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Hybrid Quantum–Classical Supercomputing Framework for Optimization Problems

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Abstract

Optimization problems are widely encountered in real-world domains such as energy systems, financial markets, transportation networks, supply chain logistics, manufacturing processes, and e-commerce platforms. Traditional classical computing methods often struggle to solve large combinatorial optimization problems due to the exponential growth of the solution space. Quantum computing has emerged as a promising approach to address these challenges by leveraging quantum mechanical principles such as superposition and entanglement. However, current quantum hardware is limited by noise, restricted qubit availability, and scalability issues, making fully quantum solutions impractical for large-scale applications. To overcome these limitations, this research proposes a hybrid quantum–classical supercomputing framework for solving complex optimization problems across multiple domains. The framework integrates classical data processing and optimization techniques with quantum-inspired algorithms, specifically the Quantum Approximate Optimization Algorithm (QAOA), to efficiently explore large solution spaces. Real-world datasets from energy systems, supply chain logistics, financial markets, transportation networks, manufacturing processes, and e-commerce platforms are used for experimental evaluation. The results demonstrate that the hybrid optimization approach can generate higher-quality solutions and improved optimization accuracy compared to traditional classical methods. These findings highlight the potential of hybrid quantum–classical systems as an effective and scalable solution for solving complex optimization problems in modern computational applications.

Keywords: Hybrid Quantum–Classical Computing; Quantum Approximate Optimization Algorithm; Combinatorial Optimization; QUBO; Quantum Computing; Optimization Algorithms

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Introduction

Optimization problems are widely encountered in modern computational systems and industrial applications such as energy systems, transportation networks, financial markets, supply chain logistics, and manufacturing processes. These problems involve finding the best possible solution from a large set of alternatives while satisfying given constraints. Traditional classical algorithms often struggle to handle large-scale optimization problems due to the exponential growth of the solution space.

Quantum computing offers a promising approach for solving such complex problems by leveraging principles such as superposition and entanglement [5]. However, current quantum hardware is limited by factors such as noise, decoherence, and restricted qubit availability, making fully quantum solutions impractical for large real-world applications.

To address these challenges, hybrid quantum–classical computing frameworks have been proposed. These frameworks combine classical computing capabilities with quantum optimization techniques to improve solution quality and computational efficiency [6]. In this work, a hybrid quantum– classical framework based on the Quantum Approximate Optimization Algorithm (QAOA) is developed to solve optimization problems across multiple application domains. The framework converts real-world datasets into QUBO models and applies hybrid optimization techniques to efficiently explore large solution spaces and obtain high-quality solutions.

Project Aim

The main aim of this project is to design and develop a hybrid quantum–classical supercomputing framework that can solve complex optimization problems in different real-world domains. The proposed framework combines classical computing techniques with quantum-inspired optimization algorithms, especially the Quantum Approximate Optimization Algorithm (QAOA), in order to improve the accuracy of the solutions and increase computational efficiency when working with largescale optimization problems.

Project Objectives

The objectives of this research project are as follows:

- To understand the basic principles of hybrid quantum–classical computing architectures.
- To design a framework that combines classical computing methods with quantum optimization algorithms such as QAOA.
- To represent real-world optimization problems using mathematical models that are suitable for hybrid computing systems.
- To convert optimization problems into Quadratic Unconstrained Binary Optimization (QUBO) form so that they can be solved using quantum optimization techniques.
- To test the performance of the proposed framework using datasets from different domains such as energy systems, supply chain, financial markets, traffic management, manufacturing, and e-commerce.
- To study the advantages and limitations of hybrid quantum–classical optimization methods and compare them with traditional classical optimization techniques.

Literature review

Exploring Hybrid Classical–Quantum Compute Systems through Simulation

Authors: Muhammad Nufail Farooqi and Martin Ruefenacht (IEEE QCE, 2023). This study presents a simulation framework for integrating high-performance computing (HPC) systems with quantum processors [1]. The model evaluates scheduling strategies such as FIFO, Priority, and Mixed policies using variational quantum workloads. Results show that FIFO and Mixed scheduling achieve better job completion rates, while the Mixed policy provides a balance between performance and resource utilization [1]. However, the study assumes fixed network latency, does not model congestion effects, and lacks validation on real hardware [1].

