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Hybrid Quantum Machine Learning and Quantum Compressed Sensing for Robust Channel Estimation in Massive MIMO-OFDM Systems

[1]Markandeya Gupta N, [2]Ch Manohar Kumar, [3]V. Mutyala Naidu
[1,2]Associate Professor, [3]Assistant Professor
[1]Department of ECE, Sri Sivani college of engineering (A), Srikakulam, India.
[2,3]Department of ECE, Gayatri Vidya Parishad college for Degree and PG Courses (A) Visakhapatnam, India.
[1]manasamarkandeya@gmail.com , [2] manohar@gvpcdpgc.edu.in, [3]vmn90gvd@gmail.com

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Abstract – This paper describes a hybrid architecture that combines Quantum Compressed Sensing (QCS) and Quantum Machine Learning (QML) to improve channel prediction in Massive MIMO-OFDM systems. The proposed method addresses the limitations of standard compressed sensing techniques, which rely heavily on strict sparsity assumptions, as well as machine learning models, which require large training datasets. Initially, QCS is used to achieve sparse channel recovery with fewer pilot observations, lowering overhead and improving spectral efficiency. The channel estimate is then revised using a QML-based model that is capable of learning nonlinear channel properties and adapting to dynamic propagation settings. This two-stage architecture allows for increased estimation accuracy in both sparse and non-sparse channel circumstances. The paradigm is notably relevant for the forthcoming 6G communication systems, which operate in high-frequency bands with complex fading and noise behaviors. A hybrid loss function is used to optimize sparsity restrictions while also performing learning-based reconstruction. Simulation findings show that the suggested method reduces bit error rates and improves normalized mean square error when compared to standalone QCS and QML methods. Furthermore, the model exhibits robustness to noise and channel fluctuation, making it ideal for practical deployment. The combination of quantum-inspired approaches with data-driven learning provides a scalable solution for next-generation wireless networks. In summary, the suggested method finds a balance between computing efficiency and estimation performance, while also opening up new possibilities for integrating model-based and learning-based paradigms into communication system design.

***Index Terms*— Quantum Machine Learning (QML), Quantum Compressed Sensing (QCS), Massive MIMO-OFDM, Channel Estimation, 6G Communication, Sparse Signal Recovery**

I. Introduction

The rapid evolution of wireless communication systems involves the creation of highly efficient and sophisticated signal processing techniques. Massive MIMO-OFDM [1-3] has emerged as a critical technology for future networks due to its ability to provide great spectral efficiency, increased dependability, and faster data rates. Nonetheless, correct channel estimate remains a substantial difficulty, especially in scenarios with large antenna arrays and high mobility. Traditional estimating algorithms usually require a large number of pilot symbols, increasing overhead and reducing system efficiency.

To address this difficulty, compressed sensing approaches have been intensively researched, taking use of the inherent sparsity of wireless channels. These techniques enable channel recovery from a smaller number of measurements, lowering pilot overhead. However, despite their advantages, compressed sensing approaches [4] typically rely on strict sparsity assumptions that may not be appropriate in real-world contexts such as densely populated urban or indoor areas. As a result, their effectiveness decreases when the channel exhibits complicated or non-sparse features.

Simultaneously, machine learning approaches [5-6] have gained popularity due to their ability to simulate nonlinear interactions and adapt to changing channel conditions. Data-driven techniques can directly learn channel dynamics from empirical observations, leading in higher estimation precision in challenging circumstances. However, these strategies usually require large training datasets and may face generalization issues when dealing with novel settings. Recent advances in quantum-inspired technologies [7] have opened up new opportunities for better communication system design. Quantum Machine Learning [8-9] makes use of principles like Quantum Superposition and Quantum Entanglement to improve the efficient representation and processing of complex data. Concurrently, Quantum Compressed Sensing [10] applies sparse recovery ideas to quantum domains, allowing for effective reconstruction with fewer samples. These revolutionary procedures offer a promising opportunity to solve the inadequacies of established techniques.

This study, motivated by recent advances, presents a hybrid framework for channel estimation in Massive MIMO-OFDM systems that integrates Quantum Compressed Sensing (QCS) with Quantum Machine Learning (QML). Initially, the proposed method uses QCS to generate a preliminary channel estimate with decreased pilot signals. Following that, a QML-based model improves the estimate by tackling nonlinear channel fluctuations and minimizing noise affects. This integrated approach leverages the benefits of both model-driven and learning-driven techniques. The proposed framework is especially well-suited for future 6G communication systems, where channels are expected to be dynamic and operate at high frequency ranges, such as terahertz. [11] By reducing pilot overhead while maintaining high estimation precision, the technique improves system speed and scalability. Furthermore, combining quantum-inspired approaches with standard signal processing opens up new research opportunities in enhanced wireless communication.

