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Fuzzy Sugeno Model for SNR-Based Adaptive Modulation in Underwater Acoustic Communication

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ABSTRACT Underwater communication faces significant challenges due to the dynamic characteristics of the channel and is strongly influenced by the physicochemical parameters of the water. This study proposes channel quality modeling using the Sugeno Fuzzy Inference System (FIS) with input variables of temperature, salinity, dissolved oxygen (DO), and turbidity. The system produces a Signal-to-Noise Ratio (SNR) output that is used as a basis for channel quality mapping, Bit Error Rate (BER) estimation, and the selection of adaptive modulation techniques (BPSK, QPSK, or 16QAM). Simulation results show that the Sugeno fuzzy model is able to follow the theoretical pattern well, where increasing temperature, salinity, and turbidity decrease the SNR value, while DO plays a role in maintaining channel stability. Based on the test results, at high SNR (≥ 15 dB) the system recommends 16QAM, at medium SNR (11–15 dB) QPSK, and at low SNR (≤ 10 dB) BPSK. This approach has proven effective in suppressing BER and increasing the reliability of underwater acoustic communications in fluctuating mangrove water environments.

KEYWORDS: adaptive modulation, BER, fuzzy Sugeno, SNR, underwater communication

I.INTRODUCTION

Underwater acoustic communication is an important technology that plays a role in supporting various marine activities, such as monitoring the quality of the aquatic environment, controlling underwater vehicles, underwater sensor networks, and collecting oceanographic data [1], [2], [3], [4]. In contrast to wireless communication on land that uses radio waves, underwater communication relies on acoustic waves as the main transmission medium because radio waves and light experience very high attenuation in water, making it inefficient for long-distance communication [1], [5], [6].

However, underwater acoustic channels have much more complex characteristics than airborne channels. Sound wave propagation in water experiences long delays, increasing attenuation with distance and frequency, and limited bandwidth. Furthermore, the phenomenon of multipath propagation due to wave reflections from the surface and seabed causes signal distortion and interference between propagation paths [1]. These conditions make acoustic communication channels nonlinear, highly dynamic, and dependent on time and aquatic environmental conditions [7], [8], [9].

In shallow waters, the complexity of the channel increases because it is influenced by the physico-chemical parameters of the water, including temperature, dissolved oxygen (DO), turbidity, and salinity [9], [10], [11]. Water temperature affects the speed of sound wave propagation, where an increase in temperature causes an increase in propagation speed and can cause refraction of sound waves due to temperature differences between water layers. The DO parameter also plays an important role, because high levels of dissolved oxygen are generally correlated with increased biological activity and particle movement in the water which has the potential to cause density fluctuations and scattering of acoustic signals. Turbidity affects wave propagation through the process of scattering and absorption of energy by suspended particles, thereby reducing the intensity of the received signal. Meanwhile, salinity determines the density of water; the higher the salinity, the faster the sound wave propagation, but accompanied by increased attenuation, especially at high frequencies [1].

These four parameters simultaneously cause fluctuations in the Signal-to-Noise Ratio (SNR) and changes in channel characteristics within a relatively short time span, especially in coastal areas and highly dynamic mangrove ecosystems [10], [11], [12]. These SNR fluctuations have a direct impact on communication system performance, as indicated by an increase in the Bit Error Rate (BER) and a decrease in data transmission efficiency [13].

Most existing underwater acoustic communication systems still use static modulation schemes such as Binary Phase Shift Keying (BPSK), Quadrature Phase Shift Keying (QPSK), and 16-Quadrature Amplitude Modulation (16QAM). These conventional approaches are unable to adapt to changing channel conditions, resulting in suboptimal performance. To overcome these limitations, the concept of adaptive modulation was introduced, which allows the system to dynamically adjust the modulation type based on channel conditions represented by the SNR value [5], [14], [15]

Building an accurate mathematical model to represent the relationship between water physico-chemical parameters and SNR values is a challenge in itself, considering that the relationship is complex, nonlinear, and influenced by natural environmental uncertainties. In this context, the fuzzy inference system approach is a promising alternative because it is able to model nonlinear relationships and handle environmental data uncertainty efficiently [16][17]. In particular, the Sugeno Fuzzy model has advantages in computational efficiency, stability of results, and ease of implementation in real-time adaptive systems [18], [19].

Therefore, this study proposes a Fuzzy Sugeno-based adaptive modulation model for underwater acoustic communication systems by considering the influence of water physico-chemical parameters, namely temperature, dissolved oxygen (DO), turbidity, and salinity. This model is used to predict SNR values based on variations in environmental parameters, which are then used as a basis for determining the most appropriate modulation type (BPSK, QPSK, or 16QAM) adaptively. This modeling is expected to be able to maintain a balance between Bit Error Rate (BER) and data rate, while increasing the efficiency and reliability of underwater acoustic communication in dynamic channel conditions, especially in environments with complex characteristics such as mangrove waters [20].

II. METHOD

This study uses the Sugeno Fuzzy Logic approach to model the relationship between water physicochemical parameters and the quality of underwater communication channels. The research methodology consists of four main stages: system simulation flow, system modeling, model design with Sugeno fuzzy logic, and simulation data testing.

