minsan, & Minsan (2023) hybridized the Whale Optimization Algorithm with Additive Holt-Winters (WOA-HW+) and Additive Decomposition (WOA-D+). The consistent findings of their research highlighted the superiority of these hybrid models when compared to other established approaches in the field of time series forecasting. This underscores the substantial potential that WOA-HW+ and WOA-D+ hold for enhancing the accuracy and effectiveness of time series predictions, reaffirming their significance in the domain of time series forecasting. Furthermore, Nadimi-Shahraki et al. (2023) provided compelling evidence of WOA growing prominence. They documented an impressive surge in the number of citations for WOA, starting with 37 citations in 2016 and skyrocketing to a remarkable 7,410 citations by the end of March 2023. This surge in citations attests to the widespread popularity and significant impact of WOA in addressing a diverse range of optimization problems.

2. Objectives

This study introduces hybrid models that integrate the WOA with both the multiplicative Holt-Winters (WOA-HWx) and multiplicative decomposition (WOA-Dx) methods to improve the accuracy of monthly forecasting the amount of water inflow into the large dam reservoirs in Southern Thailand, including Pran Buri, Rajjaprabha, Bang Lang, and Kaeng Krachan. This contributes to efficient water management in the region. We conduct a comparative analysis of the forecasting outcomes achieved with WOA-HWx and WOA-Dx against those obtained from other established methods, including Additive Classical Decomposition (Classic-D+), Multiplicative Classical Decomposition (Classic-Dx), Grid Search for Additive Holt-Winters (Grid-HW+), Grid Search for Multiplicative Holt-Winters (Grid-HWx), WOA-HW+, WOA-D+, Box-Jenkins, and Long Short-Term Memory (LSTM).

3. Materials and Methods

3.1 Whale Optimization Algorithm

Harnessing the collective intelligence of humpback whales, WOA has emerged as a promising tool for parameter estimation in time series forecasting. Introduced by Mirjalili, & Lewis's (2016), this nature-inspired optimization technique has demonstrated remarkable efficacy in navigating complex optimization landscapes across diverse domains.

In the present study, we leverage the WOA's unique blend of exploration and exploitation capabilities to optimize parameters within both the HW method and the decomposition technique. By incorporating WOA's robust optimization capabilities, we aim to enhance the accuracy and efficiency of our forecasting models. A comprehensive overview of the WOA's formulation and implementation is provided in this section, illuminating its theoretical underpinnings and practical application. In a population of N whales, each represented by m-dimensional positions $x_i=(x_i^1, x_i^2,..., x_i^m)$, $i\in\{1, 2,..., N\}$, the optimization hunt unfolds through three key movements: encircling prey, bubble-net attacking, and searching for prey. At each iteration, a whale chooses one of these actions to update its position and progress towards the optimal parameter values.

3.1.1 Encircling Prey

In the context of the WOA algorithm, there exists a strategy known as 'encircling prey,' which draws inspiration from the hunting behavior of humpback whales. This strategy is employed when two conditions are met: when the random value p<0.5, and when the absolute value of $|\vec{A}|$<1.

The concept behind the encircling prey movement involves whales coordinating their efforts to encircle a target effectively, thereby maximizing their chances of capturing it. In the algorithm, this behavior is emulated through a process of updating the positions of the whales. These updates are determined based on the current positions of the whales and the best solution found up to that point. The mathematical representation of the position update equation for the encircling prey movement is as follows:

$$\vec{X}(t+1)=\vec{X}^*(t)-\vec{A}\cdot\vec{D} \tag{1}$$

in this context, $\vec{X}(t+1)$ represents the updated position of the whale in the next iteration, while $\vec{X}^*(t)$ denotes the best position discovered by the whale up to the current iteration. The vector $\vec{A}$ represents the amplitude coefficient, and $\vec{D}$ represents a vector generated randomly. This particular movement mechanism enables the whales to efficiently explore the search space and progressively move toward more promising solutions. The calculations for vectors $\vec{A}$ and $\vec{D}$ are carried out as follows:

$$\vec{A}=2\cdot\vec{a}\cdot\vec{r}-\vec{a}$$
$$\vec{D}=\left|\vec{C}\cdot\vec{X}^*(t)-\vec{X}(t)\right| \text{ where } \vec{C}=2\cdot\vec{r}$$

here, $\vec{a}$ undergoes a linear decrease from 2 to 0 as the iterations progress, applying to both the exploitation and exploration phases. The variable $\vec{r}$ is a random vector with values ranging from 0 to 1. Additionally, $\vec{C}$ is a coefficient vector. The operation denoted by · represents element-by-element multiplication.

3.1.2 Bubble-net Attacking (Exploitation Phase)

Within the framework of the WOA algorithm, a strategic approach known as 'bubble-net attacking' is inspired by the hunting tactics of humpback whales. This tactic is brought into play under specific conditions: when the random value $p\geq0.5$.

Bubble-net attacking is characterized by the humpback whales encircling the prey within a shrinking circle while following a spiral-shaped path. To capture this simultaneous behavior, a probabilistic approach is incorporated where there is a 50% chance of selecting either the shrinking encircling mechanism or the spiral model to update the positions of the whales during the optimization process. The mathematical definition of the spiral model is as follows:

$$\vec{X}(t+1)=\vec{D}'\cdot e^{bl}\cdot\cos(2\pi l)+\vec{X}^*(t) \quad (2)$$

within the context of the WOA algorithm, 'bubble-net attacking' is a strategic approach inspired by the hunting behavior of humpback whales. $\vec{D}'=|\vec{X}^*(t)-\vec{X}(t)|$ represents the distance of the i^{th} whale to the prey (the best solution found so far), b=1, and, $l=((-1+t(-1/T_{max}))-1)\vec{r}+1$, where T_{max} represents the maximum number of iterations.

