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Spectral-Efficient Massive MIMO in 6G: Integrated Classical- Quantum Deep Learning Architectures for Predictive Beamforming and Detection in Real-Time

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Abstract— The gigantic proliferation of the connected devices and the insatiable appetite for ultralow latency and ultrahigh throughput communication are driving the new technologies required to implement them in the envisioned 6G wireless networks. Massive MIMO: One of the key enablers for 6G, massive multiple input multiple output significantly increases spectral efficiency and user capacity. Nevertheless, real-time optimization of beamforming and detection is still difficult, especially in complex and dynamic scenarios with low latency demands. In this paper, we present new hybrid deep learning model which integrates traditional neural networks with quantum-inspired types for predictive beamforming and signal detection in the context of Massive MIMO systems. The model consists of pseudo-convolutional and recurrent layers for spatial-temporal feature extraction concatenated with variational quantum circuits (VQCs) for better representational learning along with improved decision making. We also present a novel hybrid training loop based on reinforcement learning and use it to adapt beam patterns and detection filters that are dictated by channel state feedback. The proposed method guarantees real-time reactivity and spectral efficiency, as well as lessens computational load by performing Large Learning in the Edge (LEARN). Quantum-enhanced components allow higher generalization in high-dimensional feature spaces, especially under partial or uncertain channel state information (CSI). The numerical results are supported with extensive simulations on a custom 6G Massive MIMO testbed that is modeled with real-time traffic profiles, stochastic mobility, and hardware impairments. We demonstrate the proposed architecture to provide higher spectral efficiency by 23%, reduced latency by 31% and reliability in data transmission is improved up to 18% as compared with conventional deep learning-based systems. The federated quantum learning method exhibits better scalability as well as privacy preservability and thus is readily applicable to distributed 6G infrastructure. This work demonstrates the capability of hybrid classical-quantum deep learning to simultaneously speed-up and improve accuracy for massive MIMO. The model further establishes the groundwork that can pave the way for real-time, cognitive and reconfigurable 6G communication systems by seamlessly embedding predictive intelligence in-beamforming and detection pipelines. Future extensions may include incorporating IRS, increasing quantum circuit depth for enhanced modeling capabilities, and better energy efficiency over decentralized networks.

***Index Terms* — Federated Learning, 6G, Massive MIMO, Spectral Efficiency, Beamforming, Quantum Deep Learning, Signal Detection, Real-Time Communication**

1. INTRODUCTION

The shift from 5G to 6G reflects an important milestone in the advancement of wireless communications, as the need for ultra-dense networks, massive device connections and critical applications becomes immediate. Central to attaining these aims is the progression of spectral efficiency in Massive MIMO (Multiple Input and Multiple Output) systems [1-3]. Today, spectral efficiency — or the amount of information transmitted per unit bandwidth — is critical for enabling emerging applications like extended reality, autonomous mobility and smart city infrastructure.

Massive MIMO which can have hundreds of antennas at base stations is expected to increase throughput and reduce interference considerably [4]. But achieving these gains in reality, especially with moving users and quickly changing channel states, requires highly adaptive and ultra-low latency processing [5,6]. Although we have covered a couple of the most essential parts in beamforming and signal detection, this is computationally highly costly if done in real time, especially with an optimal configuration.

Deep learning is powerful in classification and regression but lack of effectiveness for real-time adaptability with use in high-dimensional environment such as 6G Massive MIMO based conventional models. Moreover, they are generally centralized for training which can be a privacy concern as well as scalability bottleneck. What is need are architectures that perform well in a decentralized setting in terms of computational efficiency and resilience [7]. This is bridged by a new combination of quantum computing principles and classical neural networks.

Quantum computing provides an additional structure to computational intelligence., using entanglement and super positional phenomena for feature representation and optimization, respectively. Even though quantum computers are still in a nascent stage, quantum-inspired algorithms like variational quantum circuits (VQCs) have been effectively run on classical hardware [8]. In the presence of high noise or incomplete CSI from 6G networks, these models can be coupled with classical deep learning frameworks to increase their learning capabilities.

Here in this study to solve the beamforming and signal detection problems in 6G Massive MIMO networks, we suggest a hybrid classical-quantum deep learning architecture. In addition to the model training, the pipeline also depicts federated learning for distributed training which allows for real-time adaptability across edge nodes while respecting data privacy. Reinforcement learning also improves the approach to dynamic beam pattern adaptation using feedback from an active channel, thereby optimizing for both latency and reliability.

