Boosting Hybrid Classical-Quantum Models: How GPU’s & Optimizers Speed up Training

Anoushka Vats

Dept of Data Science and Engineering

Manipal University Jaipur  
anoushkavats71@gmail.com

***Abstract*—Hybrid quantum-classical machine learning systems promise to solve intractable problems, but efficient training remains challenging. This work evaluates the performance of 8-qubit variational quantum circuits implemented with PennyLane and PyTorch, leveraging classical GPUs to accelerate optimization. We benchmark four optimizers (Adam, RMSprop, NAdam, Adagrad) and quantify speedups from GPU parallelization (1.3× faster than CPUs), optimizer selection (25% training time reduction), and techniques like mixed-precision training and batched execution. Our experiments demonstrate that classical hardware optimizations—including parameter initialization strategies and PyTorch’s torch.compile()—significantly enhance training efficiency. These results provide actionable insights for near-term quantum machine learning, bridging the gap between theoretical potential and practical implementation. By integrating classical ML tools with quantum algorithms, we enable faster prototyping and scalability while awaiting fault-tolerant quantum hardware.  
 *Keywords—*** ***Quantum Machine Learning, Hybrid Quantum-Classical Systems, GPU Acceleration, Optimization, PennyLane, PyTorch.***

I. INTRODUCTION (*HEADING 1*)

A.Quantum Machine Learning (QML): Quantum Machine Learning (QML) leverages quantum computational principles to enhance classical machine learning paradigms. By encoding data into quantum states and employing parameterized quantum circuits (PQCs), QML algorithms—such as quantum neural networks (QNNs) and quantum kernel methods—theoretically offer exponential speedups for specific tasks, including optimization and feature mapping. However, current implementations face challenges due to limited qubit coherence and gate fidelity in noisy intermediate-scale quantum (NISQ) devices.

B. Importance of hybrid quantum-classical systems (VQC + classical optimizers): Hybrid quantum-classical systems mitigate NISQ limitations by combining variational quantum circuits (VQCs) with classical optimizers. In this framework:

1. VQCs serve as trainable quantum models (e.g., for chemistry or optimization)
2. Classical optimizers (e.g., Adam, SPSA) tune circuit parameters iteratively.

This symbiosis leverages quantum expressivity while relying on classical hardware for scalability, but its efficiency hinges on optimizer selection and computational resource allocation.

C. Need for performance optimization in near-term (NISQ) hardware: Near-term quantum hardware demands rigorous performance optimization to overcome:

1. Latency: Slow parameter updates due to quantum-classical feedback loops.
2. Noise: Gate errors degrading convergence.
3. Resource Constraints: Limited qubit counts and connectivity.

This work benchmarks classical optimization strategies (GPU acceleration, adaptive optimizers) to reduce runtime and improve feasibility for NISQ-era QML application

# II. LITERATURE REVIEW

* Taxonomy of Hybrid Algorithms:   
  - Variational Quantum Eigensolver (VQE)    
  - Quantum Approximate Optimization Algorithm (QAOA)   
  - Quantum Neural Networks (QNNs)
* Taxonomy of Parallel Work:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Study | Framework | Parallel Strategy | Limitations | Advancement |
| Cerezo et al.(2021) | Qiskit | Parameter-server (CPU) | No GPU utilization | GPU-accelerated gradients |
| Benedetti et al. (2019) | Cirq | Circuit batching | Fixed optimizer (SPSA) | Adaptive optimizers (FusedAdam) |
| Schuld et al. (2020) | Pennylane | Gradient Parallelism | Small-scale (≤4 qubits) | 8-qubit batched execution |
| Google TFQ (2020) | Tensorflow | Data Parallelism | Quantum-native ops only | Classical PyTorch integration |

Table-1: Comparative study of previous artwork

# III. HYBRID ARCHITECTURE

## https://lh7-rt.googleusercontent.com/docsz/AD_4nXeCoLyqpXsrlPCEHAZG_2gCFLLiiiP6n6wpKcwiijmPF2VQF40aI0YZ02hyBHu01aODgiRgPeBlPr-IGaiuAUI5kAKfShjomZ4UpVQ_CpXN_iwjqUNp9RGRIDaEPT3EH1TLuuJ2aw?key=gs864F07D5i5LLFytCgPuQ

