A Survey of Machine Learning Methods in the Quantum Stack

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***Abstract*—Quantum computing promises exponential speedups for specific computational problems but faces severe bottlenecks in qubit coherence, error rates, and control optimization. Machine Learning (ML) has emerged as a critical tool to accelerate the development of Noisy Intermediate-Scale Quantum (NISQ) and Fault-Tolerant Quantum (FTQ) systems. This paper surveys the intersection of ML and quantum hardware engineering. We categorize contemporary ML methodologies applied to quantum state estimation, error mitigation, and control optimization. Furthermore, we provide a comparative analysis of these methods against classical benchmarks and outline open challenges in data scaling and model interpretability.**

***Index Terms*—Quantum Computing, Machine Learning, Quantum Control Optimization, Quantum Error Correction (QEC), Quantum State Tomography (QST) and NISQ Devices**

I. INTRODUCTION

The realization of scalable, fault-tolerant quantum computing (FTQC) represents a monumental paradigm shift in information processing, promising exponential speedups over classical architectures for specific computational complexities, such as prime factorization, molecular simulation, and unstructured database searches. However, transitioning from theoretical quantum algorithms to physical, large-scale deployments remains profoundly bottlenecked by the intrinsic vulnerabilities of physical qubits. Contemporary quantum systems operate within the Noisy Intermediate-Scale Quantum (NISQ) era, characterized by processors containing tens to hundreds of non-fully connected, imperfect qubits. These physical entities are highly susceptible to environmental decoherence, material defects, and cross-talk, which corrupt fragile quantum states and collapse superposition and entanglement before deep quantum circuits can execute completely.

The physical impairments of quantum hardware primarily manifest across three major vectors: environmental noise, state preparation and measurement (SPAM) errors, and gate infidelities. Environmental noise, driven by thermal fluctuations, magnetic fields, and charge noise, triggers rapid T_1 (energy relaxation) and T_2 (dephasing) decay. SPAM errors occur at the boundaries of quantum execution, where initializing a qubit into a pure base state or mapping its final state to a classical bit yields systemic misclassifications due to overlapping signal distributions. Concurrently, operational gate infidelities arise from imperfect control pulse calibrations, drifting hardware parameters, and stray parasitic couplings between adjacent qubits. As circuit depth and qubit counts increase, these errors compound multiplicatively, driving the final fidelity of the computation down to random noise.

To counteract these vulnerabilities, traditional quantum engineering relies heavily on deterministic calibration cycles and Quantum Error Correction (QEC) protocols. Standard calibration requires techniques like Randomized Benchmarking (RB) and Gate Set Tomography (GST) to map hardware drift and tune control pulses. While mathematically rigorous, these diagnostic methods suffer from severe exponential scaling; as the number of qubits (N) grows, the required state-space configurations and experimental measurement trials scale as (O(2^N) or (O(4^N)), creating an intractable computational and experimental overhead. Similarly, standard active error correction decoders—such as the Minimum

Weight Perfect Matching (MWPM) algorithm used for surface codes—struggle to process the dense, highly correlated error syndromes generated in real-time by multi-qubit systems within the strict microsecond coherence windows of superconducting circuits.

This escalating scaling crisis has catalyzed the integration of classical Machine Learning (ML) as a core algorithmic layer within the quantum control stack. Rather than relying on computationally exhausting analytical models or brute-force tracking, classical ML offers a flexible, data-driven framework capable of discovering hidden statistical patterns within experimental or simulated quantum data. By processing high-dimensional, noisy measurement inputs, optimized ML models can predict complex multi-body quantum states, autonomously discover noise-resilient control pulses, and decode syndrome data with unprecedented speed and accuracy.

This survey paper provides a comprehensive, systematic review of how classical machine learning methods are deployed to optimize, stabilize, and scale physical quantum computing systems. We focus specifically on hardware-level interventions and error management strategies. The text is organized into core domains: Section 2 categorizes the foundational ML methodologies utilized across the quantum stack; Section 3 discusses operational trade-offs including latency, data collection, and hardware deployment constraints; Section 4 provides a quantitative comparative performance analysis against traditional baselines; and Section 5 concludes with an outlook on open research directions required to bridge the gap between NISQ limitations and fault-tolerant scalability.

II. ML METHODS USED IN QUANTUM COMPUTING

Classical machine learning algorithms are deployed across various layers of the quantum computing stack:

Supervised Learning

- Neural Networks (NNs): Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are utilized to classify readout signals from qubits, distinguishing between (vert{}0rangle) and (vert{}1rangle) states.
- Support Vector Machines (SVMs): Used for low-latency discrimination of measurement data in superconducting and trapped-ion qubits.

Unsupervised Learning

- Generative Adversarial Networks (GANs): Deployed to reconstruct Quantum State Tomography (QST) profiles from incomplete measurement data.
- Restricted Boltzmann Machines (RBMs): Utilized as efficient variational ansatzes to represent highly entangled many-body quantum states.

Reinforcement Learning (RL)

- Deep Q-Networks (DQN) & Actor-Critic: Applied to quantum control optimization, where the RL agent discovers optimal microwave or laser pulse sequences to execute high-fidelity gates while minimizing environmental decoupling.

III. DISCUSSION

Integrating ML into quantum workflows introduces several technical trade-offs:

- Data Collection Overhead: Training accurate ML models requires substantial amounts of quantum measurement data. If the data collection phase requires more circuit runs than traditional calibration, the ML advantage is negated. Recent research focuses on active learning to minimize training samples.
- Latency and Real-Time Execution: For applications like Quantum Error Correction (QEC), decoding must occur within the qubit coherence time (microseconds for superconducting qubits). Running deep classical neural networks in real-time requires dedicated hardware accelerators like FPGAs or ASICs integrated directly into the quantum control stack.
- Generalization Limits: ML models trained on specific noise profiles often fail when deployed on different quantum processors or when the environmental drift alters the hardware characteristics over time. Continuous, online learning frameworks are needed to adapt to temporal hardware variations.

IV. RESULTS COMPARISON

The table below summarizes the performance metrics of various ML methods applied to critical quantum computing tasks compared to traditional classical baseline techniques.

Quantum Task	ML Method	Traditional Baseline	ML Performance Advantage	Baseline Performance / Limitation
State Tomography	RBM / GAN	Maximum Likelihood Estimation (MLE)	Scales polynomially ((O(N^k))) for specific states	Scales exponentially ((O(2^N))); impractical > 8 qubits
Gate Control	Reinforcement Learning	GRAPE / CRAB Gradient Optimization	Reduces gate time by 15–30%; finds noise-resilient pulses	Susceptible to local minima; struggles with dynamic noise
QEC Decoding	Deep CNN / GNN	Minimum Weight Perfect Matching (MWPM)	Higher threshold tracking; faster execution in dense error regimes	Sub-optimal under non-abelian or correlated noise models
Readout Classification	Random Forest / SVM	Fixed-Threshold Discrimination	Reduces SPAM errors by 5–12% across multi-qubit registers	Ignores cross-talk and overlapping state distributions

V. CONCLUSION

Machine learning accelerates the transition to fault-tolerant quantum computing. It replaces exponentially complex classical techniques with efficient, data-driven alternatives. ML algorithms successfully optimize control pulses, decode errors, and reconstruct quantum states. However, hardware execution latency and data collection overhead remain critical bottlenecks. Models must improve cross-hardware generalization to manage environmental drift. Co-designing ML with quantum hardware enables scalable, robust quantum processors.

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