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Design of a Naïve Bayes-Based Adaptive Modulation Model in a Time-Varying Channel Environment

ROSABELLA IKA YUANITA[1], SHOLIHAH AYU WULANDARI[2], TAUFIQ RAHMAN HUMAIDI[3]

[1]Politeknik Elektronika Negeri Surabaya, Surabaya, Indonesia
[2,3]Politeknik Negeri Jember, Jember, Indonesia

CORESPONDING AUTHOR: ROSABELLA IKA YUANITA (email: rosabella@pens.ac.id)

ABSTRACT Adaptive modulation (AM) is widely employed in Orthogonal Frequency Division Multiplexing (OFDM) systems to improve transmission efficiency under varying channel conditions. However, conventional adaptive modulation techniques generally rely on fixed Signal-to-Noise Ratio (SNR) thresholds, which often lead to suboptimal modulation decisions in time-varying channel environments. This study addresses the problem of modulation selection in dynamic channels by proposing a Gaussian Naïve Bayes-based adaptive modulation model that probabilistically determines the most appropriate modulation scheme according to the observed SNR. The proposed method was implemented in an OFDM system using BPSK, QPSK, and 16-QAM modulation schemes and evaluated over an Additive White Gaussian Noise (AWGN) channel with SNR values ranging from -5 dB to 15 dB. Simulation results show that the proposed adaptive approach consistently achieved BER performance equal to or better than conventional fixed modulation methods. At an SNR of 5 dB, the adaptive system selected QPSK and achieved a BER of 2.273×10^{-2}, while 16-QAM produced a BER of 1.9×10^{-1} under the same condition. In terms of message reconstruction, the proposed method successfully recovered the transmitted message "HELLO WORLD" at an SNR of 3 dB, whereas the conventional approach still produced reconstruction errors. These results demonstrate that the Gaussian Naïve Bayes classifier provides a lightweight and effective adaptive modulation mechanism capable of improving transmission reliability and message recovery performance in OFDM systems operating under time-varying channel conditions.

KEYWORDS: Adaptive Modulation, Classification, Naïve Bayes, OFDM, SNR Variation

I. INTRODUCTION

The digital technique called Orthogonal Frequency Division multiplexing or OFDM is used in wireless communication standards. These include Asymmetric Digital Subscriber Line (ADSL), IEEE 802.16a and IEEE 802.11a/g wireless LANs. OFDM works by dividing the signal into small subcarriers. Each of these subcarriers operates at different frequency[1]. OFDM has some advantages over other modulation techniques. It is good at handling multipath fading effects and also easy to equalize the signal. But it has a problem, the performance would be degraded when the channel conditions change quickly or affected by high noise levels [2]. Thus, using a fixed modulation scheme in these conditions is not ideal: higher-order modulation achieves higher data rate but susceptible to low SNR, otherwise low-order modulation guaranteeing the reliability but achieves lower data rate [3]. This creates a critical challenge in OFDM systems: determining the most appropriate modulation scheme when channel conditions fluctuate continuously. Incorrect modulation selection may lead to increased bit errors, reduced spectral efficiency, and degraded communication reliability. Therefore, an intelligent mechanism capable of adapting modulation decisions according to dynamic channel conditions is required. To cope with these limitations, there is an adaptive modulation scheme to adjust the modulation order. It tries to find a balance between link reliability and spectral efficiency[4], [5].Conventional AM methods use predetermined SNR thresholds or BER models correlated to each modulation level. But, it

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doesn't perform well in realistic scenarios though the method works properly in steady channel conditions. These challenges are common in several communication systems, such as underwater, mobile, vehicular, and indoor, in which the channel changes unpredictably[6], [7]. Therefore, there is a growing interest in data-driven AM techniques to derive the modulation decision based on the channel condition.

Machine learning (ML) has become a way to build smart systems which adaptively adjust to different conditions. These system can be taught to find out the perfectly matched modulation scheme, whether BPSK, QPSK, or 16-QAM according to its SNR value. Prior studies work on ML-based link adaptation represent that ML exceeded conventional threshold-based methods, especially in unstable channel states[8]. For instance, ML-based transmission mechanisms have presented performance enhancements of reliability and spectrum efficiency in MIMO-OFDM systems [9]. Likewise, ML-based adaptive modulation has been successfully employed in dynamic mobility environments, such as drone-assisted communication to increase durability [10]. One type of ML called Naïve Bayes classifier offers a compelling balance of simplicity, computational efficiency, and robustness to uncertainty [11]. This thing figures out how likely it is that each type of modulation is the one based on what the channel is doing. Some studies have found that Naïve Bayes is accurately determine and identify different modulation schemes using probabilistic modeling for real time or power-limited wireless devices without increasing the complexity [12].

