Quantum Machine Learning for Channel Estimation in Reconfigurable Intelligent Surfaces-Assisted 6G Networks

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***Abstract*—Sixth-generation (6G) wireless networks are expected to deliver transformative capabilities including ultra-reliable low-latency communications and massive connectivity. Reconfigurable intelligent surfaces (RISs) have emerged as a key enabling technology by dynamically manipulating wireless propagation through programmable reflecting elements. However, accurate channel estimation in RIS-assisted networks faces significant challenges from cascaded channel structures, passive elements, and high-dimensional parameter spaces. Quantum machine learning (QML) offers a fundamentally different computational paradigm that may address these challenges through quantum properties. This article provides a tutorial overview of QML for channel estimation in RIS-assisted 6G networks. We present RIS-assisted system architectures and channel estimation challenges, introduce quantum computing fundamentals, and survey QML architectures. As a use case, we consider a hybrid quantum-classical framework, e.g., convolutional neural network (CNN)-quantum long short-term memory (QLSTM), for channel estimation in RIS-assisted non-orthogonal multiple access (NOMA) systems. This case study shows consistent accuracy improvements compared to quantum and classical benchmarks. Finally, we discuss implementation challenges and future research directions for practical deployment of quantum-enhanced wireless systems.**

***Index Terms*—Channel estimation, non-orthogonal multiple access (NOMA), quantum machine learning (QML), reconfigurable intelligent surface (RIS).**

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I. Introduction

Following the global rollout of commercial fifth-generation (5G) systems, both academia and industry have driven their research and development toward beyond-5G (B5G) and sixth-generation (6G) [1]. To support advanced applications like smart industry, the metaverse, and autonomous transportation, next-generation networks are envisioned to provide ultra-low latency, exceptionally high data rates, massive device connectivity, and wide-area coverage. To achieve this, six key application scenarios for 6G are outlined by the international telecommunication union (ITU), which comprise enhanced versions of current 5G services, i.e., enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable low-latency communications (URLLC) [1], together with three novel focus areas, i.e., integrated artificial intelligence (AI) and communication, integrated sensing and communication (ISAC), and ubiquitous connectivity. To meet the demands of these use cases, 6G systems are expected to deliver massive device connectivity reaching 10^7 devices/km^2, peak data rates of up to 1 Tb/s, and ultra-low air interface latency of 0.01–0.1 ms, which demonstrate significant improvements in area traffic capacity, energy and spectrum efficiencies, and mobility compared to 5G. Hence, various wireless technologies like massive multiple-input multiple-output (MIMO), millimeter-wave (mmWave), and terahertz (THz) communication have been proposed to enable transformative changes in both system architecture and component design. However, practical implementation remains challenging due to complex signal processing, high energy consumption, and stringent hardware requirements.

To tackle these challenges, reconfigurable intelligent surfaces (RISs) [2] appear as a promising solution for reducing energy consumption and hardware costs in B5G and 6G wireless networks. Typically, a RIS is composed of a large number of low-cost and passive elements, and each element is controlled by a smart controller to adjust the phase of incident signals and manipulate their propagation direction. By dynamically tuning the phase shifts and coefficients of its passive elements, a RIS can control the wireless channel to improve signal strength at intended receivers and boost overall communication performance between users and the base station

(BS). Hence, deploying RISs can enhance the coverage, energy and spectral efficiencies, and throughput of B5G and 6G communication systems by adjusting its phase shifts through passive beamforming. In RIS-aided wireless communication systems, achieving the anticipated performance gains requires accurate channel state information (CSI) for beamforming, which is challenging in practice due to the passive nature of RIS's elements and the cascaded channel of the BS-RIS-user.

Although machine learning (ML) [3] plays an important role in present wireless networks, existing ML techniques such as deep learning (DL) models are likely to struggle in next-generation wireless networks because of scalability and adaptability issues. The challenges stem from: i) extremely large state and action domains: Millions of devices and different service requirement levels lead to an explosive increase in the dimensionality of the state space such as network conditions, and action space such as resource optimization choice, ii) stringent time-critical requirements: 6G applications such as autonomous vehicles and extended reality necessitate responses within ultra-tight time constraints, iii) highly dynamic environments: 6G networks must quickly adapt to fluctuating link qualities and changing spectral-temporal resources in space, air, ground integrated networks.

Recently, quantum ML (QML) emerges as a promising solution for addressing high-dimensional optimization problems. QML leverages quantum bits (qubits), which can represent information and handle computational bases due to quantum properties, e.g., superposition and entanglement. Unlike classical systems that process sequential bits, QML can process qubits in parallel, which can substantially accelerate computation. This quantum parallelism allows the computational bases number to scale exponentially with the number of qubits, thus enabling a QML algorithm with N qubits to process 2^N basis states simultaneously.

However, effectively harnessing QML models to address the unique challenges of RIS-assisted channel estimation remains an open research problem. Therefore, this article aims to provide a comprehensive perspective on applying QML to channel estimation in RIS-enabled systems. The remainder of this article is organised as follows. Section II provides an overview of the RIS-assisted 6G network architecture and discusses its integration with key technologies. Section III analyses the specific challenges associated with channel estimation in these systems. Section IV introduces the fundamentals of quantum computing and presents our proposed QML-based channel estimation framework. Section V evaluates the performance of the framework through a detailed case study and compares it against quantum and classical baselines. Section VI discusses the implementation challenges and outlines future research directions for QML in wireless communications. Finally, Section VII concludes the article.