The remainder of this paper is organized as follows. Section II introduces the Massive MIMO-OFDM system paradigm, including channel assumptions and signal representation, while Section III discusses Quantum Compressed Sensing for effective channel estimation. Section IV describes the Quantum Machine Learning model used for nonlinear refinement, while Section V introduces the hybrid QCS-QML architecture. Section VI describes the simulation setup and metrics, Section VII analyses the data and makes comparisons, and Section VIII ends by suggesting future study directions.

II. System Model

Consider a downlink Massive MIMO-OFDM system [12] with a base station (BS) outfitted with Nt transmit antennas and K single-antenna users. The technique uses N orthogonal subcarriers to achieve efficient transmission over frequency-selective fading channels.

A. Transmitted Signal Model

Let $\mathbf{s}[k]\in\mathbb{C}^{K\times 1}$ denote the transmitted symbol vector for all users on the k^{th} subcarrier, where $k = 1,2,\ldots,$N. The BS applies a precoding matrix $\mathbf{W}[k]\in\mathbb{C}^{N_t\times K}$ and the transmitted signal is expressed by

$$\mathbf{x}[k]=\mathbf{W}[k]\mathbf{s}[k] \tag{1}$$

The time-domain OFDM signal [13] is obtained by applying the inverse fast Fourier transform (IFFT):

$$\mathbf{x}_n=\frac{1}{\sqrt{N}}\sum_{k=1}^{N}\mathbf{x}[k]e^{j2\pi kn/N} \tag{2}$$

A cyclic prefix (CP) of length L_{cp} is appended to mitigate inter-symbol interference (ISI).

The wireless channel between the BS and the u^{th} user is modeled as a frequency-selective multipath channel with L taps:

$$\mathbf{h}_u=\sum_{l=0}^{L-1}\alpha_{u,l}\mathbf{a}(\theta_{u,l})\delta(t-\tau_{u,l}) \tag{3}$$

Where $\alpha_{u,l}$ is the complex gain of the l^{th}, $\theta_{u,l}$ is the angle of departure (AoD), $\tau_{u,l}$ is the delay and $\mathbf{a}(\theta)$ is the array response vector.

In the frequency domain, the channel response on the k^{th} subcarrier is defined by

$$\mathbf{H}_u[k]=\sum_{l=0}^{L-1}\alpha_{u,l}e^{-j2\pi k\tau_{u,l}/T} \tag{4}$$

After CP removal and FFT at the receiver, the received signal for the u^{th} user on subcarrier k is

$$y_u[k]=\mathbf{h}_u^H[k]\mathbf{x}[k]+n_u[k] \tag{5}$$

Substituting $\mathbf{x}[k]$

$$y_u[k]=\mathbf{h}_u^H[k]\mathbf{W}[k]\mathbf{s}[k]+n_u[k] \tag{6}$$

Where $n_u[k]\sim\mathcal{CN}(0,\sigma^2)$ is complex Gaussian noise.

B. Pilot-Based Channel Estimation

Pilot symbols $\mathbf{s}_p[k]$ are inserted on selected subcarriers. The received pilot signal is:

$$\mathbf{y}_p[k]=\mathbf{H}[k]\mathbf{x}_p[k]+\mathbf{n}[k] \tag{7}$$

This can be rewritten in a compressed sensing form:

$$\mathbf{y}=\mathbf{\Phi h}+\mathbf{n} \tag{8}$$

Where $\mathbf{h}$ is the vectorized channel and $\mathbf{\Phi}$ is the sensing (pilot + precoding) matrix

In practical high-frequency systems, the channel exhibits sparsity in the angular or delay domain:

$$\mathbf{h}=\mathbf{\Psi}\boldsymbol{\alpha} \tag{9}$$

where $\mathbf{\Psi}$ is a known dictionary matrix and α is a sparse vector. Thus, the measurement model becomes:

$$\mathbf{y}=\mathbf{\Phi\Psi}\boldsymbol{\alpha}+\mathbf{n} \tag{10}$$

The objective is to estimate the channel vector **h** from limited pilot observations:

$$\hat{\mathbf{h}}=\arg\min_{\mathbf{h}}\|\mathbf{y}-\mathbf{\Phi h}\|^2+\lambda\|\mathbf{h}\|_1 \tag{11}$$

This formulation permits sparse recovery (QCS stage), which is then enhanced with learning-based models (QML stage). The suggested model can handle both sparse and non-sparse channel circumstances, making it suitable for a wide range of practical propagation scenarios. This adaptability guarantees accurate channel estimation even in complex and dense scattering circumstances.