Many studies on ML for modulation focus on intricate frameworks or depend on deep learning models with heavy computational lifting [13]. Most other work looks at categorizing the modulation with fixed rules instead of adaptively changing the modulation in a smart way for fluctuating channels in an OFDM system. This chances us to create probabilistic ML-based AM scheme for changing modulation in real-world OFDM links that work well with different SNR [14], [15]. Although machine learning techniques have been increasingly applied to wireless communication systems, most previous studies focus on modulation classification or employ computationally intensive deep learning approaches [13]. Limited research has investigated lightweight probabilistic machine learning methods for adaptive modulation decision-making in OFDM systems operating under time-varying channel conditions. In addition, many existing adaptive modulation approaches rely on fixed SNR thresholds or deterministic decision rules, which often produce suboptimal modulation selection when channel conditions fluctuate rapidly [16]. As a result, transmission reliability may decrease due to inappropriate modulation choices under varying channel quality.

The research problem addressed in this study is how to improve modulation selection accuracy in OFDM systems operating under time-varying channel conditions while maintaining low computational complexity. To solve this problem, a decision-making mechanism is required that can adapt to channel variations without introducing excessive processing overhead.

Among various machine learning techniques, the Naïve Bayes classifier was selected because it offers several advantages for adaptive modulation applications. First, Naïve Bayes has low computational complexity and requires relatively small training data compared with deep learning approaches. Second, it provides probabilistic decision-making capabilities, allowing modulation selection to be based on the likelihood of channel conditions rather than rigid threshold values. Third, the algorithm is suitable for real-time communication systems where fast and efficient decisions are essential.

Therefore, this study proposes a Naïve Bayes-based adaptive modulation model for OFDM systems operating in time-varying channel environments. The proposed approach utilizes SNR observations to probabilistically determine the most suitable modulation scheme among BPSK, QPSK, and 16-QAM. Unlike conventional threshold-based adaptive modulation methods, the proposed model estimates modulation decisions using statistical characteristics of modulation performance, enabling more adaptive and robust operation under fluctuating channel conditions. The main contribution of this study is the development and evaluation of a lightweight probabilistic adaptive modulation framework that improves BER performance and message reconstruction quality while maintaining computational simplicity. The effectiveness of the proposed method is evaluated through BER analysis and text-message recovery performance across a wide range of SNR values.

II. METHOD

2.1 System Design

We simulate and analyze the performance of adaptive OFDM text transmission works with three modulation schemes, which are BPSK, QPSK, and 16-QAM by using MATLAB. The system we develop is proficient to select and decide which modulation to use derived from SNR, namely Naïve Bayes classifier-based adaptive modulation. This smart method purposes to improve the adaptability and accuracy of modulation choosing in fluctuating channel environments.

The simulation process used in this study consists of several main interconnected stages as shown in Figure 1. The stage begins by converting a text message into a sequence of bits, which are then modulated using three digital modulation schemes, namely BPSK, QPSK, and 16QAM to test each SNR and BER value. Each modulation scheme is then passed through an AWGN channel with varying SNR values to simulate transmission conditions degraded by noise. The received signal is then demodulated and its Bit Error Rate (BER) value is calculated for each modulation. This BER value is used as a feature for the adaptive modulation mode selection process using the Naïve Bayes algorithm, which calculates the likelihood and posterior of each modulation to determine the best option at a certain SNR. After the adaptive modulation is selected, the transmission process is repeated using that mode and the final result is evaluated through the BER and the quality of the text message that has been successfully reconstructed at the receiver side.

