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Adaptive Modulation and Coding in 5G Wireless Communication Systems

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Abstract: ***Adaptive Modulation and Coding (AMC) is a critical technique employed in 5G wireless communication systems to dynamically adjust the modulation order and coding rate based on real-time channel conditions. As 5G aims to support diverse applications ranging from enhanced mobile broadband (eMBB) to ultra-reliable low-latency communications (URLLC) and massive machine-type communications (mMTC), AMC provides the necessary flexibility and efficiency to meet these varied performance requirements. By intelligently switching between modulation schemes such as QPSK, 16-QAM, 64-QAM, and 256-QAM and adapting coding rates, AMC maximizes spectral efficiency, increases data throughput, and ensures transmission reliability under fluctuating signal-to-noise ratios (SNR). In 5G systems, AMC is tightly integrated with advanced features like massive MIMO, beamforming, and hybrid automatic repeat request (HARQ), enabling robust link adaptation and efficient use of available resources. Thus, AMC is instrumental in achieving the high capacity, performance, and resilience demanded by next-generation wireless networks.***

Keywords: Adaptive Modulation and Coding (AMC), Bit Error Rate (BER), Signal-to-Noise Ratio (SNR), Spectral Efficiency, Throughput, Wireless Communication

1. Introduction

Adaptive Modulation and Coding (AMC) has been extensively studied as an effective link adaptation technique in wireless communication systems. Early foundational work by Goldsmith and Chua [1] established the principles of adaptive coded modulation over fading channels, demonstrating significant improvements in spectral efficiency and reliability. Subsequent studies expanded on these concepts, showing that AMC dynamically adjusts modulation schemes and coding rates to match channel conditions, thereby optimizing bandwidth utilization and minimizing error rates [2]. These early contributions laid the groundwork for AMC adoption in modern wireless standards. With the evolution toward 5G systems, the importance of AMC has increased due to highly dynamic and heterogeneous network environments. Recent studies emphasize the role of accurate Channel State Information (CSI) and Channel Quality Indicators (CQI) in enabling efficient link adaptation [3].Research has also explored AMC in conjunction with advanced technologies such as massive MIMO and beamforming, which enhance channel conditions and allow higher-order modulation schemes to be utilized more effectively [4], [5].Furthermore, performance analyses under realistic channel models, such as nakagami fading, demonstrate that AMC significantly improves throughput and reduces bit error rates in 5G networks[6].In addition, the integration of AMC with Hybrid Automatic Repeat Request (HARQ) and Automatic Repeat Request (ARQ) mechanisms has been widely investigated. Wang et al. [7] analyzed cross-layer designs combining AMC and ARQ, showing improvements in Quality of Service (QoS) metrics. Other studies have proposed joint optimization frameworks that enhance reliability and latency performance in dynamic environments [8], [9]. These approaches highlight the importance of combining physical-layer adaptation with higher-layer protocols to achieve robust communication.

Moreover, AMC plays a critical role in supporting diverse 5G service categories, including enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and massive Machine-Type Communications (mMTC). Research indicates that AMC enables flexible adaptation strategies tailored to these use cases, balancing trade-offs between throughput, latency, and reliability [4], [10]. Several works have also focused on optimizing modulation and coding selection algorithms to improve overall system efficiency and user experience in dense network deployments. Recent advancements in AMC research focus on intelligent and data-driven approaches. Machine learning and reinforcement learning-based techniques have been proposed to enhance link adaptation by predicting channel conditions and optimizing modulation and coding selection [11], [12].

These approaches outperform traditional lookup table-based methods in complex and rapidly changing environments. Additionally, emerging studies explore deep learning and AI-driven frameworks for improving AMC performance and adaptability in next-generation networks [13], [14].