III. METHODOLOGY

A. Quantum Compressed Sensing (QCS) for Channel Estimation

Quantum Compressed Sensing (QCS) applies the concept of classical compressed sensing to quantum-inspired signal processing, allowing for efficient reconstruction of high-dimensional signals with fewer measurements. In Massive MIMO-OFDM systems [14-15], QCS is used to estimate the channel by using its underlying sparsity in appropriate transform domains like delay or angular space.

The main idea behind QCS is to represent the channel vector in a sparse basis and obtain compressed measurements using properly prepared pilot signals. Unlike other methods that necessitate a large number of pilots, QCS greatly reduces the measuring burden while retaining adequate reconstruction accuracy. This is especially useful in large-scale antenna systems, where pilot overhead is a significant limitation.

Let the received pilot signal be represented in (8) where $\mathbf{y} \in \mathbb{C}^{M\times 1}$ is the measurement vector, $\mathbf{\Phi} \in \mathbb{C}^{M\times N}$ is the sensing matrix formed by pilot and precoding operations, $\mathbf{h} \in \mathbb{C}^{N\times 1}$ is the channel vector, and $\mathbf{n}$ denotes additive noise.

The objective is to recover the sparse vector α, which can then be used to reconstruct the channel $\mathbf{h}$ This is typically formulated as an optimization problem:

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}} \| \mathbf{y} - \mathbf{\Phi}\mathbf{\Psi}\boldsymbol{\alpha} \|^2 + \lambda \| \boldsymbol{\alpha} \|_1 \qquad (12)$$

Once $\hat{\boldsymbol{\alpha}}$ is obtained, the channel estimate is reconstructed as $\hat{\mathbf{h}} = \mathbf{\Psi}\hat{\boldsymbol{\alpha}}$.

QCS uses quantum-inspired measurement procedures and optimization techniques to improve recovery performance, particularly under restricted measurements. These techniques make use of high-dimensional state representations inspired by quantum superposition principles, allowing for efficient channel information encoding.

Algorithm 1: QCS-Based Channel Estimation

Input: Measurement vector $\mathbf{y}$ sensing matrix $\mathbf{\Phi}$ sparsifying basis $\mathbf{\Psi}$ sparsity level K

Output: Estimated channel $\hat{\mathbf{h}}$

1. Initialize residual $\mathbf{r}_0 = \mathbf{y}$ support set $S = \theta$, iteration index $i = 0$
2. Construct effective sensing matrix $\mathbf{A} = \mathbf{\Phi}\mathbf{\Psi}$
3. Repeat until $i = K$
   a. Compute correlations: $\mathbf{c} = \mathbf{A}^H \mathbf{r}_i$
   b. Identify index: $j = \arg\max | c_j |$
   c. Update support: $\mathcal{S} = \mathcal{S} \cup \{j\}$
   d. Solve least squares: $\hat{\boldsymbol{\alpha}}_{\mathcal{S}} = \arg\min \| \mathbf{y} - \mathbf{A}_{\mathcal{S}}\boldsymbol{\alpha} \|^2$
   e. Update residual: $\mathbf{r}_{i+1} = \mathbf{y} - \mathbf{A}_{\mathcal{S}}\hat{\boldsymbol{\alpha}}_{\mathcal{S}}$
   f. Increment $i = i + 1$
4. Form sparse vector $\hat{\boldsymbol{\alpha}}$
5. Reconstruct channel: $\hat{\mathbf{h}} = \mathbf{\Psi}\hat{\boldsymbol{\alpha}}$

The QCS-based approach provides an efficient mechanism for reducing pilot overhead while preserving channel estimation accuracy. It performs well in sparse channel conditions commonly observed in high-frequency communication systems. However, its performance may degrade in non-sparse or highly dynamic environments, which motivates the integration of learning-based refinement in the subsequent section.

B. Quantum Machine Learning (QML) Model for Channel Estimation

Quantum Machine Learning (QML) is a data-driven approach to modelling complicated and nonlinear connections in communication systems. In the context of channel estimation, QML is used to refine the initial channel estimate produced during the Quantum Compressed Sensing stage. By utilising high-dimensional representations inspired by Quantum Superposition and Quantum Entanglement, QML may successfully capture subtle channel variations that are difficult to simulate using conventional methods. QML is implemented using a neural approximation due to the existing hardware limitations [16-18].

