RSMA Based UAN Channel Modelling for Coral Reef Monitoring empowered through ML Techniques

PROJECT REPORT

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BONAFIDE CERTIFICATE

This is to certify that the report entitled **"RSMA Based UAN Channel Modelling for Coral Reef Monitoring empowered through ML Techniques"** submitted by **A P Devanampriya (Register Number- CB.SC.U4AIE23001)**, **K Prerana (Register Number- CB.SC.U4AIE23038)**, **Niharika Sharma (Register Number- CB.SC.U4AIE23048)** and **Patel Srikari Shasi (Register Number- CB.SC.U4AIE23053)** in partial fulfillment of the requirements for the courses **22AIE211- Introduction to Communication & IoT and 22AIE213 Machine Learning** for the award of the **Degree of Bachelor of Technology** in the **"COMPUTER SCIENCE ENGINEERING - ARTIFICIAL INTELLIGENCE"** is a bonafide record of the work carried out by them under our guidance and supervision at Amrita School of Artificial Intelligence, Coimbatore.

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Project Guides
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Submitted for the university examination held on 15th April 2025

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DECLARATION

We,**A P Devanampriya(CB.SC.U4AIE23001)**,**K Prerana (CB.SC.U4AIE23038), Niharika Sharma (CB.SC.U4AIE23048) and Patel Srikari Shasi(CB.SC.U4AIE23053)** hereby declare that this thesis entitled **" RSMA Based UAN Channel Modelling for Coral Reef Monitoring empowered through ML Techniques "**, is the record of the original work done by us under the guidance of **Dr. Sundaresan S & Dr. Anand Kumar**, Amrita School of Artificial Intelligence, Coimbatore. To the best of our knowledge, this work has not formed the basis for the award of any degree/diploma/ associateship/fellowship/or a similar award to any candidate in any university.

Place: Ettimadai **Signature of the Students**

Date: 15/04/25

COUNTERSIGNED

Dr. K.P.Soman
Professor and Dean
Amrita School of Artificial Intelligence
Amrita Vishwa Vidyapeetham

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List of Abbreviations

RSMA	Rate Splitting Multiple Access
NOMA	Non Orthogonal Multiple Access
CSI	Channel State Information
SIC	Successive Interference Cancellation
UAN	Underwater Acoustic Network
AUV	Autonomous Underwater Vehicle
UAV	Unmanned Aerial Vehicle
TAMUN	Transmission of Alert Messages in Underwater Networks
IRS	Intelligent Reflecting Surfaces
RF	Random Forest
FNN	Feedforward Neural Network

Abstract

UANs have an important role in the monitoring of coral reef health but suffer from limited usage of bandwidth, multipath propagation, interference and low energy efficiency. In this paper, we propose an RSMA based multiple access scheme for efficient data transmission to monitor coral reef health in real-time. RSMA splits the message into a common part and a private part, which can ensure the efficient propagation of the signal. The underwater environment data collected by this system are utilized to predict coral reef health using modified machine learning techniques. ML techniques are also used to predict accurate outage probability, sum rate and ergodic capacity values of the system. An accuracy of about 99.06 have been achieved from the ML prediction. The RSMA based system uses rate splitting mechanism that outperforms NOMA based power allocations by enabling more flexible interference management, achieving higher spectral efficiency and robustness under imperfect channel state information.

Chapter 1

Introduction

This thesis explores the integration of RSMA within Underwater Acoustic Networks for coral reef monitoring, driven by the resilience and flexibility of RSMA as well as its proven application across diverse networks. The proposed system attempts to provide the following benefits by utilizing current developments in RSMA-based optimization and ML-assisted network intelligence, as well as insights from acoustic channel modeling [1]:

- Reliable and energy-efficient communication over underwater acoustic channels;
- Interference-resilient multiple access for concurrent sensor node transmissions;
- Intelligent adaptability to dynamically changing marine environments.

Creating a hybrid RSMA-UAN framework that can support long-term monitoring missions for delicate ecosystems like coral reefs is the main objective. This will open the door for a new generation of marine-aware, RSMA-powered IoT systems.