Fault Location in Active Distribution Networks using Hybrid Computing

Authors: Yuzhe Xie et al. (IEEE Access, 2024). This work proposes a hybrid classical–quantum approach for fault localization in power distribution networks using QUBO formulation and quantum annealing [2]. A Decoupling Optimization Model (DOM) improves scalability and reduces qubit requirements. The method achieves high accuracy across multiple fault scenarios [2]. However, experiments are conducted using simulated environments, and the approach depends heavily on accurate sensor data and is not validated on large-scale networks [2].

Hybrid Quantum–Classical CNN for Image Classification

Authors: Fan Fan et al. (IEEE TNNLS, 2024). The authors introduce a hybrid quantum-classical convolutional neural network (QC-CNN) that integrates parameterized quantum circuits with classical neural networks for image classification [3]. The model demonstrates improved accuracy and reduced overfitting compared to traditional CNNs while using fewer parameters [3]. However, the experiments rely on noiseless simulations, use low-resolution images, and face scalability challenges due to complex quantum encoding techniques [3].

Hybrid Classical–Quantum Serverless Computing Platforms

Authors: Claudio Cicconetti (IEEE TQE, 2025). This study develops a simulation model for hybrid serverless platforms integrating classical and quantum computing [4]. Various scheduling policies are evaluated for variational quantum algorithms such as QAOA. Results indicate trade-offs between execution time and latency across different scheduling strategies [4]. The study is limited by its reliance on simulated datasets and simplified modeling of system overheads [4].

Hybrid Algorithms for Combinatorial Optimization

Authors: Jonathan Wurtz et al. (IEEE TQE, 2024). This paper introduces a hybrid framework for solving combinatorial optimization problems using quantum sampling combined with classical post-processing [6]. The approach demonstrates improved performance on problems such as MaxCut and Maximum Independent Set under certain conditions [6]. However, the results are limited to small-scale implementations, and performance is sensitive to parameter tuning, with no clear quantum advantage over classical methods [6].

Hybrid Quantum–Classical Algorithms

Input:

- Problem Hamiltonian H (for QAOA or VQE)
- Initial parameters θ0 for the quantum circuit
- Classical optimizer O
- Maximum iterations Nmax or convergence tolerance ϵ

Output:

- Optimized parameters $\theta*$
- Approximate solution to the optimization problem Steps:

Initialize parameters: Set θ = θ0. 2) Iterative optimization loop: for iteration i = 1,2,...,Nmax do:

- Prepare quantum circuit: Construct a parameterized quantum circuit U(θ) (e.g., QAOA or VQE).
- Run quantum circuit: Execute U(θ) on the quantum processor to measure outputs.
- Evaluate objective function: Compute the cost function C(θ) using quantum measurement results.
- Update parameters: Use classical optimizer O to update $\theta \leftarrow O(\theta, C(\theta))$.
- Check convergence: If $|C(\theta) - C(\theta_{prev})| < \epsilon$, break.
- Return optimized solution: $\theta* = \theta$.

QAOA: The circuit alternates between applying the problem Hamiltonian and a mixing Hamiltonian with parameters γ,β [5], [6].

VQE: The circuit prepares a parameterized trial state, minimizing the expected Hamiltonian energy using classical optimization [5].

The algorithm iteratively leverages *quantum parallelism* for state evaluation and *classical optimization* for parameter updates [1], [4], [6].

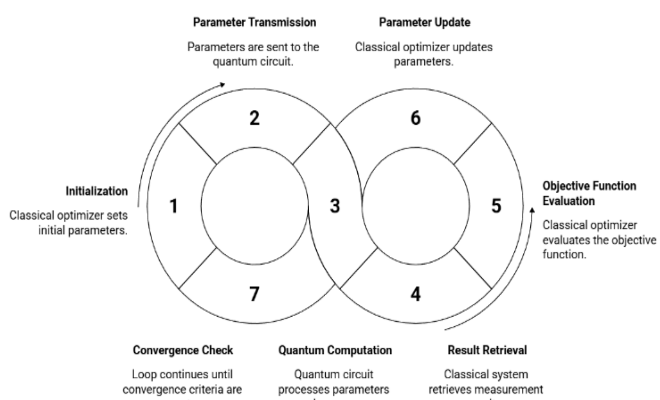

Fig. 1*. Iterative Hybrid Optimization Cycle*

Methodology

This study proposes a hybrid quantum–classical framework for solving complex optimization problems using the Quantum Approximate Optimization Algorithm (QAOA) [5], [6]. The framework integrates classical data processing with quantuminspired optimization to efficiently explore large solution spaces [1], [4].