3.1.3 Searching for Prey (Exploration Phase)

This exploration mechanism enables the whales to explore various regions within the search space, thereby enhancing the likelihood of uncovering improved solutions. During this phase, marked by an emphasis on exploration where the random value $p<0.5$, and when $|\vec{A}|\geq 1$.

The mathematical model for the exploration process entails the random adjustment of the whales' positions based on the following equations:

$$\vec{X}(t+1)=\vec{X}_{rand}-\vec{A}\cdot\vec{D} \quad (3)$$

here, $\vec{X}_{rand}$ represents a randomly selected position vector, essentially a random whale, from the current population. Additionally, $\vec{D}=|\vec{C}\cdot\vec{X}_{rand}-\vec{X}(t)|$ denotes a vector generated randomly. This mechanism, combined with a focus on exploration, strengthens the algorithm's capacity to traverse a wide spectrum of solutions, mitigating the risk of getting stuck in local optima.

These three movements are exemplified in the pseudo-code presented in Figure 1, which provides a comprehensive outline of the procedure. To enhance the performance of our forecasting model, we leveraged all three categories of whale movements.

First, we employed the 'encircling prey' movement, as described by Equation (1), for its effectiveness in optimizing local search. This movement focuses the algorithm's efforts on regions within the solution space that exhibit high fitness values, leading to the fine-tuning of potential solutions.

Second, we complemented this with the 'exploitation' technique, often referred to as 'bubble-net attacking' behavior, to promote a more diverse search strategy. This approach enhances exploration across various areas of the solution space, as described by Equation (2).

```
The number of whales: N, the number of parameters: m, maximum iterations: T_max , time limit: MaxTime, the fitness
value fails to improve after a specified: T_improve, the bound of search area: Range Initialize X_i=(x_i^j,x_i^2,...,x_i^m), X*

While (t < T_max or time < MaxTime  or the fitness value fails to improve after a specified T_improve)
    For i = 1 to N
         Check if any search agent goes beyond the search space and amend it
         For j = 1 to m
             p=rand[0,1]
             Update  a, r, A, C, D, D′, b, l, X_rand
             If  p≥0.5 then
                  Update x_i^j the position of the current search agent by the Equation (2) #Exploitation Phase
             Elseif  p<0.5 and |A|<1
                  Update x_i^j the position of the current search agent by the Equation (1) #Encircling Prey
             Elseif  p<0.5 and |A|≥1
                  Update x_i^j the position of the current search agent by the Equation (3) #Exploration Phase
             Endif
         End for
    End for
    Calculate fitness (X_i)
    Update  X* if there is a better solution
    t=t+1
End while
Return X*
```

Figure 1 Pseudo-code of the WOA (Mirjalili, & Lewis, 2016; Minsan, & Minsan, 2023)

Finally, we incorporated the 'exploration' movement for its broad search capabilities. This movement enables the algorithm to efficiently traverse a wider range of the solution space, increasing the likelihood of discovering the global optimum. This approach helps prevent premature convergence to local optima by exploring different areas of the solution space, as described by Equation (3).

Through this strategic integration of local refinement, diverse search strategy, and global search, the WOA effectively navigates the optimization landscape in pursuit of the most optimal parameter values for our forecasting model.

3.2 Forecasting Model

3.2.1 Classical Decomposition Method

The classical decomposition method is a time series forecasting approach that dissects a time series into its distinct constituents, which include the trend, seasonal, and residual components. The following are the typical steps employed in classical decomposition forecasting:

1. Data Preparation: Begin by collecting and formatting a sufficient historical dataset for forecasting purposes.

2. Visualization: Visualize the data through time series plots to discern underlying patterns, trends, and seasonality.

3. Seasonal Period Identification: Determine the duration of recurring cycles within the data.

4. Detrending: Eliminate the trend component to focus on seasonality and residuals. This typically involves using the centered moving averages. In an additive model, subtract the centered moving average values from the original time series. In a multiplicative model, divide the centered moving average values from the original time series.

5. Seasonality Estimation: Calculate average values for each season and then adjust them to determine the seasonal component. In an additive model, adjust the seasonal component by subtracting the overall average from each season. In a multiplicative model, adjust the seasonal component by dividing the overall average from each season.

6. Deseasonalization: Obtain a deseasonalized series by subtracting the seasonal component from the original time series in an additive model or dividing it in a multiplicative model.

7. Trend Calculation: Utilize linear regression to identify and quantify the trend component.

8. Forecasting: Predict future values by combining the forecasted trend and seasonal components. Mathematical equations, represented by Equations (4) - (7), are employed for both analytical modeling and prospective forecasting.

Additive Modeling: $Y_t=\beta_0+\beta_1 t+S_t+\varepsilon_t$ (4)

Additive Forecasting: $\hat{Y}_t=\hat{\beta}_0+\hat{\beta}_1 t+\hat{S}_t$ (5)

Multiplicative Modeling: $Y_t=(\beta_0+\beta_1 t)\times S_t\times\varepsilon_t$ (6)

Multiplicative Forecasting: $\hat{Y}_t=(\hat{\beta}_0+\hat{\beta}_1 t)\times\hat{S}_t$ (7)

where Y_t is the observed data at time t. $\hat{Y}_t$ is the forecasted data at time t. ε_t is the residual at time t. We assume it follows a normal distribution with a mean of zero and constant variance, and statistical independence from other time points. t is the time index. β_0, β_1 are the y-intercept, and the slope coefficient, respectively. $\hat{\beta}_0$, $\hat{\beta}_1$ are the estimated coefficients of β_0, β_1 respectively. S_t is seasonal component at time t, which falls within a specific season i (i=1,...,s). We define s as a 12-month cycle. Each time point t is thus associated with one of these 12 distinct seasons. $\hat{S}_t$ is estimated seasonal component of S_t.