2.1 System Simulation

The underwater acoustic communication system simulation is designed to model the digital data transmission process through underwater acoustic channels characterized by multipath and Gaussian noise with complex characteristics such as mangrove waters. Figure 1 shows the system workflow.

Underwater acoustic channels in shallow waters have multipath characteristics due to the reflection of sound waves by the surface and bottom of the water. In this simulation, the channel is represented by a three-path impulse response with relative amplitude coefficients h = [0.8, 0.4, 0.2], which describe the direct signal and two primary reflections. The model reflects the realistic conditions of shallow channels that are susceptible to inter-symbol interference (ISI).

The environmental noise is modeled as Additive White Gaussian Noise (AWGN) with a zero-mean normal distribution. Thus, the received signal is expressed as:

$$r(t) = h * s(t) + n(t) \tag{1}$$

with s(t) the modulated signal, h the channel impulse response, and n(t) the Gaussian noise.

2.2 System Modeling

The system modeling in this study is designed to link the physicochemical parameters of mangrove waters with the quality of underwater communication channels, particularly in terms of bit error rate (BER) and the selection of optimal modulation techniques. This system receives input in the form of data from measurements of temperature, salinity, dissolved oxygen (DO), and turbidity obtained from environmental sensors. The data is then processed through a normalization stage and processed using a fuzzy inference system (FIS) to produce output in the form of a Signal-to-Noise Ratio (SNR) value. This SNR value is the basis for mapping channel quality, estimating the BER level, and recommending the selection of appropriate modulation techniques.

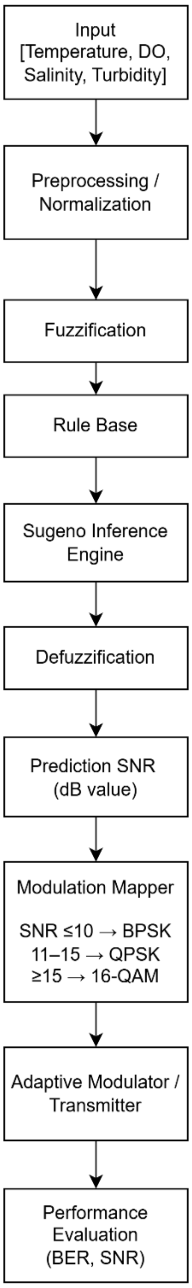

FIGURE 1. System workflow of the proposed Fuzzy Sugeno-based adaptive modulation scheme

To illustrate the relationship between water physicochemical parameters and underwater communication channel conditions, fuzzy categories were developed for each input variable. These categories were divided into three levels (low, normal/medium, and high) with value ranges tailored to the characteristics of the aquatic environment. Each category was then mapped to SNR conditions, appropriate modulation choices, and BER level estimates. A summary of the modeling is presented in Tables 1 to 4 below.

TABLE 1. Modeling the Relationship between Temperature and SNR, Modulation Techniques, and BER

Category	Range (°C)	SNR Condition	Modulation Selection	Bit Error Rate (BER)	Description
Low	≤ 25 °C	High SNR (low noise, strong signal)	16QAM	Low	High spectral efficiency, suitable for high throughput
Medium	26 – 30 °C	SNR (still quite high)	QPSK	Medium	Safe to use, compromises speed and noise resistance
High	≥ 31 °C	Low SNR (increased noise, thermal distortion)	BPSK	High	Robust against noise, even at lower data rates

TABLE 2. Modeling the Relationship between Salinity and SNR, Modulation Techniques, and BER

Category	Range (ppt)	SNR Condition	Modulation Selection	Bit Error Rate (BER)	Description
Low	≤ 5 ppt	High SNR (low conductivity, therefore low noise)	16QAM	Low	Suitable for high throughput, high-order modulation remains stable
Medium	6 – 30 ppt	Stable–Medium SNR	QPSK	Medium	Medium Compromise between speed and noise robustness
High	≥ 31 ppt	Low SNR (high conductivity, thus increasing noise)	BPSK	High	Robust against noise, despite lower data rates

TABLE 3. Modeling the Relationship between Turbidity and SNR, Modulation Techniques, and BER

Category	Range (NTU)	SNR Condition	Modulation Selection	Bit Error Rate (BER)	Description
Low	≤ 10 NTU	High SNR (small scattering and	16QAM	Low	Optimal acoustic signal, maximum throughput

		absorption)			
Medium	11 – 100 NTU	Decreasing SNR (significant scattering)	QPSK	Medium	Compromise on throughput and robustness, additional filtering required
High	≥ 101 NTU	Low SNR (strong scattering, signal degradation)	BPSK	High	Robust modulation recommended, data rate drops drastically

TABLE 4. Modeling the Relationship between DO and SNR, Modulation Techniques, and BER

Category	Range (mg/l)	SNR Condition	Modulation Selection	Bit Error Rate (BER)	Description
Low	≤ 3 mg/L	SNR Decreasing	BPSK	High	Sensor conditions are often unstable, requiring robust modulation.
Medium	4 – 8 mg/L	SNR Stable	QPSK	Medium	Optimal conditions
High	≥ 9 mg/L	SNR tends to be stable/increasing	16QAM	High	The direct effect of DO is small, but a healthy environment creates a more consistent signal.