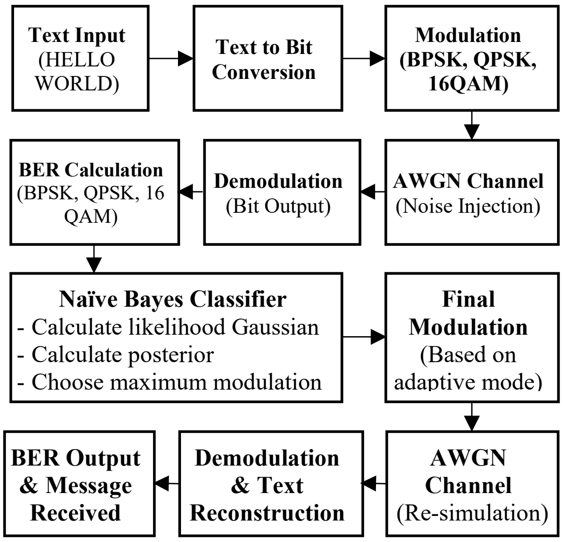

Figure 1. System Design

2.2 Data Preprocessing

2.2.1 Text-to-Bit Conversion

The text message "HELLO WORLD" is converted into an 8-bit binary representation of each character using the dec2bin function. All bits are then concatenated into an N × 1 binary vector. The total number of bits (Nbits) is used for the BER calculation.

2.3 Digital Modulation

The simulation uses three digital modulation schemes with different constellation orders:

- BPSK (M = 2)
- QPSK (M = 4)
- 16-QAM (M = 16)

The modulation functions used are:

$$s = QAMMod(b, M) \tag{1}$$

with the parameters InputType = bit and Unit Average Power = true, ensuring that all modulation schemes have a uniform average power.

2.4 AWGN Channel Model

The simulated channel is an AWGN (Additive White Gaussian Noise) channel represented by:

$$r = s + n \tag{2}$$

with complex noise:

$$n = \frac{1}{\sqrt{2}}(n_I + jn_Q), n_I, n_Q \sim \mathcal{N}(0,1) \tag{3}$$

The noise level is adjusted according to the SNR values within the range:

$$\text{SNR} = -5\text{ dB}: 2\text{ dB}: 15\text{ dB} \tag{4}$$

and added to the signal using the relation:

$$r = s + 10^{-\text{SNR}/20} \cdot n \tag{5}$$

2.5 BER (Bit Error Rate) Calculation

The evaluation process is carried out through several stages for each SNR value and each modulation scheme M. First, the signal is modulated according to the modulation scheme being tested. Next, Additive White Gaussian Noise (AWGN) is added to represent a degraded channel condition. The received signal is then demodulated to recover the processed bits. The performance of each modulation scheme is evaluated by comparing the demodulated bits with the original transmitted bits. The Bit Error Rate (BER) is calculated as:

$$\text{BER} = \frac{\sum(b_{\text{rx}} \neq b_{\text{tx}})}{N_{\text{bits}}} \tag{6}$$

The BER results for BPSK, QPSK, and 16-QAM are stored in three separate vectors.

2.6 Naïve Bayes-Based Adaptive Modulation Method

The adaptive intelligence method employed in this study utilizes a Gaussian Naïve Bayes Classifier to determine the most appropriate modulation scheme based on the observed SNR value. Each modulation class is assumed to follow a normal distribution with respect to the SNR parameter, such that the likelihood function for modulation class C_k is defined as:

$$p(x \mid C_k) = \frac{1}{\sqrt{2\pi\sigma_k^2}} \exp\left(-\frac{(x-\mu_k)^2}{2\sigma_k^2}\right) \tag{7}$$

where:

- C_k = {BPSK,QPSK,16-QAM}is the set of modulation classes,
- $x$is the observed SNR value,
- $\mu_k$is the mean SNR of class k,
- $\sigma_k^2$is the SNR variance of class k.

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The prior probability for each modulation class is assumed to be uniform, such that:

$$P(C_k) = \frac{1}{3} \tag{8}$$

The mean and variance are computed using standard statistical formulas:

$$\mu_k = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{9}$$

$$\sigma_k^2 = \frac{1}{N}\sum_{i=1}^{N} (x_i - \mu_k)^2 \tag{10}$$

where x_i represents SNR samples that characterize modulation class k.

