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Fuzzy Logic Harmony in Water: Mamdani Inference System Applied to Evaluate Pristine Pond Water Quality

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ABSTRACT

Aquatic ecosystems that are subject to urbanization and environmental changes, such as the Kapaleeswarar and Chitrakulam tanks, depend on evaluating water quality. Their complicated data present challenges for conventional approaches.The usefulness of the Mamdani fuzzy inference system in determining the water quality in these tanks is investigated in this work. It creates a comprehensive assessment based on subject-matter expertise by handling ambiguous descriptors with linguistic variables and fuzzy sets. The system's procedures for implementation are described in detail, with an emphasis on how well they can manage interrelated variables. The study shows how well the system measures the water quality in tanks and suggests ways to improve it. Tank evaluation that incorporates the Mamdani system encourages comprehensive resource management and cultural preservation.

INTRODUCTION

The well-being of humans and ecosystems are both profoundly impacted by water quality. In surface water and underground aquifers, a complex interplay of physical, chemical, biological, and microbial variables regulates fundamental biological and industrial processes (Ammar 2018). To characterize the quality of a water sample, the word "composition" is frequently used. However, it can be difficult and time-consumingto analyze data to determine the quality of the water. For efficient water resource management, planning, and assessment enhancement, accurate estimation of water quality indicators is essential (Asgari et al. 2021).

A crucial component of water quality modeling is the mathematical prediction of water pollution. The concentrations of important elements like dissolved oxygen (DO), biological oxygen demand (BOD), pH, and turbidity in a sample must be taken into account when evaluating water quality indicators (WQIs). Best-fit models are frequently used to predict WQIs once these properties have been evaluated in the lab. Many mathematical models, however, are complex and difficult to incorporate into real-time systems (Balamurugan et al. 2020).

The vast and diverse nature of water quality makes accurate data assessmentchallenging. Due to the inherent uncertainties (Bawoke et al. 2020), seeing water quality data as a fuzzy set with terms like "Good, Moderate, Poor, and Very Poor" provides a more useful framework. The effectiveness of fuzzy-based approaches in resolving subjectivity and ambiguity in environmental concerns has been established (Chauhan et al. 2023).

Fuzzy logic helps to categorize and quantify the subjective environmental effects by formalizing the evaluation of hidden data and water quality. The quality of both surface and groundwater has been predicted using fuzzy logic (Dewanti et al. 2019, Ellina et al. 2020, Gupta et al. 2019). Although multivariate analysis and artificial neural networks are effective in detecting water quality, the shortcomings of deterministic and WQI methods highlight the necessity for sophisticated classification systems that can handle ambiguous and fuzzy data (Jang et al. 2005).

Recent methods, which go beyond the conventional WQI 0-100 scale, generate acceptable fuzzy sets that reflect the inherent uncertainty in water quality evaluation by using fuzzy membership values ranging from 0 to 1. This change improves forecast accuracy while lowering computing expenses (Jha et al. 2020, Kalaivanan et al. 2017, Karunathilake et al. 2019).

Set theory is expanded by fuzzy logic, a mathematical representation of ambiguity. It has replaced conventional techniques in many scientific and engineering fieldswhere it has found applications (Kaushal et al. 2018). Even so, there hasn't been much study on WQI prediction utilizing soft computing techniques, notably fuzzy logic systems. This points to a viable area for additional research in the field of assessing water quality (Kumaravel & Vallinayagam 2016).

STUDY AREA

Two noteworthy bodies of water with important cultural and historical value in Chennai, India, are the Chitrakulam tank and the Kapaleeswarar tank. These tanks have played a significant role in research, providing insightful information on the area's history and enduring customs. In addition to having religious significance, the Kapaleeswarar tank is a vital water source for the neighborhood and is located next to the Kapaleeswarar Temple. The Chitrakulam tank, which is close to the Parthasarathy Temple, has also been important to the local community's religious and cultural practices. These two tanks provide a singular chance to investigate the connections between religion, tradition, and environmental sustainability, making them interesting topics for academic research and study.