Based on the modeling in Tables 1 to 4, each water physicochemical parameter has a different effect on the quality of underwater communication channels. Temperature and salinity affect SNR through changes in conductivity and thermal phenomena, while turbidity degrades signal quality due to scattering and absorption. Dissolved oxygen (DO) plays a role in maintaining channel stability, although its direct effect on SNR is relatively small.

Mapping low, medium, and high categories for each parameter allows the system to assess channel conditions and determine the appropriate adaptive modulation technique. 16QAM modulation is used for high SNR, QPSK for medium SNR, and BPSK for low SNR. The results of this modeling form the basis for the development of an adaptive communication system based on Sugeno Fuzzy Logic.

2.3 Sugeno Fuzzy Logic Method

The method used in this research is the Sugeno Fuzzy Inference System (FIS) to model the relationship between environmental parameters and the quality of underwater communication channels. The steps are described as follows:

1. Fuzzyfication

The membership functions for temperature, dissolved oxygen (DO), salinity, turbidity, and SNR output are illustrated in Figures 2–6. These membership functions define the fuzzy boundaries between low, moderate, and high categories and are constructed based on realistic mangrove water conditions as well as findings from previous underwater acoustic communication studies [1], [9], [10], [11]. The fuzzy sets are designed using trapezoidal and triangular functions to ensure smooth transitions between linguistic variables and to accommodate uncertainty in environmental measurements.

1.1 Temperature

Figure 2 illustrates the membership functions for the temperature variable. The temperature input is classified into three fuzzy sets: Low, Moderate, and High. Low temperature (≤ 25 °C) is associated with a high degree of membership, reflecting favorable channel conditions due to reduced thermal noise and lower signal attenuation. Moderate temperature (26–30 °C) represents transitional conditions where the channel remains relatively stable but begins to experience increased noise. High temperature (≥ 31 °C) corresponds to degraded channel conditions, where higher thermal activity causes increased attenuation and multipath distortion, leading to a reduction in the Signal-to-Noise Ratio (SNR). This modeling aligns with underwater acoustic propagation theory, which states that temperature variations significantly influence sound speed and attenuation [1], [9], [10], [11].

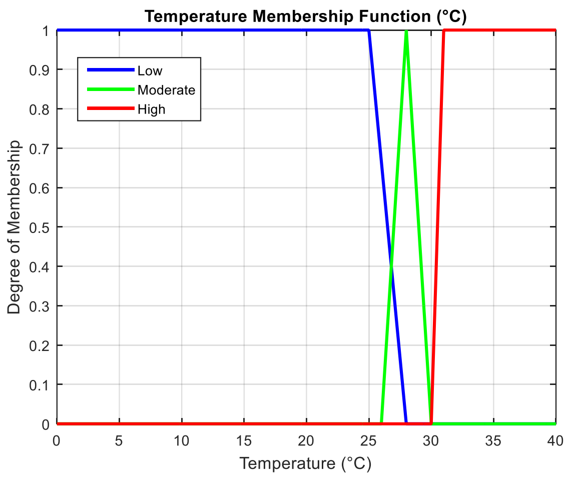

FIGURE 2. Temperature Membership Function

$$\mu_{\text{Low}}(x) = \begin{cases} 1, & x \le 27 \\ \frac{28-x}{28-27}, & 27 < x < 28 \\ 0, & x \ge 28 \end{cases} \quad (2)$$

$$\mu_{\text{Moderate}}(x) = \begin{cases} 0, & x \le 27 \\ \frac{x-27}{28.5-27}, & 27 < x \le 28.5 \\ \frac{30-x}{30-28.5}, & 28.5 < x < 30 \\ 0, & x \ge 30 \end{cases} \quad (3)$$

$$\mu_{\text{High}}(x) = \begin{cases} 0, & x \le 29 \\ \frac{x-29}{30-29}, & 29 < x < 30 \\ 1, & x \ge 30 \end{cases} \quad (4)$$

1.2 Dissolved oxygen (DO)

The membership functions for dissolved oxygen (DO) are shown in Figure 3. DO is categorized into Low, Moderate, and High levels. Low DO (≤ 3 mg/L) indicates unstable aquatic conditions that may increase particle movement and signal scattering, resulting in a decreasing SNR. Moderate DO (4–8 mg/L) corresponds to stable environmental conditions, where acoustic propagation is less disturbed, producing a moderate SNR. High DO (≥ 9 mg/L) is associated with healthy water conditions that tend to maintain channel stability, contributing to a higher SNR. Although the direct effect of DO on acoustic attenuation is limited, its indirect influence on environmental stability justifies its inclusion in the fuzzy model [10].

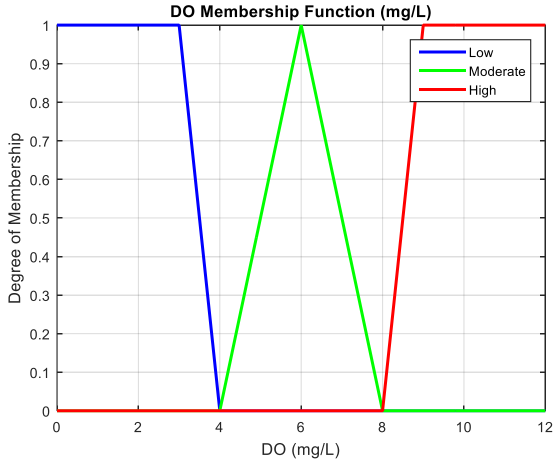

FIGURE 3. Dissolved oxygen (DO) Membership Function

$$\mu_{\text{Low}}(x) = \begin{cases} 1, & x \le 3 \\ \frac{4-x}{4-3}, & 3 < x < 4 \\ 0, & x \ge 4 \end{cases} \quad (4)$$