II. RIS-Assisted 6G Networks: System Architecture and Key Technologies

In this section, we provide an overview of RIS-assisted 6G networks by detailing their fundamental system architecture and highlighting the key enabling technologies that can integrate and improve their performance.

A. System Architecture Components

A general RIS-assisted wireless system consists of a BS, a RIS, and multiple users, as shown in Fig. 1. The BS is generally equipped with multi-antenna arrays to enable spatial multiplexing and advanced beamforming capabilities. A RIS composed of a large number of programmable reflecting elements is deployed to dynamically manipulate the wireless propagation environment. The amplitude and phase of these elements are adjusted to redirect signals toward intended users. With the help of the RIS, multiple users are simultaneously served by BS within the coverage region. While this canonical setup uses a single BS and a single RIS for clarity, the architecture extends naturally to multiple BSs and multiple distributed RIS panels: placing several RISs at different locations and coordinating them across neighbouring BSs enlarge the coverage area, create additional reflection paths around blockages, and improve spatial diversity for cell-edge users. Such multi-RIS, multi-cell deployments, however, intensify the channel estimation task, as the number of cascaded BS-RIS-user links to be estimated grows accordingly. Regardless of the deployment scale, a reliable control link between the BS and the RIS is required to configure the reflection coefficients in real-time implementation. This control channel can be implemented via wired or wireless connections depending on deployment scenarios. RIS architectures can be broadly classified into passive and active types [2]. Passive RIS consists of passive reflective elements that are not equipped with active radio frequency (RF) components, thus providing low-cost and power-efficient operation, but relies entirely on the BS for signal generation. In contrast, active RIS contains low-noise amplifiers or active circuits, which enable signal amplification but at the cost of higher power consumption and increased hardware complexity.

B. Integration with Advanced Technologies

Several advanced technologies have been integrated in RIS to further enhance the network performance.

1) RIS-assisted MIMO systems: RIS enhances beamforming capabilities by creating additional spatial degrees of freedom, thus allowing the BS to shape propagation paths more effectively and achieve higher data rates [4].

2) RIS-supported mmWave and THz communications: Higher penetration loss and reduced scattering effects are two major limitations in mmWave and THz systems. RIS can improve the propagation conditions in these high-frequency bands by offering an additional propagation path, thus reducing severe path loss and blockage issues [5], [6].

3) RIS-aided ISAC communications: RIS can steer directional beams toward specific physical directions, i.e., the communication user and the radar target, thus reducing mutual interference between the radar and communication signals. Also, RIS can create virtual line-of-sight (LoS) links when the link between BS and target/user are blocked. Furthermore, RIS can be employed to reflect artificial noise in spatial directions that degrade an eavesdropper's channel while minimally affecting communication users [7].

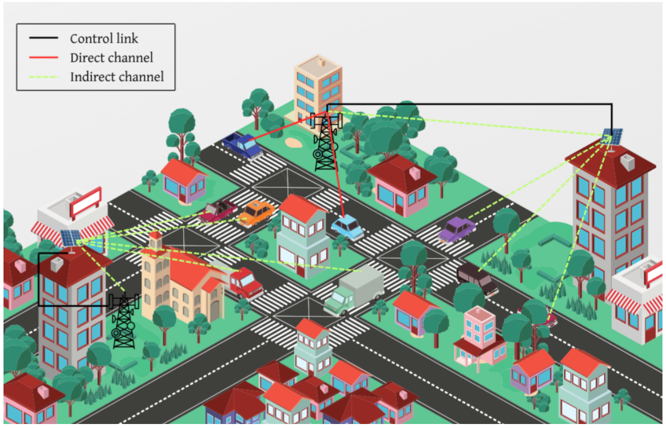

Fig. 1: RIS-assisted 6G systems architecture.

4) RIS-aided non-orthogonal multiple access (NOMA) systems: Incorporating RIS into NOMA systems can provide spectral efficiency gains by enhancing desired signal power and controlling inter-user interference through programmable reflections [8].

III. Channel Estimation for RIS-assisted 6G Networks

In this section, we discuss channel estimation task in RIS-assisted 6G networks, and highlight their associated fundamental challenges.

In RIS-assisted wireless systems, channel estimation represents a fundamental challenge due to the cascaded channel structure [2], [9]. This involves the product of two separate links, i.e., the BS-RIS channel and the RIS-user channel, in which the individual links cannot be directly observed or uniquely separated from the combined received signal. Further, since RIS is passive, it cannot transmit/receive pilots or perform baseband processing. Moreover, the problem is aggravated by the time-varying nature of the wireless environment, especially when users are mobile, which causes rapid fluctuations in both individual subchannels and the resulting cascaded channel. Furthermore, large RIS arrays with hundreds or even thousands of passive elements lead to extremely high-dimensional cascaded channels, thus significantly increasing pilot overhead and computational complexity. This complexity grows even further in multi-user settings. These collective factors make channel estimation in RIS-aided wireless systems significantly more challenging than traditional systems employing active devices such as amplified-and-forward relays.