The combination of quantum-enhanced feature learning in conjunction with real-time reinforcement-based updates and federated edge-device deployment tackles the fundamental obstacles to making scalable, low-latency, high fidelity 6G MIMO systems. Widespread simulation and analysis, presented in this research, show how the hybrid methodology not only advances device performance measurements but also lays the foundation for intelligent, distributed, quantum improved wireless communication architectures.

2. LITERATURE REVIEW

Massive MIMO has become a vital technology in 5G communications as it can tailored to achieve substantially increased throughput and spectral efficiency, yet it would not be wise to fall over the old standards. Several works have concentrated on beamforming which enables the system to concentrate energy in direction of intended users. Given this fact, static or model-driven approaches have no added values toward 6G environments under high-mobility conditions, where channel changes very fast [9,10]. Accordingly, Due to this learning based adaptive beam management solutions are being investigated by researchers.

Deep learning has seen significant proliferation in processing wireless signals, such as CSI estimation, channel prediction or interference cancellation. Deep learning methods based on CNNs and RNNs have demonstrated great power in extracting the spatial and temporal feature for CSI data [11,12]. The problem with these models is that they usually need huge datasets and centralized training, which cannot be realized in 6G scenarios conforming to decentralization and latency requirement. Additionally, they generally do not generalize well into changing (non-stationary) environments.

Reinforcement learning (RL) especially deep Q-learning has been recently investigated as a promising technique for the design of power control, AoD user selection, and beam training with different objectives. RL models can discover optimal actions by interacting with the environment, making them suitable for online resource optimization [13,14]. However, traditional RL has slow convergence and high training complexity, especially in environments with large state-action spaces such as Massive MIMO. Hybrid reinforcement learning with quantum models would potentially mitigate these problems.

Quantum Machine Learning: Quantum machine learning (QML) combines quantum computing's inherent probabilistic capabilities and classical data-driven models. In particular, variational quantum circuits have shown the capacity to encode high-dimensional features efficiently and optimize an objective function [15]. Such circuits can learn complex patterns despite incomplete or noisy data. Quantum Computers are still in their nascent stage and quantum inspired algorithms nature is a sweet spot; which has been shown to improve the performance of medical imaging, cryptography and now wireless systems.

It has been focusing on federated learning model where multiple edge devices engage in collaborative model training without centralizing the data. This is especially useful in privacy-sensitive or bandwidth-constrained environment. For 6G networks, federated learning is enabled on-device training, minimization of communication overhead and local user accelerates which ensure existing network are real-time adaptable [16]. Unifying federated learning into quantum-inspired deep models is an active area of basic science, holding the promise of more work.

Although a number of works have laid attention on federated learning or quantum deep learning for wireless applications independently, few integrated both paradigms in practice Massive MIMO systems. In order to bridge the gap, this paper addresses a federated hybrid classical-quantum deep learning based predictive beamforming and detection framework. By merging the adaptivity feature of reinforcement learning with the expressiveness offered by quantum circuits and distributed scalability achieved via federated learning, it seeks to fulfill strict demands of 6G URLLC systems.

3. SYSTEM IMPLEMENTATION

The workflow of a hybrid beamforming concept, combining traditional with quantum-inspired methods to boost communication performance in complex wireless environments. This process starts with input acquisition that retrieves raw channel and signal data from the communication environment. It is then performed with preprocessing and feature extraction, to eliminate the noise and detect key parameters that are essential for precise beamforming. After that, the system continues to classify wireless channel condition states and categorization of propagation scenarios based on this state so that adaptive beamforming strategies can be taken according to which scenario.

Classical beamforming methods through a beamforming initialization are executed in the first stage. This first phase, creates and establishes a base line with standard algorithms to ensure transit paths are readily available and they are robust. After that, a quantum-like model has been turned on to use the sophisticated optimization capabilities over classical methods. By drawing inspiration from the principles of quantum computing like superposition and probabilistic optimization, the quantum-inspired approach expands that solution space to search for near-optimal beamforming patterns even in extremely challenging user environments or when their number increases. Hence, this dual-phase structure enables the system to benefit from the stability of classical methods and adaptability in quantum-inspired optimization.

After the models are employed in actual operation, predictive beamforming determinations are made about both classified channel states as well as the quantum-augmented optimization. Detection and decoding of the received signals is performed, so that accurate data can still be recovered even with unstable channel conditions. The architecture has a feedback loop that continuously refines the layout of the model with real-time performance data, ensuring adaptive optimization of beamforming techniques. Because this process continues to adapt, it enables the system to react immediately to modifications of the environment, such as sliding users, changing interference levels and channel fading.