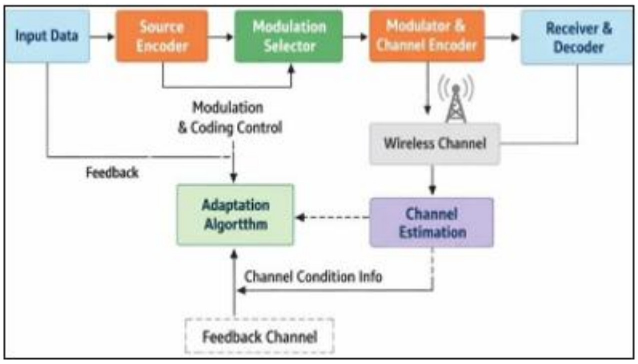
2. Literature Review

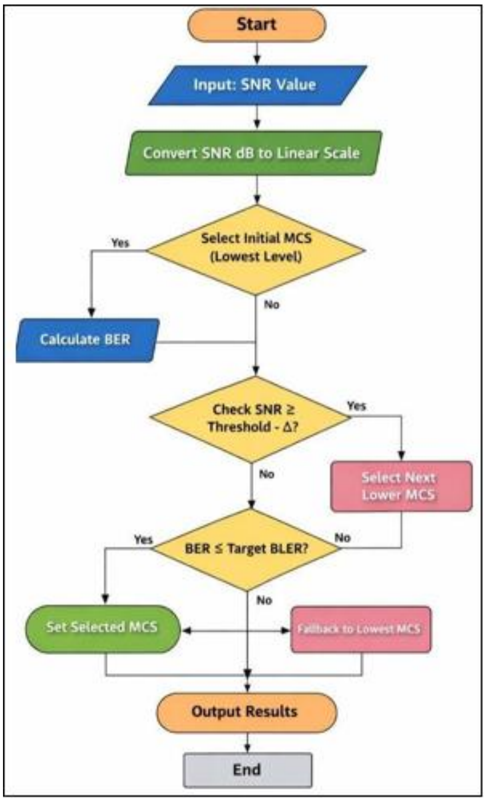
Adaptive Modulation and Coding (AMC) has been widely recognized as a key link adaptation technique for improving spectral efficiency and reliability in wireless communication systems. Several studies have explored its applications in 5G networks and beyond.

[1] Goldsmith & Chua (1998) – Introduced adaptive coded modulation for fading channels, showing that dynamically adjusting modulation and coding improves throughput and reduces error rates. [2] Mokheef (2016) – Reviewed AMC principles and techniques in modern wireless systems, emphasizing the trade-off between spectral efficiency and link reliability.[3] Lin et al. (2010) – Proposed prediction-based adaptation for AMC, demonstrating enhanced throughput using channel condition forecasts.[4] Wang et al. (2020) – Studied AMC in 5G systems, highlighting its integration with advanced network technologies to maximize spectral efficiency and reliability.[5] Huang et al. (2020) – Investigated AMC combined with massive MIMO, showing significant performance improvement through spatial diversity and adaptive link selection. [6] Bhargavi et al. (2025) – Evaluated bit error rate and throughput in 5G using AMC, demonstrating improved performance under realistic fading environments.[7] Wang, Liu & Giannakis (2007) – Analyzed AMC combined with ARQ mechanisms, showing better Quality of Service (QoS) metrics through cross-layer design.[8]Hwangetal. (2017) – Explored AMC with cooperative ARQ strategies, demonstrating enhanced reliability in dynamic wireless networks.[9] Foukalas & Zervas (2010) – Proposed cross-layer AMC design with turbo coding, improving link robustness under varying channel conditions.[10] Rappaport et al. (2019) – Provided an overview of 5G technologies, highlighting AMC's role in meeting diverse requirements of eMBB, URLLC, and mMTC.[11] Mota et al. (2019) – Introduced reinforcement learning approaches for AMC in 5G, showing improved modulation and coding adaptation in real-time channels.[12] Lin et al. (2010) – Investigated adaptive modulation using channel prediction, demonstrating more efficient spectrum use in fluctuating wireless environments.[13] Ben Chikha et al. (2025) – Applied deep learning for AMC in 5G, improving modulation classification and link adaptation in complex networks.[14] Pan et al. (2025)– Explore LLM-based AMC approaches, providing intelligent link adaptation for next-generation wireless systems.[15] Huang et al. (2020) – Studied machine learning- based AMC for wireless systems, highlighting improvements in reliability and throughput over conventional methods. Rates to ensure reliable communication. Conversely, in favourable channel conditions, higher-order modulation schemes with higher coding rates are utilized to achieve increased data throughput. Thus, the fundamental principle of AMC is to maximize spectral efficiency while maintaining a predefined target error performance, such as Block Error Rate (BLER), by continuously adapting the transmission scheme to the prevailing channel state.