A. The Channel Estimation Problem

1) Cascaded channel structure: The bilinear relationship between the BS-RIS and RIS-user channels means the overall channel is not directly measurable. This cascaded structure complicates the estimation process and prevents the use of conventional pilot-based techniques since the RIS elements are passive.

2) High dimensionality: A RIS panel typically comprises hundreds to thousands of reconfigurable reflecting elements, thus dramatically increases the dimension of the channels to be estimated. When the wireless system involves multiple users and multi-antenna BS, the computational complexity of the problem increases significantly.

3) Pilot overhead: Accurate channel estimation typically requires long pilot sequences which is proportional to the number of RIS elements. This leads to excessive training overhead, reduced spectral efficiency, and unsuitable for practical implementation requirements.

4) Time-varying channels: User mobility and dynamic environment cause rapid fluctuations in channel coefficients. Hence, frequent channel re-estimation is required, thus increases both latency and resource consumption.

5) Real-time requirements: Many advanced beyond 5G technologies such as THz, ISAC, and NOMA depend on timely and highly accurate CSI. Meeting real-time requirements while dealing with high-dimensional and time-varying channels is notably challenging.

IV. Quantum Machine Learning: A New Paradigm for Channel Estimation

This section introduces the essential concepts of quantum computing and explains how they can be applied to channel estimation problems in RIS-assisted 6G networks. We first establish the quantum computing fundamentals necessary to understand QML approaches. We then survey various QML architectures that have been proposed for wireless communications. Finally, we present our hybrid quantum-classical framework that specifically addresses the spatial and temporal characteristics of RIS-assisted channel estimation.

A. Fundamentals of Quantum Computing

Quantum computing represents a new paradigm for information processing, based on the principles of quantum mechanics [10]. The basic unit of quantum information is the qubit. Unlike a classical bit, which must be either 0 or 1, a qubit can exist in a superposition of both states simultaneously. Consequently, a register of multiple qubits can represent a superposition of an exponentially large number of states at once. This rapid scaling of the state space forms the basis of quantum data encoding. This property enables the encoding of a large, high-dimensional classical vector into a compact quantum state that requires only a small number of qubits.

A second fundamental principle is quantum entanglement [10], which creates strong, non-classical correlations between qubits. When qubits are entangled, their individual states are no longer independent; measuring one instantly influences the others, regardless of the distance separating them. In a quantum circuit, entanglement is crucial for building an expressive model. It helps to capture complex, non-linear relationships and interdependencies between data features, which a classical neural network might require significantly more layers and parameters to model effectively.

Quantum parallelism is another key concept that arises from superposition. When quantum operations, or gates, are applied to a register of qubits, the operation acts on all parts of its superposition simultaneously. This process allows the computation to be performed on an exponential number of states in a single operational step. This ability to process vast amounts of information concurrently within the quantum state is a foundational feature of quantum computation, offering a distinct approach to information processing compared to classical methods.

These principles are practically applied in variational quantum circuits (VQCs), which are central to a hybrid quantum-classical algorithm. This approach combines a parameterised quantum circuit with a classical optimiser. First, the classical input data is encoded onto the qubits. The circuit is then executed, and its output is measured to produce a classical result. This result is fed into a cost function. The classical optimiser, in turn, updates the parameters of the quantum circuit, similar to how the weights of a classical network are updated during training. This hybrid loop is repeated until the VQC is trained to accurately map the input signals to the desired output.

B. Quantum Machine Learning Architectures

Quantum neural networks (QNNs) extend the concept of classical neural networks to the quantum domain. These networks encode input data into quantum states, process information through layers of parameterised quantum circuits (PQCs), and extract outputs through measurement operations [10]. These quantum layers, often implemented as VQCs, can potentially capture complex nonlinear relationships with fewer parameters than equivalent classical networks. However, designing effective QNN architectures requires careful consideration of the quantum circuit structure, its data embedding strategies, and the measurement procedures.

Quantum reinforcement learning (QRL) applies quantum computing to decision-making problems where agents learn optimal policies through interaction with environments [11]. Quantum algorithms may offer advantages by using superposition to represent the state-action space or by potentially accelerating the learning process. For wireless communications, QRL could optimise resource allocation policies, power control strategies, or beamforming configurations. However, implementing QRL requires addressing challenges in state representation, action encoding, and reward function design.

Quantum federated learning (QFL) extends federated learning (FL) principles to quantum settings, enabling multiple parties to collaboratively train quantum models without sharing raw data. This approach is particularly relevant for 6G networks where privacy and security are critical. QFL can use quantum communication channels (such as quantum key distribution) to transmit model updates with enhanced security [12], where quantum computation at each device may offer new ways to process the local models. Research in this area is still emerging, with open questions about quantum gradient aggregation and quantum communication protocols. In the context of this article, QFL also offers a natural route to scale the proposed channel estimation framework to multi-BS, multi-RIS networks: instead of gathering received-signal data centrally, each BS or RIS controller could train a local CNN-QLSTM estimator on its own observations and exchange only the resulting model updates, enabling privacy-preserving and communication-efficient collaborative channel estimation across the network.