$$\mu_{\text{Moderate}}(x) = \begin{cases} 0, & x \le 4 \\ \frac{x-4}{6-4}, & 4 < x \le 6 \\ \frac{8-x}{8-6}, & 6 < x < 8 \\ 0, & x \ge 8 \end{cases} \quad (5)$$

$$\mu_{\text{High}}(x) = \begin{cases} 0, & x \le 8 \\ \frac{x-8}{9-8}, & 8 < x < 9 \\ 1, & x \ge 9 \end{cases} \quad (6)$$

1.3 Salinity

Figure 4 presents the salinity membership functions, which are divided into Low, Moderate, and High categories. Low salinity (≤ 5 ppt) is associated with lower conductivity and reduced acoustic attenuation, resulting in higher SNR values. Moderate salinity (6–30 ppt) represents typical coastal and mangrove water conditions, where SNR remains relatively stable. High salinity (≥ 31 ppt) increases water density and conductivity, leading to higher absorption losses and reduced SNR, particularly at higher acoustic frequencies. This fuzzy modeling reflects established underwater acoustic channel characteristics reported in previous studies [1], [9], [10], [11].

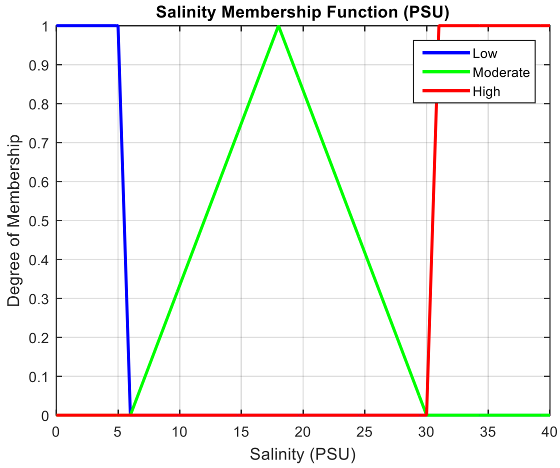

FIGURE 4. Salinity Membership Function

$$\mu_{\text{Low}}(x) = \begin{cases} 1, & x \le 5 \\ \frac{10-x}{10-5}, & 5 < x < 10 \\ 0, & x \ge 10 \end{cases} \quad (8)$$

$$\mu_{\text{Moderate}}(x) = \begin{cases} 0, & x \le 10 \\ \frac{x-10}{20-10}, & 10 < x \le 20 \\ \frac{30-x}{30-20}, & 20 < x < 30 \\ 0, & x \ge 30 \end{cases} \quad (9)$$

$$\mu_{\text{High}}(x) = \begin{cases} 0, & x \le 30 \\ \frac{x-30}{32-30}, & 30 < x < 32 \\ 1, & x \ge 32 \end{cases} \quad (10)$$

1.4 Turbidity

The turbidity membership functions are illustrated in Figure 5. Turbidity is classified into Low, Moderate, and High levels based on suspended particle concentration. Low turbidity (≤ 10 NTU) results in minimal scattering and absorption, allowing optimal signal propagation and high SNR. Moderate turbidity (11–100 NTU) introduces significant scattering effects, which gradually reduce SNR. High turbidity (≥ 101 NTU) causes severe signal degradation due to strong scattering and absorption, leading to a low SNR. This behavior is particularly relevant in mangrove environments, where sediment resuspension frequently occurs and strongly affects acoustic communication reliability [1], [9], [10], [11].

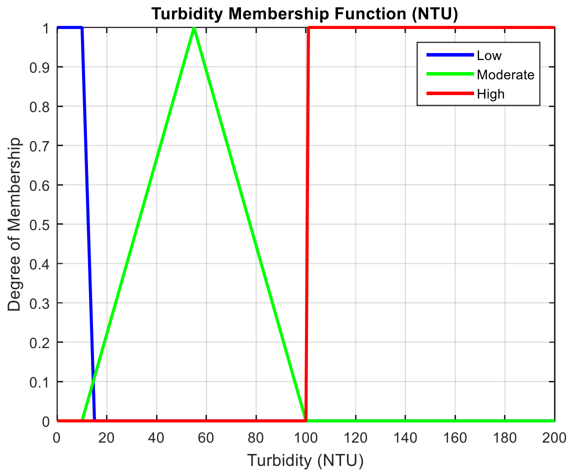

FIGURE 5. Turbidity Membership Function

$$\mu_{\text{Low}}(x) = \begin{cases} 1, & x \le 20 \\ \frac{40-x}{40-20}, & 20 < x < 40 \\ 0, & x \ge 40 \end{cases} \quad (11)$$

$$\mu_{\text{Moderate}}(x) = \begin{cases} 0, & x \le 20 \\ \frac{x-20}{60-20}, & 20 < x \le 60 \\ \frac{100-x}{100-60}, & 60 < x < 100 \\ 0, & x \ge 100 \end{cases} \quad (12)$$

$$\mu_{\text{High}}(x) = \begin{cases} 0, & x \le 100 \\ \frac{x-100}{120-100}, & 100 < x < 120 \\ 1, & x \ge 120 \end{cases} \quad (13)$$

