Shared Vision Planning for Hydrological System: Fuzzy Evaluation and Heuristic Algorithms for Water Level Prediction

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Abstract. Effectively managing hydrological systems requires a comprehensive strategy involving data collection, predictive modeling, and stakeholder engagement. This study integrates "Shared Vision Planning" principles with fuzzy evaluation and heuristic search, aiming for a balanced and sustainable hydrological system management strategy. The synergy between fuzzy evaluation and heuristic algorithms establishes a robust decision-making framework, optimizing water resource utilization and addressing varied interest groups' concerns. Tested using data from the Great Lakes region in North America, our model demonstrates effectiveness in achieving coordinated water resource management, contributing to a resilient water resource management paradigm with positive implications for regional development.

1 Introduction and Preparation

Water is vital for societal and economic development, impacting daily life and activities. Droughts and floods disrupt communities, emphasizing the need for effective hydrological control. Tranquil water surfaces and steady river flows support sustainable economies. Historical water disasters, like the 1931 Yangtze flood and the 2017 Houston flood, highlight challenges in hydrological control under unconventional climates.[1,2] Decision-makers must promptly address difficulties, ensuring actions like water storage and flood discharge for regional economic sustainability amid climatic uncertainties.

This paper outlines a methodology for predicting and controlling water levels using historical hydrological and climatic data. Sensitivity to anomalies is demonstrated, and stakeholder interests are analyzed using fuzzy analysis. A weighting method considers satisfaction levels. Specific input-output equations for subsystems are established and refined through heuristic search using current weather observations and future predictions, allowing adjustments to hydraulic engineering, guiding project operation, siting, and construction through comparative analysis of hydrological system control effects before and after changes.

To enhance the reliability and practicality of the Evaluation Model of Optimal Water Level, we have strategically formulated specific assumptions to aid in the development and validation of the model. We have categorized the year into three seasons based on most lakes' conditions all around the world: May to August is the Flood Season, April and September to November are the Normal Flow Season, and December to March is the Freezing Season, as shown in Figure 1.

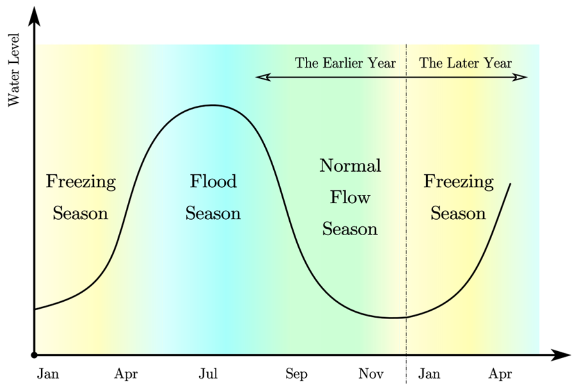

Figure 1 Lake Water Levels in Three-Seasons of the Year

2 Optimal Water Level

Prior to predicting a hydrological system's water level, a comprehensive evaluation follows Shared Vision Planning principles, involving stakeholder identification, region evaluation, and understanding water demands [3] The target water level is categorized into intervals based on these principles, ensuring considerate Affiliate Functions. Aligned with Shared Vision Planning, the approach prioritizes systematic water level categorization, emphasizing inclusivity, with primary stakeholders being Ecological Factors, Residents, Hydroelectricity Works, Tourism, and Shipping Economy.[4] Natural disasters create outliers, impacting model accuracy, so we use the boxplot method for data pre-processing, efficiently identifying outliers beyond predefined warning water levels.

Applying the box plot discriminant method, non-outliers are defined within the range [QL-1.5IQR,QU+1.5IQR], which is shown as Figure 2,

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and Figure 3 shows the comparison between the conditions before and after the outlier cleaning.