Quantum long short-term memory (QLSTM) networks adapt the classical long short-term memory (LSTM) architecture to quantum computing by replacing classical internal network components with quantum circuits. The QLSTM maintains the fundamental LSTM structure with forget gate, input gate, and output gate, but implements these operations through VQCs. This design enables QLSTM to capture temporal dependencies in sequential data, such as those found in time-varying wireless channels. This approach can also be more parameter-efficient, potentially capturing these dynamics with fewer trainable parameters than a classical LSTM.

Hybrid quantum-classical architectures combine the complementary strengths of quantum and classical processing. In these frameworks, classical components handle tasks where classical algorithms excel, such as feature extraction. Quantum components tackle computationally difficult parts of the problem, such as modelling complex, non-linear patterns or temporal dependencies. These hybrid architectures are particularly practical for current, noisy quantum hardware, which remains limited in qubit count and coherence time. By carefully partitioning computations, hybrid systems can achieve performance benefits but remain implementable on existing technology.

C. Proposed QML Framework for Channel Estimation

The proposed framework is a hybrid quantum-classical architecture that integrates convolutional neural networks (CNNs) and QLSTM networks [13], as shown in Fig. 2. This hybrid model is designed to address the high-dimensional complexity of RIS-assisted systems and the inherent time-varying nature of wireless channels. This hybrid design separates the problem into two parts: the classical CNN performs spatial feature extraction, and the QLSTM uses quantum circuits to model the complex temporal dependencies. The first component of the framework is the CNN module, which functions as a dedicated spatial feature extractor. The module collects received signal data which is typically organised into a matrix, representing features like the magnitude and phase of the signals from different users or antennas. Convolutional layers apply a set of learnable filters to the input matrix. Each filter scans the input to detect local spatial patterns and correlations between the signal features. Following convolution, max-pooling layers are used to downsample the feature maps. This process reduces the dimensionality of the data, making the model more computationally efficient and helping it retain the most significant spatial features while discarding noise. The final feature map is flattened into a one-dimensional vector and reshaped into a temporal sequence, which serves as the input for the QLSTM module.

The QLSTM module processes the sequence of feature vectors extracted by the CNN module to model the evolution of the channel. As illustrated in Fig. 2, this module is built from two stacked QLSTM layers: the first captures the temporal dependencies within the incoming feature sequence, while the second refines this representation to model the higher-order, longer-range dynamics of the time-varying channel. Using two layers was found to balance temporal expressiveness against

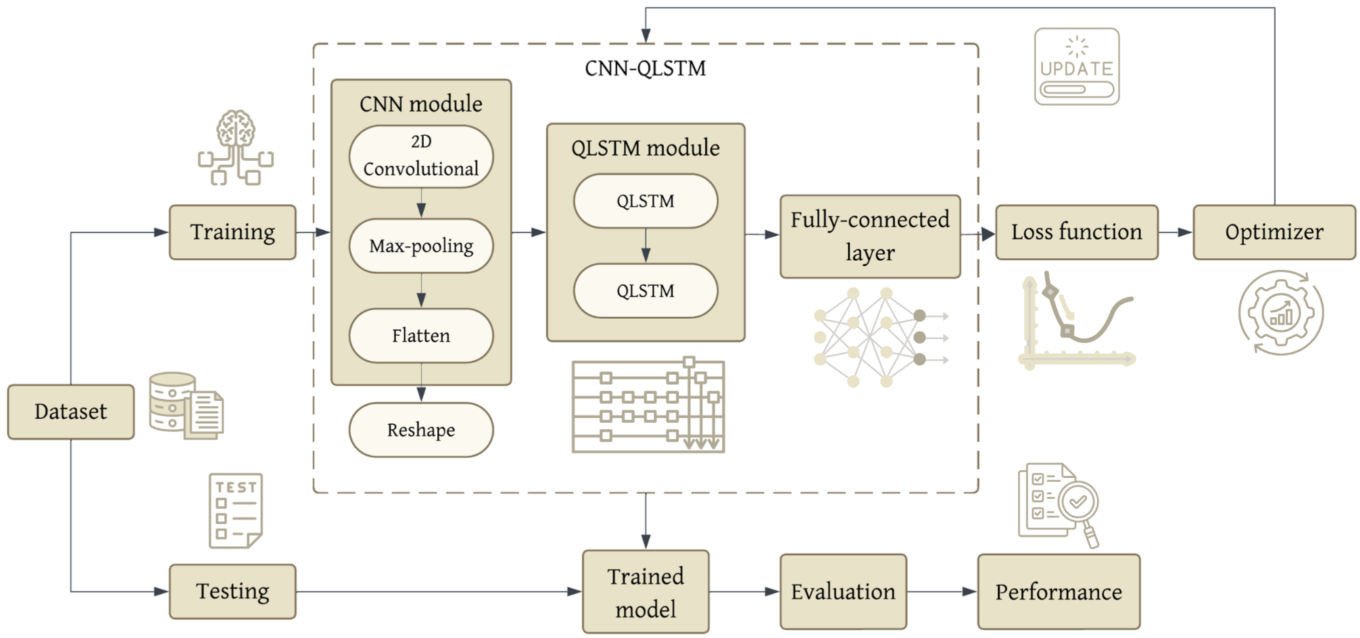

Fig. 2: The proposed channel estimation framework.