3. Methodology

In this work, an Adaptive Modulation and Coding (AMC) framework is implemented to evaluate the dynamic link adaptation performance of multiple QAM schemes under varying channel conditions. The simulation is performed using MATLAB, with the methodology structured as follows. The principle of Adaptive Modulation and Coding (AMC) is based on the dynamic adaptation of transmission parameters in response to time-varying channel conditions. Specifically, AMC selects an appropriate Modulation and Coding Scheme (MCS) according to the instantaneous channel quality, typically measured in terms of Signal-to-Noise Ratio (SNR) or Signal-to-Interference-plus-Noise Ratio (SINR) In poor channel conditions, AMC employs lower-order modulation schemes with lower coding rates to ensure reliable communication. Conversely, in favourable channel conditions, higher-order modulation schemes with higher coding rates are utilized to achieve increased data throughput. Thus, the fundamental principle of AMC is to maximize spectral efficiency while maintaining a predefined target error performance, such as Block Error Rate (BLER), by continuously adapting the transmission scheme to the prevailing channel state. Lower-order modulation schemes with lower coding





***System configuration*:**
The simulation environment is initialized by defining key system parameters, including the target Block Error Rate (BLER) of 1×10−51\times10^ {-5}1×10−5 and a Signal-to-Noise Ratio (SNR) offset to provide conservative link

adaptation. A modulation and coding scheme (MCS) table is constructed, comprising multiple modulation orders (QPSK, 8-QAM, 16-QAM, 32-QAM, 64-QAM, 256-QAM), corresponding code rates, spectral efficiencies, and unique CQI indices. Each MCS is associated with a threshold SNR that defines the minimum channel quality required for its activation. Simulated SNR values are generated over multiple time slots to emulate realistic, time-varying simulation environment is initialized by defining key system parameters, including the target Block Error Rate (BLER) of 1×10−51\times10^ {-5}1×10−5 and a Signal-to- Noise Ratio (SNR) offset to provide conservative link adaptation. A modulation and coding scheme (MCS) table is constructed, comprising multiple modulation orders (QPSK, 8-QAM, 16-QAM, 32-QAM, 64-QAM, 256-QAM), corresponding code rates, spectral efficiencies, and unique CQI indices. Each MCS is associated with a threshold SNR that defines the minimum channel quality required for its activation. Simulated SNR values are generated over multiple time slots to emulate realistic, time-varying wireless channel conditions.

A. Modulation and Coding Scheme (MCS) Design:

A predefined MCS table is constructed consisting of multiple modulation schemes, including QPSK, 8-QAM, 16- QAM, 32-QAM, 64-QAM, and 256-QAM.Each entry in the table is characterized by: Channel Quality Indicator (CQI) index, Modulation order M=2kM = 2^kM=2k, Coding rate, Spectral efficiency (SE), The spectral efficiency is defined as:
SE = (log2 M) * code rate
AMC Selection Algorithm: ***Steps of AMC Selection Algorithm:***

1) **Measure Channel Quality:** The receiver measures channel quality using SNR or CQI values.
2) **Send Feedback:** The receiver sends the CQI value back to the transmitter.
3) **Select MCS:** The transmitter selects a suitable modulation and coding scheme (e.g., BPSK, QPSK, 16-QAM, 64-QAM, 256-QAM) based on CQI.
4) **Transmit Data:** Data is transmitted using the selected modulation and coding scheme.
5) **Adjust if Needed:** If error rate increases, the system switches to a lower MCS; if conditions improve, a higher MCS is selected.

Parameter	Formula / Expression
SNR (Signal-to-Noise Ratio)	$\mathrm{SNR\ (dB)} = 10 \cdot \log_{10}\left(\frac{P_{signal}}{P_{noise}}\right)$
BER – QPSK	$\mathrm{BER_{QPSK}} = Q\left(\sqrt{2 \cdot \mathrm{SNR}}\right)$
BER – 16-QAM	$\mathrm{BER_{16\text{-}QAM}} \approx \frac{3}{8} \cdot Q\left(\sqrt{\frac{4}{5} \cdot \mathrm{SNR}}\right)$
BER – 64-QAM	$\mathrm{BER_{64\text{-}QAM}} \approx \frac{7}{24} \cdot Q\left(\sqrt{\frac{12}{63} \cdot \mathrm{SNR}}\right)$
BER – 256-QAM	$\mathrm{BER_{256\text{-}QAM}} \approx \frac{15}{128} \cdot Q\left(\sqrt{\frac{8}{255} \cdot \mathrm{SNR}}\right)$
CQI (Channel Quality Indicator)	$\mathrm{CQI} = f(\mathrm{SNR})$
MCS Rate	$R = k \cdot r$
Throughput (bps)	$T = R \cdot \mathrm{BW}$
Target BLER Adjustment	$\mathrm{SNR_{req}} = \mathrm{SNR_{measured}} + \Delta_{\mathrm{SNR}}$
Effective SNR (multi-subcarrier)	$\mathrm{SNR_{eff}} = -\beta \cdot \ln\left(\frac{1}{N}\sum_{n=1}^{N} e^{-\mathrm{SNR}_n/\beta}\right)$