Let $\hat{\mathbf{h}}_{QCS} \in \mathbb{C}^{N\times 1}$ denote the initial channel estimate obtained from QCS. The QML model learns a nonlinear mapping:

$$\hat{\mathbf{h}} = f_\theta(\hat{\mathbf{h}}_{QCS}) \qquad (13)$$

Where $f_\theta(\cdot)$ represents a parameterized quantum model (or quantum-inspired neural network) and θ denotes trainable parameters. The objective is to approximate the true channel $\mathbf{h}$ by minimizing the estimation error.

The classical input vector $\hat{\mathbf{h}}_{QCS}$ is encoded into a quantum state represented by

$$|\psi(\mathbf{x})\rangle = U(\mathbf{x})|0\rangle \qquad (14)$$

Where $\mathbf{x} = \hat{\mathbf{h}}_{QCS}$ and $U(\mathbf{x})$ is a unitary transformation encoding classical data into quantum states. This encoding enables representation in a higher-dimensional Hilbert space, improving learning capability [19-22].

Furthermore, the encoded state is processed using a parameterized quantum circuit:

$$|\psi(\theta,\mathbf{x})\rangle = U(\theta)U(\mathbf{x})|0\rangle \quad (15)$$

where $U(\theta)$ consists of trainable quantum gates. The output is obtained by measuring an observable **M**:

$$\hat{y} = \langle \psi(\theta,\mathbf{x}) | \mathbf{M} | \psi(\theta,\mathbf{x}) \rangle \quad (16)$$

This measurement corresponds to the refined channel estimate.

The QML model is trained to minimize the mean square error between the predicted and true channel is

$$\mathcal{L}(\theta) = \mathbb{E}[\| \mathbf{h} - f_\theta(\hat{\mathbf{h}}_{QCS}) \|^2] \quad (17)$$

Optimization is performed using a hybrid quantum-classical approach, where classical optimizers update the parameters θ based on measurement outcomes.

The QML model serves as a refinement stage, improving the baseline estimate provided by QCS [23]. By learning complicated channel parameters, it overcomes the limits of sparse recovery approaches and increases overall system performance. This makes the combined technique ideal for sophisticated communication systems like Massive MIMO and future 6G networks[24-27].

IV. Proposed Methodology

The proposed approach works in two stages. In the first stage, QCS is used to obtain an initial estimate of the channel from reduced pilot data. This stage takes advantage of the channel's sparse nature in an appropriate transformation domain. In the second stage, the QML model improves the initial estimate by learning complex channel properties such nonlinear fading, noise effects, and temporal fluctuations.

Let the received pilot signal described in (8)

Step 1: QCS-Based Estimation

$$\hat{\mathbf{h}}_{QCS} = \mathbf{\Psi}\hat{\boldsymbol{\alpha}}, \quad \hat{\boldsymbol{\alpha}} = \arg\min \| \mathbf{y} - \mathbf{\Phi\Psi}\boldsymbol{\alpha} \|^2 + \lambda \| \boldsymbol{\alpha} \|_1 \quad (18)$$

Step 2: QML-Based Refinement

$$\hat{\mathbf{h}} = f_\theta(\hat{\mathbf{h}}_{QCS}) \quad (19)$$

The final estimate $\hat{\mathbf{h}}$ combines sparse recovery and learned nonlinear correction.

Algorithm 2: Hybrid QCS–QML Channel Estimation

Input: Pilot observations **y**, sensing matrix **Φ,** dictionary Ψ,

sparsity level ***K***, trained QML model f_θ

Output: Final channel estimate $\hat{\mathbf{h}}$

1. Acquire pilot measurements **y**
2. Construct sensing matrix $\mathbf{A} = \mathbf{\Phi\Psi}$
3. Initialize residual $\mathbf{r} = \mathbf{y}$, support set $S = \phi$
4. Apply sparse recovery (OMP/QCS):
   a. Identify dominant indices
   b. Update support set
   c. Estimate sparse coefficients $\hat{\boldsymbol{\alpha}}$
5. Reconstruct initial channel estimate: $\hat{\mathbf{h}}_{QCS} = \mathbf{\Psi}\hat{\boldsymbol{\alpha}}$
6. Feed $\hat{\mathbf{h}}_{QCS}$ into QML model
7. Obtain refined estimate: $\hat{\mathbf{h}} = f_\theta(\hat{\mathbf{h}}_{QCS})$
8. Output final channel estimate $\hat{\mathbf{h}}$