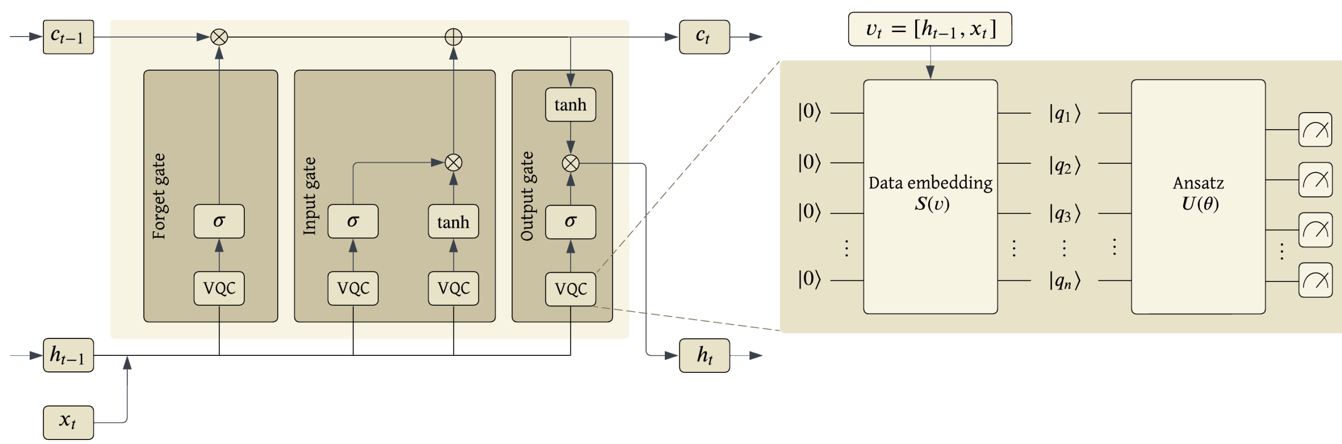

Fig. 3: The QLSTM cell and the VQC architecture.

model compactness for this task. It retains the classical LSTM structure, including the forget, input, and output gates that manage its memory, as depicted in Fig. 3. The innovation lies in how these gates compute their values. Instead of using classical fully-connected layers, the QLSTM uses VQCs as the core, trainable function approximators. As shown in Fig. 3, this begins with a data embedding stage that relies on angle encoding: the real-valued features derived from the received signals, specifically the magnitude and phase of the signals at the users, are mapped directly onto single-qubit rotation angles to prepare the quantum state. This approach keeps the circuit shallow, since each feature requires only a single rotation, which is well suited to near-term quantum hardware. Once encoded, the quantum circuit processes the information using its own set of trainable parameters. A measurement is then performed to extract a classical result from the quantum state. This classical result is then passed through an activation function (such as a sigmoid) to produce the final output. This quantum-based processing allows the QLSTM to model these complex, non-linear dynamics by leveraging the unique expressive power of quantum computation.

The entire proposed model is trained end-to-end as a single system. A loss function, such as mean square error (MSE), measures the error between the final prediction of the model and the actual target channel values. This error is then used to update all trainable parameters in the model. A classical optimiser, such as adaptive moment estimation (Adam), manages this process. To compute the necessary updates, gradients are calculated for both components: standard backpropagation is used for the classical CNN parameters, while a compatible method such as the parameter shift-rule, is used to find the gradients for the quantum parameters within the VQCs. The optimiser uses these gradients to adjust all parameters, both classical and quantum, in a unified step to minimise the overall estimation error. Compared with a purely classical estimator, this design provides two concrete advantages for RIS channel estimation. First, by embedding the gate computations in variational quantum circuits, the QLSTM can represent the highly non-linear, high-dimensional temporal correlations of the cascaded channel using far fewer trainable parameters than a classical LSTM of comparable accuracy, owing to the expressive state space afforded by superposition and entanglement. Second, this parameter efficiency yields a compact, low-depth model that is better matched to the memory and latency constraints of practical 6G deployment, while the CNN front end preserves the proven strengths of classical spatial feature extraction.

V. Case Study and Performance Insights

To demonstrate the practical applicability of the proposed CNN-QLSTM framework, we evaluate its performance through a detailed case study of a RIS-NOMA downlink system. This case study serves two purposes: it illustrates how the framework operates in a realistic 6G scenario, and it provides concrete evidence of the performance advantages that hybrid quantum-classical architectures can offer. This section first describes the system configuration and key parameters of the case study. We then present the performance insights obtained from the evaluation, comparing the proposed framework against several benchmark approaches. Finally, we discuss the key observations and their implications for practical deployment.

A. Scenario Description

To demonstrate the proposed framework, we consider a downlink RIS-NOMA communication scenario [13]. The system comprises a single-antenna BS, a RIS with programmable reflecting elements, and two single-antenna users located at different distances from the BS. The RIS is positioned to assist users whose direct links to the BS experience significant path loss or blockage. All channels experience both large-scale fading from distance-dependent path loss and small-scale fading from multipath propagation.