9. Evaluation and Refinement: Assess the forecast against the actual data to gauge its accuracy and effectiveness.

Our approach is referred to as 'Classic-D+' for the additive model and 'Classic-Dx' for the multiplicative model.

3.2.2 Holt-Winters Method

The HW method is well-regarded for its adaptability in handling both additive and multiplicative seasonal variations within time series data, even when the training dataset is relatively small in size. In the context of additive fluctuations, Equations (8) - (11) intricately describe the necessary computations, offering a thorough guidance. Likewise, when dealing with multiplicative seasonality, Equations (12) - (15) provide a clear and methodical framework for the calculations.

Additive Forecasting:

$$\hat{Y}_{t+p}=\hat{T}_t+p\hat{\beta}_t+\hat{S}_{t-s+1+((p-1)\bmod s)} \quad \text{for } p=1,2,... \quad (8)$$

$$\hat{T}_t=\alpha(Y_t-\hat{S}_{t-s})+(1-\alpha)(\hat{T}_{t-1}+\hat{\beta}_{t-1}) \quad (9)$$

$$\hat{\beta}_t=\gamma(\hat{T}_t-\hat{T}_{t-1})+(1-\gamma)\hat{\beta}_{t-1} \quad (10)$$

$$\hat{S}_t=\delta(Y_t-\hat{T}_t)+(1-\delta)\hat{S}_{t-s} \quad (11)$$

Multiplicative Forecasting:

$$\hat{Y}_{t+p}=(\hat{T}_t+p\hat{\beta}_t)\times\hat{S}_{t-s+1+((p-1)\bmod s)} \text{ for } p=1,2,... \quad (12)$$

$$\hat{T}_t=\alpha(\frac{Y_t}{\hat{S}_{t-s}})+(1-\alpha)(\hat{T}_{t-1}+\hat{\beta}_{t-1}) \quad (13)$$

$$\hat{\beta}_t=\gamma(\hat{T}_t-\hat{T}_{t-1})+(1-\gamma)\hat{\beta}_{t-1} \quad (14)$$

$$\hat{S}_t=\delta(\frac{Y_t}{\hat{T}_t})+(1-\delta)\hat{S}_{t-s} \quad (15)$$

in the forecasting context, p is the number of time periods into the future for which predictions are made. s set at 12 months in this study, $\hat{T}_t$ is the level of the time series, $\hat{\beta}_t$ is the trend, and $\hat{S}_t$ is the seasonality component.

In this study, the smoothing coefficients α, γ, and δ are within the range of 0 to 1. These coefficients play a crucial role in determining the influence of the current observation and previous smoothed values when updating the model's level, trend, and seasonal components. A lower coefficient value, closer to 0, results in more pronounced smoothing, while values near 1 assign greater importance to recent observations. We can define two extreme cases in which smoothing coefficients are either 0 or 1. When researchers allow for smoothing coefficients equal to 1, this represents the least smoothed (or unsmoothed) version of the original time series. Conversely, when smoothing coefficients equal 0, this represents the smoothest version of the pattern that the actual time series follows (Montgomery et al., 2007). In commercial software like Minitab, smoothing coefficients can specifically be defined as 0 for maximum smoothing and 1 for minimal smoothing.

To optimize these parameters, we employ the Grid Search method. This approach involves systematically varying the coefficients in increments of 0.01, spanning the range from 0 to 1. This meticulous search process results in a total of 101^3 = 1,030,301 iterations. We label our method as 'Grid-HW+' for the additive model and 'Grid-HWx' for the multiplicative model. The selection of optimal parameters is based on minimizing the Mean Absolute Error (MAE).

Objective Minimize MAE(α, γ, δ)

Variable range $\begin{cases} 0\leq\alpha\leq1 \\ 0\leq\gamma\leq1 \\ 0\leq\delta\leq1 \end{cases}$

$$\text{MAE}=\frac{1}{m}\sum_{t=1}^{m}\left|Y_t-\hat{Y}_t\right| \quad (16)$$

where m is the length of dataset, with m=48 for the model construction and m=72 for the future forecasting; Y_t is the actual value, and $\hat{Y}_t$ is the forecasted value produced by either Grid-HW+ or Grid-HWx.

3.2.3 Hybrid the Whale Optimization Algorithm with Holt-Winters (WOA-HW)

We utilized the WOA to optimize the α, γ, and δ parameters for the HW model. The computational steps for this process are outlined in the pseudo-code provided in Figure 2.

We evaluated the performance of the HW model with the optimal parameters by assessing forecast accuracy. This assessment involves measuring the error between the forecasted data and the dataset. The objective function for the WOA-HW model is defined by the following Equation (16). Where m is for the length of dataset; Y_t is the actual value, and $\hat{Y}_t$ is the forecasted value produced by either WOA-HW+ or WOA-HWx.

3.2.4 Hybrid the Whale Optimization Algorithm with Decomposition (WOA-D)

The optimization of parameters has a great impact on the performance of the WOA-D model. In this study, WOA was used to solve the $\hat{\beta}_0, \hat{\beta}_1, \hat{S}_1, \hat{S}_2, \hat{S}_3, \hat{S}_4, \hat{S}_5, \hat{S}_6, \hat{S}_7, \hat{S}_8, \hat{S}_9, \hat{S}_{10}, \hat{S}_{11}$ and $\hat{S}_{12}$ parameters of decomposition. This process are outlined in the pseudo-code provided in Figure 3.

Scaling Parameters

1) Setting Constraints for Upper and Lower Bounds of Parameters:

1.1) Constraints on the Upper and Lower Bounds of $\hat{\beta}_0$ and $\hat{\beta}_1$.

