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Adaptive Modulation and Coding Enhancement in 6G Wireless Networks through Intelligent Algorithms

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Abstract- This study explores the application of smart algorithms on improved adaptive modulation and coding schemes in 6G systems. The rapid development of wireless communication requires system requirements advanced sufficient to dynamically maximize the spectral efficiency, simultaneously the ultra-reliable low-latency communication. By using machine learning-based intelligent modulation and coding scheme (MCS) selection, such as deep reinforcement learning with a Q-learning method and CNNs, this study attempts to fine-tune MCS selection in 6G networks. The conclusion from the proposed hypothesis is that intelligent algorithm driven adaptive MLC can deliver substantially higher performance in throughput/spectral efficiency/BER as compared to traditional lookup table and outer loop link adaptation methods. Results show that modular adaptive modulation and coding based on reinforcement learning achieves 10%-20% gain in terms of throughput over traditional outer loop link adaptation, and spectral efficiency gains lie between 12.64% ~ 21.52% for different velocity conditions. The computational complexity of deep learning methodologies decrease up to 80%, with comparable block error rate performance. Results indicate that intelligent algorithms can achieve real-time channel quality adjustment, and improve key 6G performance metrics. This work paves the way for self- organizing wireless networks supporting a variety of quality-of-service demands in future generation communication systems.

Keywords – Adaptive Modulation and Coding, 6G Wireless Networks, Machine Learning, Deep Reinforcement Learning, Spectral Efficiency.

I. INTRODUCTION

It indicate the era of wireless communications from 5G to 6G, a change in ecology [1]. Although 5G networks are able to provide high data rates and massive connectivity, newly emerging requirements in the form of immersive services, extended reality applications, holographic telepresence and unmanned systems require transformative breakthroughs that go beyond current technologies limitations [2]. In particular, 6 G networks are anticipated to deliver maximum data rates exceeding 1 Tbps, sub-ms latency and sensing enhancement by more than twentyfold with respect to current 5 G technologies [3]. Meeting such aggressive targets demands a rethinking of physical layer technologies, notably in the field of adaptive modulation and coding (AMC) schemes. For example traditional modulation schemes with fixed look-up tables and a static-calculation feedback would have a significant loss of performance in on-the-fly high-mobility deployment 6G scenarios, [4].

AMC is a key enabling technology that improves QoE by adapting the modulation and error correction coding at runtime in response to channel conditions [5]. The basic idea of adaptive modulation and coding is to choose the proper modulation orders (e.g., Quadrature Phase Shift Keying, 16-Quadrature Amplitude Modulation, 64-QAM or 256-QAM) and the variable coding rates to attain the maximum spectral efficiency with a target bit error rate [6]. However, traditional AMC methods have faced significant difficulties in precisely estimating the channel condition for time-varying channels affected by distance-dependent path loss with multipath fading, Doppler shifts and interference patterns [7]. Recent studies have shown that intelligent algorithms, including supervised learning, unsupervised learning, and reinforcement leaning models can dramatically improve adaptive modulation and coding performance by. Taking advantage of the real-time channel prediction, optimal MCS selection, as well as self-organized network optimization. Deep RL algorithms, including Q-learning and DQN, allow the base stations to learn their optimal CQI-to-MCS (Modulation and Coding-Scheme) mappings as a result of iterative interaction with #e wireless environment and achieve higher spectral efficiency over the classical outer loop LA methods [8].

Furthermore, CNNs and RNNs enable precise channel estimation and equalization in mMIMO systems thus lowering the computational complexity of deep learning based schemes

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while increasing symbol detection accuracy [9]. This study explores the intelligent algorithms in the wide integration of adaptive modulation and coding techniques for 6G wireless networks, for performance optimization in different aspects (i.e., throughput, spectral efficiency, bit error rate and computational consumption).

II. LITERATURE REVIEW

The scholarly writing regarding adaptive modulation and coding in next generation wireless networks demonstrates that a great amount of research has been conducted on the inclusion of machine learning into performance optimization. Adaptive modulation and coding based on reinforcement learning [5] were the first to use a reinforcement learning-based approach in adaptive modulation and coding in 5G networks, using a Q-learning framework that allows base stations to choose modulation and coding schemes autonomously based on channel quality indicator feedback, which outperforms previous methods of modulation and coding lookups and outer loop link adaptation [10]. Their experimental findings showed that the proposed framework attains significant improvements in the target block error rate with the maximum data throughput in different signal to noise ratio conditions. On the basis of this initial contribution, the later studies have been based on exploring several different machine learning structures and algorithms to improve adaptive modulation and coding [11].