The BS employs power-domain NOMA to serve both users simultaneously. It allocates different power levels to users based on their channel conditions, with weaker users receiving higher power. Each user implements successive interference cancellation (SIC) [8] to decode its intended signal. The near user first decodes the signal of the far user, treats it as known interference, and then decodes its own signal. The far user treats the signal of the near user as noise and decodes directly. This NOMA protocol achieves higher spectral efficiency than orthogonal multiple access (OMA) but requires accurate CSI to determine optimal power allocations.

The RIS operates in passive mode with all elements configured to maximise the signal power at user locations. Each element applies a phase shift while maintaining unit amplitude reflection. The BS-RIS-user channels remain relatively stable over short time scales, but user mobility causes gradual channel variations that must be tracked. Users move at constant speeds away from the BS, creating the temporal channel patterns that the model must learn.

System parameters are configured to represent realistic 6G deployment scenarios. Signal-to-noise-ratios (SNRs) range from 10 to 20 decibels (dB), which represent moderate to good channel conditions. Power allocation factors vary from 0.1 to 0.35. The number of RIS elements ranges from 20 to 70. These parameter ranges enable comprehensive evaluation of the proposed framework under diverse operating conditions.

B. Performance Insights

The CNN-QLSTM architecture demonstrates consistent improvements in estimation when compared to several benchmarks as shown in Fig. 4. These baselines span the main families of classical deep learning used for wireless channel estimation, i.e., purely convolutional (CNN), recurrent (LSTM), bidirectional recurrent (BiLSTM), and the convolutional-recurrent hybrid (CNN-LSTM), alongside a pure-quantum QNN. The hybrid CNN-QLSTM achieves lower estimation errors across all measured metrics, including root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). As summarised in the rightmost panel of Fig.4, this performance advantage is achieved at a markedly lower model complexity: CNN-QLSTM uses only a few hundred trainable parameters, several times to an order of magnitude fewer than the classical recurrent and hybrid baselines.

Increasing the SNR improves the estimation accuracy of the proposed model. As expected from information theory principles, a stronger signal relative to the noise provides a more reliable input, which leads to more precise channel estimates. The evaluations show a consistent decrease in all error metrics for the CNN-QLSTM model as the SNR increases from 10 to 20 dB as shown in Fig. 5(a).

Variations in the power allocation factor also affect the performance of the model. The results in Fig. 5(b) show that as the power allocation factor increases, the estimation error for the CNN-QLSTM model consistently decreases. The framework maintains its ability to estimate the channel accurately across the full range of tested power allocations, demonstrating robustness to different NOMA configurations. This flexibility is valuable for practical deployments where power allocation must adapt dynamically.

Scaling the number of RIS elements generally improves estimation accuracy. The results in Fig. 5(c) show a clear trend of reduced estimation error as the number of RIS elements increases from 20 to 70. This suggests the model can effectively leverage the increased channel diversity provided by a large number of elements. The CNN-QLSTM architecture shows it can handle the increasing dimensionality of these larger RIS configurations, a scalable property important for future systems that may use hundreds or thousands of RIS elements. One apparent exception is the slight rise in MAPE when moving from 60 to 70 elements, even though the absolute-error metrics (RMSE and MAE) do not increase. This stems from the nature of MAPE, which normalises each error by the true channel value and is therefore highly sensitive to samples

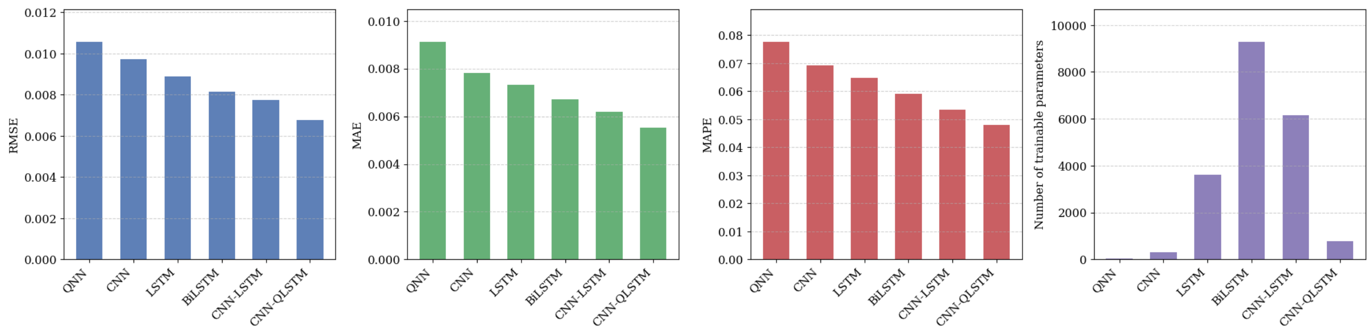

Fig. 4: Performance and complexity comparison of the proposed CNN-QLSTM framework against baseline models.