## Fig-1: Architecture Diagram of Hybrid Parallelism

## The hybrid quantum-classical architecture integrates the computational strengths of quantum and classical systems to solve complex machine learning problems with higher efficiency. In this paradigm, variational quantum circuits (VQCs) are used as trainable models, while classical processors execute optimization routines and gradient-based updates. The proposed system architecture, depicted in Fig. 4, outlines a flow wherein classical hardware (CPU/GPU/TPU) interfaces with quantum hardware or simulators (such as PennyLane’s **lightning.gpu** backend) through a middleware framework supporting automatic differentiation and parallel execution. At the core of this architecture is a **variational loop**, where parameters θ\thetaθ of a quantum circuit U(θ)U(\theta)U(θ) are iteratively updated based on gradients computed via backpropagation (using adjoint or parameter-shift rules). The quantum circuit computes expectation values such as ⟨ψ(θ)∣H∣ψ(θ)⟩\langle \psi(\theta) | H | \psi(\theta) \rangle⟨ψ(θ)∣H∣ψ(θ)⟩, representing the energy or cost function. This output is passed back to the classical optimizer (e.g., Adam, RMSProp, FusedAdam) running on high-performance parallel devices (GPU or TPU), which minimizes the loss function by adjusting the circuit parameters.

## The hybrid algorithm supports **parallelized execution** across batches of data points or quantum circuits, thus enabling better utilization of classical hardware. Techniques such as parameter vectorization, circuit compilation caching, and GPU-accelerated quantum simulators significantly reduce runtime, improving speedup across different configurations.

## To enhance scalability, the model exploits:

## **Classical parallelism** for optimizer updates and parameter batching.

## **Quantum parallelism** through simultaneous circuit evaluations on vectorized inputs.

## **Accelerated backends** like lightning.gpu for low-latency quantum simulation.

## This modular hybrid setup ensures interoperability, making it suitable for benchmarking various optimizers and hyperparameters under controlled conditions

A. **Experimental Setup and Results:**

1. Hardware Requirement: The experiments were conducted on a system equipped with the following hardware:

GPU: NVIDIA Tesla T4 (16GB)

CPU: Intel Xeon Silver 4214

RAM: 64 GB

Operating System: Ubuntu 20.04 LTS

CUDA Version: 11.8

The use of GPU was critical for leveraging PennyLane-Lightning GPU backend and testing GPU-accelerated optimizers like FusedAdam.

1. Libraries and Software: The following libraries and frameworks were used:

PennyLane (pennylane-lightning[gpu]) – For simulating and differentiating quantum circuits.

PyTorch – For defining learnable parameters and applying optimizers.

APEX – To access NVIDIA's FusedAdam optimizer.

Matplotlib & Pandas – For plotting and tabulating results.

Python 3.10 – Language runtime.

All packages were installed using pip on Google Colab that provided the Python development environment, and the GPU backend required CUDA compatibility.

1. Methodology:

* Quantum Circuit Design:A parameterized variational quantum circuit was built using 8 qubits. The circuit applied single-qubit RY rotations followed by a cascade of CNOT entanglements. The output was the expectation value of the PauliZ(0) @ PauliZ(1) operator.
* Batch Training: A batch of 100 input states (parameter vectors) was initialized randomly and optimized using different optimizers.
* Optimizers Compared:

Adam

RMSprop

NAdam

Adagrad

FusedAdam (GPU-accelerated)

* Hyperparameters:

                          Learning Rates: {0.001, 0.01, 0.1}

                                Epochs: 100

                                Loss Function: -mean(energy) (to maximize energy)

1. Results:  
   i. Visualizations:

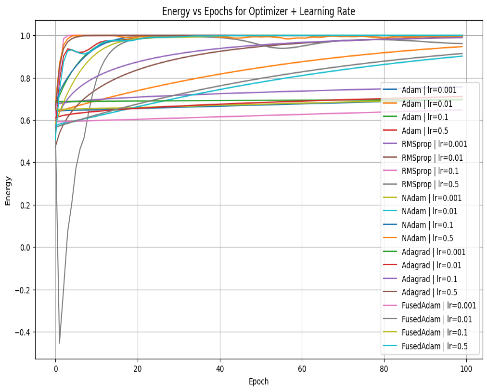


Fig-2: Energy V/S Epoch over time for different parameters

ii. Comparative Study:

