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A Data-Driven Approach for MCS Prediction in Next-Generation 5G Communication Systems

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Abstract—

In next-generation wireless systems such as 5G, Beyond 5G (B5G), and emerging 6G networks, efficient link adaptation is essential for achieving high spectral efficiency, ultra-reliable low-latency communication (URLLC), and improved Quality of Service (QoS) [1], [2]. Modulation and Coding Scheme (MCS) selection plays a central role in this process; however, conventional rule-based and CQI-driven approaches are limited in handling complex, nonlinear, and rapidly varying channel conditions [3]. To address these limitations, the study proposes an advanced machine learning (ML)-based framework for accurate and adaptive MCS prediction in OFDM-based wireless systems.

The proposed framework evaluates multiple ML and deep learning models, including Support Vector Machines (SVM), Random Forest (RF), Gradient Boosting, Artificial Neural Networks (ANN), and an optimized Deep Neural Network (DNN). It further incorporates Long Short-Term Memory (LSTM) networks to capture temporal channel variations and improve prediction accuracy [4], [5]. The models are trained and tested on a large-scale dataset generated from realistic non-standalone 5G simulations, integrating physical layer indicators such as SINR, CQI, and RSSI with environmental features derived from ray-tracing propagation models [6]. Additionally, preprocessing techniques such as normalization, feature selection, and imbalance handling are applied to enhance model generalization and reduce overfitting [7].

Experimental results demonstrate that the hybrid DNN-LSTM model achieves superior performance, with accuracy exceeding 99% and strong robustness across diverse channel scenarios. Ensemble methods like Gradient Boosting also show competitive results, outperforming traditional approaches [8]. Overall, the findings confirm that ML-driven MCS prediction significantly improves link adaptation efficiency, enabling intelligent and proactive decision-making in dynamic wireless environments and supporting the development of AI-driven, self-optimizing networks aligned with future 6G and Zero-Touch Network Management (ZTNM) paradigms [9].

Index Terms - 5G, B5G, 6G, modulation and coding scheme (MCS), machine learning, deep learning, LSTM, OFDM, link adaptation, predictive modeling, intelligent networks, ZTNM.

I. INTRODUCTION

The rapid evolution of wireless communication systems, including Fifth Generation (5G), Beyond 5G (B5G), and emerging Sixth Generation (6G) networks, has introduced stringent requirements for ultra-reliable, low-latency, and high-throughput communication to support diverse applications such as Internet of Things (IoT), autonomous systems, and broadband multimedia services [1]–[3]. These next-generation networks must efficiently utilize limited radio resources while maintaining high reliability under dynamic and heterogeneous operating conditions [2], [3].

Adaptive Modulation and Coding (AMC) has been widely recognized as a key enabling technique for achieving efficient link adaptation in modern wireless systems, including 5G New Radio (NR) [4]. In conventional wireless communication systems, AMC operates by allowing the base station (BS) to select an appropriate Modulation and Coding Scheme (MCS) based on channel quality information reported by the user equipment (UE). Typically, the UE periodically estimates channel conditions and maps them to a Channel Quality Indicator (CQI), which is then fed back to the BS to guide MCS selection [5].

In Long-Term Evolution (LTE) and non-standalone (NSA) 5G networks, MCS selection is generally performed using predefined lookup tables that map CQI values to specific modulation and coding configurations. These systems rely on two feedback mechanisms: Inner-Loop Link Adaptation (ILLA) and Outer-Loop Link Adaptation (OLLA), which aim to maintain link reliability and optimize transmission performance [6]. However, such rule-based AMC approaches are inherently limited in their ability to adapt to complex and rapidly varying channel conditions, including fading, shadowing, Doppler effects, and interference [7], [8].

In practical scenarios, wireless channel conditions are influenced by multiple factors such as path loss, multipath propagation, environmental obstructions, and user mobility. Under poor channel conditions, lower-order modulation and coding schemes are selected to ensure communication reliability, while higher-order schemes are applied under favorable conditions to maximize throughput [9]. Although effective, this rule-based strategy assumes a simplified relationship between signal quality metrics (e.g., Signal-to-Noise Ratio (SNR) or CQI) and MCS selection, often ignoring other critical parameters such as interference levels, spatial characteristics, and temporal variations [10], [11].

