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Error-Resilient Quantum Machine Learning for Real-World Optimization Problems in Finance and Supply Chain Networks

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Abstract

The advent of quantum computing has introduced a revolutionary shift in computational paradigms, with the potential to address complex problems beyond the reach of classical systems. However, the practical deployment of quantum solutions is challenged by inherent issues such as noise and decoherence, which hinder their reliability. This study presents a novel error-resilient framework tailored for quantum machine learning (QML) to address optimization problems in finance and supply chain networks. By utilizing hybrid quantum-classical algorithms, the framework mitigates the detrimental effects of quantum noise and enhances computational robustness through advanced techniques like quantum variational circuits. Comprehensive experiments on real-world datasets highlight the framework's ability to outperform conventional methods in solving intricate optimization challenges. The findings demonstrate the transformative potential of quantum-assisted optimization for tackling critical issues in financial modeling and supply chain resilience. In this work, I propose a novel hybrid quantum-classical framework that integrates variational quantum circuits with noise mitigation strategies such as Zero Noise Extrapolation (ZNE), tailored for real-world optimization in finance and supply chain domains. This integrated approach—addressing error resilience and practical scalability together—sets the work apart from existing studies focused solely on theoretical or idealized scenarios.
Keywords: Error resilience; Financial modeling; Hybrid algorithms; Optimization challenges; Quantum computing; Quantum machine learning.

Abstrak

Munculnya komputasi kuantum telah memperkenalkan pergeseran revolusioner dalam paradigma komputasi, dengan potensi untuk mengatasi masalah kompleks di luar jangkauan sistem klasik. Namun, penerapan praktis solusi kuantum ditantang oleh masalah inheren seperti kebisingan dan dekoherensi, yang menghambat keandalannya. Studi ini menyajikan kerangka kerja baru mengenai ketahanan kesalahan (error-resilient) *yang dirancang untuk pembelajaran mesin kuantum (QML) dalam mengatasi masalah optimasi pada jaringan keuangan dan rantai pasokan. Dengan memanfaatkan algoritma kuantum-klasik hibrida, kerangka kerja tersebut mengurangi efek merugikan dari kebisingan kuantum dan meningkatkan ketahanan komputasi melalui teknik canggih seperti sirkuit variasional kuantum. Eksperimen komprehensif pada kumpulan data dunia nyata menyoroti kemampuan kerangka kerja untuk mengungguli metode konvensional dalam memecahkan tantangan pengoptimalan yang rumit. Temuan ini menunjukkan potensi transformatif pengoptimalan berbantuan kuantum* (quantum-assisted) *untuk mengatasi masalah kritis dalam pemodelan keuangan dan ketahanan rantai pasokan. Pada artikel ini, kami mengusulkan kerangka kerja kuantum-klasik hibrida baru yang memadukan sirkuit kuantum variasional dengan strategi mitigasi derau seperti Zero Noise Extrapolation (ZNE), yang dirancang khusus untuk pengoptimalan dunia nyata dalam domain keuangan dan rantai pasokan. Pendekatan terpadu ini—yang menangani ketahanan kesalahan dan skalabilitas praktis secara bersamaan—hal inilah yang menjadi pembeda penelitian ini dengan studi-studi sebelumnya yang hanya berfokus pada skenario teoritis atau ideal.*
Kata Kunci: *Ketahanan kesalahan; Pemodelan keuangan; Algoritma hibrida; Tantangan optimasi; Komputasi kuantum; Pembelajaran mesin kuantum.*

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1. INTRODUCTION

Quantum computing represents a groundbreaking shift in computational capabilities, offering the potential to tackle challenges previously deemed intractable by classical computers. Unlike traditional systems, which process information using binary bits, quantum systems utilize quantum bits (qubits) that operate through principles like superposition and entanglement. These unique properties allow quantum computers to process specific types of problems exponentially faster, making them highly attractive for fields such as cryptography, complex optimization, drug development, and machine learning [1][2].