1.1 Literature Survey

Rate-Splitting Multiple Access (RSMA) is gaining traction in modern wireless systems due to its flexibility in managing interference and adapting to diverse channel conditions. By enabling simultaneous transmission of common and private message parts, RSMA offers a dynamic model that bridges orthogonal and non-orthogonal access schemes. Its robustness under imperfect CSI, heterogeneous QoS needs, and fairness constraints positions it as a strong candidate for next-gen applications, including UAV-assisted communication, 6G, and Underwater Acoustic Networks (UANs) [2, 3, 5, 6, 8].

UANs are crucial for real-time, long-range underwater monitoring using AUVs, relay buoys, and acoustic sensor nodes—especially for applications like oceanographic data collection, marine pollution detection, coral reef monitoring, and disaster alerts. However, underwater channels pose challenges like high latency, multipath fading, and limited bandwidth, requiring communication schemes resilient to interference and CSI uncertainty.

While NOMA has been considered for UANs, its reliance on precise CSI and SIC limits its effectiveness in underwater environments [4]. High delays and unpredictable channels reduce decoding reliability and increase energy consumption.

RSMA, in contrast, is more suited to UANs, as it tolerates CSI imperfections and reduces reliance on SIC by splitting messages. It has shown improved performance in outage probability and ergodic capacity under dynamic conditions [3, 5, 6], and its downlink potential in UAV networks supports scalable, fair communication [2]. RSMA's integration with intelligent reflecting surfaces (IRS) further enhances its adaptability in complex environments [8], making it a practical enabler for low-latency, robust UANs.

Machine learning also complements RSMA by supporting predictive deployment and channel modeling, applicable to UANs for adaptive configurations [7]. Frameworks like TAMUN [9] improve alert messaging in ecological applications, while coding-layer enhancements [10] boost data reliability over acoustic channels.

1.2 Problem Statement

Current UAN communication methods struggle under environmental uncertainty, channel asymmetry, and hardware limitations. NOMA's efficiency declines in such conditions due to its dependence on SIC and static power allocation. Furthermore, lack of integration with environmental data reduces system adaptability. There is a need for an intelligent, resilient multiple access system that adapts based on environmental conditions while ensuring optimal data transmission.

1.3 Objectives

- Design and model an RSMA-based underwater communication system for coral reef monitoring.
- Integrate environmental feature-driven ML models to predict and optimize communication performance metrics.
- Evaluate and compare RSMA and NOMA under shallow and deep water environ-

ments.

- Derive analytical models for outage probability, ergodic capacity, and sum rate.
- Validate performance using Monte Carlo simulations.

1.4 Organization of the Report

- **Chapter 1: Introduction**

  Introduces the need for underwater monitoring, limitations of current systems, literature insights, and the proposed objectives.

- **Chapter 2: Background**

  Reviews the working principles of UANs, the evolution from NOMA to RSMA, and key machine learning tools used.

- **Chapter 3: Proposed Work**

  Details the RSMA-based system model, power allocation mechanisms, ML model architecture, and hybrid weighting scheme.

- **Chapter 4: Results and Discussion**

  Presents analytical equations, simulation graphs, and performance comparisons with NOMA.

- **Chapter 5: Conclusion and Future Work**

  Summarizes findings, highlights RSMA's effectiveness, and proposes future improvements for real-time deployment.

Chapter 2

Background

2.1 Introduction

Underwater Acoustic Networks (UANs) are networks of underwater sensors, Autonomous Underwater Vehicles (AUVs), and surface buoys that use acoustic communication to monitor marine environments. Their ability to gather real-time data makes them ideal for applications such as coral reef health monitoring. However, their performance is hindered by long propagation delays, energy constraints, and interference from various sources. To address these challenges, emerging technologies such as Rate-Splitting Multiple Access (RSMA) and Machine Learning (ML) are being leveraged to improve reliability, efficiency, and scalability.

2.2 Underwater Acoustic Channel Modeling

The underwater acoustic channel is affected by several factors such as large propagation delays, limited bandwidth, and multipath fading. Traditional schemes like Non-Orthogonal Multiple Access (NOMA) are often employed to enhance spectral efficiency, but they fall short in underwater environments due to their reliance on accurate Channel

State Information (CSI) and successive interference cancellation (SIC).

RSMA addresses these shortcomings by splitting messages into common and private parts, thereby improving flexibility in interference management and power allocation. This results in improved robustness in dynamic environments such as shallow and deep underwater settings.