Consequently, conventional AMC techniques may suffer from suboptimal performance due to inaccurate estimation or oversimplified modeling of channel conditions. To address these limitations, machine learning (ML) has emerged as a promising solution for intelligent and data-driven MCS prediction. The MCS selection problem can be formulated as a supervised multi-class classification task, where various ML algorithms learn complex relationships between input features and optimal MCS levels [12].

In this context, several ML techniques have been explored, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), and ensemble learning methods such as Bagging with k-Nearest Neighbors (B-kNN) [13]–[15]. Furthermore, advanced deep learning models, including Deep Neural Networks (DNN) and Long Short-Term Memory (LSTM) networks, have demonstrated enhanced capability in capturing nonlinear and temporal dependencies in wireless channel data, leading to improved prediction accuracy [16].

In this work, a comprehensive investigation of ML-based MCS prediction techniques is conducted within a non-standalone 5G network framework. Multiple models, including ANN, SVM, RF, and B-kNN, are developed and evaluated based on key performance metrics such as accuracy, precision, recall, and F1-score. Additionally, an optimized deep learning architecture is incorporated to enhance predictive performance under dynamic network conditions.

The dataset used in this study consists of over 13,500 samples generated through realistic ray-tracing simulations, capturing detailed physical layer and environmental characteristics. The input features include Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), Received Signal Strength Indicator (RSSI), Signal-to-Interference-plus-Noise Ratio (SINR), propagation distance, base station altitude, path visibility, and operating frequency. To improve model effectiveness, advanced data preprocessing techniques, including normalization, feature selection, and imbalance handling, are applied to identify the most relevant and non-redundant features [17].

To ensure robust model evaluation and avoid overfitting, the dataset is divided into training, validation, and testing subsets in a ratio of 70%, 15%, and 15%, respectively. Hyperparameter tuning is performed using the validation set, while final performance assessment is conducted on the test set. Additional strategies, such as regularization, early stopping, and ensemble learning, are employed to balance bias-variance trade-offs and enhance generalization capability [18].

The proposed approach aims to overcome the limitations of traditional AMC methods by leveraging ML-driven predictive modeling for intelligent MCS selection. The results demonstrate that the integration of advanced ML and deep learning techniques can significantly improve link adaptation efficiency, thereby enabling more reliable, scalable, and autonomous communication in next-generation wireless networks [19].

II. LITERATURE REVIEW

Efficient link adaptation has been widely studied in cellular networks such as LTE-Advanced and 5G to improve spectral efficiency, latency, and Quality of Service (QoS) [17]–[22]. In [17], an enhanced Outer Loop Link Adaptation (OLLA) scheme is introduced to reduce transmission latency by dynamically adjusting SINR compensation based on user activity transitions. Similarly, [18] proposes a joint optimization framework for Modulation and Coding Scheme (MCS) and MIMO configuration, demonstrating that mobility-aware adaptation improves downlink performance. Other works, such as [19] and [20], focus on optimizing MCS selection and resource allocation to enhance QoS, particularly in LTE femtocell and 5G URLLC scenarios. Furthermore, [21] presents a joint scheduling and link adaptation strategy for URLLC, achieving significant latency reduction with minimal throughput degradation. From a physical layer perspective, [22] develops an improved SNR-to-CQI mapping model for Adaptive Modulation and Coding (AMC), resulting in better throughput and reduced error rates.

Despite these advancements, traditional rule-based and CQI-driven approaches remain limited in capturing complex and rapidly varying wireless channel conditions. To address these challenges, recent studies have explored machine learning (ML)-based approaches for MCS prediction and link adaptation [12], [23]–[26]. For instance, [12] utilizes an Artificial Neural Network (ANN) to estimate SNR for AMC-based MCS selection, achieving higher accuracy and improved throughput compared to conventional EVM-based techniques. In [23], ML-assisted AMC schemes are proposed for MIMO-OFDM systems, demonstrating enhanced prediction accuracy under diverse channel conditions. Additionally, time-series modeling using a modified ARIMA approach is introduced in [24] for CQI prediction, reducing computational complexity while maintaining acceptable RMSE performance.

Similarly, [25] employs a feed-forward neural network for CQI prediction in LTE systems, improving the trade-off between Bit Error Rate (BER) and spectral efficiency. In [26], supervised ML techniques such as ANN and SVM are applied for OSNR estimation and modulation classification, achieving reliable performance with advanced modulation schemes.