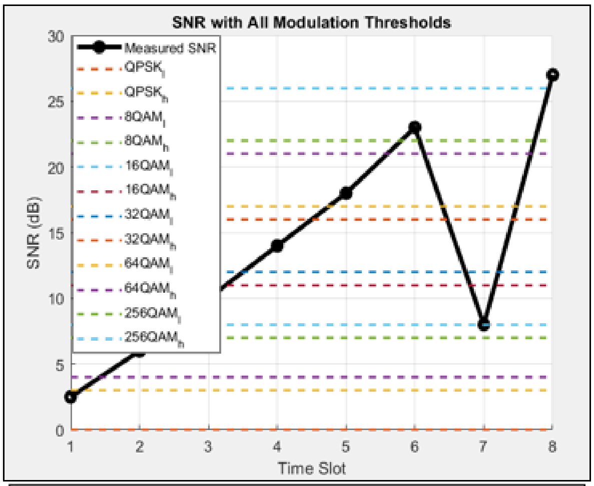
***Overall Framework*:**

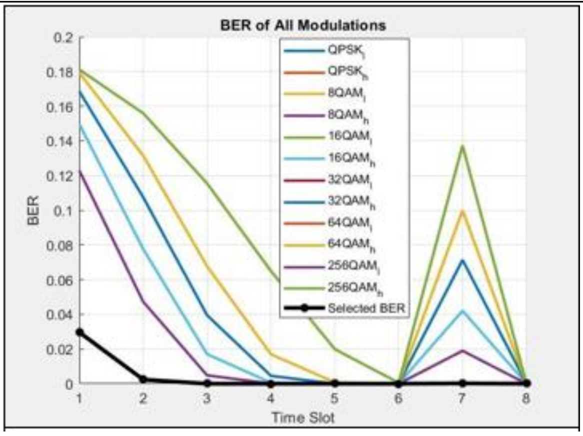
Adaptive Modulation and Coding (AMC) is a closed-loop framework designed to optimize wireless communication performance by dynamically adapting transmission parameters according to channel conditions. In this framework, the receiver continuously estimates channel quality metrics such as Signal-to-Noise Ratio (SNR) and maps them into a Channel Quality Indicator (CQI). This CQI is then fed back to the transmitter through a feedback channel, enabling the transmitter to make informed decisions about the appropriate Modulation and Coding Scheme (MCS). The selection process ensures a balance between achieving higher data rates and maintaining reliable communication under varying channel conditions. Based on the received CQI, the transmitter adjusts the modulation order (e.g., QPSK to 256-QAM) and coding rate to suit the current channel environment. The adapted signal is transmitted and representations of the encoded features. Processed at the receiver through demodulation and decoding, where performance metrics like error rates are evaluated. This information is used for continuous refinement of CQI feedback, forming an adaptive loop. Overall, this framework improves spectral efficiency, maximizes throughput, and minimizes transmission errors, making AMC an essential technique in modern communication systems such as LTE and 5G.