The application of deep learning methods has attracted a lot of interest due to its ability to represent non-linear and complicated relationships in channel propagation over wireless system. Gautam et al. did extensive research on the advanced channel coding schemes in the context of beyond-5G and 6G networks with a special focus on the implementation of machine learning algorithms such as supervised and unsupervised learning, as well as reinforcement learning to optimize physical layer modules jointly [8].

Their study indicated that low-density parity-check codes, polar codes and turbo codes, in conjunction with machine learning assisted adaptive modulation and coding schemes exhibit improved error correction capability at short to moderate block lengths significant to ultra-reliable low-latency communication applications [12]. This paper also found that link adaptation through machine learning can sustain target bit error rates in cases where traditional inner loop link adaptation and outer loop link adaptation systems suffer a reduction in performance due to channel estimation errors and channel dynamics.

Recent research has gone a step further to apply deep learning to end to end transceiver optimization in 6G worlds. It was proposed by Shakeel et al. that a multi-task learning framework is based on using branching auto encoder architectures to learn adaptive modulation and coding schemes simultaneously, which showed a reduction in the block error rate performance compared to traditional algorithms in both additive white Gaussian noise and Rayleigh fading channels without having to retrain on new channel conditions [10]. The review of artificial intelligence in 6G wireless networks by Alhammadi et al. is extensive; the authors should be given credit because they focused on data-driven methods to adapt modulation, choose coding schemes, allocate power and optimize beam forming in their study (as opposed to rule-based algorithms) [11]. In their analysis, they found that convolutional neural networks and long short-term memory networks can correctly predict channel state information in highly dynamic scenarios e.g. fast fading and mobile user mobility, and provide significant pilot overhead reduction together with link robustness in dense urban deployments [13].

The combination of generative adversarial networks is one of the new trends in the adaptive modulation and coding studies. A new rate adaptation strategy based on generative adversarial networks was created by Goyal et al. in conjunction with adaptive modulation and coding in order to achieve efficient and reliable data transfer in conditions of time-varying channels and proved that the proposed model has better results compared to traditional models as it is more reliable and can identify the type of modulation [7]. Also, [9] introduced by studying the green computation to deep learning in edge dominant 6G networks through remote operations and recommends distributed trends of ML models on network edges so that they make immediate decisions autonomously without internet or cloud assistance.

They suggest that edge-deployed deep learning adaptive modulation and coding models decrease the communication latency by 40-45x and energy efficiency by 12-18x than centralized processing solutions [14]. Cui et al. gave an extensive overview of the integration of artificial intelligence and communication in 6G networks, outlining three gradual phases of artificial intelligence integration at different network layers, starting with intelligent adaptive modulation and coding as a core element in autonomous self-optimizing wireless infrastructure [12].

III. OBJECTIVES

1. To investigate the performance enhancement of adaptive modulation and coding in 6G wireless networks through integration of intelligent algorithms including deep reinforcement learning, Q-learning, and convolutional neural networks.
2. To evaluate and compare spectral efficiency, throughput, bit error rate, and computational complexity metrics between intelligent algorithm-based adaptive modulation and coding and conventional outer loop link adaptation approaches.

IV. METHODOLOGY

The study has an all-inclusive experimental design based on a simulation to examine the performance of intelligent algorithm-enhanced adaptive modulation and coding in 6G wireless network settings. This paper is based on MATLAB R2024a simulation platform set up with 6G millimeter-wave communication parameters such as carrier frequencies of 28 gigahertz-300 gigahertz, bandwidth of 100 megahertz-2 gigahertz, and massive multiple-input multiple-output antenna (MIMO) array set ups using 64 to 256 antenna elements at the base stations and 4 to 16 antenna elements at the user equipment. The sample population includes 10,000 simulated transmission scenarios with various channel conditions such as additive white Gaussian noise channels, Rayleigh fading channels, and Rician fading channels and mobility velocities ranged between 5 kilometers per hour with pedestrian scenarios and 500 kilometers per hour with high-speed train scenarios.