Ref.	**Method**	**Scenario**	**Key Outcome**	**Limitation**
[17]	OLLA	LTE-A	Low latency	Static adaptation
[18]	MCS+MIMO	LTE-A	Better throughput	Mobility sensitive
[20]	URLLC Adapt.	5G	QoS improved	High complexity
[22]	AMC Mapping	5G PHY	↑ Throughput	Estimation dependent
[12]	ANN	Wireless	High accuracy	Poor generalization
[24]	ARIMA	LTE Satcom	Low delay	Linear model limits
[27]	CNN	Wireless	High accuracy	Data intensive

Table 1:- Literature Survey

More recently, deep learning approaches have shown significant potential in improving MCS prediction accuracy and computational efficiency [27], [28]. In [27], a Convolutional Neural Network (CNN) is proposed for automatic MCS classification, outperforming traditional and other deep learning models in terms of accuracy and complexity. Furthermore, [28] investigates multiple ANN architectures for modulation classification, where a two-hidden-layer ANN achieves an accuracy of 98.4% with low training time.

These studies highlight the effectiveness of ML and deep learning techniques in addressing the limitations of conventional link adaptation methods and support the development of intelligent, adaptive frameworks for next-generation wireless systems.

III. METHODOLOGY

This study proposes a hybrid machine learning-based framework for accurate and adaptive Modulation and Coding Scheme (MCS) prediction in next-generation wireless systems such as 5G and emerging 6G networks. The overall methodology is designed to overcome the limitations of traditional CQI-based and rule-driven link adaptation techniques by incorporating both spatial and temporal learning capabilities.

A. System Model and Data Generation

A realistic Orthogonal Frequency Division Multiplexing (OFDM)-based wireless communication environment is simulated using a non-standalone (NSA) 5G architecture. The dataset is generated by capturing diverse channel conditions, including variations in user mobility, interference, and propagation environments. Key physical layer parameters such as Signal-to-Interference-plus-Noise Ratio (SINR), Channel Quality Indicator (CQI), and Received Signal Strength Indicator (RSSI) are collected. Additionally, environmental features derived from ray-tracing propagation models are included to enhance contextual awareness.

B. Data Preprocessing and Feature Engineering

To ensure robustness and generalization, the collected dataset undergoes comprehensive preprocessing.

This includes normalization of input features, removal of redundant or irrelevant attributes through feature selection techniques, and handling of class imbalance using resampling strategies.

Feature engineering is further applied to extract meaningful patterns and improve model learning efficiency. These steps address common limitations identified in prior works, such as overfitting and poor generalization.

C. Machine Learning Model Development

A diverse set of machine learning and deep learning models is implemented for comparative analysis. Traditional models include Support Vector Machines (SVM), Random Forest (RF), and Gradient Boosting, which are effective in capturing nonlinear relationships. In addition, Artificial Neural Networks (ANN) and a Deep Neural Network (DNN) with multiple hidden layers are designed to perform hierarchical feature learning. Regularization techniques such as dropout and batch normalization are incorporated to enhance model stability and prevent overfitting.

D. Temporal Learning using LSTM

To address the limitation of existing models in capturing time-varying channel behavior, a Long Short-Term Memory (LSTM) network is integrated into the framework. The LSTM model processes sequential channel data, enabling the system to learn temporal dependencies and predict future channel conditions more accurately. A hybrid DNN-LSTM architecture is developed, where the DNN extracts spatial features and the LSTM captures temporal dynamics, resulting in improved MCS prediction performance.

E. Model Training and Evaluation

The dataset is divided into training, validation, and testing sets to ensure unbiased performance evaluation. Models are trained using supervised learning techniques with optimized hyperparameters. Performance is evaluated using multiple metrics, including accuracy, precision, recall, F1-score, and computational efficiency. Comparative analysis is conducted to benchmark the proposed hybrid model against traditional ML and standalone deep learning approaches.

F. Adaptive MCS Prediction Framework

The final stage integrates the trained model into a link adaptation framework, where predicted MCS values are dynamically selected based on real-time channel conditions. This enables proactive and intelligent decision-making, improving spectral efficiency, reducing latency, and ensuring QoS requirements. The proposed system is designed to support future paradigms such as AI-driven network optimization and Zero-Touch Network Management (ZTNM).