The mean and variance parameters are set as initial estimates based on the general performance characteristics of each modulation scheme with respect to SNR. The following table shows the parameters used:

Table 1. General Performance Characteristics

Class	Mean (μ)	Variance (σ²)
BPSK	0	6
QPSK	7	6
16-QAM	13	6

2.6.1 Posterior Calculation

The adaptive modulation system determines the most suitable modulation type for the given channel condition based on the observed SNR value. The classification process is performed by calculating the posterior probability for each modulation class using the Naïve Bayes rule. For each SNR value, the posterior probability is estimated by multiplying the likelihood and the prior probability. This step enables the system to assess how likely each modulation type is to be the optimal choice under the given channel conditions. The final modulation class is then selected by choosing the class with the highest posterior value. Thus, this process serves as the core decision-making mechanism within the Naïve Bayes–based adaptive modulation system, allowing it to adapt efficiently to variations in channel quality.

For each SNR, the following is computed:

$$P(C_k \mid x) \propto p(x \mid C_k) \cdot P(C_k) \tag{11}$$

The chosen modulation corresponds to the class with the highest posterior probability can be denoted as

$$\hat{C} = \arg\max_{C_k} P(C_k \mid x) \tag{12}$$

where:

- C_k is the k-th modulation class: BPSK, QPSK, or 16-QAM.
- x is the observed feature or parameter, in this case the SNR value.
- $p(x \mid C_k)$ is the likelihood, representing the probability of observing a particular SNR value assuming the signal belongs to modulation class C_k.
- $P(C_k)$ is the prior probability for modulation class C_k, representing the system's initial assumption before considering the observed data.
- $P(C_k \mid x)$ is the posterior probability, indicating how likely modulation class C_k is to be selected based on the observed SNR.

2.6.2 Modulation Selection and BER Calculation

The modulation selected by the classification process (BPSK, QPSK, or 16-QAM) is then used to re-execute the entire transmission chain. This includes re-modulating the signal, adding noise according to the tested SNR level, and demodulating the signal at the receiver. The demodulated output is then analyzed to compute the adaptive Bit Error Rate (BER) for the Naïve Bayes–based system. This approach enables a comprehensive evaluation of the adaptive modulation performance while accounting for dynamic channel variations.

2.7 Performance Evaluation

The performance evaluation of the system is carried out using two main metrics. First, the Bit Error Rate (BER) is compared between the conventional system—which uses fixed modulation schemes BPSK, QPSK, and 16-QAM—and the Naïve Bayes–based adaptive modulation system. This comparison aims to measure the performance improvement gained through the adaptive modulation mechanism.

Second, the evaluation examines the demodulated text message to assess the robustness of each modulation scheme against noise interference. The test focuses on the system's ability to correctly recover the message "HELLO WORLD" at various SNR levels. The testing results are presented in the form of BER vs. SNR graphs using a logarithmic scale, allowing performance differences among modulation schemes to be observed more clearly and informatively.

III. RESULTS AND DISCUSSION

3.1 BER Simulation Results

The simulation was conducted over an SNR range of −5 to 15 dB for the three modulation schemes, namely BPSK, QPSK, and 16-QAM. In addition, an adaptive mode—Adaptive Naïve Bayes—was also evaluated. The graph of the simulated BER versus SNR is shown in Figure 2.

The overall simulation results show that BPSK produces the lowest BER across nearly the entire SNR range, consistent with theory since its constellation size is the smallest (M = 2), making it more robust against noise. QPSK demonstrates better performance than 16-QAM, especially under low to medium SNR conditions. Meanwhile, 16-QAM only begins to stabilize at SNR values above 10 dB, as its tighter symbol spacing makes it more sensitive to noise interference.

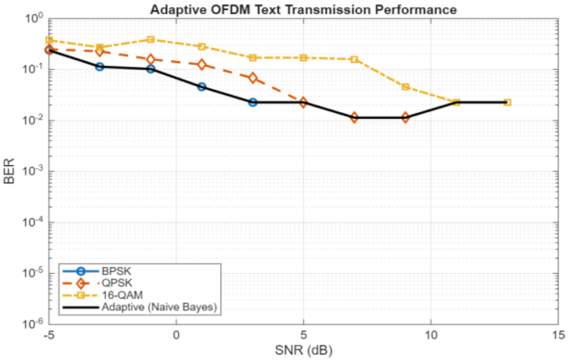

Figure 2. BER Performance Curves for BPSK, QPSK, 16-QAM, and Adaptive Mode

The Adaptive Mode scheme based on Naïve Bayes shows the ability to follow the most optimal modulation for each SNR condition, resulting in a BER curve that always lies at—or better than—the performance of each static modulation scheme. This adaptive mechanism effectively maintains transmission quality by keeping BER low without locking the system into a single modulation type.