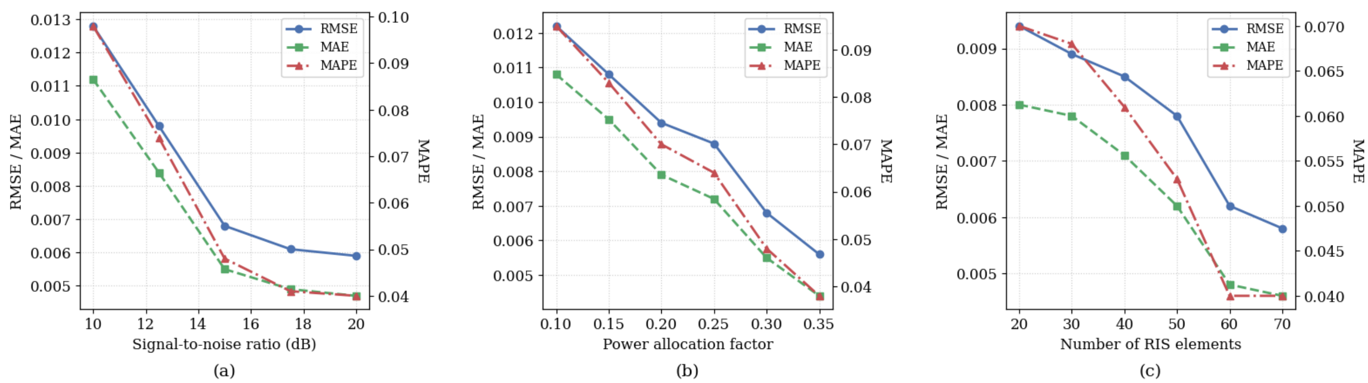

Fig. 5: Impact of key system parameters on the estimation accuracy of the CNN-QLSTM model. The estimation accuracy (RMSE, MAE, and MAPE) is evaluated under varying conditions: (a) increasing SNR, (b) varying NOMA power allocation factors, and (c) scaling the number of RIS reflecting elements.

with near-zero magnitudes introduced by the higher statistical variability of the 70-element dataset. Absolute estimation accuracy, however, is strictly maintained.

C. Key Observations

The hybrid quantum-classical architecture outperforms both pure quantum and pure classical approaches, confirming the value of combining complementary processing paradigms. Pure QNNs struggle with learning the spatial structure of received signals, as evidenced by their high estimation error. Pure classical models, such as LSTM, require many more parameters to model the temporal dependencies. The hybrid approach uses the CNN for spatial processing, a task for which it is highly effective, while deploying quantum circuits specifically for the temporal modelling, where quantum advantage in parameter efficiency emerges.

Quantum components enable more parameter-efficient temporal modelling. The CNN-QLSTM model achieves the highest accuracy with significantly fewer trainable parameters than both the classical LSTM and the classical CNN-LSTM. This efficiency stems from the expressive power of the VQCs in the QLSTM cells. For resource-constrained devices in wireless networks, this parameter efficiency translates directly to reduced memory requirements, as shown by the small size of the model.

The model demonstrates robust performance across all tested system parameters. The evaluations show that estimation error consistently decreases as the SNR improves, as the power allocation factor increases, and as more RIS elements are added. This scalability is a key finding; it shows the CNN-QLSTM architecture can handle the increasing dimensionality from larger RIS configurations and can effectively leverage the improved channel diversity to enhance estimation accuracy.

Implementation considerations suggest that this framework is well-suited for deployment on near-term quantum hardware. The quantum circuits used in the QLSTM cells require a modest number of qubits (four, in this work) and a low circuit depth, which is compatible with current noisy quantum processors. The hybrid execution model, where the intensive CNN operations run on classical hardware, makes this approach a practical and viable strategy for applying quantum computation today, well before fault-tolerant quantum computers become available.

VI. Research Challenges and Future Directions

While the case study demonstrates the potential of QML for channel estimation in RIS-assisted 6G networks, the path from laboratory demonstrations to practical deployment involves significant challenges that must be acknowledged and addressed. This section provides a balanced assessment of the current implementation challenges facing QML-based wireless systems and outlines promising research directions that could accelerate practical deployment. We first discuss the technical and practical obstacles that must be addressed, including hardware limitations, training difficulties, and integration challenges. We then present future research directions that could extend the capabilities and applicability of QML approaches in next-generation wireless networks.

A. Implementation Challenges

Hardware limitations [10] represent the most immediate obstacle to widespread QML deployment in wireless systems. Current quantum processors support only limited number of qubits with short coherence times, constraining the size and depth of implementable quantum circuits. While the CNN-QLSTM architecture proposed here operates within these constraints, scaling to larger systems with more RIS elements or users may exceed near-term hardware capabilities. Continued advances in quantum hardware are essential for realising the full potential of quantum approaches.

Barren plateaus [10] pose a training challenge for VQCs, particularly as circuit depth increases. This phenomenon manifests as flat loss landscapes where gradients become exponentially small, preventing effective parameter updates through gradient-based optimisation. Careful circuit design and initialisation strategies can mitigate barren plateaus, but no universal solution exists. Research into quantum-specific optimisation methods and circuit architectures that avoid barren plateaus remains crucial for enabling efficient training of QML models.