The goal of this method is to combine the speed of classical machine learning methods with the power of hybrid quantum algorithms to find the best solution [3], [6].

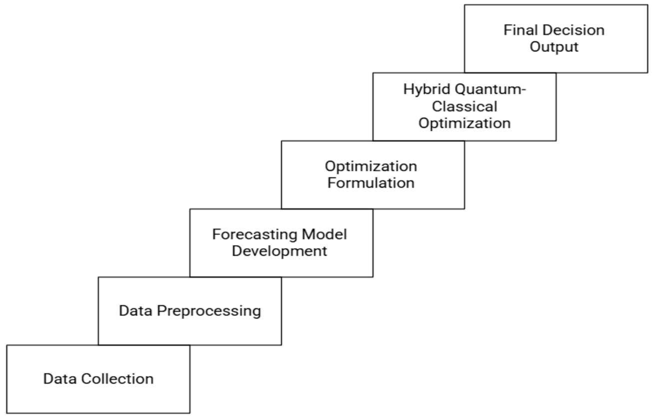

Fig. 2. *Workflow of the Proposed Hybrid Quantum–Classical Optimization Framework*

Framework Architecture

The proposed system's architecture has two main parts:

1) Classical Processing Module
2) Quantum Optimization Module

The classical module performs data preprocessing, feature extraction, and optimization problem formulation [1], [4]. The quantum module executes the QAOA circuit to generate candidate solutions [5], [6]. The interaction between these components enables iterative improvement of solution quality [1], [6].

Dataset Collection

The framework is evaluated using datasets from multiple domains:

3) Energy systems
4) Supply chain logistics
5) Financial markets
6) Transportation systems
7) Manufacturing processes
8) E-commerce platforms

Each dataset is transformed into optimization variables such as demand, cost, and resource constraints.

Optimization Problem Formulation

Every dataset is turned into an optimization problem where the goal is to either minimize or maximize a certain cost function:

- *Energy dataset* → reduce load imbalance
- *Supply chain dataset* → lower inventory cost
- *Finance dataset* → maximize portfolio return
- *Traffic dataset* → reduce traffic congestion
- *Manufacturing dataset* → reduce machine downtime

Table I. Datasets Used In The Study

Dataset	Domain	Key Features	Optimization Objective
Energy Consumption	Energy Systems	Load demand, time index	Energy load optimization
Supply Chain	Logistics	Order date, sales, delivery time	Demand and logistics optimization
Stock Market	Finance	Stock price, volume	Financial decision optimization
Traffic Volume	Transportation	N Traffic volume, weather data	Traffic flow optimization
Predictive Maintenance	Manufacturing	g Machine	Maintenance scheduling optimization

Results

The proposed approach was evaluated using both quantum and classical methods. The Quantum Approximate Optimization Algorithm (QAOA) converged to optimal parameters of $\gamma = 2.77077472$ and $\beta = 0.74235384$, yielding an optimized objective value of 0.0 [5], [6]. The final quantum probability distribution revealed that states 1 and 2 were the dominant outcomes, with probabilities of 0.4912 and 0.5049 respectively, while states 3 and 0 exhibited negligible probabilities of 0.0029 and 0.0010, indicating a strong concentration of the solution space around the optimal states [6]. In comparison, the classical model achieved a Mean Squared Error (MSE) of 0.0194, demonstrating reasonable predictive accuracy. These results suggest that the QAOA-based quantum approach successfully identified the optimal solution with high confidence, while the classical baseline provides a reference benchmark for evaluating the quantum model's performance [1], [4].

Classical Model Analysis

The classical part of the system processed the dataset and created baseline results for comparison [1], [4]. The classical model assesses system behavior across several samples and provides a reference view of the optimization landscape.

