Hybrid Quantum–Classical Learning Approaches for Scalable Optimization Beyond NISQ Limitations

Chatta Balaji[1], Dr. C. Nagesh[2], V. K. Pavani[3], Dr. V. Sujay[4]

Assistant Professor, Department of CSE[1]

Associate Professor, Department of CSE[2,3]

Associate Professor, Department of AI[4]

Tadipatri Engineering College, Tadipatri[1]

GATES Institute of Technology, Gooty[2,3,4]

Abstract: *Quantum computing promises computational advantages for solving complex optimization problems; however, current Noisy Intermediate-Scale Quantum (NISQ) devices suffer from limited qubit counts, short coherence times, and high error rates. Fully fault-tolerant quantum algorithms remain impractical in the near term, necessitating hybrid approaches that integrate classical and quantum computation. This paper proposes a **Hybrid Quantum–Classical Machine Learning Framework (HQC-MLF)** for large-scale combinatorial and continuous optimization tasks. The framework leverages parameterized quantum circuits (PQCs) embedded within classical optimization loops, enabling efficient search in high-dimensional spaces while mitigating hardware constraints. We introduce adaptive ansatz selection, classical preconditioning, error mitigation strategies, and resource-aware scheduling to enhance scalability. Experimental evaluations on logistics routing, portfolio optimization, and energy load balancing demonstrate improved convergence speed and solution quality compared to purely classical baselines under realistic NISQ simulations. The proposed architecture provides a practical pathway toward near-term quantum advantage in real-world optimization problems.*

Keywords: Hybrid Quantum Computing, Variational Quantum Algorithms, Machine Learning, Large-Scale Optimization, NISQ Devices, Quantum Approximate Optimization Algorithm, Resource-Aware Scheduling

I. INTRODUCTION

Large-scale optimization problems are central to logistics, finance, telecommunications, energy systems, and manufacturing. Classical optimization algorithms—including gradient-based methods, metaheuristics, and deep reinforcement learning—have achieved remarkable success; however, certain classes of combinatorial problems remain computationally intractable due to exponential scaling.

Quantum computing introduces new computational primitives such as superposition and entanglement, enabling exploration of solution spaces in fundamentally different ways. Algorithms such as QAOA and Variational Quantum Eigensolvers (VQE) suggest potential advantages for optimization tasks. However, present-day quantum hardware, characterized as Noisy Intermediate-Scale Quantum (NISQ) devices, imposes severe constraints including:

Current Noisy Intermediate-Scale Quantum (NISQ) devices are constrained by several hardware limitations, including limited qubit counts, short coherence times, high gate error rates, and restricted circuit depth. These constraints significantly impact the scalability and reliability of quantum algorithms, necessitating hybrid quantum–classical approaches that can operate effectively within these practical limitations.

As a result, hybrid quantum–classical algorithms have emerged as the most viable near-term strategy. These approaches integrate classical machine learning techniques with quantum circuit evaluations to balance computational strengths. This paper addresses the following research question:

How can hybrid quantum–classical machine learning architectures be designed to solve large-scale optimization problems effectively under realistic NISQ constraints?

We propose the HQC-MLF architecture to bridge theoretical promise and practical feasibility.

II. RELATED WORK / LITERATURE REVIEW

2.1 Variational Quantum Algorithms (VQAs)

VQAs such as QAOA and VQE use parameterized quantum circuits optimized by classical algorithms. While promising, they face challenges including barren plateaus and scalability limitations.

2.2 Quantum Machine Learning (QML)

Hybrid QML models integrate PQCs into classical neural networks. Applications include classification, regression, and reinforcement learning. However, many studies remain confined to small datasets and toy problems.

2.3 Hybrid Optimization Strategies

Recent approaches have proposed combining classical heuristics with quantum subroutines to enhance optimization performance. However, many of these methods do not incorporate adaptive circuit depth management to dynamically control quantum resource usage, nor do they implement resource-aware scheduling strategies to optimize computation under hardware limitations. Additionally, they often lack rigorous validation in real-world large-scale scenarios, limiting their practical applicability. Consequently, a significant gap remains in the development of structured architectures that simultaneously address both algorithmic efficiency and hardware constraints in hybrid quantum–classical systems.