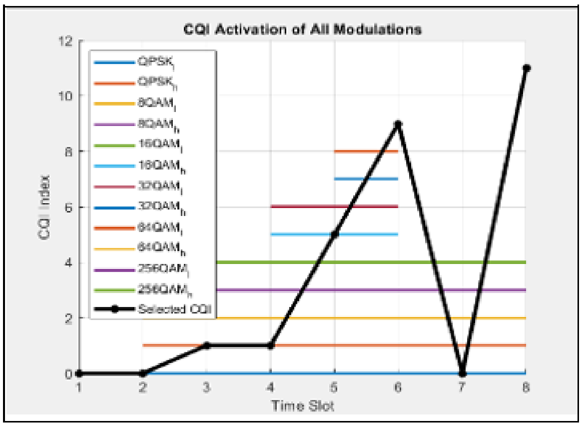
4. Results

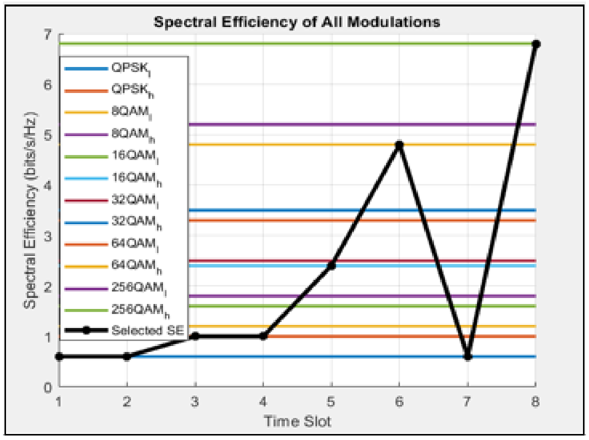
The performance of the Adaptive Modulation and Coding (AMC) system was evaluated under varying channel conditions using key parameters such as Signal-to-Noise Ratio (SNR), Bit Error Rate (BER), Channel Quality Indicator (CQI), and spectral efficiency. The results show that as SNR increases, the system adaptively selects higher-order modulation schemes, progressing from QPSK to 16-QAM, 64-QAM, and up to 256-QAM. At low SNR values, robust modulation with lower coding rates is chosen to maintain reliable communication with minimal errors. As the channel quality improves, higher-order modulation and higher coding rates are employed, significantly increasing data throughput and spectral efficiency while keeping error rates within acceptable limits.

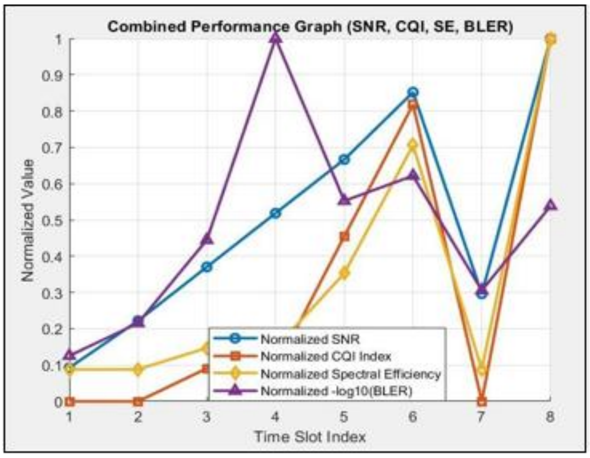
The analysis also demonstrates that AMC effectively balances the trade-off between reliability and efficiency. The BER and Block Error Rate (BLER) decrease with increasing SNR, validating the accuracy of CQI-based MCS selection. Additionally, the system shows smooth transitions between different modulation schemes, avoiding abrupt performance degradation. Overall, the results confirm that AMC enhances system performance by dynamically adapting to channel variations, ensuring optimal utilization of bandwidth and improved communication reliability, which is critical for modern wireless systems such as LTE and 5G.











TimeSlot	SNR_dB	Selected_CQI	Spectral_Efficiency	BER
1	2.5	0	0.6	0.029655
2	6	0	0.6	0.0023883
3	10	1	1	3.8721e-06
4	14	1	1	6.8102e-13
5	18	5	2.4	1.9e-07
6	23	9	4.8	2.7276e-08
7	8	0	0.6	0.00019091
8	27	11	6.8	2.8007e-07

5. Conclusion

The Adaptive Modulation and Coding (AMC) technique plays a vital role in enhancing the performance of modern wireless communication systems by dynamically adjusting modulation schemes and coding rates according to channel conditions. This project demonstrated that AMC effectively improves spectral efficiency and data throughput while maintaining acceptable error rates under varying Signal-to-Noise Ratio (SNR) conditions. By utilizing Channel Quality Indicator (CQI) feedback, the system intelligently selects appropriate Modulation and Coding Schemes (MCS), ensuring reliable and efficient communication. The results confirm that AMC provides a balanced trade-off between performance and reliability, making it a key technology in advanced systems such as LTE and 5G.

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