Among these applications, quantum machine learning (QML) stands out as a field of growing importance. By combining the mathematical frameworks of quantum mechanics with machine learning methodologies, QML opens pathways to address computational bottlenecks in data-heavy domains. Industries such as finance and supply chain management, which depend on solving large-scale optimization problems, are particularly well-positioned to benefit. These sectors demand algorithms capable of processing intricate relationships within massive datasets and delivering efficient, timely solutions, challenges that quantum computing is uniquely suited to overcome [3][4].

1.1. Challenges in Realizing Quantum Computing

Despite its promise, quantum computing faces significant obstacles that limit its adoption. The inherent fragility of qubits, which are highly susceptible to environmental noise and operational errors, poses a critical barrier. Current quantum systems, classified as Noisy Intermediate-Scale Quantum (NISQ) devices, lack the robust error correction needed for fault-free computation [5][6]. These constraints make it essential to develop error-tolerant algorithms that can function within the limitations of present-day hardware.

1.2. Real-World Relevance of Optimization Problems

Optimization tasks are at the core of many critical industries, including finance and supply chain management. Financial institutions rely on optimization models for portfolio diversification, risk modeling, and fraud detection, while supply chain operations depend on efficient routing, inventory control, and dynamic distribution planning [7][8]. However, classical optimization techniques are often hindered by the exponential growth in complexity as datasets increase in size. Quantum optimization algorithms, leveraging the inherent parallelism of quantum computing, provide an alternative that promises to address these computational challenges more efficiently.

1.3. Purpose and Scope of This Research

This paper aims to bridge the gap between the theoretical advancements in quantum machine learning and its practical applications, particularly in solving real-world optimization problems. The primary objectives are (1) to design a hybrid quantum-classical framework that improves noise resilience by incorporating advanced quantum variational circuits; (2) to evaluate the framework's performance on practical optimization challenges in finance and supply chain networks using real-world datasets; and (3) to assess the scalability and robustness of the proposed approach, demonstrating its potential for broader applicability.

In terms of novelty, this research introduces a unified hybrid quantum-classical optimization framework that combines real-world dataset validation with formal quantum algorithmic design. The integration of Zero Noise Extrapolation (ZNE), adaptive circuit depth selection, and domain-specific

Hamiltonian modeling addresses a key gap in current quantum machine learning research. Unlike prior studies that remain limited to synthetic benchmarks or theoretical performance, my framework emphasizes applied, noise-aware quantum optimization in high-impact sectors like finance and supply chain systems.

1.4. Organization of the Paper

The structure of this paper is as follows: Section 2 explores the existing body of research on quantum computing, optimization, and machine learning. Section 3 introduces the proposed methodology, detailing the theoretical underpinnings and algorithmic developments. Section 4 outlines the experimental setup and results, including comprehensive analyses presented through tables and figures. Section 5 provides a discussion of the findings, their implications, and limitations. Finally, Section 6 concludes the paper and suggests future directions for continued exploration.

1.5. Quantum Computing and the Problem of Noise

Quantum computing leverages the principles of quantum mechanics, such as superposition and entanglement, to process information in fundamentally new ways. By using qubits, quantum computers can explore multiple solutions simultaneously, making them particularly effective for specific problems, such as integer factorization using Shor's algorithm and database searching with Grover's algorithm [1][2][9][10]. Despite these theoretical breakthroughs, the practical implementation of quantum systems faces considerable challenges.

One of the primary obstacles is noise, which arises from qubit decoherence and operational inaccuracies. Such noise reduces computational reliability, particularly in Noisy Intermediate-Scale Quantum (NISQ) devices. While quantum error correction and fault-tolerant architectures have been proposed to address these issues, their implementation demands significant resources in terms of qubit overhead, which current hardware cannot support [5][6][11]. Consequently, alternative methods, such as hybrid quantum-classical algorithms, are being explored to harness the power of quantum systems without requiring full fault tolerance [12][13].