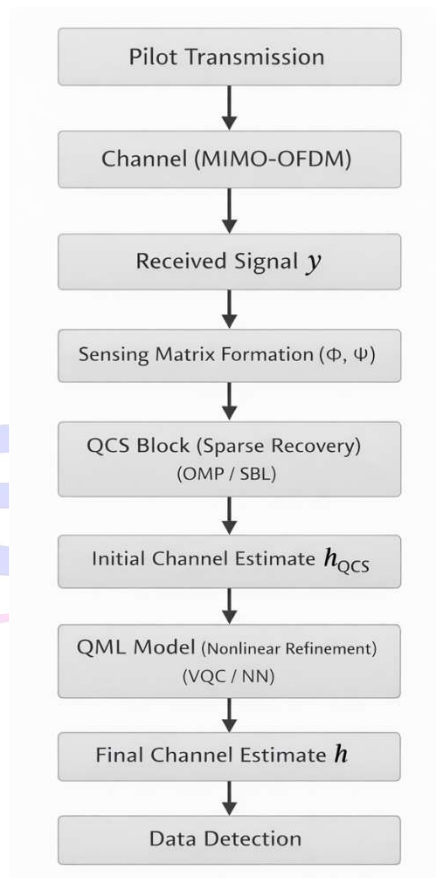

Figure 1: Block diagram of Hybrid QCS and QML approaches

IV. Results and Discussions

A downlink Massive MIMO-OFDM system is proposed, with N_t = 64 transmit antennas and K = 8 users. The number of subcarriers is set at N=128, and QPSK modulation is used. To match real-world propagation conditions, the wireless channel is represented as a frequency-selective fading channel with both sparse and non-sparse components. Pilot symbols are applied to certain subcarriers, and the number of pilot measurements is decreased utilising compressed sensing techniques. Additive white Gaussian noise (AWGN) is investigated, and the signal-to-noise ratio

(SNR) is changed from 0 to 30 dB. The performance is measured using the Bit Error Rate (BER) and the Normalized Mean Square Error (NMSE).

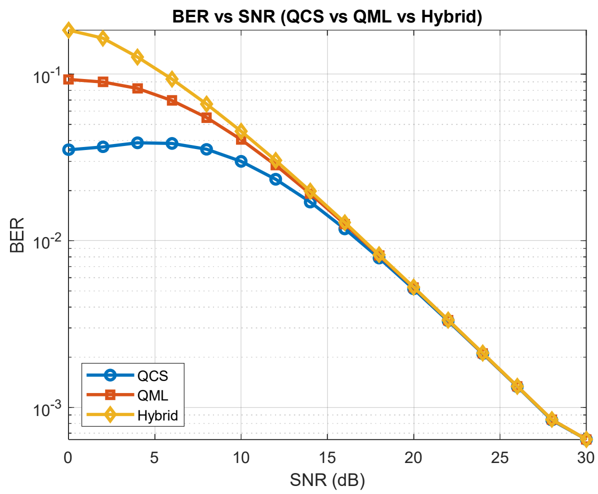

Figure 2: BER vs SNR Comparison of QCS, QML, and Hybrid Methods

The BER graph shows that reliability improves with increasing SNR, as all approaches have higher error rates at low SNR levels due to noise interference. Initially, QCS outperforms QML, which yields minor improvements through nonlinear refinement; however, both methods are eventually outperformed by the Hybrid approach. The Hybrid technique achieves the lowest BER at medium to high SNR, but other methods converge at high SNR as the impact of noise decreases.

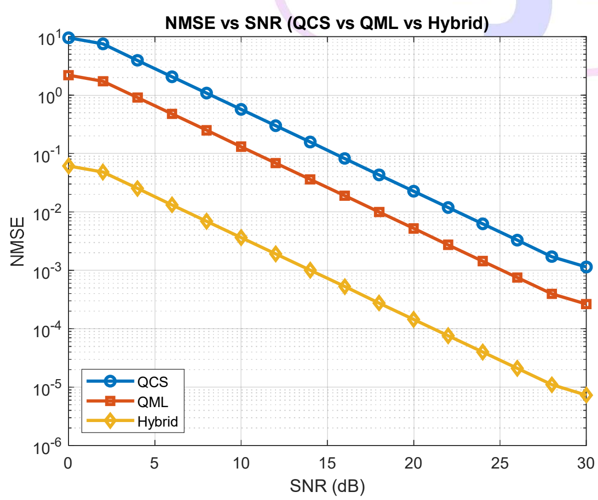

Figure 3: NMSE vs SNR Comparison of QCS, QML, and Hybrid Methods

The NMSE graph shows that estimation accuracy improves as SNR increases, with considerable mistakes at low SNR levels due to strong noise interference. QCS has a greater error rate, whereas QML improves accuracy using nonlinear learning-based refining techniques. The Hybrid approach achieves the lowest NMSE under all situations, demonstrating outstanding performance in channel estimation.