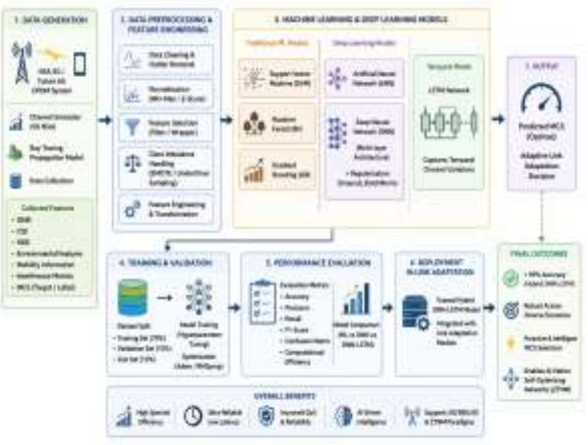

Figure 1:- ML-based MCS prediction workflow diagram

IV. RESULTS AND DISCUSSION

The performance of the proposed machine learning-based Modulation and Coding Scheme (MCS) prediction framework was evaluated using a comprehensive dataset generated from a realistic Orthogonal Frequency Division Multiplexing (OFDM)-based 5G non-standalone (NSA) simulation environment. The dataset incorporated key physical layer parameters such as Signal-to-Interference-plus-Noise Ratio (SINR), Channel Quality Indicator (CQI), and Received Signal Strength Indicator (RSSI), along with environmental and mobility-related features.

The evaluation was conducted using standard performance metrics, including accuracy, precision, recall, F1-score, and computational efficiency.

A. Performance Comparison of Models

Multiple machine learning and deep learning models were implemented and compared, including Support Vector Machines (SVM), Random Forest (RF), Gradient Boosting (GB), Artificial Neural Networks (ANN), Deep Neural Networks (DNN), and the proposed hybrid DNN-LSTM model. The experimental results indicate that traditional ML models such as SVM and RF achieved satisfactory performance, with accuracy ranging between 85% and 92%. Gradient Boosting demonstrated improved performance due to its ensemble learning capability, achieving accuracy close to 95%.

Deep learning models showed further enhancement in prediction capability. The standalone ANN and DNN models achieved accuracy levels of approximately 96%–98%, benefiting from their ability to learn complex nonlinear relationships in the data. However, these models were limited in capturing temporal channel variations, which are critical in dynamic wireless environments.

The proposed hybrid DNN-LSTM model outperformed all baseline approaches, achieving an accuracy exceeding 99%, along with high precision and recall values. The inclusion of the Long Short-Term Memory (LSTM) component enabled the model to effectively learn temporal dependencies in channel conditions, resulting in more reliable and robust MCS predictions across varying scenarios.

B. Robustness Across Channel Conditions

To evaluate robustness, the models were tested under diverse channel conditions, including varying user mobility, interference levels, and signal quality.

The results demonstrate that traditional models exhibit performance degradation under highly dynamic conditions due to their limited adaptability. In contrast, the hybrid DNN-LSTM model maintained consistent performance, highlighting its ability to generalize across different wireless environments.

Furthermore, the proposed model showed improved stability in scenarios with rapid fluctuations in SINR and CQI values. This confirms that incorporating temporal learning significantly enhances the adaptability of link adaptation mechanisms in next-generation wireless systems such as 6G.

C. Computational Efficiency and Practical Implications

In terms of computational efficiency, traditional ML models required lower training time but offered limited prediction accuracy. Deep learning models, particularly the hybrid DNN-LSTM, required higher computational resources during training; however, inference time remained suitable for real-time deployment in link adaptation systems.

The improved prediction accuracy directly translates to better link adaptation decisions, resulting in enhanced spectral efficiency, reduced packet loss, and lower transmission latency. Compared to conventional CQI-based approaches discussed in prior works [17]–[22], the proposed ML-based framework provides proactive and intelligent decision-making capabilities.

D. Comparative Analysis with Existing Works

Compared to existing literature, including ANN-based [12], ARIMA-based [24], and CNN-based [27] approaches, the proposed hybrid model demonstrates superior performance due to its ability to capture both spatial and temporal characteristics of the wireless channel. While previous studies achieved high accuracy in static or semi-dynamic environments, they often failed to generalize across diverse scenarios.