1.5 SNR Output

Figure 6 shows the membership functions for the SNR output variable, which is classified into Low, Moderate, and High categories. Low SNR (≤ 10 dB) represents poor channel conditions dominated by noise, requiring robust modulation techniques such as BPSK. Moderate SNR (11–15 dB) indicates relatively stable channel conditions where QPSK provides a balance between robustness and spectral efficiency. High SNR (≥ 15 dB) reflects favorable channel conditions with strong signal dominance, enabling the use of higher-order modulation such as 16QAM to maximize data rate [20]. The SNR membership functions serve as the decision basis for adaptive modulation selection in the proposed Sugeno fuzzy system.

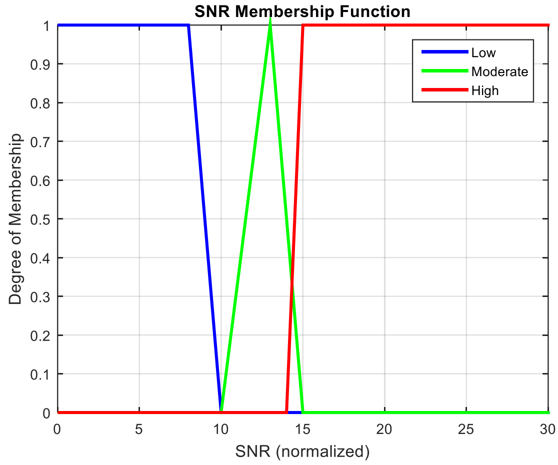

FIGURE 6. SNR Membership Function

$$\mu_{low}(x) = \begin{cases} 1 & x \le 8 \\ \frac{10-x}{10-8} & 8 < x < 10 \\ 0 & x \ge 10 \end{cases} \quad (14)$$

$$\mu_{\text{Moderate}}(x) = \begin{cases} 0, & x \le 10 \\ \frac{x-10}{13-10}, & 10 < x \le 13 \\ \frac{15-x}{15-13}, & 13 < x < 15 \\ 0, & x \ge 15 \end{cases} \quad (15)$$

$$\mu_{\text{High}}(x) = \begin{cases} 0, & x \le 14 \\ \frac{x-14}{15-14}, & 14 < x < 15 \\ 1, & x \ge 15 \end{cases} \quad (16)$$

By explicitly defining and visualizing the membership functions for each environmental parameter and the SNR output, the proposed fuzzy system ensures transparency, interpretability, and consistency in the inference process. The graphical representation of these functions clarifies how environmental variations influence channel quality and supports the reliability of the adaptive modulation decision mechanism.

2. Inference Rule

The fuzzy rule base constructed consists of 81 rules, representing all combinations of input variables: temperature, DO, salinity, and turbidity ($3^4 = 81$). Each rule produces an output in the form of an SNR category classified into three levels: low, medium, and high.

This SNR category reflects the quality of the communication channel based on tables 1, 2, 3, and 4:

a) Low SNR indicates poor channel conditions with noise dominance, potentially resulting in a high bit error rate (BER).
b) Medium SNR indicates intermediate channel conditions, where signal quality is relatively stable but still requires a compromise between noise resilience and spectral efficiency.
c) High SNR indicates a good channel with a strong signal and minimal noise dominance, resulting in a low BER.

The fuzzy inference process is performed using the product operator as a logical representation of AND to determine the firing strength of each rule. Next, the inference results are combined through an aggregation process and defuzzified using the Sugeno method to obtain the final SNR value in numerical form in the range 0–100.

The SNR output results are the basis for selecting modulation techniques:
a) At low SNR, systems tend to prefer low-order modulation (BPSK) because it is more robust against interference.
b) At moderate SNR, intermediate modulation (QPSK) can be used, which balances throughput and noise robustness.
c) At high SNR, higher-order modulation (16QAM) can be used to maximize spectral efficiency and data rate.