Kapaleeswarar Tank

One of the most venerated and historic holy sites in Chennai is thought to be the Kapaleeswarar Temple (Fig. 1). In Mylapore, a Chennai suburb, is the temple dedicated to Lord Shiva, Kapaleeswarar. The inscriptionsfound on the temple grounds date around 1250 AD. The temple was reportedly constructed by the governing Pallava Dynasty in the eighth century AD, but it is possible that the Portuguese damaged it. The Vijayanagar Kings of the Tuluva dynasty (1491-1570 CE) then reconstructed it.

The sacred tank is situated on the west side of the temple, enhancing the picture view of the temple from the three Mada streets. The brilliant lights from the stores, which are constantly crowded with locals shopping, make the four Mada (east, west, north, and south) streets look incredibly attractive at night. Another noticeable aspect of the tank's water is the way the light reflects off of it. In the center of the tank is a Neerazhi mandapam, which enhances its attractiveness. Kapali Theertham, or holy water, is the name of the liquid in the tank. Sakthi Gangai and Mukthi Theertham are two names used by many followers. The tank is also known as Thamarai thadagam because, in its early years, it was covered in a profusion of lotus creepers that were blossoming and multicolored lotus. 629 feet long and 475 feet wide, the tank is a large structure. On the west side of the tank is a mandapam that is 40 square meters.

Chitrakulam Tank

In Chennai, Tamil Nadu, the Chitrakulam tank (90607 m) (Fig. 2) is around two km northeastof Royapettah. In terms of latitude and longitude, it is located close to 13^o 1'52" N and 80^o 16'14" E. The Kapaleeswarar temple tank is in Chennai, Tamil Nadu, about 7 km southeast of Mylapore. Geographically, it is located close to 13^o 27'71" Nlatitude and 80^o 16'5" E longitude. Both of the above tanks are multipurpose tanksused for a variety of summertime activities such as gardening and residential use.

MATERIALS AND METHODS

The assessment contents are chosen based on the results of

Fig. 1: Kapaleeswarar tank.

Fig. 2: Chitrakulam tank.

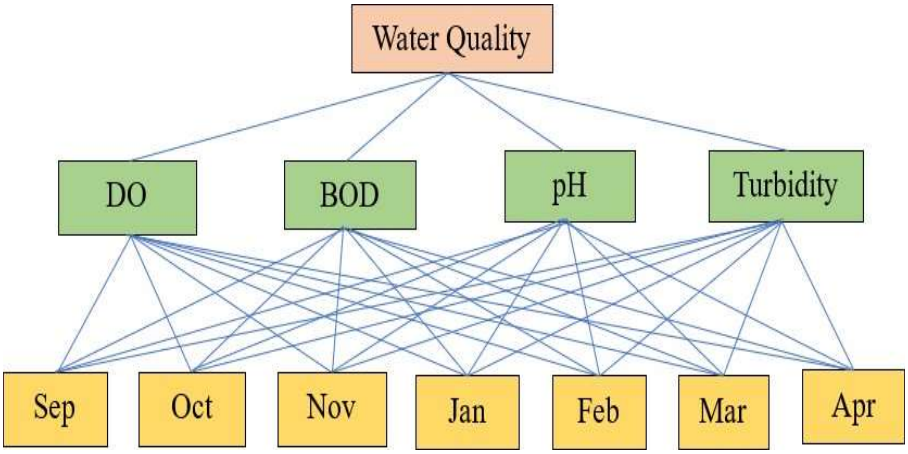


Fig. 3: Hierarchy of water quality assessment.

the field investigations and the monitoring data for water quality at the two tanks. For the parameters Dissolved Oxygen (DO), Biological Oxygen Demand (BOD), pH, and Turbidity (Fig. 3).

Introduction to the Water Quality Index

Water quality index ranges from 1 to 100; a higher number is indicative of better water quality. WQI rating scale is as follows: 91-100: excellent water quality, 71-90: good water quality, 51-70: medium water quality, 26-50: fair water quality, 0-25: poor water quality (11). The parameters used in defining WQI are pH, Biological Oxygen Demand (BOD), Dissolved Oxygen (DO), and Turbidity. The criteria are given in Table 1 to determine how healthy the water is on a given day (Kumaravel et al. 2020).