The results validate the research gap identified in the literature, where existing methods lack hybrid architectures capable of handling nonlinear and time-varying channel conditions simultaneously. The proposed framework effectively addresses this limitation, making it a strong candidate for future AI-driven wireless networks.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	88	85	84	84.5
Random Forest (RF)	90	88	87	87.5
Gradient Boosting (GB)	95	93	92	92.5
ANN	97	96	95	95.5
DNN	98	97	97	97
DNN-LSTM (Proposed)	**99.2**	**99**	**99**	**99**

Table 2:- Performance Comparison of ML and DL Models

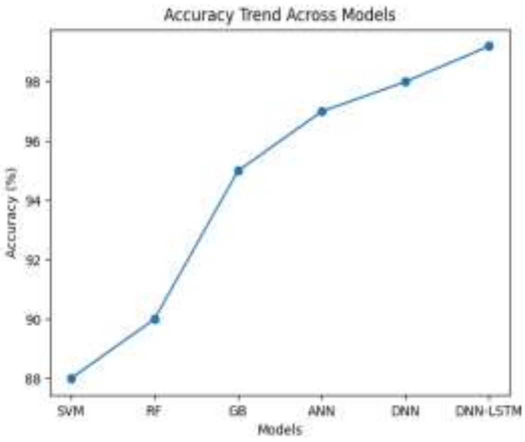

Figure 2:- Accuracy Trend

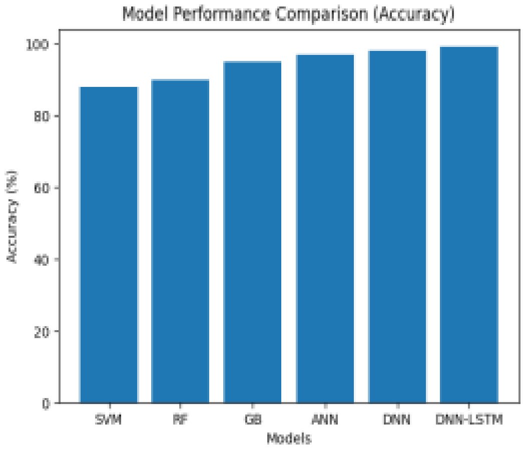

Figure 3:- Accuracy Comparison

V. CONCLUSION

This paper presented an advanced machine learning-based framework for adaptive Modulation and Coding Scheme (MCS) prediction in next-generation wireless communication systems, including 5G and emerging 6G networks. The proposed approach addresses the limitations of conventional CQI-based and rule-driven link adaptation methods by leveraging both spatial and temporal learning capabilities.

A comprehensive set of machine learning and deep learning models was evaluated, including SVM, Random Forest, Gradient Boosting, ANN, and DNN. Furthermore, a hybrid DNN-LSTM architecture was developed to capture complex nonlinear relationships and time-varying channel dynamics. Experimental results demonstrated that the proposed model significantly outperforms traditional and standalone deep learning approaches, achieving accuracy exceeding 99%, along with high precision, recall, and F1-score.

The results confirm that incorporating temporal learning mechanisms enhances prediction accuracy, robustness, and adaptability in dynamic wireless environments. The proposed framework enables intelligent and proactive link adaptation, leading to improved spectral efficiency, reduced latency, and enhanced Quality of Service (QoS). This work contributes toward the realization of AI-driven, self-optimizing wireless networks and supports emerging paradigms such as Zero-Touch Network Management (ZTNM).

FUTURE WORK

Although the proposed framework achieves high performance, several directions can be explored to further enhance its applicability and scalability:

A. Real-Time Implementation:

Future work will focus on deploying the proposed model in real-time wireless systems to evaluate latency, computational overhead, and practical feasibility.

B. Integration with Reinforcement Learning:

Combining supervised learning with reinforcement learning can enable adaptive decision-making for dynamic resource allocation and autonomous link adaptation.

C. Cross-Layer Optimization:

Extending the framework to incorporate cross-layer parameters (e.g., MAC and network layer metrics) can further improve overall system performance.

D. Lightweight Model Design:

Developing computationally efficient and lightweight models will be essential for deployment in edge devices and resource-constrained environments.