Calculate the trend component using linear regression on the dataset to obtain $\hat{\beta}_0'$ and $\hat{\beta}_1'$. We recommend constraining the upper and lower bounds of the parameters $\hat{\beta}_0$ and $\hat{\beta}_1$ according to the following equation:

Constraint the upper bound of
$\hat{\beta}_0$ as $1.2\hat{\beta}_0'$ and $\hat{\beta}_1$ as $1.2\hat{\beta}_1'$

Constraint the lower bound of
$\hat{\beta}_0$ as $0.8\hat{\beta}_0'$ and $\hat{\beta}_1$ as $0.8\hat{\beta}_1'$

Note: These constraints apply when the parameter is positive. Conversely, if the parameter is negative, the upper and lower bounds should be switched.

1.2) Constraints on the Upper and Lower Bounds of $\hat{S}_i$ (i=1, 2,..., 12).

```
The number of whales: N=100, the number of parameters: m=3, maximum iterations: T_max=300, time limit:
MaxTime=30 sec., the fitness value fails to improve after a specified: T_improve=50, the bound of search area:
Range Initialize X_i=(x_i^j, x_i^2, x_i^3), X^*

While (t < T_max or time < MaxTime or the fitness value fails to improve after a specified T_improve)
    For i = 1 to N
        Check if any search agent goes beyond the search space and amend it
        For j = 1 to m
            p=rand[0,1]
            Update a, r, A, C, D, D′, b, l, X_rand
            If p≥0.5 then
                Update x_i^j the position of the current search agent by the Equation (2) #Exploitation Phase
            Elseif p<0.5 and |A|<1
                Update x_i^j the position of the current search agent by the Equation (1) #Encircling Prey
            Elseif p<0.5 and |A|≥1
                Update x_i^j the position of the current search agent by the Equation (3) #Exploration Phase
            Endif
        End for
    End for
    Calculate fitness (X_i) using HW by the Equation (16)
    Update X^* if there is a better solution
    t=t+1
End while
Return X^*=(x^1*, x^2*, x^3*) #Objective Minimize MAE(α^*, γ^*, δ^*) where α^*=x^1*, γ^*=x^2*, δ^*=x^3*
```

Figure 2 Pseudo-code of the WOA-HW

```
The number of whales: N=100, the number of parameters: m=14, maximum iterations: T_max=300, time limit:
MaxTime=30 sec., the fitness value fails to improve after a specified: T_improve=50, the bound of search area:
Range Initialize X_i=(x_i^j, x_i^2,..., x_i^14), X^*

While (t < T_max or time < MaxTime or the fitness value fails to improve after a specified T_improve)
    For i = 1 to N
        Check if any search agent goes beyond the search space and amend it
        For j = 1 to m
            p=rand[0,1]
            Update a, r, A, C, D, D′, b, l, X_rand
            If p≥0.5 then
                Update x_i^j the position of the current search agent by the Equation (2) #Exploitation Phase
            Elseif p<0.5 and |A|<1
                Update x_i^j the position of the current search agent by the Equation (1) #Encircling Prey
            Elseif p<0.5 and |A|≥1
                Update x_i^j the position of the current search agent by the Equation (3) #Exploration Phase
            Endif
        End for
    End for
    Scaling Parameters
    Calculate fitness (X_i) using Decomposition by the Equation (17)
    Update X^* if there is a better solution
    t=t+1
End while
Return X^*=(x^1*, x^2*,..., x^14*)
#Objective Minimize MAE(β̂_0^*, β̂_1^*, Ŝ_1^*, Ŝ_2^*, Ŝ_3^*, Ŝ_4^*, Ŝ_5^*, Ŝ_6^*, Ŝ_7^*, Ŝ_8^*, Ŝ_9^*, Ŝ_10^*, Ŝ_11^*, Ŝ_12^*) where β̂_0^*=x^1*, β̂_1^*=x^2*,..., Ŝ_12^*=x^14*
```

Figure 3 Pseudo-code of the WOA-D

Remove the trend component from the time series using differencing ($\Delta Y_t = Y_t - Y_{t-1}$). We recommend constraining the upper and lower bounds of parameters $\hat{S}_1, \hat{S}_2, ..., \hat{S}_{12}$ according to the following equation:
Constraint the upper bound (UB) is +(extreme value) of amplitude of ΔY_t.
Constraint the lower bound (LB) is -(extreme value) of amplitude of ΔY_t.

2) We configure the WOA to search for parameters within the boundary of [0, 1]. Therefore, it is necessary to adjust the units of the parameters before calculating the fitness value. The following equation is employed for this purpose:
Original Value = Scaled Value × (UB – LB) + LB.

If the original values are denoted as ($\hat{S}_i$), the seasonal adjustment can be calculated using the formula:

Additive decomposition Adjust $\hat{S}_i = \hat{S}_i - \sum_{i=1}^{12} \frac{\hat{S}_i}{12}$ then $\sum_{i=1}^{12} \hat{S}_i = 0$

Multiplicative decomposition Adjust $\hat{S}_i = \frac{\hat{S}_i}{\sum_{i=1}^{12} \frac{\hat{S}_i}{12}}$ then $\sum_{i=1}^{12} \hat{S}_i = 12$.

In this equation, the original value represents the parameter value based on the original data unit, while the scaled value is the value obtained by the WOA within the range of [0, 1]. This step holds significant importance, especially when dealing with parameters of different units and a considerable number of parameters.