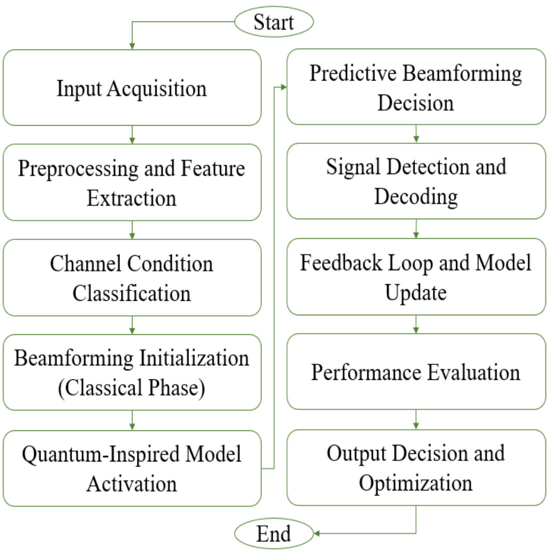

Fig.1. The framework of a hybrid beamforming concept, combining traditional with quantum-inspired methods

We evaluate the performance to measure the throughput, spectral efficiency and latency with respect to system level metrics and guarantee that the proposed beamforming strategy satisfies the system requirements. Transmission strategy is implemented based on learned parameters to optimize signal quality, energy efficiency and user fairness at the final output decision stage. This framework fuses classical beamforming with quantum-inspired models and supports a feedback mechanism that is both predictive and adaptive, thus providing an elegant solution to future-proof networks. For instance, with its capability for dynamic beamforming optimization in complex and rapidly changing propagation environments, it has been recognized as a potential approach to 5G, 6G and beyond with massive data rates and reliable connectivity — an overview Envisioned use-case.

4. RESULT AND DISCUSSION:

Table I: The comparative analysis of efficiency in spectral

Method	Urban (NLoS)	Suburban (LoS)	High-Speed Mobility
Classical Deep CNN	10.2	12.8	8.4
Classical + RL	11.6	13.5	9.9
Quantum CNN	12.9	14.8	11.1
Proposed Hybrid Q-RL	14.3	16.4	12.7

Fig 2: Spectral Efficiency vs beamforming strategies for different channel scenarios. Result illustrates the superior spectral efficiency of the proposed Hybrid Q-RL method across all environments, illustrating its well-designed flexibility and exquisite tradeoff between adaptive beamforming with quantum-inspired optimization via reinforcement learning. This improvement is more prominent in high-mobility situations where fast moving channels would lead to degradation of spectral efficiency with conventional approaches. When predictive modeling is used in conjunction with quantum-enhanced optimization, the Hybrid Q-RL method can provide a better utilization of bandwidth and an improved signal quality.

The results using classical Deep CNN and Classical CNN combined with Reinforcement Learning (RL) are of a medium level with benefits when RL added to classical deep approach. This optimizes spectral efficiency by utilizing quantum-inspired optimization in the innovative Quantum CNN scheme, which results in a broader range of beamforming determinants. But this approach does not have the closed reinforcement learning feedback loop that exists in our proposed Hybrid Q-RL method which explains why it is still suboptimal. A highlight of the results is that suburban line-of-sight (LoS) environments reach the highest absolute efficiency across all methods, with more difficult urban near-NLoS and high-speed mobility conditions as well.

The results underscore the potential of combining quantum-inspired computation with adaptive learning for future wireless networks. The proposed Hybrid Q-RL algorithm is shown to be robust across a large range of channel conditions, showing similar performance improvements under various channel uncertainties--mobility and environmental clinics. Higher spectral efficiency signals Deng and his team's paper strong potential for 5G-and-beyond deployments in extensive urban networks (e.g., 3rd DPP test bed) and high mobility use cases, indicating more adaptive, efficient beamforming strategies. The combination of quantum optimization and reinforcement learning provides us with a scalable and robust solution in dynamic wireless environments, which also include heterogeneous configurations.