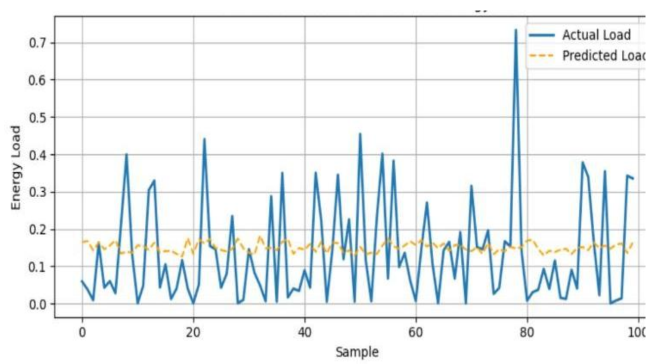

Fig. 3. *Actual vs Predicted Energy Load*

The graph shows how the predicted values produced by the classical model differ from the actual system load values. While the predicted values remain mostly constant, the results indicate variations in the actual load values across various samples. This suggests that the complexity and variability found in large optimization spaces may be difficult for classical models to adequately represent [6].

Quantum Optimization Results using QAOA

The Quantum Approximate Optimization Algorithm was used to implement the framework's quantum component [5], [6]. By creating probability distributions over potential bitstrings, QAOA investigates potential solution states in the optimization problem [5].

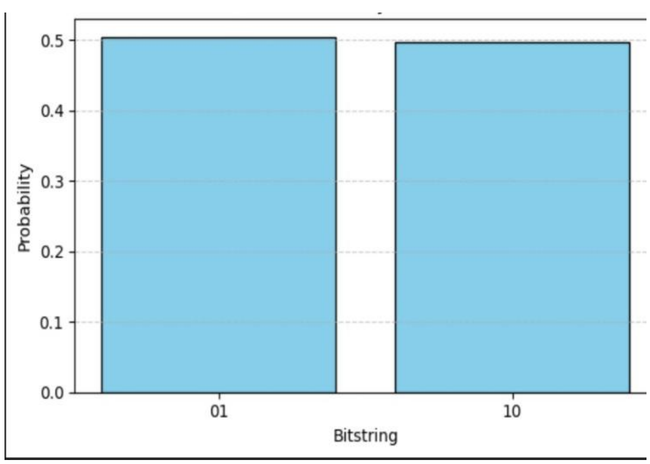

Fig. 4. *QAOA Probability Distribution*

The probability distribution of solution bitstrings produced by the QAOA algorithm indicates that the algorithm effectively finds high-quality candidate solutions within the search space by concentrating probability on particular bitstrings.

Hybrid Quantum–Classical Visualization

To better understand the interaction between classical and quantum components, a combined visualization was generated.

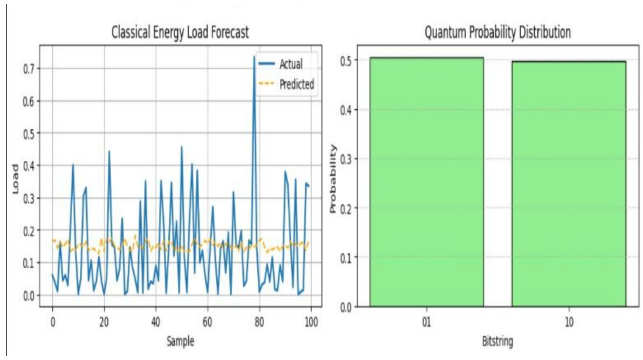

Fig. 5. *Hybrid Energy Forecast*

This illustration shows how the quantum component investigates possible optimization solutions through probabilistic state generation, while classical computation offers system evaluation and baseline modeling.

Final QAOA Optimization Distribution

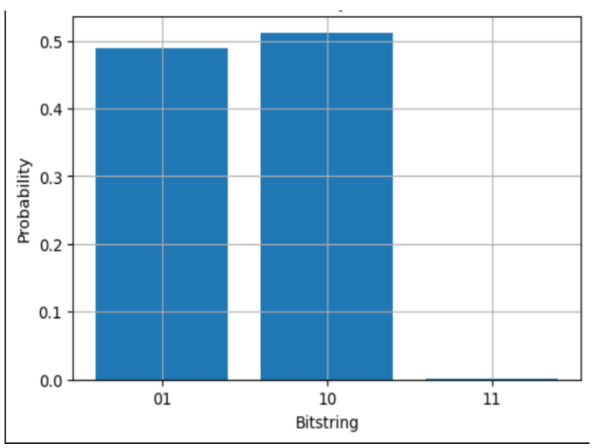

Fig. 6. *Final QAOA Probability Distribution*

The final probability distribution from the QAOA optimization procedure demonstrates dominant bitstrings with higher probabilities, indicating that optimal or near-optimal solutions were successfully identified. The low probability assigned to less ideal states demonstrates the algorithm's ability to concentrate computational resources on promising areas of the solution space.