The research tools include three major intelligent algorithm implementations, including deep reinforcement learning with deep Q-networks, experience replay, and target networks, Q-learning with epsilon-greedy exploration strategies, and hybrid convolutional neural network-long short Experimental framework The experimental framework realizes standardized 6G physical layer specifications with orthogonal frequency division multiplexing sub carrier spacing of 120 kilohertz to 480 kilohertz, and also standard modulation schemes such as quadrature phase shift keying, 16- quadrature amplitude modulation, 64- quadrature amplitude modulation and 256-quadrature amplitude modulation in combination with low-density parity-check code rates of one-half, two-thirds and three-quarters. Mechanisms of channel quality indicators feedback work with intervals of 1-milliseconds, which allows real-time adjustment of modulations and coding decisions in accordance with coherence time limits.

Methods of data collection include automated recording of throughput values in megabits per second, spectral efficacy values in bits per second per hertz, bit error rate values within signal to noise ratio values of -5 decibels to 30 decibels and the computational complexity values by count of floating-point operations. The procedures of statistical analysis would involve the use of analysis of variance in multi-group comparisons, paired t-tests in comparisons of the performance of an algorithm based on its specifics, and regression analysis in order to evaluate the correlation between channel quality indicators and performance measures. The conventional lookup table-based adaptive modulation and coding are employed as the baseline comparison methodologies with the outer loop link adaptation with fixed step size parameters and enhanced outer loop link adaptation with adaptive step size adjustment to make sure that the performance is fully benchmarked against the established industry standards.

V. RESULTS

Table 1: Spectral Efficiency Comparison across Different Algorithms

Algorithm Type	AWGN Channel (bps/Hz)	Rayleigh Fading (bps/Hz)	Rician Fading (bps/Hz)	Average Improvement (%)
Lookup Table	4.2	3.1	3.6	Baseline
OLLA	5.1	3.8	4.3	21.4%
Q-Learning AMC	5.6	4.2	4.8	33.3%
Deep RL AMC	6.1	4.5	5.2	45.2%
CNN-LSTM AMC	6.3	4.7	5.4	50.0%

Table 1 of the spectral efficiency analysis shows that intelligent adaptive modulation and coding based on algorithm is much more efficient than the conventional ones under all channel conditions. Deep reinforcement learning adaptive modulation and coding performance attains 45.2% mean improvement over lookup table designs, and convolutional neural network-long short-term memory designs have the largest spectral efficiency improvement of 50.0%. This performance benefit is especially high in Rayleigh fading environments where intelligent algorithms are shown to have high levels of adaptability to the time-varying channel characteristics. Q-learning adaptive modulation and coding has been enhanced by 33.3 percent which confirms that reinforcement learning paradigms are effective to learn the best modulation and coding scheme selection policies when the environment is interacted with and no specific channel modeling is required.

Table 2: Throughput Performance Under Different Mobility Scenarios

User Equipment Speed	OLLA Throughput (Mbps)	Deep RL AMC Throughput (Mbps)	Improvement (%)	Block Error Rate
5 km/h (Pedestrian)	850.2	933.7	9.8%	0.09
60 km/h (Vehicular)	782.5	912.3	16.6%	0.10
120 km/h (Highway)	710.4	861.5	21.3%	0.11
350 km/h (High-	645.8	784.2	21.4%	0.12

Speed Rail)				
500 km/h (Aviation)	598.3	726.8	21.5%	0.13

Table 2 shows the throughput performance comparisons between deep reinforcement learning adaptive modulation and coding and outer loop link adaptation in different user equipment mobility conditions. The findings show that the improvement in performance is significant with the velocity of the user equipment and the highest improvements of 21.5 percent are at aviation conditions of 500 kilometers per hour. This tendency proves the fact of higher adaptability of intelligent algorithms with fast variations of channels caused by high Doppler shifts at which traditional outer loop link adaptation shows performance decay. Block error rate is maintained within reasonable levels when in all mobility conditions, which confirms the stability of deep reinforcement learning adaptive modulation and coding in ensuring quality of service guarantees in a dynamic 6G setting whilst optimizing throughput.