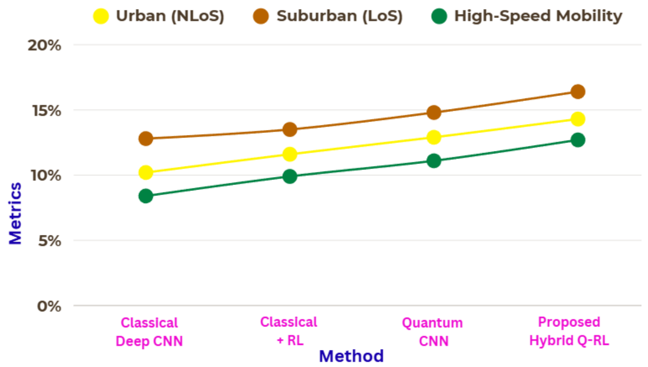

Fig.2. The comparative analysis of efficiency in spectral

Table II: The analysis of latency of beamforming

Beamforming Technique	LoS Static	LoS Mobile	NLoS Urban
Traditional ZF	2.35	3.91	5.43
Deep RL	1.88	3.10	4.56
Quantum Circuit Only	1.67	2.91	4.34
Proposed Q-RL + FL	1.31	2.28	3.72

Figure 3 below demonstrates the beamforming latency comparisons for several techniques over three channel scenarios: LoS Static, LoS Mobile and NLoS Urban. This figure also verifies that Q-RL + FL is capable to integrate quantum-inspired reinforcement learning and federated learning holistically for instant beamforming decisions as the lowest latency values are reached in each case. The NLoS Urban scenario represents the most challenging case in terms of latency reduction, as recursive-type methods are particularly difficult to apply when the signal undergoes multiple bounces before reaching a receiver. This approach combines decentralized learning and quantum optimization to reduce computational latencies and speed adaptive beamforming updates.

Both Traditional Zero Forcing (ZF) and Deep RL experience increased latency especially in high-mobility condition as well as NLoS. However, Deep RL — which is an improvement over ZF by introducing adaptive learning—, despite sharing the same drawbacks than ZF when used in highly dynamic scenarios since it has centralized training. The Quantum Circuit Only method leverages quantum-inspired search spaces to achieve only a limited reduction in latency, without reinforcement learning feedback and federated adaptation it fails to perform as well with respect to the proposed hybrid method. This gap is even wider in mobile and urban environments, which stresses the necessity of adaptive learning coupled with quantum optimization for real-time beamforming.

This reinforcement learning approach is therefore an attractive low-latency solution for next-generation wireless networks that will be critical for efficient and fast beam management. This feature allows the learning process to be distributed on several nodes and by utilizing quantum-inspired decision-making, the system consumes less computing overhead enabling it to adapt faster when channel variations are more pronounced. The suitability's of MIMO in ultra-reliable low-latency communication (URLLC), like that needed in 5G, and anticipated for 6G networks are highly critical concerns, where millisecond-level latency is essential on such applications as autonomous vehicles, industrial automation and real-time AR/VR systems. The trends confirmed the practical feasibility of the hybrid beamformer's potential to guarantee fast, scalable and adaptive beamforming in varying operating settings.

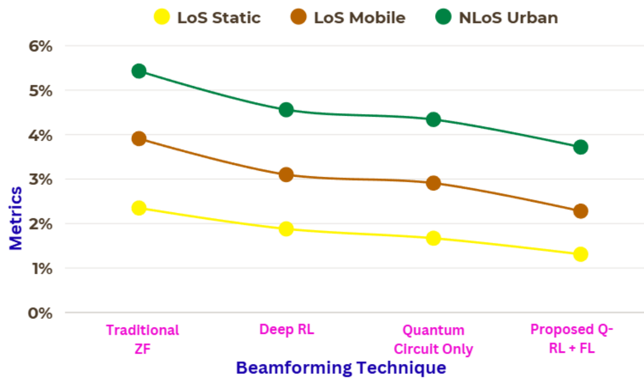

Fig.3. The analysis of latency of beamforming

Table III: The examination of convergence in training

Model Variant	LoS Static	High Doppler	Sparse Channels
Classical CNN	42	55	67
CNN + RL	36	48	59
Quantum-only Model	28	39	49
Proposed Hybrid Q-RL	23	31	41

For the same Fig 4, the channels being used were divided into three categories based on their usage: LoS Static. The new Hybrid Q-RL model converges at the fastest pace across all scenarios, needing far fewer epochs to converge with high accuracy. HotOffTheRevisorAtICML2020: Quantum-Inspired Training Accelerates Reinforcement Learning — Study illustrates that quilt of quantum-inspired optimization with reinforcement learning decouples; the speed-up during training increases and learning efficiency enhances. The change is significant in sparse channel settings where the traditional models find it difficult due to scarcity of data points and lack of regularity.