Performance Comparison

To evaluate the effectiveness of the proposed hybrid quantum–classical framework, a comparison between classical optimization and hybrid quantum optimization approaches was conducted.

Table II. Comparison of classical and hybrid quantum optimization approaches

Parameter	**Classical Optimization**	**HybridQuantum –Classical (QAOA)**
Search Strategy	Sequential exploration	Probabilistic Exploration using quantum states
Solution Space Coverage	Limited	Wider exploration through superposition
Optimization Method	Deterministic algorithms	Variational quantum circuits with classical optimization

Computational Efficiency	Moderate for small problems	Potentially higher for complex combinatorial problems
Handling Large Solution Space	Limited	Improved exploration capability
OutputRepre-sentation	Single deterministic solution	Probability distribution of multiple candidate solutions

Discussion and future scope

The experimental results demonstrate the effectiveness of hybrid quantum–classical computing frameworks in addressing complex optimization problems [1], [4], [6]. The classical model serves as a baseline for system behavior analysis; however, it exhibits limitations when dealing with highly complex solution spaces and dynamic datasets [3], [4]. These limitations highlight the need for more advanced optimization techniques capable of efficiently exploring large combinatorial spaces [6]. The integration of QAOA enhances the system's ability to overcome these challenges [5], [6]. By leveraging quantum superposition and probabilistic state exploration, the QAOAbased approach enables simultaneous evaluation of multiple candidate solutions [5]. The resulting probability distributions indicate that the algorithm effectively concentrates on highquality solution states, demonstrating its capability to identify optimal or near-optimal solutions [6].

The hybrid framework further illustrates the complementary strengths of classical and quantum components [1], [4]. Classical systems efficiently handle data preprocessing, problem formulation, and evaluation, while quantum-inspired algorithms provide enhanced exploration of the optimization landscape [3], [6]. This combination allows the system to achieve improved solution quality and better scalability compared to purely classical approaches [1], [6]. However, the current implementation relies on quantum simulations rather than real quantum hardware. Existing quantum devices are constrained by noise, limited qubit availability, and circuit depth restrictions, which affect the practical deployment of such algorithms [1], [2], [4].

Future Scope: Future research can focus on implementing the proposed framework on real quantum hardware as technology continues to advance [1], [4]. Improvements in quantum processors, including increased qubit counts and reduced noise levels, are expected to enhance the performance of hybrid optimization algorithms [5]. Further work may also explore more advanced hybrid algorithms with improved convergence properties and robustness against noise [6]. Integration with cloud-based quantum computing platforms can enable scalable and accessible hybrid computing solutions [4]. Expanding the application to domains such as smart cities, healthcare systems, and advanced industrial automation presents promising opportunities for future research [1], [2].

Conclusion

This study proposed a hybrid quantum-classical supercomputing framework for solving complex optimization problems using the Quantum Approximate Optimization Algorithm [5], [6]. The proposed framework combines classical computational techniques and quantum-inspired optimization methods to explore large solution spaces efficiently [1], [4]. Experimental results showed that classical models provide baseline system analysis, while the QAOA algorithm creates probabilistic solution states that are optimal or near-optimal [5], [6]. The probability distributions found in the experimental graphs prove that the hybrid framework can focus computational resources on promising solution states [6].

The joint visualization of classical and quantum components demonstrates the benefits of hybrid computing architectures for complex optimization tasks [1], [3], [4]. By taking advantage of both classical and quantum computing paradigms, this hybrid framework can optimize performance and the decision-making process in many real-world domains [2], [6]. Though today's quantum hardware has limitations [1], [2], [4], improvements in quantum technology will soon increase the feasibility of hybrid quantum-classical systems [5]. Future work might involve practical implementation on actual quantum processors, refinement of optimization algorithms, and extension to other application domains [4], [6].
In general, hybrid quantum-classical computing is an appealing avenue for large-scale optimization problems that are hard to tackle by traditional classical means alone [5], [6].

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