The objective function of WOA-D to the following equation:

Objective Minimize

$$\text{MAE}(\hat{\beta}_0, \hat{\beta}_1, \hat{S}_1, \hat{S}_2, \hat{S}_3, \hat{S}_4, \hat{S}_5, \hat{S}_6, \hat{S}_7, \hat{S}_8, \hat{S}_9, \hat{S}_{10}, \hat{S}_{11}, \hat{S}_{12})$$

$$\text{Variable range} \begin{cases} 0.8\hat{\beta}_0' \leq \hat{\beta}_0 \leq 1.2\hat{\beta}_0' \\ 0.8\hat{\beta}_1' \leq \hat{\beta}_1 \leq 1.2\hat{\beta}_1' \\ \text{LB} \leq \hat{S}_i \leq \text{UB for } i = 1, 2, ..., 12 \end{cases}$$

$$\text{MAE} = \frac{1}{m} \sum_{t=1}^{m} \left| Y_t - \hat{Y}_t \right| \quad (17)$$

where m is the length of dataset, with m = 48 for the model construction and m = 72 for the future forecasting; Y_t is the actual value, and $\hat{Y}_t$ is the forecasted value produced by either WOA-D+ or WOA-Dx.

3.3 Data Preparation

This study utilizes secondary data from the Royal Irrigation Department (2024) regarding water inflow into four major southern Thai dam reservoirs (Big Dams or large reservoirs): Pranburi, Rajjaprabha, Bang Lang, and Kaeng Krachan Dams. The dataset inherently displays both seasonality and a time trend. Analysis using the Autocorrelation Function (ACF), depicted in Figure 4 provided compelling evidence for these characteristics and solidified the case for using this dataset in our experiments. (Definition: A large reservoir is defined as one with a water storage volume exceeding 100 million cubic meters, a reservoir area exceeding 15 square kilometers, or an irrigation area exceeding 80,000 rai.)

The dataset spans January 2018 to December 2023, comprising 72 data points. This data was divided into training (48 points, Jan 2018 - Dec 2021) and test (24 points, Jan 2022 - Dec 2023) datasets. The training dataset formed the basis for constructing the forecasting model, while the test dataset evaluated its accuracy. Finally, upon obtaining the appropriate model, all 72 data points were used to forecast the water inflow into these large dam reservoirs for the period of January 2024 to December 2025 (24 data points).

3.4 Evaluation Criteria

Our evaluation framework is divided into two distinct categories:

The initial category's objective is to determine the most effective modeling approach by evaluating which one results in the lowest MAE during the training dataset phase. Here $\text{MAE} = \frac{1}{n_1} \sum_{t=1}^{n_1} \left| Y_t - \hat{Y}_t \right|$, n_1=48 is the length of the training dataset, while Y_t and $\hat{Y}_t$ are the actual and forecasted values of the training dataset, respectively. We will choose the modeling approach with the lowest MAE after comparing Classic-D with WOA-D and Grid-HW with WOA-HW.

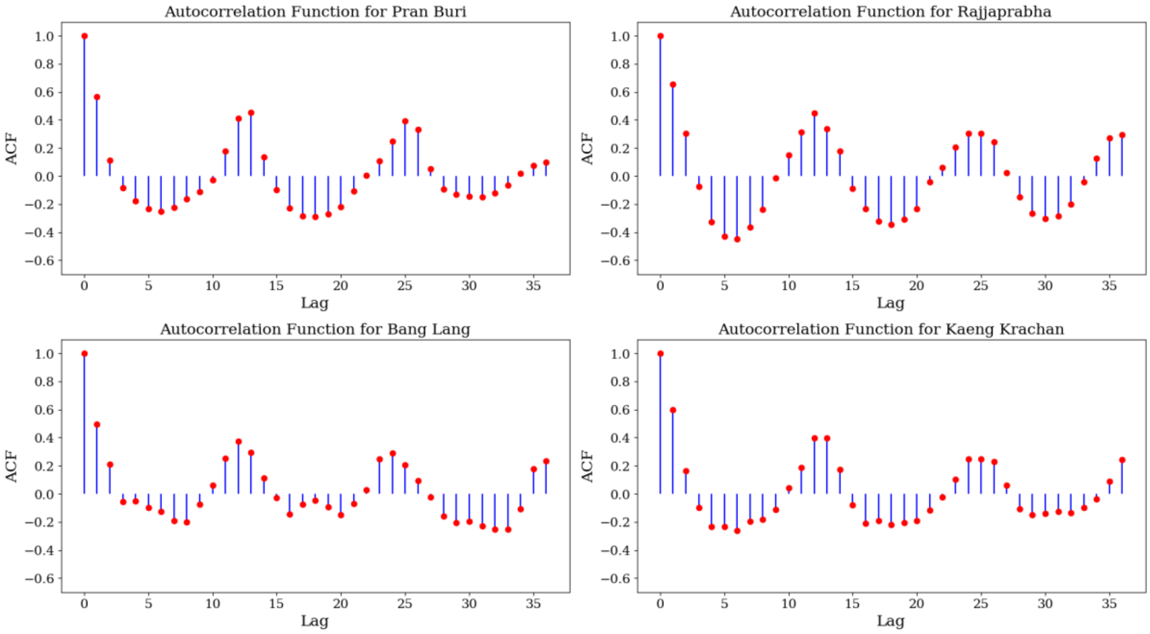

Figure 4 ACF of water inflow for each dam

The second category, to accurately evaluate the effectiveness of our water inflow prediction model for large dam reservoirs in Southern Thailand, and draw meaningful conclusions about its strengths and weaknesses, we will utilize three established metrics: Root Mean Square Error (RMSE), MAE, and Symmetric Mean Absolute Percentage Error (sMAPE). RMSE captures the average magnitude of prediction errors, giving us a sense of overall accuracy. MAE focuses on the average absolute difference, highlighting how consistently close the predictions are to actual values. Finally, sMAPE expresses the average error as a percentage of the actual inflow, allowing for fair comparison across dam reservoirs with varying inflow rates. By analyzing these metrics together, we gain a comprehensive understanding of the model performance and can confidently use this information to optimize water resource management for large dam reservoirs in Southern Thailand.