TABLE 5. Rule base fuzzy

No	Suhu	DO	Salinitas	Kekeruhan	SNR
1	Low	Low	Low	Low	Low
2	Low	Low	Low	Med	Low
3	Low	Low	Low	High	Low
4	Low	Low	Med	Low	Low
5	Low	Low	Med	Med	Low
6	Low	Low	Med	High	Low
7	Low	Low	High	Low	Low
8	Low	Low	High	Med	Low
9	Low	Low	High	High	Low
10	Low	Med	Low	Low	Med
11	Low	Med	Low	Med	Med
12	Low	Med	Low	High	Low
13	Low	Med	Med	Low	Med
14	Low	Med	Med	Med	Med
15	Low	Med	Med	High	Low
16	Low	Med	High	Low	Med
17	Low	Med	High	Med	Med
18	Low	Med	High	High	Low
19	Low	High	Low	Low	High
20	Low	High	Low	Med	Med
21	Low	High	Low	High	Low
22	Low	High	Med	Low	High
23	Low	High	Med	Med	Med
24	Low	High	Med	High	Low
25	Low	High	High	Low	High
26	Low	High	High	Med	Med
27	Low	High	High	High	Low
28	Med	Low	Low	Low	Low
29	Med	Low	Low	Med	Low
30	Med	Low	Low	High	Low
31	Med	Low	Med	Low	Low
32	Med	Low	Med	Med	Low
33	Med	Low	Med	High	Low
34	Med	Low	High	Low	Low
35	Med	Low	High	Med	Low
36	Med	Low	High	High	Low
37	Med	Med	Low	Low	Med
38	Med	Med	Low	Med	Med
39	Med	Med	Low	High	Low
40	Med	Med	Med	Low	Med
41	Med	Med	Med	Med	Med
42	Med	Med	Med	High	Low
43	Med	Med	High	Low	Med
44	Med	Med	High	Med	Med
45	Med	Med	High	High	Low
46	Med	High	Low	Low	High
47	Med	High	Low	Med	Med
48	Med	High	Low	High	Low
49	Med	High	Med	Low	High
50	Med	High	Med	Med	Med
51	Med	High	Med	High	Low
52	Med	High	High	Low	High
53	Med	High	High	Med	Med
54	Med	High	High	High	Low
55	High	Low	Low	Low	Low
56	High	Low	Low	Med	Low
57	High	Low	Low	High	Low
58	High	Low	Med	Low	Low
59	High	Low	Med	Med	Low
60	High	Low	Med	High	Low
61	High	Low	High	Low	Low
62	High	Low	High	Med	Low
63	High	Low	High	High	Low
64	High	Med	Low	Low	Med
65	High	Med	Low	Med	Med
66	High	Med	Low	High	Low
67	High	Med	Med	Low	Med
68	High	Med	Med	Med	Med
69	High	Med	Med	High	Low
70	High	Med	High	Low	Med
71	High	Med	High	Med	Med
72	High	Med	High	High	Low
73	High	High	Low	Low	High
74	High	High	Low	Med	Med
75	High	High	Low	High	Low
76	High	High	Med	Low	High
77	High	High	Med	Med	Med
78	High	High	Med	High	Low
79	High	High	High	Low	High
80	High	High	High	Med	Med
81	High	High	High	High	Low

The predicted SNR value is then used as the basis for selecting an adaptive modulation technique. In high SNR conditions (≥ 15 dB), the system recommends the use of high-order modulation (16QAM) to maximize data rates. When the SNR is in the medium category (11–15 dB), the system selects QPSK modulation because it offers a balance between efficiency and noise resistance. Meanwhile, in low SNR (≤ 10 dB), the system switches to BPSK modulation, which is more robust against interference. This approach allows the system to dynamically adapt to varying channel conditions, thus maintaining optimal underwater communication quality.

3. Defuzzyfication

The final SNR value is calculated using the weighted average method according to Sugeno's formulation:

$$SNR = \frac{\sum_{i=1}^{81} \omega_i z_i}{\sum_{i=1}^{81} \omega_i} \quad (1)$$

Where:

ωi = membership degree (weight) of the i-th rule
zi = crisp output value generated from the i-th rule

2.4 Simulation Test Data

This study uses simulation data compiled based on a range of physicochemical parameter values that represent the general conditions of mangrove waters.

This simulation data was used because the research focused on conceptual modeling and testing of the Sugeno Fuzzy Inference System, rather than direct field measurements. The range of values used represents realistic conditions in mangrove waters.

Four main parameters were used as system inputs: temperature (°C), dissolved oxygen (DO) in mg/L, salinity (ppt), and turbidity (NTU). This data was then used to test the model's response to various waterway conditions.

TABLE 6. Simulation Test Data

No	Temperature (°C)	DO (mg/L)	Salinity (ppt)	Turbidity (NTU)
1	28	5	15	20
2	24	7	4	8
3	32	4	20	120
4	20	2	2	3
5	26	3	31	90

Each parameter combination is processed to generate variations in underwater channel conditions, which are used as input to the fuzzy system. The system outputs a predicted Signal-to-Noise Ratio (SNR) value, which is then used as the basis for modulation technique recommendations.

III.RESULT AND DISCUSSION

This chapter presents the results of the implementation and testing of the Sugeno Fuzzy system in modeling the influence of aquatic environmental parameters on the quality of underwater communication channels. Through simulations, the system is tested to assess the accuracy of the fuzzy rules and its adaptability in determining the appropriate modulation technique based on the SNR value. The discussion covers three main parts: system modeling, fuzzy logic implementation, and overall system performance analysis.

3.1 System Modeling Analysis

The test was conducted through simulations with input data in the form of water physicochemical parameters, including temperature, salinity, dissolved oxygen (DO), and turbidity. The data was processed using the Sugeno Fuzzy Inference System (FIS) method to produce output in the form of a predicted Signal-to-Noise Ratio (SNR) value. The SNR value was then classified into three categories: Low, Medium, and High, as the basis for selecting the appropriate modulation technique.

In the simulation test data (Table 5), the input data used were: temperature 28 °C, DO 5 mg/L, salinity 15 ppt, and turbidity 20 NTU. Based on the modeling in Tables 1–4, all four parameters are in the Med category, indicating a channel condition with a Med SNR. The results of processing using the fuzzy system produced a predicted SNR value of 12.5 dB, so the system automatically recommended the use of QPSK modulation. The system output results are shown in Figure 7.

```
--------------------------------------------
 Water Parameters and Channel Prediction
--------------------------------------------
Temperature  : 28.0 °C
DO (mg/L)    : 5.0
Salinity     : 15.0 ppt
Turbidity    : 20.0 NTU
--------------------------------------------
Predicted SNR          : 12.5 dB
SNR Level              : Moderate
Recommended Modulation : QPSK
--------------------------------------------
```

FIGURE 7. The results of the fuzzy system output testing are in the form of SNR values and modulation technique recommendations.