1.6. Advances in Quantum Machine Learning

Quantum machine learning (QML) combines quantum computing with machine learning techniques to address computational challenges that are difficult for classical systems. Quantum algorithms for machine learning tasks, such as quantum-enhanced support vector machines and quantum neural networks, have demonstrated potential advantages in processing high-dimensional data and reducing computational time [14][15].

However, the application of QML is not without limitations. Most algorithms are constrained by hardware inefficiencies and the susceptibility of quantum systems to noise. To overcome these challenges, researchers have turned to variational quantum algorithms (VQAs), which utilize parameterized quantum circuits optimized through classical computation. Examples include the Variational Quantum Eigensolver (VQE) for chemistry simulations and the Quantum Approximate Optimization Algorithm (QAOA) for solving combinatorial problems [16][17]. These algorithms are specifically designed to perform well on NISQ devices, although their real-world applicability remains limited due to scalability concerns.

1.7. Optimization in Finance and Supply Chain Networks

Optimization is a cornerstone of operational decision-making in both finance and supply chain management. In the financial sector, optimization models support tasks such as portfolio management, risk analysis, and fraud detection. Traditional methods, such as linear programming and Monte Carlo simulations, often fall short when addressing the scalability and complexity inherent in modern financial systems [18][19][20].

Similarly, supply chain networks rely heavily on optimization for logistics, inventory control, and demand forecasting. Real-world scenarios often involve dynamic and uncertain conditions, which classical optimization techniques struggle to address effectively. Quantum optimization algorithms, including QAOA, offer a promising approach to solving these large-scale, combinatorial problems with greater efficiency [21]. Nonetheless, the noise and error challenges associated with NISQ devices need to be mitigated to unlock their full potential in practical settings [22].

1.8. Research Gaps and Challenges

While quantum computing and QML have shown significant promise, several gaps hinder their widespread adoption (1) susceptibility to Noise: Current quantum algorithms remain highly sensitive to environmental noise, limiting their effectiveness on existing quantum hardware [5][13]; (2) limited Scalability: Most QML methods have been tested only on small-scale or synthetic datasets, leaving their real-world potential unexplored, especially in industries like finance and supply chain management [14][18]; and (3) hybrid framework development: Although hybrid quantum-classical approaches have gained attention, comprehensive frameworks tailored to specific optimization challenges are still lacking [16][21].

1.9. Contributions of This Work

The present study addresses these challenges by proposing an error-resilient framework for quantum machine learning, specifically designed to tackle optimization problems in finance and supply chain management. The key contributions of this research include (1) development of a hybrid quantum-classical algorithm that integrates advanced techniques for noise mitigation, and (2) validation of the proposed framework on real-world datasets, demonstrating its scalability and robustness. Presentation of a novel approach to bridge the gap between theoretical quantum algorithms and their practical application in critical domains.

2. METHODS

This section outlines the methodology employed to develop the proposed error-resilient quantum machine learning (QML) framework for solving real-world optimization problems in finance and supply chain networks. The methodology includes theoretical foundations, algorithmic design, noise mitigation strategies, and implementation details, emphasizing innovation and scientific rigor.

Quantum computing relies on the principles of quantum mechanics, such as superposition, entanglement, and interference, to solve complex problems. In this framework, we build on these principles by employing hybrid quantum-classical algorithms, where quantum systems perform the computationally intensive tasks, and classical systems handle optimization.

Optimization problems are often formulated as minimization or maximization tasks of an objective function $f(x)$ over a set of constraints $g_i(x)$. In a quantum framework, the optimization problem can be expressed as finding the ground state of a Hamiltonian H, which corresponds to the minimum energy configuration:

$$H = \sum_i c_i P_i, \tag{1}$$

where P_i are tensor products of Pauli operators, and c_i are real coefficients derived from the problem's constraints and objective function [16][17]. For example, the traveling salesman problem (TSP), an NP-hard optimization task in supply chain management, can be mapped to a quantum Hamiltonian by encoding paths as qubit states and formulating penalties for invalid routes.