The simulation results at an SNR of 5 dB show that QPSK achieves a BER of 2.273×10^{-2}, while 16-QAM performs significantly worse with a BER reaching 1.9×10^{-1} due to its high sensitivity to noise at medium SNR levels. The Naïve Bayes adaptive algorithm then selects the modulation with the best performance under these conditions—QPSK—so the BER produced by the adaptive system is also 2.273×10^{-2}. These findings reinforce that the adaptive approach can dynamically adjust to channel conditions, ensuring optimal modulation selection for each SNR value and consistently delivering better performance than conventional static schemes.

3.2 Text Demodulation Results

The message **"HELLO WORLD"** was transmitted through the system to practically evaluate system performance. The demodulated results at various SNR conditions are presented below.

3.2.1 Results of Static Modulation Schemes

High noise levels cause many bit errors at low SNR values (−5 to 1 dB), resulting in invalid received messages represented by random ASCII characters. However, improvements begin to appear at **SNR = 3 dB**, where the message becomes partially readable. Starting at **SNR = 9 dB**, the system is able to reconstruct the message perfectly.

Simulation Results:

[Conventional] SNR = -5 dB | Mode = BPSK | BER = 2.386e-01
Output: DMÜ WÍMV

[Conventional] SNR = -3 dB | Mode = BPSK | BER = 1.136e-01
Output: HÇLdO wOè@

[Conventional] SNR = -1 dB | Mode = BPSK | BER = 1.023e-01
Output: \ALLJ$V_ÒdÁ

[Conventional] SNR = 1 dB | Mode = BPSK | BER = 4.545e-02
Output: ÌELO"VkR\

[Conventional] SNR = 3 dB | Mode = BPSK | BER = 2.273e-02
Output: HMLLG WORLD

[Conventional] SNR = 5 dB | Mode = QPSK | BER = 2.273e-02
Output: HE\O WOLD

[Conventional] SNR = 7 dB | Mode = QPSK | BER = 1.136e-02
Output: HELLO WOLD

[Conventional] SNR = 9 dB | Mode = QPSK | BER = 1.136e-02
Output: HELLO WORLD

[Conventional] SNR = 11 dB | Mode = 16QAM | BER = 2.273e-02
Output: LELL_ WOÒLD

[Conventional] SNR = 13 dB | Mode = 16QAM | BER = 2.273e-02
Output: HELLO WORLD

[Conventional] SNR = 15 dB | Mode = 16QAM | BER = 0.000e+00
Output: HELLO WORLD

The simulation results for static schemes demonstrate that the quality of the received message is highly dependent on the SNR value. At low SNR values (−5 to 1 dB), the high noise level produces numerous bit errors, causing the reconstructed message to appear as unreadable random ASCII characters. Improvements begin at SNR 3 dB, as the BER decreases and parts of the message become readable, and eventually at SNR 9 dB, the system successfully reconstructs the entire message.

This general pattern highlights that higher SNR values lead to lower BER and, therefore, better received message quality. However, it also reveals the limitations of conventional fixed modulation. At high SNR conditions such as 15 dB, higher-order modulation like 16-QAM can achieve low BER and good message quality. Conversely, forcing the system to use BPSK or QPSK under the same channel condition leads to suboptimal results, as the modulation order is not matched to the actual channel quality-resulting in unnecessary errors.

This demonstrates that conventional modulation selection cannot adapt to dynamic channel variations. Therefore, an adaptive modulation mechanism is needed to handle channel uncertainty and select the most suitable scheme for each SNR value. Such an adaptive approach becomes increasingly important in unpredictable and rapidly changing channel environments, commonly encountered in modern communication systems.

3.2.2 Results of the Adaptive Naïve Bayes Method

The Naïve Bayes method produces better message quality compared to the conventional approach, particularly in the 1–5 dB SNR range. This is because the probabilistic model can still choose the optimal modulation type even when conditions are near the decision threshold.