The simulation results show that the system is able to adapt to the underwater communication channel conditions. Under normal temperature conditions (26–30 °C), medium salinity (6–30 PSU), Med turbidity (11–100 NTU), and DO within the optimal range (4–8 mg/L), the resulting SNR value is in the Med category. This condition indicates that the channel is still quite stable, but there is potential noise that can increase the bit error rate (BER) if High order modulation is used. Therefore, the selection of QPSK modulation in this scenario is considered appropriate because it is able to maintain a balance between throughput and resistance to noise.

Furthermore, these results confirm that the Sugeno fuzzy system can adaptively adjust modulation techniques based on varying aquatic environmental conditions. This approach makes underwater communications more efficient and reliable, especially under changing channel conditions.

3.2 Implementation of Sugeno Fuzzy Logic

The implementation of the Sugeno Fuzzy Logic method was carried out to test whether the inference rules (rule base) developed accurately represented the relationship between water physicochemical parameters and underwater communication channel conditions. The inference process used four input variables: temperature, dissolved oxygen (DO), salinity, and turbidity, each of which was divided into three fuzzy categories: Low, Med, and High.

The simulation test data used refers to Table 5, with several scenarios representing different water conditions. Each input combination is processed through the Sugeno FIS system to produce a Signal-to-Noise Ratio (SNR) value in the Low, Medium, or High categories. Based on the SNR category, the system automatically determines the most appropriate modulation technique: BPSK, QPSK, or 16QAM.

The results of the fuzzy implementation are shown in Table 7, which shows the relationship between the simulation input data and the system output based on the active fuzzy rules.

The table shows that the system's inference results align with the logical relationships built into the fuzzy rule base. Under Med parameter conditions (scenario 1), the system produces Med SNR and selects QPSK as the optimal modulation. Meanwhile, under extreme conditions such as high temperature and turbidity (scenario 3), the system downgrades to BPSK to maintain communication reliability.

In case 1, with a temperature of 28 °C, DO 5 mg/L, salinity 15 ppt, and turbidity 20 NTU, the system produces a Med SNR so it is recommended to use QPSK modulation. This result is in accordance with the 41st fuzzy rule with Med output. These parameter conditions describe a relatively stable channel, with a moderate noise level, so the fuzzy method is proven to be able to provide output that matches the actual channel conditions.

TABLE 7. System Test Results

Temperature (°C)	DO (mg/L)	Salinity (ppt)	Turbidity (NTU)	SNR Prediction (dB)	Rule Fuzzy/ SNR Categoration	Modulation Recommendations
28	5	15	20	12,5	Rule 41 / Med	QPSK
24	7	4	8	18,2	Rule 12 / High	16QAM
32	4	20	120	7,8	Rule 67 / Low	BPSK
20	2	2	3	5,0	Rule 5 / Low	BPSK
26	3	31	90	9,5	Rule 52 / Low	BPSK

In case 2, the temperature values of 24 °C, DO 7 mg/L, salinity 4 ppt, and turbidity 8 NTU produce High SNR with a recommended 16QAM modulation. This result arises from the 12th fuzzy rule with a High output, which describes ideal channel conditions: cool temperature, High oxygen, Low salinity, and clear water. This confirms that the system is able to recognize channel conditions with optimal signal quality and responds by selecting a High-order modulation that is efficient with bandwidth.

In case 3, with a temperature of 32 °C, DO 4 mg/L, salinity 20 ppt, and turbidity 120 NTU, a Low SNR was obtained with BPSK modulation recommendations, in accordance with the 67th fuzzy rule. This condition indicates channel degradation due to High temperatures and extreme turbidity, which increases signal attenuation and decreases the signal to noise ratio. The selection of BPSK is appropriate because it has better resilience to channel interference.

In case 4, a temperature of 20 °C, DO of 2 mg/L, salinity of 2 ppt, and turbidity of 3 NTU resulted in a Low SNR with the 5th active rule. The low DO value indicates a lack of stability in the aquatic environment, which results in a decrease in signal propagation quality. The system successfully classifies this condition into the poor channel category, so BPSK modulation is again the most appropriate choice.

In case 5, with a temperature of 26 °C, DO 3 mg/L, salinity 31 ppt, and turbidity 90 NTU, the system produces a Low SNR output with the 52nd fuzzy rule. High salinity increases water conductivity and causes greater signal attenuation, while DO and turbidity worsen the channel condition. These results indicate that the fuzzy system is able to identify the dominant factors that affect transmission performance.

Overall, the test results show that the designed fuzzy rule base works well and is consistent with the physicochemical conditions of the waters. The Sugeno FIS system successfully classifies channel conditions accurately and provides adaptive modulation recommendations that are in accordance with the resulting SNR level. This proves that the model with the Sugeno fuzzy approach is able to represent the nonlinear relationship between environmental parameters and the quality of underwater communication channels with a good level of accuracy, and can be used as a basis for automatic modulation control in acoustic communication systems in dynamic environments such as mangrove ecosystems.