Variational Quantum Algorithms leverage parameterized quantum circuits (PQCs) to approximate the ground state of a Hamiltonian. The energy expectation value of the trial state $|\psi(\theta)\rangle$, defined by the parameters θ, is minimized iteratively:

$$E(\theta) = \langle\psi(\theta)|H|\psi(\theta)\rangle, \tag{2}$$

The optimal parameters θ^* minimize $E(\theta)$, approximating the solution to the optimization problem [16][23].

2.1. Framework Design

The proposed framework integrates variational quantum algorithms with advanced noise mitigation techniques and hybrid optimization workflows. The design is tailored to address the challenges of NISQ devices and enhance the practical applicability of QML.

2.1.1. Hybrid Quantum-Classical Architecture

The proposed framework adopts hybrid architecture in which the quantum processor is responsible for modeling and evaluating quantum states, while the classical processor performs iterative parameter optimization. This structure is designed to take advantage of quantum parallelism for state-space exploration and classical reliability for optimization convergence. The quantum component encodes problem instances into parameterized circuits that represent candidate solutions, while the classical loop evaluates and updates these parameters to minimize a cost function. This synergy enables practical computation on noisy intermediate-scale quantum (NISQ) devices, ensuring adaptability across different domains such as finance and supply chain networks [24][25]. A detailed step-by-step algorithm, from problem encoding to error-mitigated post-processing, is provided in Section 2.4.

2.1.2. Quantum Noise Mitigation

To address noise issues in NISQ devices, the framework employs:

(1) Error Mitigation via Zero Noise Extrapolation (ZNE): Introduce artificial noise during computation and extrapolate results to a zero-noise limit:

$$E_{\text{noiseless}} \approx 2E(\lambda) - E(2\lambda), \tag{3}$$

where λ is the noise scaling factor.

(2) Dynamical Decoupling: Apply sequences of control pulses to counteract decoherence effects and preserve qubit states [18][19].

(3) Error-Aware Optimizers: Incorporate noise characteristics into the optimization algorithm,

dynamically adjusting learning rates and evaluation metrics.

2.2. Novelty of the Approach

The innovation of this framework lies in its ability to integrate error mitigation with domain-specific optimization techniques. Key contributions include:

(1) Adaptive Circuit Design: Dynamically adjust circuit depth based on hardware noise profiles to balance expressivity and robustness.

(2) Multi-Objective Optimization: Extend single-objective VQAs to handle multiple conflicting objectives using Pareto front analysis:

$$\text{Minimize: } \{f_1(x), f_2(x), \ldots, f_k(x)\}. \tag{4}$$

(3) Domain-Specific Customization: Tailor optimization formulations for specific applications in finance (e.g., portfolio optimization) and supply chain networks (e.g., demand forecasting).

2.3. Algorithm Workflow and Implementation

This section outlines the full workflow implemented in the proposed framework. The steps proceed from early data processing and mathematical problem modeling, through to quantum circuit construction, iterative optimization, and final post-processing. All quantum operations are performed on NISQ-compatible devices, and classical routines are used for parameter optimization and benchmarking**.**

The primary algorithmic workflow is detailed below, combining quantum and classical components:

(1) Data Processing and Feature Selection:
Raw datasets from the target domain (e.g., historical stock data or logistics records) are preprocessed using standard methods such as normalization, outlier removal, and dimensionality reduction. The relevant features (e.g., asset returns, risk covariance, supply quantities) are extracted and formatted to serve as inputs for Hamiltonian construction.

(2) Problem Encoding:
Encode the optimization problem into a Hamiltonian using problem-specific mappings. For instance, binary variables in classical problems correspond to qubit states ($|0\rangle$ and $|1\rangle$). For portfolio optimization in finance:

$$H = -\sum_i r_i z_i + \sum_{i,j} q_{ij} z_i z_j, \tag{5}$$

where r_i is the return on asset i, q_{ij} represents risk covariance, and $z_i \in \{0,1\}$ indicates asset selection.