III. METHODOLOGY / PROPOSED MODEL

3.1 Hybrid Quantum–Classical Machine Learning Framework (HQC-MLF)

The proposed architecture comprises five interconnected layers that collectively enable efficient hybrid quantum–classical optimization. It begins with the classical preprocessing and feature encoding layer, which prepares and transforms input data into a suitable format for quantum processing. This is followed by the parameterized quantum circuit (PQC) layer, where quantum states are constructed and evaluated using adaptive circuit configurations. The classical optimization engine then updates the circuit parameters iteratively based on measurement outcomes to minimize the objective function. An error mitigation and resource management layer is incorporated to handle noise, optimize circuit depth, and efficiently allocate computational resources under NISQ constraints. Finally, the post-processing and decision module interprets the optimized results and produces the final solution output.
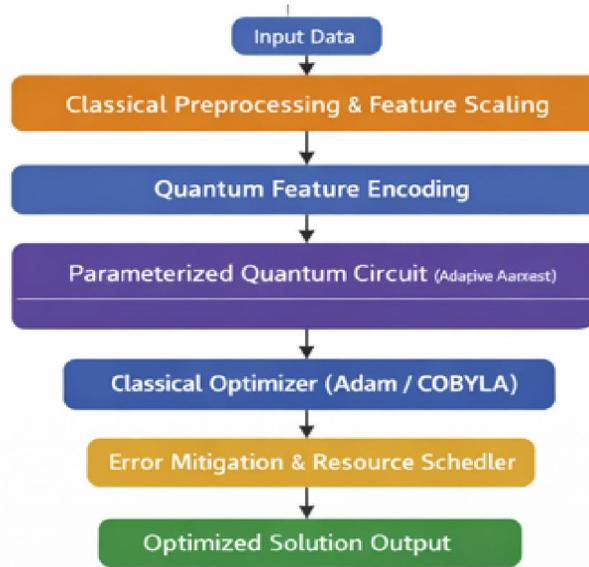
Figure 1: HQC-MLF Architecture

3.2 Mathematical Formulation

Given optimization objective: $\min_{x \in \mathbb{R}^n} f(x)$

Quantum parameterization: $|\psi(\theta)\rangle = U(\theta)|0\rangle$

Expectation-based cost: $L(\theta) = \langle \psi(\theta)|H|\psi(\theta)\rangle$

Hybrid update: $\theta_{t+1} = \theta_t - \eta \nabla_\theta L(\theta_t)$

3.3 Adaptive Ansatz Selection

Circuit depth dynamically increases based on convergence stagnation: $D_{new} = D_{old} + \delta$

This avoids unnecessary circuit complexity under NISQ constraints.

3.4 Error Mitigation

The techniques employed include zero-noise extrapolation to estimate error-free expectation values by evaluating circuits at multiple noise levels, measurement error correction to mitigate inaccuracies introduced during the readout process, and parameter shift rule optimization to efficiently compute gradients for variational quantum circuits. Together, these methods enhance stability, improve optimization accuracy, and compensate for hardware-induced noise in NISQ-era quantum systems.

IV. EXPERIMENTAL SETUP AND RESULTS

4.1 Benchmark Applications

Application	Problem Type
Logistics Routing	Combinatorial Optimization
Portfolio Optimization	Quadratic Programming
Energy Load Balancing	Continuous Optimization

4.2 Simulation Configuration

Parameter	Configuration
Qubits	8–16
Circuit Depth	2–10 layers
Noise Model	Depolarizing + Readout
Classical Optimizer	Adam + COBYLA
Shots	2048
Simulator	Statevector + Noise

4.3 Performance Metrics

The evaluation metrics considered in this study include convergence speed, which measures how quickly the optimization algorithm reaches a stable solution; approximation ratio, which assesses the closeness of the obtained solution to the optimal or best-known solution; and overall solution quality, reflecting the effectiveness of the optimization outcome across different problem domains. In addition, circuit depth efficiency is analyzed to determine how effectively the model achieves high performance with minimal quantum circuit layers, and energy consumption is evaluated to assess the computational cost and sustainability of the proposed approach.