The classical-quantum interface introduces latency and resource overhead that could offset quantum computational advantages. Transferring data between classical and quantum processors, encoding classical information into quantum states, and extracting measurement results all require time and energy. For real-time channel estimation where latency is critical, these interface costs must be carefully managed. Co-designing classical and quantum components with attention to communication overhead is essential for achieving practical performance improvements. Specifically, the energy efficiency and latency of quantum-assisted processing must be explicitly weighed. On the energy side, because the QLSTM captures the channel dynamics with compact variational circuits of only a few qubits and low depth, it reaches the accuracy of much larger classical recurrent networks while storing and updating far fewer parameters, which lowers the memory footprint and the computational energy per channel estimate. This gain must be balanced against the energy and delay introduced by the interface itself, where state preparation, circuit execution, and the repeated measurements (shots) needed to read out each result consume both time and power that grow with the circuit width and the number of shots. For latency-critical 6G channel estimation, the net benefit thus hinges on partitioning the workload so that the parameter-efficiency savings of the quantum component are not outweighed by this interface overhead.

Standardisation gaps hinder the development of interoperable QML systems. Unlike classical ML, where frameworks such as TensorFlow and PyTorch provide common interfaces, quantum computing still lacks universal standards. While powerful ecosystems like Qiskit and PennyLane exist, they often represent competing, hardware-specific approaches rather than a single, unified standard for circuit representation, measurement protocols, or hybrid algorithm design. This fragmentation complicates research collaboration and practical deployment. Industry and academia must work together to establish standards that enable reproducible research and system integration.

Scalability concerns extend beyond hardware to algorithmic and system aspects. As wireless networks grow to support a massive number of devices, channel estimation models must scale efficiently in both computational requirements and implementation complexity. Quantum approaches must demonstrate clear advantages over classical methods even as classical hardware itself continues to improve. Additionally, distributing quantum processing across multiple devices or quantum processors introduces new challenges in quantum communication and distributed quantum computation.

B. Future Research Directions

Algorithmic advances offer multiple paths to improving QML for channel estimation. Novel quantum circuit architectures could capture wireless channel properties more effectively, perhaps by incorporating domain knowledge about propagation physics or channel structure directly into circuit design. Quantum-classical co-design methodologies that jointly optimise both components during training may achieve better performance than independent optimisation. Adaptive quantum circuits that dynamically adjust depth or gate selection based on input characteristics could balance estimation accuracy and computational cost more effectively.

Hardware evolution will gradually expand the range of feasible QML applications [14], [10]. As qubit counts increase, coherence time lengthen, and gate fidelities improve, more sophisticated quantum algorithms become practical. Future quantum processors may integrate specialised features for ML workloads, such as efficient data encoding circuits or hardware-accelerated measurement operations. Hybrid quantum-classical processors that tightly couple quantum and classical computation could reduce interface overhead and enable new algorithm designs.

Application extensions could demonstrate QML value beyond channel estimation. Resource allocation problems in wireless networks involve complex optimisations over large decision spaces where quantum approaches might excel. Beamforming optimisation, particularly for massive MIMO systems with hundreds of antennas, represents another high-dimensional problem potentially amenable to quantum techniques. Signal detection in the presence of complex interference could benefit from quantum pattern recognition capabilities. Each application domain requires careful analysis to identify where and if quantum advantages emerge.

Integration with emerging technologies creates opportunities for synergistic improvements. Quantum-enhanced edge computing could deploy quantum processors at network edges, enabling distributed QML closer to data sources. Quantum communication protocols [14] could secure model parameter exchanges in FL scenarios. Quantum sensing technologies [15] might provide enhanced channel measurements that QML algorithms could process more effectively. These integrations require interdisciplinary research spanning quantum information science, wireless communications, and systems engineering.

Theoretical foundations for QML in wireless applications remain underdeveloped. While some quantum advantages have been proven for specific problems, a generalised understanding of when and why quantum approaches outperform classical methods in wireless contexts is lacking. Research should establish theoretical frameworks that characterise quantum advantages for wireless communication problems, identify problem structures that favour quantum approaches, and provide guidance for practitioners on when quantum methods are worth pursuing. Such foundations would accelerate practical deployment by enabling informed decisions about quantum versus classical implementation.

VII. Conclusion

This article presents a comprehensive overview of QML for channel estimation in RIS-assisted 6G networks. We examine RIS-assisted system architectures and their integration with advanced technologies. The fundamental challenges of channel estimation are identified. We also introduce quantum computing fundamentals and survey QML architectures applicable to wireless systems. The proposed hybrid quantum-classical CNN-QLSTM framework illustrates how complementary processing paradigms can effectively address spatial and temporal characteristics of RIS-assisted channel estimation. The case study demonstrates that this framework achieves superior estimation accuracy compared to conventional baselines, while maintaining a favourable trade-off between performance and model complexity. However, the path to practical deployment still faces challenges related to hardware maturity, system integration, and standardisation. Overcoming these barriers requires sustained research into algorithmic innovation and the development of theoretical foundations. As quantum hardware capabilities advance, such hybrid architectures are poised to become essential tools for addressing the complex computational demands of next-generation wireless networks.

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