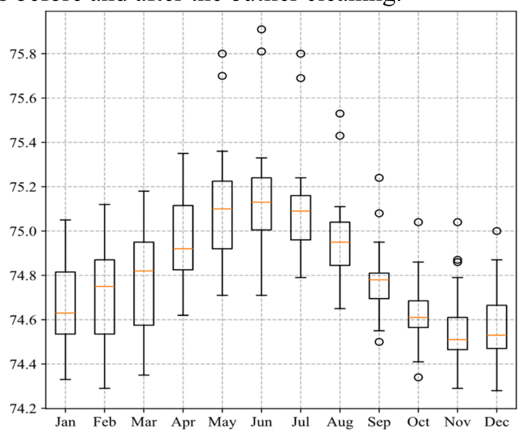

Figure 2 Raw Data Plot

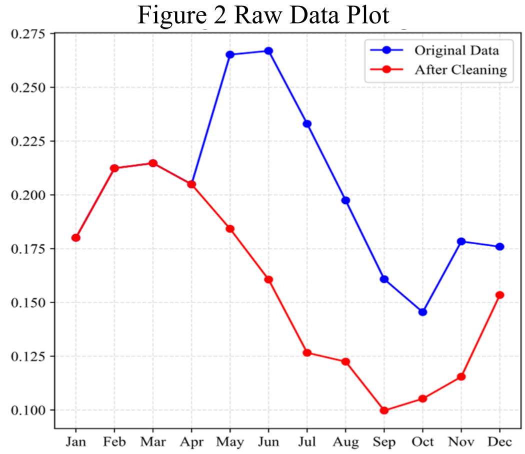

Figure 3 Comparison Plot

Historical water level data outside this range are considered outliers and excluded. This criterion is rigorously validated using North American historical water level data and corresponding weather conditions, consistently identifying outlier years during floods or droughts. Importantly, this standard is adaptable to accommodate the hydrological characteristics of different regions.

2.1 Target Water Level with Fuzzy Evaluation

Addressing the challenge of diverse stakeholder preferences in achieving precise optimal water level assessment, the Fuzzy Comprehensive Evaluation Method proves suitable. This method involves several steps.

Initially, establish the element set, comprising evaluation indicators forming the evaluation indicator system. Designate each demand from the hydrological system's comprehensive evaluation as an element set, denoted as U， $U = u_1, u_2, \ldots, u_i$, where i is the total number of demands to be considered. Secondly, after determining the factor set, establish the Commentary Set for evaluation outcomes. Considering long-term fluctuations, use the arithmetic mean (μ) and standard deviation (σ) of historical data processed with the Box Plot Discriminant Method as evaluation indicators. Following validation, it's found that the water level of $\mu + 3\sigma$ closely approaches the warning level each month. To enhance safety, upper and lower limits are prudently narrowed. Thus, we derive the evaluation set $V = \{v_1, v_2 \cdots, v_7\}$. In which, $v_i = \mu + \left[(i-4)/2\right] \cdot \sigma$.

Due to seasonal variations in the hydrological system, the Affiliated Functions are streamlined. Each demand-side assesses water levels during annual periods instead of monthly. Taking the flood season shipping company as an example, the membership function is shown in Formula 1.

$$A(x) = \begin{cases} 0, & x < -3 \\ x+3, & -3 < x \le -2 \\ 1, & -2 < x \le 1.5 \\ 2.5 - x, & 1.5 < x \le 2.5 \\ 0, & x > 2.5 \end{cases} \tag{1}$$

It's crucial to note that upstream ice levels correlate with downstream spring flow, prompting stakeholders to avoid high water levels during this period. Hence, in the dry season, when all stakeholders share the same Affiliated Functions, maintaining moderate or lower water levels is recommended for safety reasons.

Finally, establishing decision weights for each demand side requires careful consideration of varying influences on the regional economy and livelihoods during different periods. Consulting with local experts is crucial, and due to challenges in obtaining data, the entropy weighting method is employed for objective weighting, showcasing feasibility. Any weighting method aligned with Shared Vision Planning principles is acceptable.

In the practical application of our methodology for deriving the optimal water level, we initiate the process with standardizing water level data using the formula $Z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}$. Subsequently, the probability matrix is calculated as $p_{ij} = \frac{\tilde{z}_{ij}}{\sum_{i=1}^{n} \tilde{z}_{ij}}$. Information entropy for each indicator is then computed using the formula $e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln(p_{ij})$ $(j = 1,2,\cdots,m)$. Entropy weights for each indicator are determined as $W_j = \frac{1-e_j}{\sum_{j=1}^{m}(1-e_j)}$. These weights guide forming the Judgment Matrix R based on water levels. The final vector B is obtained by multiplying entropy weights with R using $B = A \cdot R$. This holistic assessment ensures accurate target water levels, considering varied stakeholder concerns.