$$\text{RMSE}=\sqrt{\frac{1}{24}\sum_{t=49}^{n_2}\left(Y_t-\hat{Y}_t\right)^2} \quad (18)$$

$$\text{MAE}=\frac{1}{24}\sum_{t=49}^{n_2}\left|Y_t-\hat{Y}_t\right| \quad (19)$$

$$\text{sMAPE}=100\times\frac{1}{24}\sum_{t=49}^{n_2}\frac{|Y_t-\hat{Y}_t|}{\frac{(Y_t+\hat{Y}_t)}{2}} \quad (20)$$

(Hyndman, & Koehler, 2006)

where n_2=72, which is the length of the test dataset; Y_t and $\hat{Y}_t$ are the actual value and forecasting value of the test dataset, respectively.

The experiments were carried out using a Google Colab (2023) environment, which offers seamless access to Python programming capabilities.

4. Results

4.1 Analysis of Comparative Performance During the Training Dataset Phase

This section assesses the performance of the WOA-HW and WOA-D models in forecasting water inflow into large dam reservoirs, with their effectiveness being compared against two classical forecasting models, namely Classic-D and Grid-HW, all applied to the same dataset. The outcomes of this analysis are detailed in Table 1. The parameter optimization capabilities of the WOA models seamlessly integrate with both HW and decomposition techniques.

- WOA-HW vs. Grid-HW: The WOA's parameter optimization significantly improved the HW model. In pairwise comparisons, the WOA-HW model demonstrated lower MAE for three dams (Pran Buri, Bang Lang, and Kaeng Krachan) compared to Grid-HW. However, for Rajjaprabha Dam, the Grid-HW model (in both its additive and multiplicative models) had lower MAE values than WOA-HW.

- WOA-D vs. Classic-D: Across all dams, WOA-D, in both its additive and multiplicative models, consistently showed lower MAE values than Classic-D, indicating a stronger performance of the WOA-enhanced Decomposition approach over the traditional method.

Integrating the WOA with HW and decomposition methods proves advantageous, leading to more precise model fitting compared to classical forecasting approaches. This improvement is evident in the pairwise comparisons and across all dams, underscoring the effectiveness of WOA in enhancing forecasting models.

4.2 Analysis of Comparative Performance During the Testing Dataset Phase

In this phase of the study, we generated long-term forecasts spanning a two-year period, equivalent to 24 months. To evaluate the performance of various forecasting models, we employed key metrics including RMSE, MAE, and sMAPE. We conducted a comprehensive comparative analysis, pitting two traditional statistical models, Grid-HW and Classic-D, against advanced models incorporating the WOA, namely WOA-HW and WOA-D. Additionally, we included the Box-Jenkins model and the Long Short-Term Memory (LSTM) technique for thorough evaluation.

For the Box-Jenkins model, parameter identification followed a multi-step process. This included analyzing the time series curve, the Autocorrelation Function (ACF), and the Partial Autocorrelation Function (PACF). We employed the Dickey-Fuller (DF) test to detect unit roots, with a maximum lag order set at 12. Model selection was facilitated by minimizing the Akaike Information Criterion (AIC) value. Non-stationary time series data were transformed into stationary forms through differencing to obtain d and D values or via the Box-Cox transformation (natural logarithm transformation). The hyperparameters p, q, P, and Q were all set within a range of 0 to 2. We utilized a grid search, a machine learning optimization technique, for hyperparameter tuning and to identify models that achieved the minimum AIC values. The process of selecting the order with the lowest AIC continued until all tests were passed for the model residuals. Minitab was used to test residual values. These tests included assessing normality using the Anderson-Darling test (AD), verifying a mean of zero using the t-test, ensuring constant variance with Levene's test, and checking for statistical independence from other time points using the Ljung-Box (Lag 12) test. The model that met these criteria and had the minimum AIC value was chosen as the forecasting model.

For the LSTM model, we configured hyperparameters as follows: the loss function was set to MAE, the optimizer was Adam, and the number of epochs was fixed at 100. We experimented with three different look back hyperparameter values: 12, 18, and 24. The number of neurons in the LSTM layer was set to 50. The implementation was carried out in Python. We determined the forecasting model based on the one that yielded the lowest MAE values in the test dataset.

This comprehensive approach allowed us to thoroughly evaluate and compare the performance of these forecasting models during the testing dataset phase.

A summary of the model performance metrics for various dams is detailed in Table 2 (RMSE), Table 3 (MAE), and Table 4 (sMAPE). Notably, the WOA-HWx model demonstrated the most accurate forecasts for Pran Buri dam, achieving the lowest MAE and sMAPE values. Similarly, the WOA-D+ model outperformed other models in all metrics at Bang Lang dam, while the WOA-Dx model excelled in all metrics at Kaeng Krachan dam. These findings indicate that the integration of the WOA models with HW and decomposition methods is effective for forecasting water inflow into these reservoirs and will be utilized for the forecast period from January 2024 to December 2025. In the case of Rajjaprabha dam, the Box-Jenkins model, enhanced with a Box-Cox transformation using a natural logarithm, emerged as the superior model. It met all the necessary statistical assumptions, including residual normal distribution (AD = 0.359, p-value = 0.433), constant variance (homoscedasticity) (Levene = 1.24, p-value = 0.274), independence of residuals (Ljung-Box (Chi-square) = 14.10, p-value = 0.169), and residuals with zero mean (t = -0.39, p-value = 0.702). The model also recorded the lowest MAE and sMAPE values. Based on its strong performance, the Box-Jenkins method will be the preferred forecasting model for Rajjaprabha dam for the period January 2024 to December 2025.