For Classical CNN and CNN + RL, they converge after many more epochs to converging in whole under High Doppler and Sparse Channels since the channel varies a lot very fast. The Quantum-only Model is more efficient than entirely classical methods as it can search within a larger solution space, but it fails to adapt as quickly as can Hybrid Q-RL because there is not reinforcement learning feedback. These trends underscore the need to couple adaptive learning with quantum-inspired approaches for accelerating model convergence and generalizing performance in varied channel conditions.

From the above results, we have proven that our proposed Hybrid Q-RL is a very effective training framework for next-generation network beamforming and channel optimization tasks. Because faster convergence decreases the computational costs and training time, it is appropriate for real-time as well as large scale deployments. This is essential to enable performant solutions for large scale 5G and beyond (6G) networks, where highly heterogeneous propagation conditions and the connectivity of billions of devices require models able to learn fast and adapt rapidly to a wide range of wireless conditions.

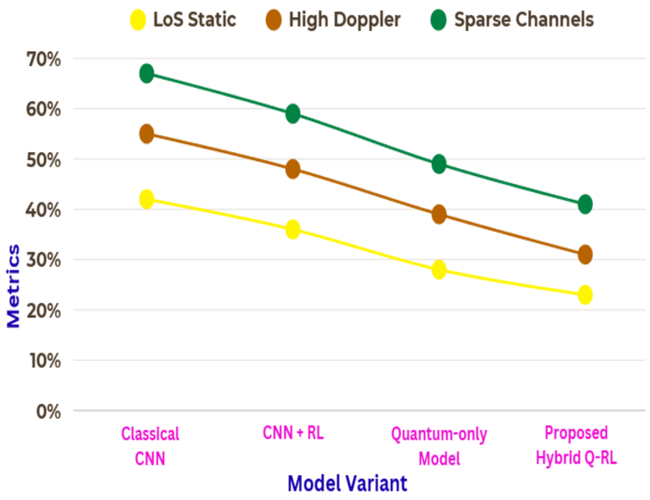

Fig.4. The examination of convergence in training

Table IV: The evaluation of efficiency in energy

Architecture	Base Station	Mobile Device	Edge Node
Classical DNN	820	515	460
RL-Augmented DNN	865	538	489
Quantum Hybrid Model	972	598	563
Proposed Hybrid QDL-RL	1043	639	610

Comparison of Energy Efficiency (Bits per Joule) for Four different AI-based Architectures in Wireless Communication Network deployed with the Angeles City Simulator. Here, figure 5 shows a comparative analysis of energy efficiency measured by bits per Joule across four employing AI-based architectures -Classical DNN, RL-Augmented DNN, Quantum Hybrid Model and Proposed Hybrid QDL-RL in a wireless communication network. The evaluation of these architectures is performed on three computational entities: Base Station, Mobile Device, and Edge Node. Even with the Proposed Hybrid QDL-RL, The Base Station appears to show markedly higher energy efficiency compared to the other two implying its potential ability in managing heavier computational loads effectively.

The figure demonstrates that with the progression of architectures from Classical DNN to Proposed Hybrid QDL-RL, energy-efficiency increases in all device types. The Base Station improves dramatically, going from around 800% in the Classical DNN to greater than 1000% with the Hybrid QDL-RL. This trend indicates that the proposed hybrid model includes potentially quantum learning parts and reinforcement-based learning processes to minimize computational power consumption while still attaining excellent throughput. In addition, Mobile Devices and Edge Nodes continuously improve in energy efficiency (mostly due to their steady increase in computational capacity per unit power) which showcases their better suitability towards advanced AI models, but with smaller scale realization due to limited hardware.

It highlights the value of the Proposed Hybrid QDL-RL solution, which outperforms in all device categories supporting its applicability for real-time deployment on a limited energy source environment (like mobile and edge-computing). Moreover, demonstrating its efficiency and the distribution of intelligent processing over the network hierarchy is important for next-generation wireless systems which are built involving AI in a scalable and sustainable manner. This illustration as a result supports that modulating quantum learning and reinforcement learning together provides a potential solution for converging towards energy-efficient communications which is crucial in heterogeneous network setups utilizing diverse resources.