Table 1: Water Quality Criteria.

S. No.	Parameter	Good Quality	Moderate	Poor Quality
(a)	pH	7.5-9.0	6.5-7.5	5-6.5
(b)	DO	2-4.5	4.5-7	7-10
(c)	BOD	Below 2	2-3	3-6
(c)	Turbidity	5-10	10-25	-

Fuzzy Inference System

In this study, we used an FIS model, a mathematical method that uses fuzzy logic to translate an input into an output. Three essential steps make up the fuzzy inference process: fuzzification, if-then rules, and defuzzification (40). A fuzzy inference approach may be useful for resolving ambiguity and assessing water quality because the data on water quality are ambiguous and unclear (Nayak et al. 2020). The Mamdani method is the most used fuzzy inference approach. In 1965, Zadeh presented the fuzzy logic model (Oladipo et al. 2021).

Operation of Fuzzy Inference System

Fuzzification of variables, rule evaluation, rule aggregation, and defuzzification are the four key components of the robust Mamdani fuzzy inference system. The fundamental design of the FIS is shown in Fig. 4.

Step 1. Fuzzification

Fuzzification is the first stage of the FIS. Through a variety of membership functions, crisp inputs are converted in this stage into fuzzy inputs known as linguistic variables. A membership function is a visual representation that quantitatively expresses linguistic concepts and visually depicts a fuzzy collection (Palanichamy et al. 2022). To relate the numerical input values to membership grades in fuzzy sets provided with text, fuzzification is used. In this investigation, the input and output parameters were both subjected to a trapezoidal membership function. The trapezoidal membership function, one of the most extensively used membership functions (MF) in fuzzy controller design, has the advantage of simplicity (Ram et al. 2021, Ramirez et al. 2007, Ren et al. 2021 & Rustum et al. 2020).

Step 2. Inference Engine

The fuzzy output is produced by the inference engine using the fuzzy rules from the knowledge base. An expression with if-then conditions is known as a fuzzy rule. The following is the ambiguous rule: Y must be B if X is A. In this fuzzy rule, A and B are fuzzy sets, while X and Y are linguistic variables. The aggregation method is used to merge all of the If-then rules into a single fuzzy set after all of the rules have been defined.

Step 3. Defuzzification

An expert system's defuzzifier is a crucial part. The processing of fuzzy inference systems ends with defuzzification (Sajan & Christoper 2023). It involves turning a hazy input into a clear output (Shitong et al. 2005). The mean of maximum method (MOM), the centroid of area (COA), the biggest of maximum (LOM), the bisector of area (BOA), and the smallest of maximum (SOM) are some of the different types of defuzzifiers. The most popular defuzzification technique, known as the center of area (CoA) defuzzification method, is also known as the center of gravity (CoG) defuzzification technique. The fuzzy controller in this defuzzification method (CoA) calculates the area under the scaled membership functions and within the output variable's range first.

RESULTS

Step 1. Input and Output Variables

The identification of the variables that make up the system, sometimes referred to as the input and output variables, is the first step in the system modeling process. The factors that have a substantial impact on the result have been selected as inputs. The complexity increases as the number of rules required to manage the inputs increases. Depending on the physical nature of the issue, the conversation may go further or shorter.

Step 2. Membership Function

Fuzzy sets are used to express linguistic values. Typically, a fuzzy set's membership functions are used to define it. The employment of the trapezoidal membership function to normalize the acute inputs is made possible by its computational efficiency and simplicity. The membership functions for the inputs and outputs are depicted in Fig. 5 and 6.