3.3 System Performance Analysis

Test results show that the Sugeno Fuzzy-based system has adaptive capabilities in determining modulation techniques appropriate to underwater communication channel conditions. This mechanism functions to suppress the Bit Error Rate (BER) and maintain data transmission efficiency by selecting modulation based on the Signal-to-Noise Ratio (SNR) value resulting from the water's physicochemical parameters.

In High SNR conditions (≥ 15 dB), the system recommends the use of High-order modulation (16QAM) to maximize data rates. When the SNR is in the Med category (11–15 dB), the system chooses QPSK modulation because it offers a balance between efficiency and resilience to noise. Meanwhile, in Low SNR (≤ 10 dB), the system switches to BPSK modulation which is more robust against interference. With this adaptation mechanism, underwater acoustic communication becomes more reliable and efficient, especially in mangrove ecosystems that have High environmental dynamics and unpredictable channel characteristics.

The test results in Table 7 show that the Fuzzy Sugeno system is able to accommodate various water environmental conditions consistently. In the first scenario, the SNR value is in the Med category so the system recommends QPSK modulation. In the second scenario, optimal environmental conditions produce a High SNR, allowing the use of 16QAM to increase throughput. Conversely, in the third scenario, High temperatures and high turbidity levels reduce the SNR to the Low category, and the system automatically selects BPSK as the most noise-resistant modulation technique.

The comparison of Bit Error Rate (BER) and Signal-to-Noise Ratio (SNR) performance for conventional models with the adaptive model created is shown in Figure 8. The black curve depicts the theoretical performance in the conventional BPSK model, red for QPSK, and the blue curve for 16QAM. The simulation results show that the higher the modulation order, the greater the SNR requirement to achieve a low BER. The five test points on the graph show that the Fuzzy Sugeno system is able to follow the dynamics of water channel variations well.

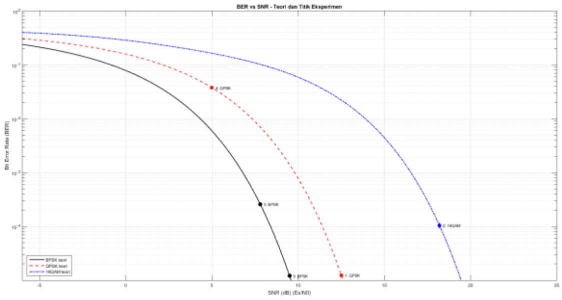

FIGURE 8. SNR vs BER Test results compared with theory

For example, at the first point, the system recommends using QPSK when the SNR is in the Med category. As channel conditions improve and the SNR increases, the system switches to 16QAM to improve transmission efficiency. Conversely, when the channel degrades due to increased temperature or turbidity, the system downgrades the modulation rate to BPSK to maintain communication reliability.

The modulation change pattern indicates that the system is capable of adaptively adjusting modulation techniques to changing aquatic environmental conditions. Thus, the Fuzzy Sugeno approach has proven effective in accommodating the uncertainty and dynamics of underwater acoustic channels, as well as improving communication performance through the selection of appropriate modulation schemes in real-time. For further research, this system needs to be tested experimentally in the field with integration on real underwater communication devices to validate the effectiveness of modulation adaptation in more complex and dynamic environmental conditions.

3.4 Results and Discussion

The results obtained in this study are consistent with several previous works on adaptive modulation and environment-aware underwater acoustic communication. Stojanovic and Preisig [1] emphasized that underwater channel quality is strongly influenced by environmental parameters and exhibits highly nonlinear behavior, which supports the use of intelligent modeling approaches such as fuzzy logic.

Kumar et al. [2], Akyildiz et al. [10], and Wulandari et al [5] highlighted that conventional fixed-modulation schemes are inefficient in dynamic underwater environments, particularly in shallow and coastal waters. The proposed Sugeno Fuzzy-based adaptive modulation model addresses this limitation by dynamically adjusting the modulation scheme based on environmental conditions.

Compared to machine learning-based adaptive modulation approaches such as reinforcement learning or neural networks [13], [15], the proposed Sugeno FIS offers lower computational complexity, better interpretability, and faster decision-making, making it more suitable for real-time underwater acoustic systems with limited processing capability.

In contrast to previous modulation based studies that rely solely on SNR estimation [5], [6], [15], [20], this research incorporates physicochemical water parameters (temperature, salinity, DO, and turbidity) as direct inputs, enabling earlier channel quality prediction before severe degradation occurs. This contribution is particularly relevant for highly dynamic environments such as mangrove waters.

IV.CONCLUSION

This study successfully demonstrates that the Sugeno Fuzzy Inference System can effectively model the relationship between water physicochemical parameters: temperature, salinity, dissolved oxygen, and turbidity, and underwater acoustic channel quality. The proposed model accurately predicts SNR levels and enables adaptive modulation selection between BPSK, QPSK, and 16QAM according to channel conditions. Simulation results confirm that the adaptive scheme reduces BER and improves communication reliability in dynamic mangrove water environments. Therefore, the Sugeno fuzzy-based approach is suitable as a lightweight and interpretable solution for real-time adaptive underwater acoustic communication systems.

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