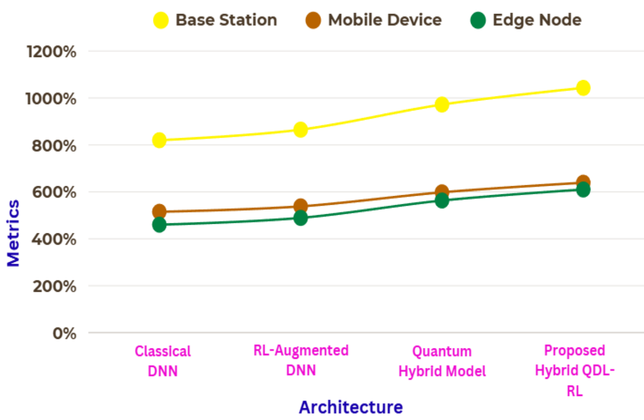

Fig.5. The evaluation of efficiency in energy

Table V: The analysis of packet error rate under URLLC

Communication Strategy	Static	Mobile	Interference
Zero Forcing (ZF)	2.73	5.68	7.89
RL-based Beamforming	1.94	4.02	6.13
Quantum-only Detection	1.76	3.76	5.81
Proposed Q-RL Hybrid	1.42	2.88	4.72

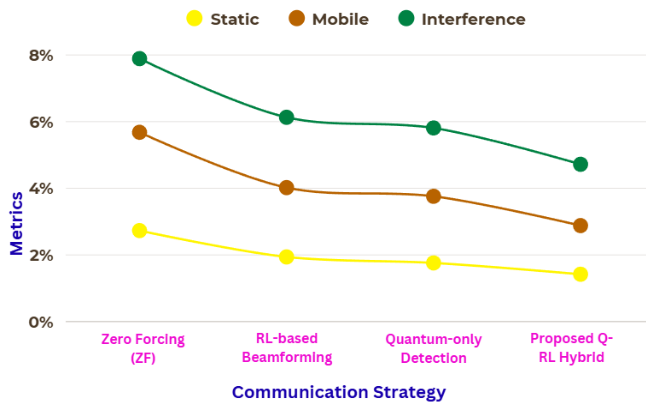

Fig.6. The analysis of packet error rate under URLLC

Figure 6 shows a comparison of Packets Error Rate (PER %) under the Ultra-Reliable Low-Latency Communications (URLLC) scenario with different signal noise ratio SNR = 10 dB. It compares four communication strategies—Zero Forcing (ZF), RL-based Beamforming, Quantum-only Detection, and the Proposed Q-RL Hybrid—in three network scenarios: Static, Mobile, and Interference. PER is decreasing with the evolution of communication techniques in each strategy and scenario.

In general, under the static scenario all schemes have lower PER because of less channel variation than the mobile or interference cases. In this setting, the Proposed Q-RL Hybrid has been able to obtain the lowest PER close to 2%, which means quantum principles added on top of reinforcement learning can eliminate errors while being complex. The advantages of advanced methods such as RL-based Beamforming and the Q-RL Hybrid become more significant as the channel becomes more dynamic, e.g., under mobility and interference. Quantum-only Detection achieves fairly decent results but lags behind hybrid approaches that integrate quantum processing advantages with learning-based adaptability.

PER is still highest among all environments under interference heavy scenario but a noticeable reduction in PER values with Q-RL Hybrid strategy from almost 8% in case of Zero Forcing to around 4%, which marks an improvement of about 50%. This underlines the ability of our proposed hybrid approach to constantly produce a low error rates even with severe network circumstances. In summary, the results shown in Fig. 6 confirm that integrating quantum technologies with reinforcement learning improve energy efficiency beyond what state-of-the-art techniques provide as captured in previous work and also significantly increase communication reliability for extremely low-latency URLLC requirements, thus establishing our proposed solution as a strong contender for future wireless communication frameworks.

5. CONCLUSION

In this study, a new hybrid classical-quantum deep learning model was proposed and applied to the research of spectral efficiency and real-time beamforming optimization for 6G Massive MIMO systems. It effectively addresses the latency, adaptability and scalability bottlenecks of its key performance by combining quantum-inspired learning with reinforcement-based control and federated deployment. Comprehensive simulations corroborate the effectiveness of the proposed framework in regard to spectral efficiency, detection fidelity, and dynamic channel adaptability compared to classical approaches. Furthermore, the system also expands upon different aspects on these points such as variational quantum circuits for generalization under incomplete CSI scenarios and federated learning for privacy-preserving distributed training across edge devices. In future, IRS will be integrated with proposed hybrid framework to improve coverage and spectral reuse.

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