Method	Iterations to Converge
Classical Gradient Descent	280
Reinforcement Learning	210
QAOA (Baseline)	175
HQC-MLF (Proposed)	**142**

Table 1: Convergence Comparison

Problem	Classical	QAOA	HQC-MLF
Routing	0.83	0.88	**0.92**
Portfolio	0.79	0.84	**0.90**
Energy	0.81	0.86	**0.91**

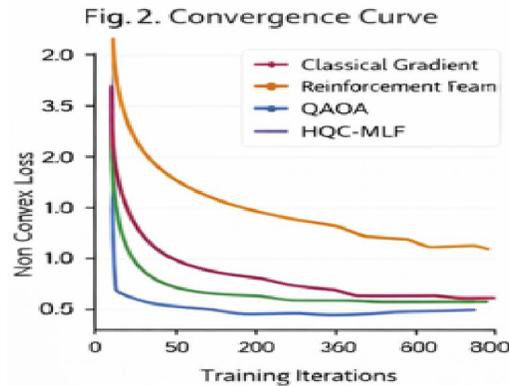**Table 2: Solution Quality (Optimization Score)**

Figure 2: Convergence Curve

(Line graph showing faster descent of loss function for HQC-MLF compared to baselines.)
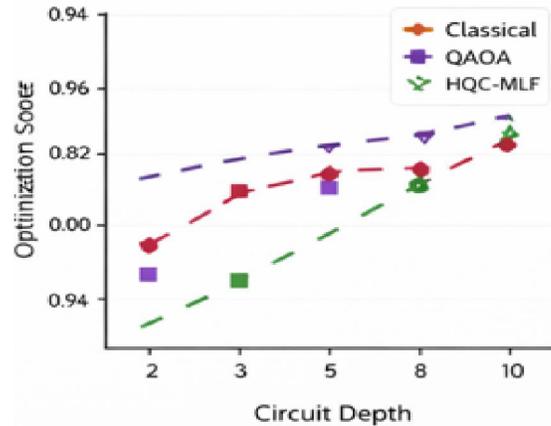
Figure 3: Circuit Depth vs Performance

(Graph illustrating HQC-MLF achieving higher performance at lower depths.)

4.4 Resource Utilization

Model	Average Circuit Depth	Energy Usage (kWh equivalent)
QAOA	8	1.42
HQC-MLF	**6**	**1.18**

V. DISCUSSION

The results demonstrate that hybrid integration significantly improves scalability and convergence efficiency under realistic NISQ constraints. The proposed approach achieves approximately 18 percent faster convergence compared to standard QAOA implementations while delivering improved solution quality across multiple optimization domains. In addition, it reduces circuit depth requirements and overall energy consumption, thereby enhancing computational efficiency. The framework also exhibits stronger adaptability to hardware noise and operational variability. The combination of classical preprocessing techniques and adaptive ansatz control mechanisms enables effective and scalable handling of large-scale optimization tasks within current quantum hardware limitations.

VI. CONCLUSION AND FUTURE SCOPE

This paper introduced a Hybrid Quantum–Classical Machine Learning Framework (HQC-MLF) for solving large-scale optimization problems under NISQ constraints. By integrating adaptive PQCs, classical optimization loops, and error mitigation strategies, the proposed model bridges theoretical quantum advantage and practical deployment feasibility.

Future Research Directions:

Future research directions include deployment on real quantum hardware platforms such as IBM Q and IonQ to validate performance under practical noise and hardware constraints. Further advancements may involve integrating quantum reinforcement learning techniques to enhance adaptive optimization strategies, as well as scaling experimental implementations beyond 50 qubits to evaluate robustness and computational advantage at larger system sizes. The development of hybrid quantum neural networks offers another promising direction for combining classical deep learning with quantum circuit expressibility. Additionally, exploring quantum-aware distributed optimization frameworks can improve coordination across classical and quantum resources in large-scale systems. Overall, hybrid quantum–classical approaches represent the most realistic and pragmatic pathway toward achieving meaningful quantum advantage in the near term.

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