Step 3. Establishing a Linguistic Rule Base

The relationship between the input and the output was

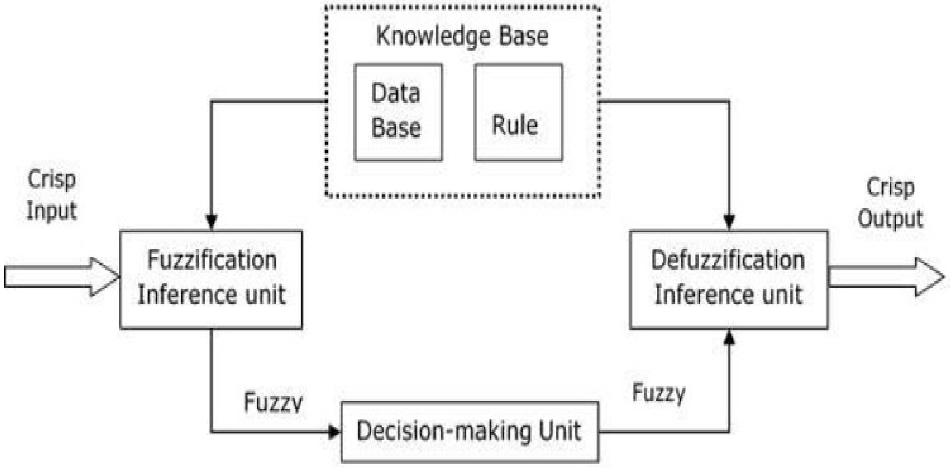
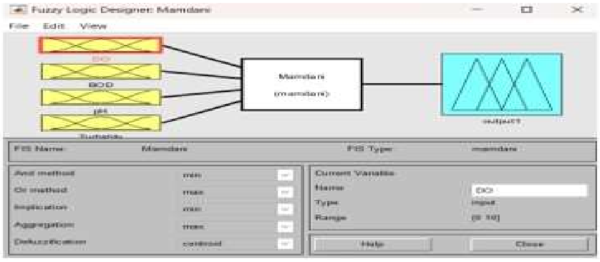


Fig. 4: Structure of fuzzy inference system.



FIS Name: Mamdani
FIS Type: mamdani
And method: min
Or method: max
Implication: min
Aggregation: max
Defuzzification: centroid
Current Variable
Name: DO
Type: input
Range: [0 10]

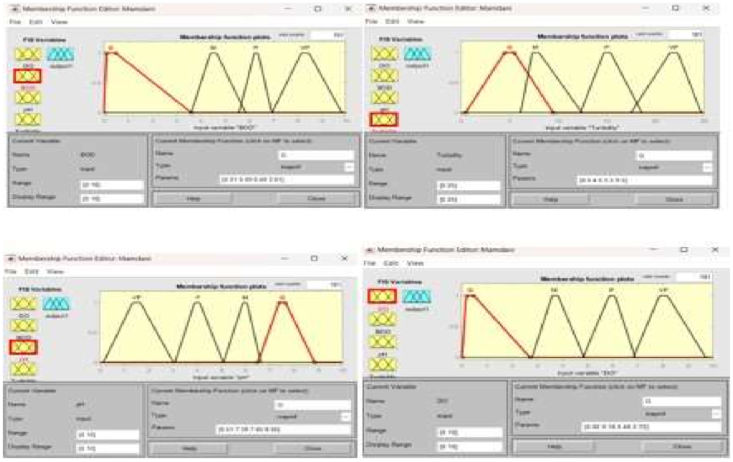
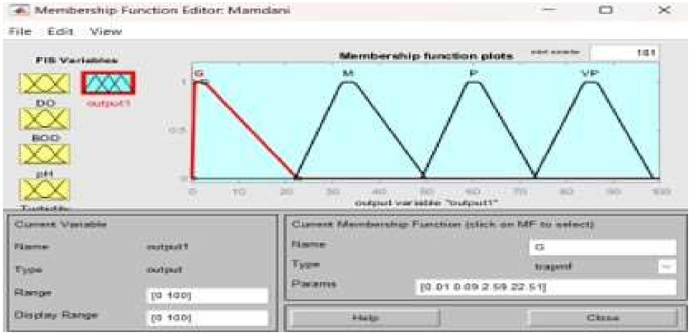


Fig. 5: Input membership function.