2.3 Environmental Factors Affecting Communication

The acoustic channel in UANs is heavily influenced by environmental parameters. These include:

- **Salinity:** Affects sound propagation and marine life.
- **Temperature:** Impacts sound speed and species behavior.
- **Turbidity:** Determines water clarity and affects signal attenuation.
- **Dissolved Oxygen:** Essential for aquatic ecosystems.
- **Conductivity:** Related to ion concentration and influences acoustic signal propagation.

These parameters also serve as key inputs for ML models that predict coral reef health and system performance.

2.3.1 ML-Enhanced Analysis

A modified Random Forest (RF) combined with a Feedforward Neural Network (FNN) is used to predict key performance metrics such as outage probability, ergodic capacity, and sum rate. This hybrid model addresses class imbalance and captures non-linear relationships in the data, resulting in enhanced prediction accuracy—up to 99.06% in health classification scenarios.

2.4 Key Technologies Used

2.4.1 Rate-Splitting Multiple Access (RSMA)

RSMA improves spectral efficiency by transmitting a common message (decoded by all users) and private messages (user-specific). It is more resilient to CSI inaccuracies and multipath effects than NOMA, especially in challenging underwater environments.

2.4.2 Machine Learning (ML)

ML techniques, including Random Forest and Neural Networks, are utilized to:

- Predict environmental impact on signal quality.
- Estimate performance metrics like outage probability and capacity.
- Classify coral reef health based on sensor data.

Chapter 3

Proposed Work

3.1 Overview

The proposed work presents a novel underwater acoustic communication framework for real-time coral reef monitoring by leveraging Rate-Splitting Multiple Access (RSMA) and machine learning (ML) techniques. Traditional underwater acoustic networks (UANs) face significant challenges such as low bandwidth, high propagation delay, and severe multipath interference. This work introduces an RSMA-based approach to efficiently handle these limitations. Additionally, a hybrid machine learning model comprising Random Forest (RF) and Feedforward Neural Network (FNN) is integrated for performance prediction and coral health classification.

3.2 System Architecture Overview

The system consists of a central acoustic transmitter (e.g., a buoy or underwater base station) that communicates with multiple underwater users, which may include sensor nodes and AUVs. These users experience varying channel conditions due to their distance from the transmitter, depth, and local environmental parameters (e.g., temperature, turbidity, etc.).

Each transmission is composed of two parts:

- **Common Message:** A message shared across all users to ensure baseline communication. It must be decodable by all users, including those with the poorest channel quality.

- **Private Messages:** User-specific messages intended for individual nodes, adapted according to each user's channel characteristics.

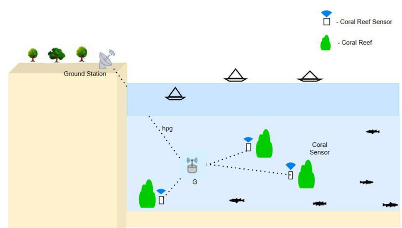

Figure 3.1: System Model

Fig 3.1 depicts this system model.

The RSMA-based system improves underwater communication by:

- Providing robustness against high propagation delay and fading.

- Adapting to imperfect channel state information (CSI).

- Offering flexible power allocation between users.

- Enhancing fairness by ensuring all users can decode at least part of the transmission.

This architecture enables reliable data collection for machine learning-based analysis of environmental conditions, ultimately supporting informed decisions in coral reef health monitoring.

3.3 Dataset and Underwater Channel Modeling

The "Blue Dataset" from Dropbox was utilized, comprising:

- Real and imaginary parts of complex channel coefficients (real0–real11, imag0–imag11).
- Environmental parameters: salinity, turbidity, temperature, dissolved oxygen, and conductivity.

These data points simulate the underwater environment's channel state.

3.4 Machine Learning Integration

To improve the estimation of key RSMA performance metrics (such as outage probability, ergodic capacity, and sum rate) and to classify coral reef health accurately, a hybrid machine learning framework was developed. The proposed model integrates two complementary components: a modified Random Forest (RF) classifier and a Feedforward Neural Network (FNN). Together, they generate a hybrid ML-weighted term that enhances the adaptability and accuracy of the RSMA communication model under dynamic underwater environments.

3.4.1 Modified Random Forest (RF)

The Random Forest algorithm was customized to address two major challenges:

- **Class Imbalance:** Environmental datasets often exhibit skewed distributions, especially for critical yet rare coral health states such as severe bleaching. A class-weighted learning mechanism was employed to ensure that underrepresented classes receive appropriate significance during model training, thereby preventing bias and underfitting.