2.2 Results and Analysis

We validate it using actual data. To compute the optimal water level for distinct time periods, we segment the data into Three-Periods. Given the flexibility in each demand side's expectations for water levels during different periods, weights for each indicator are obtained during the wet and normal periods, as illustrated in Table 1.

Table 1 The Weight of each Stakeholder

Stakeholders	**Flood Season**	**Normal Flow Season**
Shipping Economy	0.2314	0.0861
Ecological Factors	0.2256	0.2681
Residents	0.2307	0.2749

Hydroelectricity Works	0.0833	0.0990
Tourism	0.2289	0.2720

According to the description of water level standardization in Section 2.1, the optimal water levels during the flood season and normal periods for the example area are set at the historical mean and one standard deviation above the historical mean, denoted as μ and $\mu + 1\sigma$ respectively. This data essentially meets the demands of all stakeholders in the example, with specific emphasis on addressing the preferences of different demand sides during distinct periods. This provides evidence of the method's effectiveness.

3 Water Level Prediction and Regulation Method

3.1 Method Preparation and Dataset Selection

Irregular lake bottoms, a common challenge, are effectively managed by adopting a technique treating the lake bottom as an inverted cone.[5] Evaluating changes in surface area and depth, akin to calculating a column's volume, allows straightforward computation of storage volume changes. To implement our hydrological system prediction and control method, crucial data support is needed. We selected historical data from the well-established meteorological and hydrological observations in the US. Our hydrological system includes five lakes and two hydraulic projects. Lakes Huron and Michigan are treated as a single subsystem due to special connectivity.[6] The remaining lake subsystems are labeled Lake 1 to 4, and the two hydraulic projects are Dam 1 and 2. Ensuring outflow equals inflow between lakes and matches the river flow connecting them is crucial, achieved through strategic manipulation of the two hydraulic projects.[7]

3.2 Mathematical Derivation Process

For any given lake, changes in water level are determined by changes in storage volume, primarily influenced by inflow, outflow, surface runoff, precipitation, and evaporation.[8,9,10] While the total lake water volume fluctuates due to external inflows and outflows, these variations are inconsequential compared to the substantial volume beneath the lake's surface. Consequently, changes in storage volume can be computed by assessing alterations in surface area and depth, much like calculating the volume of a column, which can be shown as Figure 4.

Thus, we can derive the expression for the change in lake water level (Δd_j),as shown in Fomula 2.

$$\Delta d_j = \frac{\left(f_{i,j} + R_j - f_{o,j}\right) \cdot t}{A_j} + \varepsilon_j \qquad (2)$$

In this Formula, $j = 1,2,3,4$, $f_{i,j}$ and $f_{o,j}$ represent the inflow and outflow, respectively. For Lake 1, the outflow is controlled by Dam 1, denoted as k_1 to distinguish it. Similarly, the outflow for Lake 4 is k_2.

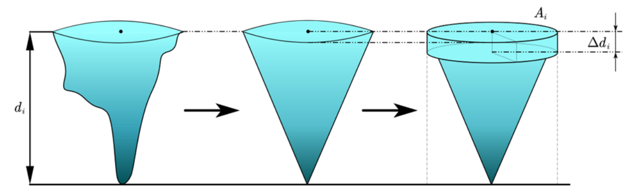

Figure 4 Simplified Method for Calculating Lake Levels

We also need to determine the water level d_j. Water levels of the Great Lakes exhibit certain monthly variations throughout the year, so we consider the baseline water level for each month in the Great Lakes as the average value of the water level for that month over the past two decades, denoted as $\bar{d}_j$. The sum of $\bar{d}_j$ and Δd_j represents the water level d_j of the respective lakes.

By plotting the scatterplot of river water flow against lake water levels, we observed that the relationship between river water flow and lake water levels approximates a first-order linear relationship. With these conclusions, we utilized the linear regression method to fit the river water flow and lake water levels for each lake. Ultimately, Formula 3 can be derived.

$$f_j\left(h_j\right) = a_j h_j + b_j, \quad j = 1,2,3,4 \qquad (3)$$

After this, the expression for Δd_j can be obtained, and subsequently, the water level d_j can be determined. Taking Lake 2 as an example, the expression for the water level change Δd_2 is presented in Formula 3.

$$\Delta d_2 = \frac{\left(k_1 + R_2 - a_2 \bar{h}_2 - b_2\right) t + A_2 \varepsilon_2}{A_2 + a_2 t} \quad (4)$$

3.3 Heuristic Search Method for Solving Control Matrix

The derivation of the water level control method involves several key steps. Initially, the change in water level for each lake is determined as a function of the dam-released water, corresponding to river 1 flow. The specific water level of each lake is calculated by adding this change to the original water level value, derived from previous years' data.