Current Variable
Name: output1
Type: output
Range: [0 100]
Display Range: [0 100]

Current Membership Function (click on MF to select)
Name: G
Type: trapmf
Params: [0.01 0.09 2.59 22.51]

Fig. 6: Output membership function.

demonstrated using IF-THEN rules. As X_1, X_2, X_3, and X_4 respectively, the inputs DO, BOD, pH, and turbidity are employed. The values y1 indicate the output of the system (Wu 2019). The model that is suggested in this paper has two fuzzy systems. In this setup, the inputs for X_1, X_2, X_3, and X_4 each have four MF. The very first fuzzy system consists of 256 rules. The proposed fuzzy model is built on the architecture of the Mamdani fuzzy model and employs Max-Min inference. The Mamdani fuzzy system's rules are created with the following techniques (Figs. 7 and 8):

Step 4. Defuzzification

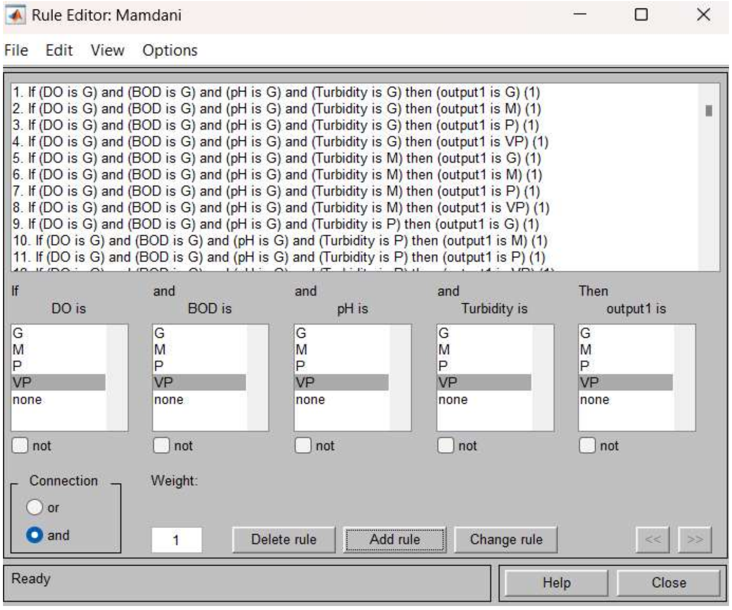
The recommended model employs the Centroid of Area (COA) method of defuzzification to arrive at the answer.

DISCUSSION

The main objective of this study is the thorough evaluation of water quality indicators for two different ponds, and this evaluation is done in accordance with the recognized Indian water quality standards. Kapaleeswarar Pond receives a 50% weighting in the evaluation procedure, whereas Chitrakulam

Pond receives a 70% weighting, representing the different levels of significance and value that these two aquatic ecosystemshave in relation to the study's objectives.

The study's findings are: (1) The FIS method is appropriate for addressing ambiguous and uncertain environmental issues, particularly assessing water quality to get a clear output and overcome the uncertainty of water quality; (2) The FIS method can be used to evaluate the quality of various types of water; and (3) The Mamdani fuzzy inference system is easier to understand because it is rule-based, and (4) The FIS can apply various defuzzification techniques and, additionally, it is possible to apply various