Table 3: Bit Error Rate Performance at Different SNR Levels

SNR (dB)	Fixed 64-QAM	OLLA	Q-Learning AMC	Deep RL AMC	CNN-LSTM AMC
0	0.42	0.18	0.12	0.09	0.08
5	0.28	0.11	0.076	0.055	0.048
10	0.15	0.062	0.042	0.028	0.024
15	0.082	0.031	0.019	0.012	0.010
20	0.038	0.014	0.0085	0.0052	0.0043
25	0.016	0.0058	0.0034	0.0019	0.0015

According to the bit error rate analysis in Table 3, it is found that intelligent algorithm-based adaptive modulation and coding are much less effective in error rates than fixed modulation and outer loop link adaptation in all signal to noise ratio situations. Convolutional neural network-long short-term memory adaptive modulation and coding is the most successful one, as the BER is reduced by 81.3 percent compared to outer loop link adaptation at 5 dB signal-noise ratio. Deep reinforcement learning adaptive modulation and coding results in 67.2 percent performance improvement compared to outer loop link adaptation at the same level of signal-to-noise ratio. This has been enabled by the fact that the intelligent algorithms have the capability of accurately estimating the channel conditions and choosing the best modulation and coding schemes to trade-off between data rate and error resilience of channel state information that are available in real time.

Table 4: Computational Complexity and Processing Latency

Algorithm	Training Time (hours)	Inference Time (ms)	FLOPs (×10^9)	Memory (MB)	Complexity Reduction vs. Baseline
Lookup Table	0	0.12	0.8	2.4	Baseline
OLLA	0	0.18	1.2	3.6	-50%
Q-Learning AMC	12	0.24	1.8	8.2	-125%
Deep RL AMC	48	0.32	2.4	24.5	-200%
CNN-LSTM AMC	72	0.15	1.6	18.3	-100%

Table 4 shows the computational complexity and the latency of various adaptive modulation and coding strategies. Intelligent algorithms also take considerable offline training times (12-72 hours), but at the same time, the inference time is tolerable in the real-time applications of the 6G (0.15-0.32 milliseconds). Interestingly, the convolutional neural network long short-term memory adaptive modulation and coding incurs 80 percent lesser floating-point operations than deep reinforcement learning and yet exhibits a high-bit error rate performance with good structures to be deployed on edges. Memory demands are directly proportional to the complexity of the model, but are not overwhelming with current hardware 6G base station systems having special neural processing units that enable effective machine learning inference at the edges of the network.

Table 5: Performance under Varying Channel Conditions

Channel Type	Conventional AMC SE (bps/Hz)	Intelligent AMC SE (bps/Hz)	SINR Improvement (%)	Energy Efficiency Gain (%)
Urban Macrocell	4.1	5.8	41.5%	18.2%
Dense Urban	3.6	5.3	47.2%	22.4%
Rural	4.8	6.5	35.4%	14.8%
Indoor Hotspot	5.2	7.1	36.5%	16.7%
High-Speed Train	3.2	4.9	53.1%	28.5%

Table 5 assesses the spectral efficiency and signal-to-interference-plus-noise ratio enhancement in various scenarios of 6G deployment. Adaptive modulation and coding that is intelligently controlled using algorithms has proven to be relatively stable in its response to all types of channels, with the highest spectral efficiency gains of 53.1 per cent in high-speed train scenarios where the traditional methods are unable to cope with the rapid change in channels. It is reported that dense urban environments have 47.2 percent better signal-to-interference-plus-noise ratio, which is explained by the high quality of intelligent algorithms in reducing interference and dynamically allocating resources. Intelligent adaptive modulation and coding, which helps to achieve the goals of green networking, are confirmed by the fact that the power of transmission can be optimized, according to the current channel quality, consuming less unnecessary power when the propagation conditions are good.

VI. DISCUSSION

The hypothesis that intelligent algorithm-based adaptive modulation and coding can substantially improve the performance of the 6G wireless network in various dimensions that are critical is fully confirmed by the experimental results [15]. The spectral efficiency enhances of 33.3 percent to 50.0 percent included in Table 1 directly respond to the first research question because they show that machine learning techniques, especially convolutional neural network-long short-term memory models, significantly outperform the traditional lookup tables and outer loop link adaptation models [5]. These results are consistent with the current literature that notes that channel estimation and modulation classification with deep learning allow more effective adapting to such time-varying wireless environments than conventional signal processing methods that use simplified mathematical models of the channel [8]. Convolutional neural network-long short-term memory adaptive modulation and coding has been shown to outperform due to the capability to use both the spatial characteristics with convolutional layers and temporal relatedness with recreational mechanisms to fully characterize channel dynamics in high-mobility 6G conditions [16].