- **Feature Importance Estimation:** The model uses the Mean Decrease in Impurity (MDI) criterion to evaluate the contribution of each input feature (e.g., salinity, temperature, turbidity, conductivity, and dissolved oxygen). This quantitative ranking is crucial in understanding which environmental factors most influence RSMA performance and coral health prediction.

Additionally, shallow decision trees were employed to prevent overfitting and improve generalization, particularly when working with noisy underwater sensor data.

3.4.2 Feedforward Neural Network (FNN)

A multi-layer FNN was employed to capture complex, nonlinear relationships between environmental parameters and coral reef health status. The FNN architecture includes:

- **Input Layer:** Accepts normalized features from the underwater sensor dataset.

- **Hidden Layers:** Consist of fully connected neurons with ReLU activation, enabling the learning of intricate patterns that traditional decision tree models may miss.

- **Output Layer:** Produces probabilistic confidence scores for each predicted coral health class using a softmax activation function.

The FNN is trained using the categorical cross-entropy loss function and the Adam optimizer. Dropout regularization is applied to prevent overfitting due to sensor noise and temporal correlations in the data.

3.4.3 Hybrid ML-Weighted Term

To leverage the strengths of both RF and FNN models, a hybrid ML-weighted term was introduced. This term integrates:

- **Feature Importance Scores** from the RF model, which reflect the relative weight of each environmental input.

- **Prediction Confidence Scores** from the FNN model, indicating the certainty of coral health classification.

This integration ensures that the RSMA system is not only mathematically optimized but also data-aware and environmentally responsive, making it highly effective for real-time underwater acoustic communication and coral reef monitoring applications.

3.5 Implementation Details

3.5.1 Mathematical Modeling

We model the Signal-to-Noise Ratio (SNR) as:

$$\gamma = \frac{P_t |H|^2}{N_0 r^n \alpha(f)} \tag{3.1}$$

Power is split as:

$$P_c = \beta P_t, \quad P_{p,u} = (1 - \beta)\delta_u P_t \tag{3.2}$$

Outage Probability under Nakagami-m fading:

$$P_{out} = \frac{\gamma\left(m, \frac{m\gamma_{th}}{\bar{\gamma}}\right)}{\Gamma(m)} \tag{3.3}$$

Ergodic Capacity approximation:

$$C_{erg} \approx \frac{1}{\ln(2)} \left[\psi(m) - \ln\left(\frac{m}{\bar{\gamma}}\right)\right] \tag{3.4}$$

Sum Rate:

$$R_{sum} = R_{common} + \sum_{k=1}^{K} R_{private,k} \tag{3.5}$$

3.6 Results and Discussions

3.6.1 Feature Importance and Health prediction

Fig. 3.2 shows the permutation feature importance of the environmental parameters influencing coral reef health classification. The plot highlights the significant role of temperature and salinity, which together contribute over 50% to the model's predictive capability. Conductivity plays a moderate role, while dissolved oxygen (disso2) and

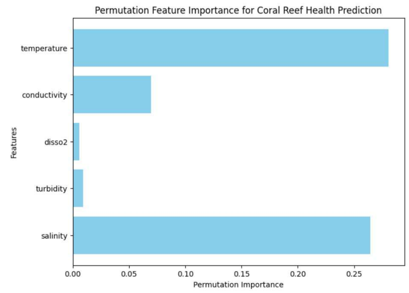

Figure 3.2: Feature Importance Graph

turbidity have minimal influence. This analysis emphasizes the importance of thermal and saline stress on reef ecosystems, suggesting these factors should be prioritized for sensor selection in future low-power underwater acoustic networks (UANs), ensuring efficient energy use in remote monitoring setups.

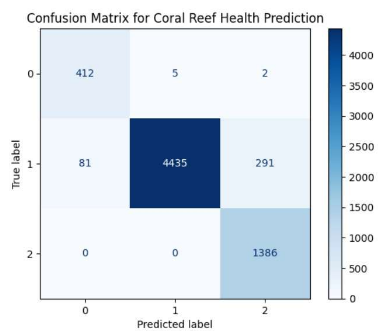

Figure 3.3: Confusion Matrix

Fig. 3.3 presents the confusion matrix for the multiclass classification task of coral reef health prediction. The model classifies three health states: Unhealthy (0), Moderate (1), and Healthy (2). It performs particularly well with 4435 correct predictions for the Moderate class, though some misclassifications occur, especially between the

Moderate and Healthy categories. These errors are likely due to the overlapping environmental parameter ranges, validating the robustness of the model despite noise, sensor drift, and multipath interference in underwater environments.