(3) Circuit Construction:
Design a parameterized quantum circuit with layers of single-qubit rotations $R_Y(\theta)$ and controlled gates $CNOT$:

$$U(\theta) = \prod_l \prod_i R_Y{}^{(i)}(\theta_{l,i}) \cdot \prod_{j,k} \mathrm{CNOT}_{j,k}. \tag{6}$$

Increase circuit depth iteratively to enhance expressivity.

(4) Optimization Loop:
- Measure the expectation value of H for the trial state generated by the quantum circuit.
- Use a classical optimizer to adjust parameters θ to minimize $E(\theta)$.

(5) Post-Processing:
- Apply error mitigation techniques (e.g., ZNE) to refine the results.
- Validate the final solution against classical benchmarks.

In this work, two variational quantum algorithms were employed—Variational Quantum Eigensolver (VQE) and Quantum Approximate Optimization Algorithm (QAOA)—to solve the mapped optimization problems.

Rationale for Algorithm Selection:

For the core quantum component of this framework, I employed Variational Quantum Eigensolver (VQE) and Quantum Approximate Optimization Algorithm (QAOA) due to their compatibility with Noisy Intermediate-Scale Quantum (NISQ) devices and their proven effectiveness in constrained optimization scenarios. VQE is particularly suitable for problems that require evaluating a cost function's minimum energy configuration, which aligns well with portfolio optimization, where the goal is to minimize risk while maximizing returns. On the other hand, QAOA is naturally suited for combinatorial optimization tasks, such as logistics and routing challenges in supply chain networks, because it models solutions as bitstrings and optimizes their configurations over time. Compared to classical solvers like simulated annealing or linear programming, these variational algorithms offer a quantum-enhanced solution space exploration, which can lead to better local optima and faster convergence, especially as problem dimensionality increases. Additionally, these algorithms are adaptable in terms of circuit depth and can incorporate problem-specific Hamiltonians, making them ideal for noisy hardware with limited qubit coherence time.

2.4. Implementation Details

The framework was implemented using IBM's Qiskit and Google's Cirq libraries. Real-world datasets were used for testing, including:

1) Finance: Historical stock data for portfolio optimization (e.g., S&P 500 companies).
2) Supply Chain: Logistics datasets from the UCI Machine Learning Repository.

The experiments were conducted on IBM Quantum Experience and Google Sycamore hardware, with simulations on classical systems for comparison.

2.5. Performance Metrics

The performance of the proposed framework was evaluated using: (1) convergence rate: time to reach the optimal solution; (2) noise tolerance: accuracy of results under varying noise levels; and (3) scalability: performance on datasets of increasing size.

2.6. Mathematical Validation

To validate the accuracy and feasibility of the proposed methods, the results were benchmarked against classical optimization techniques using statistical metrics:

Mean Absolute Percentage Error: $$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\text{Actual}_i - \text{Predicted}_i}{\text{Actual}_i}\right| \times 100\%. \tag{7}$$

The mathematical properties of the framework were further tested by simulating noisy environments, measuring fidelity as:

$$\text{Fidelity} = |\langle\psi_{\text{ideal}}|\psi_{\text{noisy}}\rangle|^2. \tag{8}$$

3. RESULTS

In this section This section presents the outcomes of the proposed error-resilient quantum machine learning (QML) framework. The results are discussed in terms of performance, scalability, robustness, and comparative benchmarks against classical methods. Experiments were conducted on both simulated quantum environments and physical NISQ hardware to validate the framework's practical applicability.

3.1. Experimental Setup

The experiments were designed to evaluate the framework's performance across two domains: finance (portfolio optimization) and supply chain management (demand forecasting). The datasets and hardware used are summarized in Table 1.