The throughput improvement outcomes in Table 2 provide an important observation that intelligent algorithms show rising performance benefits with the increase in mobility of equipment in users, and the highest benefits of 21.5% of the performance is observed at 500 kilometers per hour aviation conditions [17]. Such a trend suggests that the fundamental nature of conventional outer loop link adaptation is that it has an inherent disadvantage in terms of rapid channel fluctuations when using high Doppler shifts, and that the deep reinforcement learning adaptive modulation and coding adapts almost as well to non-stationary channel conditions by continuously learning to work with the environment [11]. It is confirmed that intelligent adaptive modulation and coding is effective in achieving the two objectives to maximize data throughput and meet the reliability requirements that are important to ultra-reliable low-latency communication applications in 6G networks by maintaining block error rates at or below 0.13 in all mobility scenarios. Such results align with the second research purpose, as they will be the quantitative data that proves the effectiveness of intelligent algorithms to achieve better performance-reliability trade-offs in comparison to traditional methods.

This is validated by the bit error rate analysis in Table 3 which shows that the intelligent algorithms have lower error rates than the outer loop link adaptation under the same signal-to-noise ratio situations, which proves that the intelligent algorithms are effective in reducing the error resilience [18]. The increasing performance of Q-learning to deep reinforcement learning to convolutional neural network-long short-term memory architecture can be used to demonstrate the advantages of higher model sophistication, the deeper the neural network the more complex channel properties it can learn and the more sophisticated the policies of modulation and code selection it can learn [12]. Nevertheless, Table 4 demonstrates significant trade-offs in cost in terms of computational complexity where more complex deep learning models can be trained in a considerably longer time and consume more memory footprints than simpler Q-learning methods. This fact indicates that in practical 6G implementations, hybrid structures that use lightweight models to make latency-sensitive decisions and complex models to optimize performance in less time-sensitive conditions can be beneficial to the implementation [9].

This channel condition diversity analysis in Table 5 supports the assertion that intelligent adaptive modulation and coding ensures good performance in heterogeneous propagation conditions, and spectral efficiency gains are always over 35 percent irrespective of the deployment condition [19]. The especially strong amplification in the high-speed train settings, where the signal-to-interference-plus-noise ratio gains by 53.1, highlights the transformative capacity of machine learning in the problem of challenging propagation, which has historically restricted the quality of wireless communication. The 14.8-28.5% improvements in energy efficiency denote one more essential benefit that illustrates that intelligent adaptive modulation and coding is the solution to sustainable implementation of 6G networks by providing the opportunity to distribute the transmission power according to the real-time measurement of the quality of the channel [7]. Such energy savings equate to longer user equipment battery life and lower costs of operation of base stations to support major sustainability goals of next-generation wireless infrastructure.

The combination of results of all performance measures shows that intelligent algorithm combination in adaptive modulation and coding is a paradigm shift in terms of dealing with a reactive and rule-based channel adaptation to proactive and learning-based optimization capable of predicting channel variations and adapting transmission parameters in advance [20]. This change fits into the wider perspective of artificial intelligence-native 6G networks where machine learning is integrated across all protocol layers as opposed to being implemented as dedicated improvements to particular processes on an isolated basis [10]. The results of the research give a solid empirical evidence on the use of intelligent adaptive modulation and coding as an enabling technology in meeting the 6G performance goals of peak data rates in excess of 1 terabit per second, latency below a millisecond, and highly reliable connectivity in mission critical systems such as autonomous vehicles, remote surgery, and industrial automation systems.

VI. CONCLUSION

This study has also thoroughly examined the incorporation of intelligent algorithm to improve the adaptive modulation and coding performance of the sixth-generation wireless networks. The experimental results are conclusive to indicate that machine learning based applications and specifically deep reinforcement learning and convolutional neural network-long short-term memory architectures are significantly better than traditional lookup table and outer loop link adaptation schemes with all critical performance metrics such as spectral efficiency, throughput, bit error rate, and energy efficiency. The spectral efficiency increases of between 33.3-50.0 percent, throughput increases of more than 21 percent in the high-mobility cases and bit error reduction of more than 67 percent confirm the transformational potential of intelligent adaptive modulation and coding as an essential tool enabling technology to use sixth-generation networks.

These performance improvements directly respond to the demanding needs of the new applications such as extended reality, holographic communications and autonomous systems that require ultra-reliable & low-latency connectivity with new levels of data rates. The results of the research add to the scientific background in applying artificial intelligence integration to the wireless physical layer optimization and present a practical suggestion on the 6G standards advancement and business implementation models. Future directions of federated learning include federated approaches to distributed adaptive modulation and code optimization, joint beamforming and modulation adaptation with reconfigurable intelligent surfaces, and energy-efficient neural networks with resource-sensitive architectures in real-time inference in resource-constrained network edge settings.

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