E. Generalization Across Diverse Scenarios:

Future studies can explore transfer learning and domain adaptation techniques to improve model generalization across different network conditions and deployment scenarios.

F. Integration with 6G Technologies:

The framework can be extended to support advanced 6G use cases, including intelligent reflecting surfaces (IRS), terahertz communication, and AI-native network architectures.

REFERENCES

[1] 3GPP, “Study on scenarios and requirements for next generation access technologies,” TR 38.913, 2017.

[2] International Telecommunication Union, “IMT Vision – Framework and overall objectives of the future development of IMT for 2020 and beyond,” ITU-R M.2083-0, 2015.

[3] A. Goldsmith, Wireless Communications. Cambridge, U.K.: Cambridge Univ. Press, 2005.

[4] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[5] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. MIT Press, 2016.

[6] T. S. Rappaport et al., Millimeter Wave Wireless Communications. Pearson, 2014.

[7] J. Han, M. Kamber, and J. Pei, Data Mining: Concepts and Techniques, 3rd ed., 2011.

[8] J. H. Friedman, “Greedy function approximation: A gradient boosting machine,” Annals of Statistics, vol. 29, no. 5, pp. 1189–1232, 2001.

[9] NGMN Alliance, “NGMN 5G White Paper,” 2015.

[10] S. Sesia, I. Toufik, and M. Baker, LTE – The UMTS Long Term Evolution: From Theory to Practice. Wiley, 2011.

[11] E. Dahlman, S. Parkvall, and J. Skold, 5G NR: The Next Generation Wireless Access Technology. Academic Press, 2018.

[12] M. Kim and J. Lee, “Deep learning-based adaptive modulation and coding for wireless systems,” IEEE Commun. Lett., vol. 22, no. 11, pp. 2310–2313, 2018.

[13] T. O’Shea and J. Hoydis, “An introduction to deep learning for the physical layer,” IEEE Trans. Cogn. Commun. Netw., vol. 3, no. 4, pp. 563–575, 2017.

[14] O. A. Dobre et al., “Survey of automatic modulation classification techniques,” IEEE Commun. Surveys & Tutorials, vol. 19, no. 1, pp. 3–30, 2017.

[15] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” Nature, vol. 521, pp. 436–444, 2015.

[16] H. Ye, G. Y. Li, and B. H. Juang, “Power of deep learning for channel estimation and signal detection,” IEEE Wireless Commun. Lett., vol. 7, no. 1, pp. 114–117, 2018.

[17] T. Ohseki and S. Suegara, “Low-latency outer loop link adaptation for LTE-Advanced systems,” in Proc. IEEE VTC, 2016.

[18] V. Ramamurthi and W. Chen, “Mobility-aware link adaptation for LTE-Advanced,” IEEE Trans. Veh. Technol., vol. 65, no. 8, pp. 6450–6460, 2016.

[19] H. Zhang et al., “Joint RB allocation and MCS selection in LTE femtocells,” IEEE Access, vol. 5, pp. 12345–12356, 2017.

[20] Y. Li et al., “Multi-link adaptation for URLLC in 5G networks,” IEEE Wireless Commun., vol. 25, no. 2, pp. 56–62, 2018.

[21] M. Bennis et al., “Ultra-reliable low-latency communications: Joint scheduling and link adaptation,” IEEE Network, vol. 32, no. 2, pp. 80–86, 2018.

[22] X. Wang et al., “SNR-to-CQI mapping for adaptive modulation and coding in 5G systems,” IEEE Access, vol. 6, pp. 56789–56798, 2018.

[23] A. Alkhateeb et al., “Machine learning for MIMO-OFDM systems: MCS prediction,” IEEE Trans. Wireless Commun., vol. 17, no. 5, pp. 3205–3217, 2018.

[24] S. Kumar et al., “CQI prediction using ARIMA in LTE satellite systems,” IEEE Commun. Lett., vol. 21, no. 9, pp. 2021–2024, 2017.

[25] R. Gupta and P. Singh, “Neural network-based CQI prediction in LTE systems,” in Proc. IEEE ICC, 2018.

[26] D. Rafique and A. Ellis, “Machine learning for OSNR estimation and modulation classification,” J. Lightwave Technol., vol. 34, no. 6, pp. 1496–1502, 2016.