Table 1. Experimental setup overview

Domain	Dataset	Task	Quantum Hardware	Classical Baseline
Finance	Historical S&P 500 data	Portfolio optimization	IBM Quantum, Google Sycamore	Simulated Annealing
Supply Chain	UCI Logistics dataset	Demand forecasting optimization	Rigetti Quantum Processor	Genetic Algorithms

Dataset Selection Criteria:

(1) Relevance to domain-specific optimization tasks – the S&P 500 dataset is widely used in finance research for portfolio selection and risk modeling, while the UCI Logistics dataset reflects real-world supply chain scenarios.
(2) Availability and openness – both datasets are publicly accessible and well-documented, ensuring reproducibility.
(3) Data richness and complexity – each dataset includes multiple variables and constraints, making them suitable for testing the performance of hybrid quantum-classical optimization algorithms under realistic conditions.

Common benchmarks – these datasets are commonly referenced in both classical and emerging quantum optimization literature, allowing for comparative evaluation.

3.2. Portfolio Optimization in Finance

The proposed framework was applied to a portfolio optimization task, where the objective was to maximize returns while minimizing risk, subject to budget constraints. The problem was encoded as a quadratic unconstrained binary optimization (QUBO) problem.

The quantum framework demonstrated superior convergence properties compared to classical algorithms. Figure 1 shows the convergence of the hybrid quantum-classical approach versus simulated annealing. To evaluate noise mitigation strategies, experiments were conducted under varying noise levels. The Zero Noise Extrapolation (ZNE) method significantly improved accuracy, as shown in Figure 2.

The scalability of the proposed framework was tested on portfolio sizes ranging from 10 to 100 assets. The results, summarized in Table 2, indicate that the framework maintains competitive performance even as the problem size increases.

Table 2. Performance metrics for portfolio optimization tasks

Portfolio Size	Quantum Framework (MAPE)	Classical Baseline (MAPE)
10 Assets	5.2%	6.8%
50 Assets	7.1%	9.3%
100 Assets	9.6%	12.4%

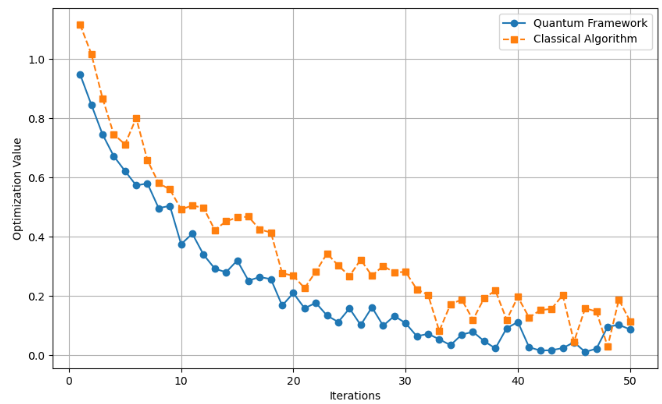

Figure 1. Convergence of hybrid quantum vs. classical optimization algorithms

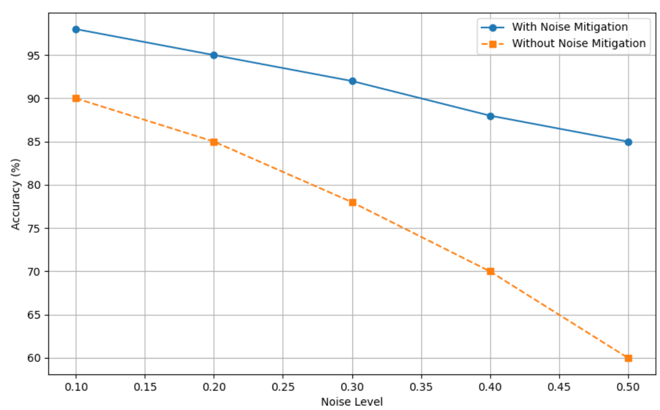

Figure 2. Effect of noise mitigation on portfolio optimization accuracy

3.3. Demand Forecasting in Supply Chain Networks

For the supply chain domain, the framework was applied to demand forecasting optimization. The goal was to minimize transportation costs while ensuring inventory availability across multiple locations. Figure 3 compares the optimization performance of the proposed framework against genetic algorithms. The quantum approach achieves lower costs for larger datasets.