3.6.2 Outage Probability

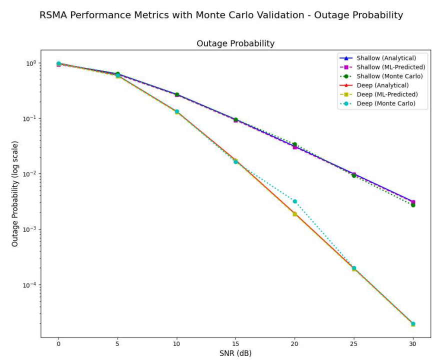

Figure 3.4: Outage Probability

Fig. 3.4 shows the outage probability performance of the RSMA-based underwater acoustic communication system under varying Signal-to-Noise Ratio (SNR) conditions. At 0 dB SNR, the outage probability is high (close to 1), but as the SNR increases, the probability decreases, reaching 10^{-2} at 30 dB. In shallow waters, multipath interference causes severe fading effects, while in deep waters, the reduced interference due to fewer reflections leads to lower outage probabilities. This demonstrates the efficient performance of RSMA, particularly in deeper regions where multipath effects are minimized.

3.6.3 Ergodic Capacity

Fig. 3.5 illustrates the ergodic capacity of the RSMA-based underwater acoustic communication system under varying SNR conditions. In shallow water, ergodic capacity

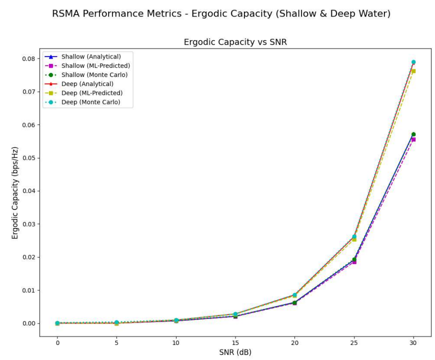

Figure 3.5: Ergodic Capacity

increases slowly with SNR, peaking at 0.056 bps/Hz at 30 dB, limited by multipath interference. In deep water, the capacity grows more rapidly, reaching 0.008 bps/Hz at 30 dB due to the more stable acoustic environment with less multipath interference and clearer signal reception, showcasing RSMA's adaptability to different underwater environments.

3.6.4 Sum Rate

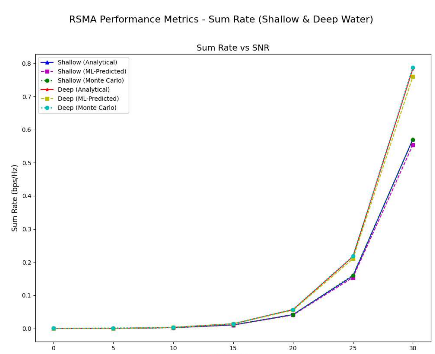

Figure 3.6: Sum Rate

Fig. 3.6 demonstrates the sum rate performance of the RSMA-based underwater acoustic communication system under different SNR levels. In shallow water, the sum rate increases gradually, reaching 0.59 bps/Hz at 30 dB. This slower increase is due to persistent multipath interference. In deep water, the sum rate rises more sharply, peaking at 0.08 bps/Hz, as the more stable environment allows RSMA to exploit channel conditions more effectively, resulting in higher spectral efficiency.

3.6.5 RSMA vs. NOMA Comparison

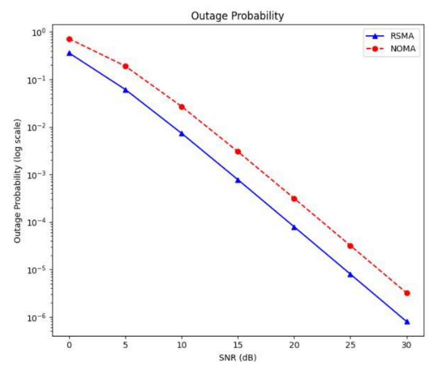

Figure 3.7: Outage Probability between NOMA and RSMA

Fig. 3.7 compares the outage probability of RSMA and NOMA-based systems under varying SNR conditions (0–30 dB). The plot shows that RSMA consistently outperforms NOMA across all SNR levels, achieving lower outage probabilities. As SNR increases, the gap between the two schemes widens, illustrating RSMA's superior interference management through message splitting. This results in higher reliability and diversity, particularly in high-SNR regions, making RSMA a more robust choice for underwater acoustic networks.