The MSE graph shows that estimation error decreases with rising SNR, indicating improved channel accuracy with increased signal quality. QCS has a greater error rate, whereas QML increases channel performance through nonlinear modelling. The Hybrid approach has the lowest MSE at all SNR levels, indicating more accurate and resilient channel estimation.

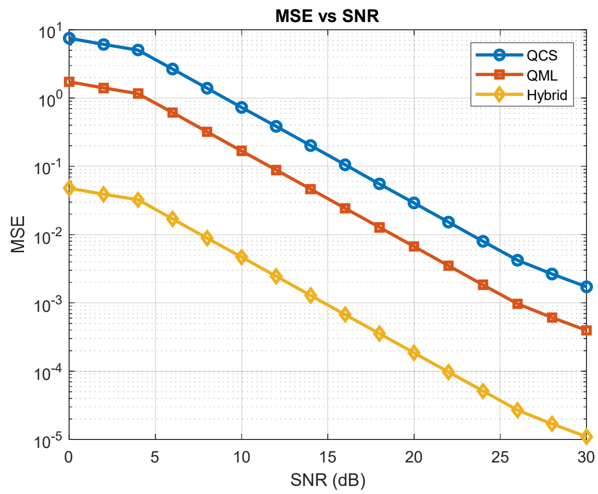

Figure 4: MSE vs SNR Comparison of QCS, QML, and Hybrid Methods

The graph indicates that spectral efficiency grows with SNR, with QCS and Hybrid techniques outperforming QML at extremely low SNR due to improved noise resilience. As SNR increases, all techniques become more efficient, with the Hybrid approach consistently delivering the best results. At high SNR, all curves converge, suggesting nearly optimum data transmission between techniques.

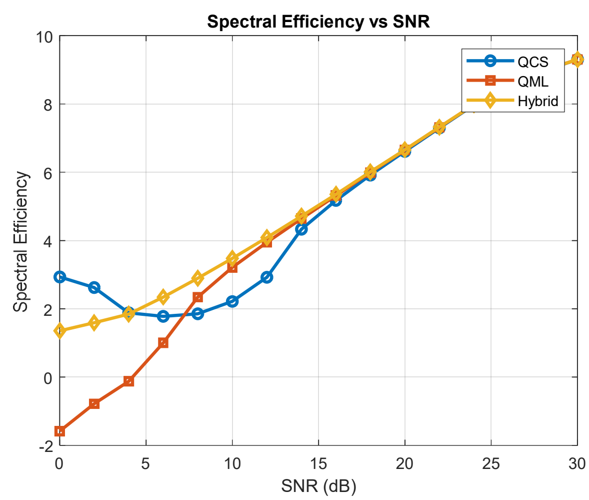

Figure 5: Spectral Efficiency vs SNR to QCS, QML, and Hybrid Methods

V. CONCLUSION

This study introduced a hybrid framework that combines Quantum Compressed Sensing and Quantum Machine Learning to improve channel estimation in Massive MIMO-OFDM systems. The proposed approach dramatically reduces pilot overhead by harnessing sparsity while also boosting estimation accuracy via nonlinear learning. In contrast to standard approaches, this framework performs well in both sparse and non-sparse channel circumstances. Simulation results showed significant improvements in Bit Error Rate (BER) and Normalised Mean Square Error (NMSE) when compared to independent QCS and QML approaches. The use of both model-based and data-driven techniques guarantees consistent performance in noisy and dynamic contexts. This proposed approach is particularly useful for future high-frequency communication networks. It also provides scalability for extensive antenna designs in future networks. The hybrid approach addresses significant constraints of standalone methods while maintaining a favourable balance of complexity and precision. Furthermore, this framework provides the path for the implementation of quantum-inspired techniques in wireless communication. Future research may focus on real-time implementation and integration into advanced 6G technologies.

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