[AdaptiveNaïveBayes] SNR = -5 dB | Mode = BPSK | BER = 2.386e-01
Output: IGLÏ ÕKRN%

[AdaptiveNaïveBayes] SNR = -3 dB | Mode = BPSK | BER = 1.136e-01
Output: ÙInoWMDÅ

[AdaptiveNaïveBayes] SNR = -1 dB | Mode = BPSK | BER = 1.023e-01
Output: XEÌL {oRN@

[AdaptiveNaïveBayes] SNR = 1 dB | Mode = BPSK | BER = 4.545e-02
Output: HELLO(WRLA

[AdaptiveNaïveBayes] SNR = 3 dB | Mode = BPSK | BER = 2.273e-02
Output: HELLO WORLD

[AdaptiveNaïveBayes] SNR = 5 dB | Mode = QPSK | BER = 2.273e-02
Output: HEÌLO!WoZLD

[AdaptiveNaïveBayes] SNR = 7 dB | Mode = QPSK | BER = 1.136e-02
Output: HELLO WORLD

[AdaptiveNaïveBayes] SNR = 9 dB | Mode = QPSK | BER = 1.136e-02
Output: HELLO WORLD

[AdaptiveNaïveBayes] SNR = 11 dB | Mode = 16QAM | BER = 2.273e-02
Output: HEDLO UORLT

[AdaptiveNaïveBayes] SNR = 13 dB | Mode = 16QAM | BER = 2.273e-02
Output: HELLO WORLD

[AdaptiveNaïveBayes] SNR = 15 dB | Mode = 16QAM | BER = 0.000e+00
Output: HELLO WORLD

The simulation results show that the adaptive Naïve Bayes method provides better message reception quality than the conventional method, particularly in the low-SNR range of 1–5 dB, where the channel is highly prone to errors. The probabilistic model can select the most suitable modulation scheme even when the SNR is near threshold levels, making the decision-making process more adaptive and less rigid than that of conventional modes.

This can be observed at SNR 3 dB, where Naïve Bayes is already able to reconstruct the "HELLO WORLD" message correctly, while the conventional method becomes stable only at around 5–7 dB. At higher SNR levels, both methods exhibit nearly identical performance; however, at low SNR, random ASCII characters still appear due to high BER, an expected phenomenon in digital modulation.

Overall, with the adaptive Naïve Bayes scheme, the system can dynamically adjust the modulation type based on channel conditions, thereby improving message quality by reducing error rates across varying SNR levels.

3.3 Comparative Discussion of the Methods

The simulation results demonstrate that the proposed Naïve Bayes–based adaptive modulation method achieves superior performance compared with conventional fixed modulation schemes. In terms of Bit Error Rate (BER), the adaptive method consistently selects the most suitable modulation according to the current SNR condition, resulting in a BER curve that remains equal to or lower than those of the static modulation schemes. This adaptive capability enables the system to maintain transmission reliability while avoiding the limitations associated with using a single modulation scheme under varying channel conditions.

From the perspective of message reconstruction, the proposed method also shows improved performance, particularly in low-to-medium SNR environments. The adaptive Naïve Bayes model successfully reconstructs the transmitted message "HELLO WORLD" at an SNR of 3 dB, whereas the conventional approach only achieves stable reconstruction at higher SNR levels, approximately 5–7 dB. This result indicates that the probabilistic decision-making mechanism employed by Naïve Bayes can identify the most appropriate modulation scheme even when channel conditions are close to decision boundaries.

These findings are consistent with previous studies on machine-learning-based link adaptation and adaptive modulation. Dong et al. [8] reported that machine learning techniques can outperform conventional threshold-based approaches by providing more flexible adaptation to channel variations. Similarly, the proposed Naïve Bayes model improves modulation selection by utilizing posterior probabilities instead of fixed SNR thresholds, leading to more robust performance under fluctuating channel conditions.

The results also support the work of Ha et al. [9], who demonstrated that machine learning can improve transmission reliability and spectral efficiency in MIMO-OFDM systems. While their study employed more sophisticated machine learning models, the present work shows that comparable adaptive behavior can be achieved using a significantly simpler probabilistic classifier. This indicates that high computational complexity is not always required to obtain effective adaptive modulation performance.