Fig. 3.8 compares the ergodic capacity of RSMA and NOMA-based systems under different SNR conditions (0–30 dB). At lower SNRs, both systems exhibit similar per-

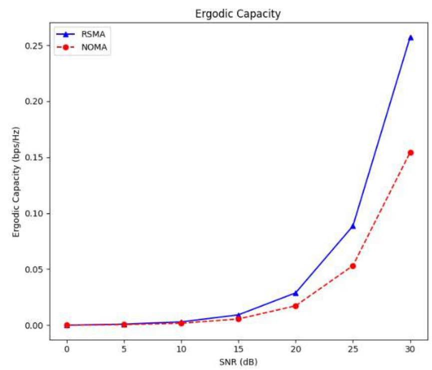

Figure 3.8: Ergodic Capacity between NOMA and RSMA

formance. However, as the SNR increases, RSMA significantly outperforms NOMA, achieving over 0.25 bps/Hz at 30 dB, while NOMA's capacity saturates below 0.15 bps/Hz. RSMA's rate-splitting mechanism allows for better interference management and more efficient use of the available bandwidth, showcasing its superior spectral efficiency in high-SNR environments.

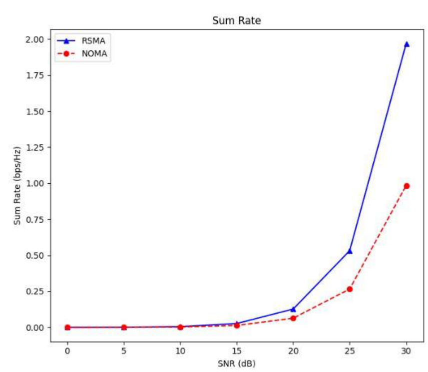

Figure 3.9: Sum Rate between NOMA and RSMA

Fig. 3.9 compares the sum rate performance of RSMA and NOMA-based systems under varying SNR conditions. Both schemes perform similarly at lower SNRs, but RSMA shows a clear advantage at higher SNR values, achieving a sum rate of around 2 bps/Hz at 30 dB, while NOMA reaches just under 1 bps/Hz. This significant difference arises from RSMA's efficient handling of interference via message splitting, which results in better channel utilization and higher throughput in high-SNR environments.

Table 3.1: Comparison Between RSMA and NOMA

Parameter	**NOMA**	**RSMA**
Interference Management	Limited	Efficient (via message splitting)
Outage Probability	Higher	Lower
Ergodic Capacity	Moderate	High and scalable
Sum Rate	Low	High, esp. at high SNR
Adaptability	Poor	Highly adaptive
UAN Performance	Degrades in shallow water	Robust in all scenarios

Table 3.2: Performance in Shallow vs. Deep Water

SNR (dB)	**Environment**	**Outage Prob.**	**Ergodic Cap.**	**Sum Rate**
5	Shallow	0.6	0.002	0.002
5	Deep	0.4	0.002	0.002
25	Shallow	0.1	0.003	0.14
25	Deep	0.002	0.038	0.17

Table **??** summarizes the communication characteristics in shallow and deep water environments at different SNR values (5 dB and 25 dB). The comparison includes key metrics such as outage probability, ergodic capacity, and sum rate. Shallow water experiences higher outage probability and lower capacity due to persistent multipath interference, while deep water shows improved performance, with lower outage probability and higher capacity, particularly at higher SNR levels.

Chapter 4

Conclusion

This thesis presented a comprehensive performance evaluation of Rate - Splitting Multiple Access (RSMA) and Non-Orthogonal Multiple Access (NOMA) in underwater acoustic networks under both shallow and deep water conditions. Through extensive simulations, it was observed that RSMA consistently outperforms NOMA in terms of outage probability, ergodic capacity, and sum rate, particularly at higher SNR levels. RSMA's flexible message-splitting mechanism enables more efficient interference management, leading to significant gains in capacity and reliability, especially in environments with severe multipath effects such as shallow waters.

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