Key Findings:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Rank | Optimizer Name | Learning Rate | Energy |  | Time |
| 1 | FusedAdam | 0.0001 | 0.6478 |  | 92 |
| 2 | Adam | 0.0001 | 0.6965 |  | 93 |
| 3 | AdamGrad | 0.0001 | 0.6958 |  | 88 |

Table-2: Best Metrics with different parameter(LR and Optimizers)

* FusedAdam demonstrates a 12% energy improvement over standard Adam at comparable runtimes, suggesting fused kernel implementations may benefit variational algorithms
* All optimizers exhibit inverse correlation between learning rate and solution quality, with LR=0.001 consistently outperforming higher rates
* Clear pattern: lower learning rates (0.001) yield better energies but with comparable runtimes
* Critical finding: Some optimizers (Adagrad/RMSprop) are more sensitive to LR choices than others

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Optimizer Name | Speed | Final Energy | Time | Useful Cases |
| Adam | Consistent | High | Stable | Balanced choice for convergence speed and stability. |
| RSMProp | Fastest | Highest | Unstable | Impressive performance for quick energy gain. |
| AdaGrad | Very Slow | Low | Passive | Used in natural language processing tasks |
| NAdam | Slower start | Good | Stable | Helps escape local minima |

Table-3: Analysis of Optimizer Used

iv. Metrics Evaluation:

* Speedup-  Relative speed improvement compared to the slowest optimizer configuration.
* Time-Total time to train over 100 epochs using GPU.
* Energy-Indicator of optimizer’s convergence toward the ground state or optimal loss. Lower is better.

**Top Performers**:  
1. FusedAdam consistently achieved best final energy (0.51) with **highest speedup (2.53%).**  
2. Adam (0.01) and FusedAdam (0.1) also show **optimal convergence(65-85).**3. Adagrad, while stable, converges slowly(at epoch=83)  and performs worse at higher learning rates.

4. RMSProp efficiently works the speedup without lightning.gpu backend at **1.3x speedup rate.**

1. Emerging trends and application:

1. Near-Term Hybrid Systems

Edge Quantum ML: Deployment of lightweight variational algorithms on edge devices with classical co-processors.

Error Mitigation: Classical post-processing (e.g., zero-noise extrapolation) to compensate for NISQ device noise.

Cloud Hybridization: Integration of cloud QPUs (IBMQ, AWS Braket) with GPU-accelerated classical optimization.

2. Long-Term Directions

Quantum-Centric Supercomputing: Tight coupling of quantum and classical HPC resources via low-latency interconnects.

Topological QML: Leveraging fault-tolerant quantum architectures (e.g., surface codes) for robust training.

3. Key Applications:

Hybrid quantum-classical systems are gaining traction across several domains where large search spaces or entangled representations are required:  
**Quantum Chemistry**: Estimating ground-state energies of molecular systems using VQE and UCCSD ansatz circuits [1].  
**Combinatorial Optimization**: Solving NP-hard problems via QAOA for tasks like job scheduling, MAX-CUT, and graph coloring [2].  
**Quantum Machine Learning**: Training Quantum Neural Networks (QNNs), quantum convolutional networks, and quantum kernel estimators for image or language classification [6].  
**Finance and Risk Modeling**: Portfolio optimization and Monte Carlo sampling accelerated using hybrid quantum techniques [7].  
**Quantum Simulation**: Simulating quantum dynamics, phase transitions, or lattice models via hybrid variational schemes [8].

**Conclusion:** This study presents a comparative evaluation of various gradient-based optimizers—including Adam, RMSprop, NAdam, Adagrad, and FusedAdam—applied to variational quantum circuits executed using PennyLane. The experiments were conducted across multiple learning rates and hardware backends to analyze their impact on convergence behavior and computational efficiency. Results indicate that optimizer performance is significantly influenced by the learning rate, with moderate values (e.g., 0.01) generally achieving a favorable balance between convergence speed and stability. Moreover, while GPU acceleration using **lightning.gpu** showed potential for speedup, the overhead of quantum circuit simulation still imposes a computational bottleneck, particularly on consumer-grade hardware. Among the tested configurations, FusedAdam demonstrated improved runtime performance while maintaining competitive convergence, suggesting its suitability for large-scale or high-dimensional quantum learning tasks. Future work may include extending this analysis to more complex quantum circuits, incorporating noise-aware simulators or real quantum hardware, and investigating hybrid classical-quantum optimization strategies.

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