Furthermore, the findings are aligned with the study of Gopi et al. [10], which applied machine-learning-assisted adaptive modulation in dynamic drone communication systems. Both studies demonstrate the benefits of intelligent modulation selection under changing channel conditions. However, unlike previous studies that focused on highly dynamic mobility scenarios and more advanced learning frameworks, this research emphasizes computational simplicity through the use of a Gaussian Naïve Bayes classifier.

The effectiveness of the proposed approach can be attributed to the probabilistic nature of Naïve Bayesclassification. Unlike deterministic threshold-based methods, the classifier evaluates the likelihood of each modulation class based on the observed SNR and selects the modulation with the highest posterior probability. This mechanism reduces sensitivity to abrupt channel fluctuations and enables smoother adaptation across different SNR regions.

Overall, the main contribution of this study is the development of a lightweight probabilistic adaptive modulation framework for OFDM systems operating in time-varying channel environments. The proposed method not only improves BER performance and message reconstruction quality compared with conventional fixed modulation schemes but also demonstrates that a computationally efficient Gaussian Naïve Bayes classifier can serve as an effective alternative to more complex machine-learning approaches. These characteristics make the proposed method particularly suitable for real-time OFDM communication systems with limited computational resources.

IV. CONCLUSION

This study proposed a Gaussian Naïve Bayes–based adaptive modulation model for OFDM systems operating under time-varying channel conditions. The simulation results demonstrate that the proposed method can dynamically select the most suitable modulation scheme according to the observed SNR and maintain BER performance comparable to or better than conventional fixed modulation approaches. At an SNR of 5 dB, the adaptive system selected QPSK and achieved a BER of 2.273×10^{-2}, whereas 16-QAM produced a significantly higher BER of 1.9×10^{-1} under the same condition. In terms of message reconstruction, the proposed method successfully recovered the transmitted message “HELLO WORLD” at an SNR of 3 dB, while the conventional approach produced the erroneous output “HMLLG WORLD”. Similarly, at an SNR of 7 dB, the adaptive method reconstructed “HELLO WORLD” correctly, whereas the conventional method generated “HELLO WOLD”. These results indicate that the Gaussian Naïve Bayes classifier can improve modulation decision reliability and message recovery quality while maintaining low computational complexity, making it suitable for real-time OFDM communication systems.

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ROSABELLA IKA YUANITA received the B.A.Sc. degree in telecommunication engineering from Politeknik Elektronika Negeri Surabaya (EEPIS), Surabaya, Indonesia, in 2016, and the M.Eng. degree in electrical engineering and M.Sc. degree in electronic and computer engineering from Institut Teknologi Sepuluh Nopember (ITS), Surabaya, Indonesia and National Taiwan University of Science and Technology (NTUST), Taipei, Taiwan, respectively, all Master Degrees in 2018. She is currently an assistant professor with the Department of Electrical Engineering, Politeknik Elektronika Negeri Surabaya (EEPIS), since 2025. Her research interests include optimization and energy efficiency in wireless communications.

SHOLIHAH AYU WULANDARI received her Diploma (D3) degree in Telecommunication Engineering in 2015 and her Applied Bachelor (D4) degree in Telecommunication Engineering in 2017, both from the Electronic Engineering Polytechnic Institute of Surabaya (EEPIS), Surabaya, Indonesia. She later earned her Applied Master of Engineering (M.Tr.T) degree in Electrical Engineering from the same institution in 2019. Her major field of study is intelligent systems and digital signal processing.

She is currently a Lecturer in the Department of Information Technology, Jember State Polytechnic, Indonesia. Her research interests include artificial intelligence, digital signal processing, the Internet of Things (IoT), and Digital Marketing. She is also active in research and publications in the field of underwater communication based on intelligent computing methods.

Ms. Wulandari is a member of APTIKOM. She has participated in various national and international scientific activities. She can be contacted at sholihah.ayuwulan@polije.ac.id

TAUFIQ RAHMAN HUMAIDI, received the S.TP. degree in Agricultural Technology from Universitas Negeri Jember (UNEJ), Jember, Indonesia, in 2012, and the M.M. degree in Management from Universitas Airlangga, Surabaya, Indonesia, in 2018. He has been a lecturer in the Department of Agribusiness Management, Politeknik Negeri Jember, since 2024. His research interests include marketing management and agribusiness management.