Specific forecasting methods to the entire time series dataset for a two-year period from January 1, 2024, to December 31, 2025, which spans 24 months. The results, illustrated in Figure 5 and Table 5, demonstrate a close alignment between the actual and forecasted water inflow values for each dam reservoir, indicating the accuracy of the forecasting methods.

Table 1 MAE of training dataset for each dam

Model			Dam reservoir			
			Pran Buri	**Rajjaprabha**	**Bang Lang**	**Kaeng Krachan**
Decomposition	Additive	Classic-D+	24.7008	79.1668	53.6908	53.6645
		WOA-D+	24.0992	69.6281	49.2657	43.4409
	Multiplicative	Classic-Dx	24.5530	73.7793	57.4436	48.2138
		WOA-Dx	18.1602	68.2925	48.1075	42.3196
Holt-Winters	Additive	Grid-HW+	31.8431	98.2238	68.8142	67.7132
		WOA-HW+	31.6274	98.5740	68.6812	67.6597
	Multiplicative	Grid-HWx	31.9394	85.6059	68.8875	67.7132
		WOA-HWx	31.9394	86.1263	68.8567	67.6952

Note: The lowest MAE value between Classic-D and WOA-D, and between Grid-HW and WOA-HW is highlighted

Table 2 RMSE of test dataset for each dam reservoir

Model			Dam reservoir			
			Pran Buri	**Rajjaprabha**	**Bang Lang**	**Kaeng Krachan**
Decomposition	Additive	Classic-D+	53.26	105.75	108.83	61.73
		WOA-D+	44.60	113.24	100.55	43.96
	Multiplicative	Classic-Dx	118.92	104.34	111.76	49.67
		WOA-Dx	81.19	101.98	104.80	33.77
Holt-Winters	Additive	Grid-HW+	51.51	128.10	113.04	60.28
		WOA-HW+	50.69	220.46	113.08	60.15
	Multiplicative	Grid-HWx	51.13	258.68	110.11	60.28
		WOA-HWx	51.04	290.77	110.28	60.32
Box-Jenkins			61.63	109.66	172.36	44.04
LSTM			53.70	116.34	150.44	33.84

Note: The lowest RMSE value for each dam reservoir is highlighted

Table 3 MAE of test dataset for each dam reservoir

Model			Dam Reservoir			
			Pran Buri	**Rajjaprabha**	**Bang Lang**	**Kaeng Krachan**
Decomposition	Additive	Classic-D+	42.70	77.07	90.41	41.88
		WOA-D+	38.98	75.31	76.78	30.10
	Multiplicative	Classic-Dx	72.92	72.26	93.64	32.02
		WOA-Dx	48.33	70.09	88.56	22.10
Holt-Winters	Additive	Grid-HW+	35.13	88.89	87.57	42.75
		WOA-HW+	34.64	188.26	87.56	42.57
	Multiplicative	Grid-HWx	33.05	180.22	87.55	42.75
		WOA-HWx	33.00	203.07	87.78	42.77
Box-Jenkins			38.39	69.33	126.03	30.20
LSTM			33.71	76.62	96.98	25.26

Note: The lowest MAE value for each dam reservoir is highlighted

Table 4 sMAPE of test dataset for each dam reservoir

Model			Dam Reservoir			
			Pran Buri	**Rajjaprabha**	**Bang Lang**	**Kaeng Krachan**
Decomposition	Additive	Classic-D+	94.44	42.00	45.04	88.74
		WOA-D+	93.48	30.75	39.13	51.33
	Multiplicative	Classic-Dx	99.03	33.02	47.46	40.02
		WOA-Dx	85.57	31.56	44.59	31.71
Holt-Winters	Additive	Grid-HW+	84.81	35.64	43.72	49.05
		WOA-HW+	85.23	69.31	43.75	48.80
	Multiplicative	Grid-HWx	80.23	56.08	43.92	49.05
		WOA-HWx	80.19	59.77	44.01	49.09
Box-Jenkins			81.32	29.59	54.66	37.45
LSTM			89.85	37.53	45.09	43.52

Note: The lowest sMAPE value for each dam reservoir is highlighted

Table 5 Forecasted water inflow into dam reservoirs (million cubic meters), January 2024 - December 2025

Month/Year	Dam Reservoir			
	Pran Buri (WOA-HWx)	**Rajjaprabha (SARIMA(0,0,2)(1,1,0)$_{12}$)**	**Bang Lang (WOA-D+)**	**Kaeng Krachan (WOA-Dx)**
Jan-2024	5.93	86.41	283.38	11.43
Feb-2024	5.97	79.61	180.94	10.22
Mar-2024	4.62	84.40	169.81	9.53
Apr-2024	5.31	96.28	155.66	18.19
May-2024	7.32	142.27	214.75	17.22
Jun-2024	18.75	168.33	192.69	21.35
Jul-2024	19.67	497.23	179.90	40.69
Aug-2024	68.34	362.86	162.09	108.31
Sep-2024	81.19	410.47	160.33	78.65
Oct-2024	63.06	356.94	263.44	76.03
Nov-2024	34.27	174.86	320.51	19.55
Dec-2024	7.61	108.77	375.95	8.77
Jan-2025	5.93	81.00	302.76	8.38
Feb-2025	5.97	61.93	200.32	7.43
Mar-2025	4.62	66.96	189.18	6.87
Apr-2025	5.31	81.77	175.04	12.99
May-2025	7.32	114.73	234.12	12.18
Jun-2025	18.75	171.83	212.06	14.95
Jul-2025	19.67	465.52	199.27	28.18
Aug-2025	68.34	434.91	181.47	74.12
Sep-2025	81.19	482.13	179.71	53.15
Oct-2025	63.06	311.96	282.81	50.70
Nov-2025	34.27	171.93	339.88	12.85
Dec-2025	7.61	100.77	395.33	5.68