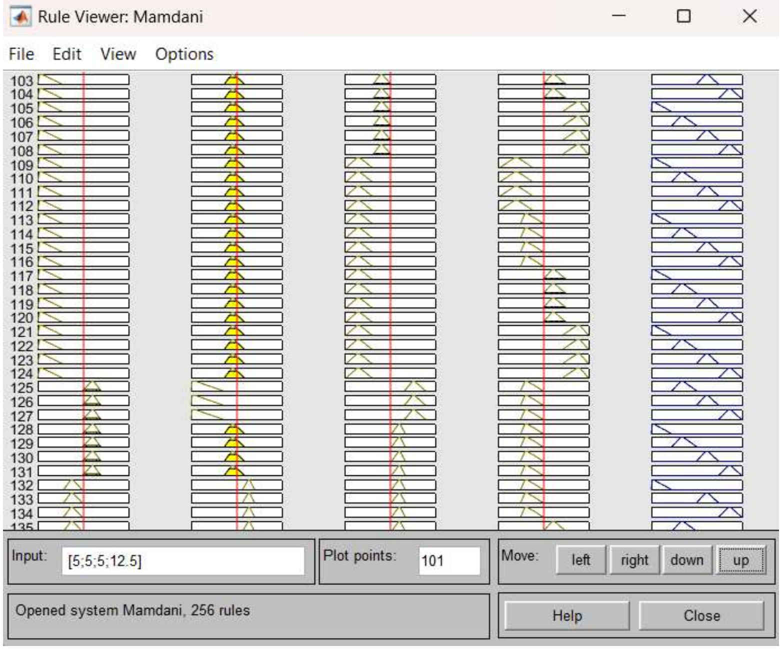
1. If (DO is G) and (BOD is G) and (pH is G) and (Turbidity is G) then (output1 is G) (1)
2. If (DO is G) and (BOD is G) and (pH is G) and (Turbidity is G) then (output1 is M) (1)
3. If (DO is G) and (BOD is G) and (pH is G) and (Turbidity is G) then (output1 is P) (1)
4. If (DO is G) and (BOD is G) and (pH is G) and (Turbidity is G) then (output1 is VP) (1)
5. If (DO is G) and (BOD is G) and (pH is G) and (Turbidity is M) then (output1 is G) (1)
6. If (DO is G) and (BOD is G) and (pH is G) and (Turbidity is M) then (output1 is M) (1)
7. If (DO is G) and (BOD is G) and (pH is G) and (Turbidity is M) then (output1 is P) (1)
8. If (DO is G) and (BOD is G) and (pH is G) and (Turbidity is M) then (output1 is VP) (1)
9. If (DO is G) and (BOD is G) and (pH is G) and (Turbidity is P) then (output1 is G) (1)
10. If (DO is G) and (BOD is G) and (pH is G) and (Turbidity is P) then (output1 is M) (1)
11. If (DO is G) and (BOD is G) and (pH is G) and (Turbidity is P) then (output1 is P) (1)

Connection
○ or
● and

Weight: 1

Ready

Fig. 7: Rules.



Input: [5;5;5;12.5]

Plot points: 101

Opened system Mamdani, 256 rules

Fig. 8: Rule viewer.

types of membership functions. The FIS can also be used to understand and evaluate the impact of each input parameter on the final water quality.

The outcomes from the proposed Fuzzy Inference System (FIS) model are brought into sharp focus after completing a thorough examination. Comparing these data to the established water quality guidelines reveals an incredibly high degree of similarity. In essence, the predictions and analyses produced by the FIS model show a startlingcongruence with the exact water quality standards set by Indian regulatory bodies.

This extraordinary agreement between the FIS model's predictions and the legally required water quality criteria highlights the model's accuracy in determining the water quality of Kapaleeswarar Pond and Chitrakulam Pond. It highlights the FIS model's potential as a reliable instrument for continued monitoring, management,and conservation efforts targeted at preserving and enhancing the water quality in these essential aquatic ecosystems. Furthermore, it demonstrates the crucial role that cutting-edge modeling and simulation methods may play in improving our comprehension and management of important natural resources.

CONCLUSION

This article represents an extension of a fuzzy inference system for pond water quality using MATLAB research endeavors, where our primary objective was to developa comprehensive fuzzy model for water quality evaluation. In our ongoing pursuit of enhancing environmental assessment methodologies, we have delved deeper into the intricacies of this model, refining and expanding its capabilities to provide even more valuable insights into the assessment of water quality. Our approach continues to rely on the Mamdani fuzzy inference system, a powerful tool known for its ability to handlecomplex and uncertain environmental data. Within this framework, we meticulously consider four crucial input parameters and an extensive network of 256 fuzzy rules forms the foundation of each fuzzy model. This intricate structure enablesus to address the complexities inherent in assessing water quality in diverse contexts. This article represents a continuation of our commitment to advancing the field of water quality assessment. We recognize that there is always room for improvement, and our model is designed to evolve continually. Future directions include the incorporation of additional input parameters and the exploration of different membership functions, such as sigmoid and Gaussian, to enhance accuracy and comprehensiveness. In essence, this extended article builds upon the foundation established in our earlier research, offering a deeper and more nuanced exploration of our hierarchical fuzzy model's capabilities. It is a testament to our ongoing dedication to refining and expanding our methodologies for assessing and managing water quality, ultimately contributing to a more sustainable and environmentally conscious future.

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