For the River 1 flow-time function curve, a search algorithm is employed.[11] An initial value is set for the River 1 flow, and adjustments are made based on differences between obtained water levels for each lake and their ideal levels. Each lake's impact is considered by assigning weights, combined with the differences to score the results. The objective is to control the loss value (River 1 flow rate) below a specified threshold, aligning with desired water level differences for the lakes. This iterative process optimizes parameters to achieve targeted water levels for the lakes.

For example, provide the initial matrix K based on historical data, as shown in Formula 4.

$$K_{2\times12} = \begin{pmatrix} 2 & 2 & \dots & 2 & 2 \\ 7 & 7 & \dots & 7 & 7 \end{pmatrix} \qquad (5)$$

Here, k_{ij} represents the water flow rate for the i-th dam in the j-th month.

Next, Compute the water level matrix R for the lakes for each month over the past years using Formula 1.

Evaluate the water level regulation effectiveness by calculating the difference between the water levels and the optimal water levels obtained in the section before. This difference serves as an indicator, reflecting the gap between the current state and the target state.

Then, Evaluate the water level regulation effectiveness. If the water level adjustment for a certain month is unsatisfactory, modify the matrix K according to the search step and repeat the steps before.

When the water level adjustment meets the expected target, stop the search, and determine the current matrix K as the optimal values for each month.

Based on the aforementioned heuristic search method, it is noted that the deviation of the data for the 12 months after regulation from the optimal water level is approximately 0.01875 meters, with a maximum error not exceeding 0.05 meters. This level of accuracy satisfactorily meets our practical requirements.

4 Results and Sensitivity Analysis

Due to the noticeably elevated hydrological data for the Great Lakes in 2017, the data for that year serves as a robust test for evaluating the effectiveness of the control model in water level regulation. We input the water level data for 2017 into the model and obtained the corresponding Figure 5. While occasionally surpassing the optimal level, the control model ensures the protection of the Great Lakes region from flooding, especially since the optimal level is considerably lower than the alert level. Even in extreme wet conditions, the control model proves capable of safeguarding the area against flood incidents.

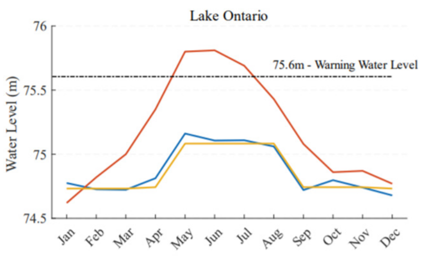

Figure 5 Water Level Regulation Effects in 2017

In sensitivity analysis, we primarily consider the effects of precipitation, winter snowpack, and ice jams on the model. While precipitation has been discussed in the model establishment, quantifying the impact of winter snowpack and ice jams on water levels proves challenging. We attempt to address these factors by amplifying spring precipitation and surface runoff by a certain factor since more winter snowfall can translate into increased surface runoff during the spring snowmelt. Under this assumption, we obtain new control results, as illustrated in Figure 6.

It is evident that when the amplification factor does not exceed 3.0, the control system effectively accommodates the abnormal input of winter snowfall and ice jams during the spring. This threshold is difficult to achieve under typical weather anomalies. Hence, we assert that our control model exhibits robustness against adverse weather conditions.

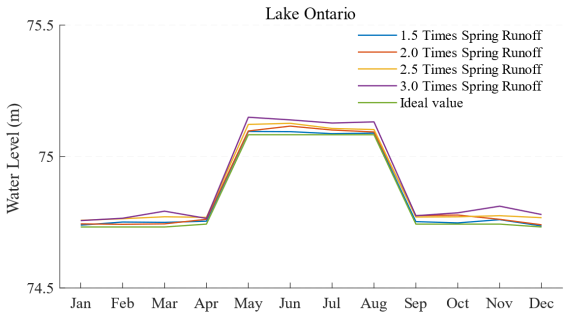

Figure 6 Effect of Different Anomalous Inputs on Water Levels in Spring

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