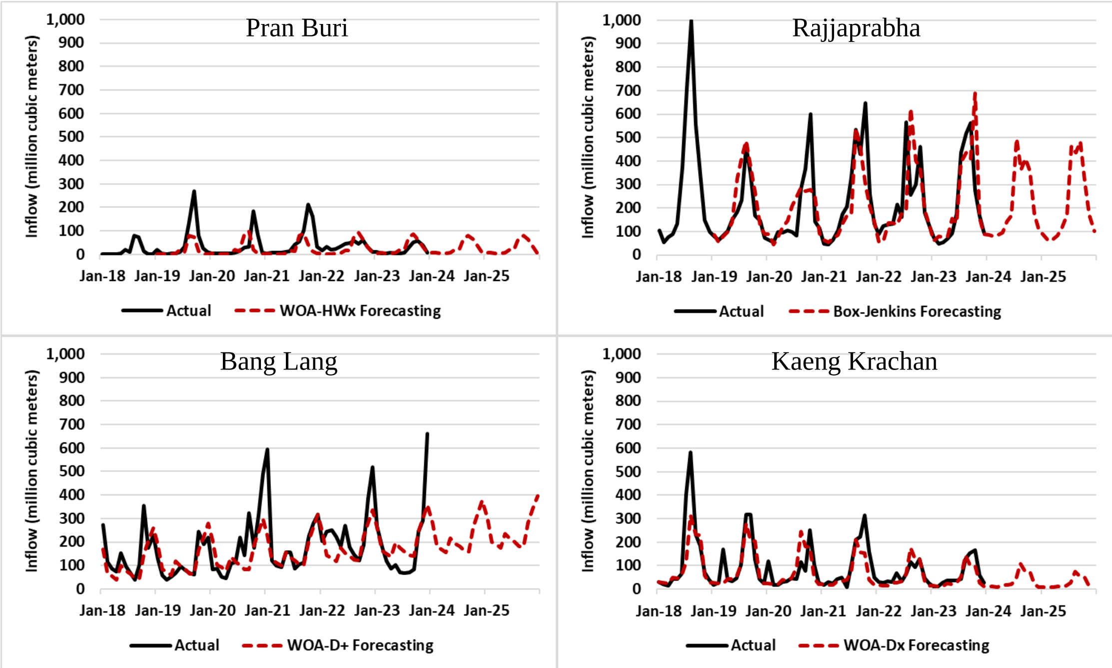

Figure 5 Actual and forecasted values for each dam reservoir using the most suitable forecasting method

5. Discussion

The results from the training dataset phase indicate that integrating the WOA with HW and decomposition methods leads to more precise model fitting compared to classical forecasting approaches. This improvement was evident in the pairwise comparisons and across all dams, underscoring the effectiveness of WOA in enhancing forecasting models.

In the testing dataset phase, the WOA integrated with HW and decomposition methods demonstrated exceptional accuracy across various dams. Specifically, for Pran Buri dam, the model had the lowest MAE and sMAPE, indicating highly accurate forecasts. Similarly, at Bang Lang and Kaeng Krachan dams, it outperformed all other models in every metric, demonstrating its effectiveness in diverse forecasting scenarios. For Rajjaprabha dam, however, the Box-Jenkins model emerged as the top performer. Enhanced with a Box-Cox transformation, this model met all necessary statistical assumptions and achieved the lowest MAE and sMAPE values, demonstrating its robust performance.

Our new hybrid model integrates advanced optimization techniques with forecasting methods, enabling more precise parameter tuning and improved adaptability to complex time series patterns. By leveraging the WOA alongside HW and Decomposition, our model optimizes both additive and multiplicative components, enhancing forecast accuracy through a comprehensive and adaptable framework represented by equations (1) – (3) for Encircling Prey, Exploitation Phase, and Exploration Phase.

These findings demonstrate the effectiveness of integrating the WOA with HW and decomposition methods for forecasting water inflow into reservoirs, and they will be utilized for the upcoming forecast period. The success of the Box-Jenkins model at Rajjaprabha Dam also highlights the continued relevance of traditional methods in certain scenarios.

6. Conclusions

When forecasting, it is beneficial to compare multiple models to identify the best method for a given dataset. This comparison often involves evaluating the performance of each model on a testing dataset using error metrics such as RMSE, MAE, and sMAPE, which measure discrepancies between actual and forecasted values. Additionally, visual inspection of plotted actual versus forecasted values can offer insights into each model fit.

Each model, including decomposition, HW, Box-Jenkins, and LSTM, has unique strengths and limitations. Decomposition models excel in dissecting time series into trend, seasonal, and irregular components. HW, known for their simplicity, are effective in data with trend and seasonality. Box-Jenkins models offer greater flexibility but require more extensive data for training. LSTM models, a branch of deep learning, are adept at forecasting data with complex patterns. This research also reaffirms the efficacy of traditional methods, such as the Box-Jenkins approach, which continue to yield robust results, as evidenced in the Rajjaprabha dam dataset.

Building upon the research of Minsan, & Minsan (2023), which utilized only the additive model for integrating the WOA with HW and decomposition methods, our study expanded the approach to include both additive and multiplicative models. This enhancement significantly improved the versatility and precision of model fitting, surpassing the performance of traditional forecasting methods. Notably, the models demonstrated robust forecasting capabilities up to 24 months in advance, as evidenced by their performance in both the training and testing phases.

In conclusion, this research has successfully introduced an innovative forecasting methodology by integrating the WOA with HW and decomposition models, demonstrating superior predictive accuracy across all four dams studied. Future research will focus on refining these techniques and expanding their application to various time series datasets to assess their adaptability and effectiveness in diverse scenarios.

7. Acknowledgements

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