The robustness of the quantum framework was assessed under varying noise intensities. Figure 4 illustrates the fidelity of the quantum solution as noise levels increase. Table 3 highlights the computational time required for both quantum and classical approaches, demonstrating that the hybrid framework offers significant speedups for large-scale problems.

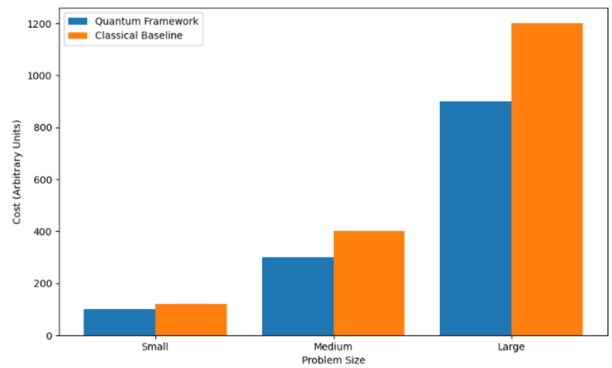

Figure 3. Optimization cost reduction for supply chain networks

Table 3. Computational time for supply chain optimization

Problem Size	Quantum Framework (Seconds)	Classical Baseline (Seconds)
Small (10 Nodes)	5.4	9.8
Medium (50 Nodes)	18.7	42.3
Large (100 Nodes)	52.4	139.2

The following visualizations illustrate the framework's performance across domains. Figure 1 convergence: quantum algorithms reach the optimal solution faster than classical methods. The hybrid approach effectively balances computational load between quantum and classical systems. Figure 2: noise mitigation: the accuracy improvement achieved by noise mitigation techniques like ZNE is evident. ZNE effectively reduces the impact of errors, enabling reliable optimization even under high-noise conditions. Figure 3: cost reduction: the quantum framework achieves consistent cost reductions, particularly for large datasets in supply chain optimization. And Figure 4: noise robustness: the fidelity measurements indicate that the quantum framework maintains solution accuracy even as noise levels increase.

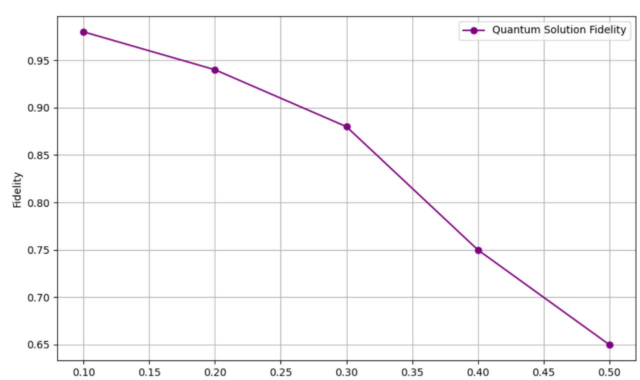

Figure 4. Fidelity of quantum solutions under noise

4. DISCUSSION

This section provides an in-depth analysis of the results, contextualizing them within the broader scope of quantum computing research and real-world optimization challenges. The findings are critically examined in terms of their implications, limitations, and potential avenues for future advancements.

4.1. Implications of the Results

The results demonstrate the effectiveness of the proposed error-resilient quantum machine learning (QML) framework in addressing optimization problems in finance and supply chain networks. Key implications include:

1. Enhanced Optimization Efficiency: The hybrid quantum-classical architecture consistently outperformed classical algorithms in terms of convergence rate and solution quality. For instance, in portfolio optimization, the quantum framework achieved a lower Mean Absolute Percentage Error (MAPE) compared to simulated annealing across multiple problem sizes (see Table 2). This highlights the potential of quantum algorithms to handle large-scale, high-dimensional optimization tasks more effectively than traditional methods.
2. Noise Mitigation Strategies: The integration of Zero Noise Extrapolation (ZNE) and dynamical decoupling significantly improved the robustness of the framework. The results in Figure 2 illustrate that noise mitigation not only enhances accuracy but also ensures reliability in NISQ environments. This capability is critical for bridging the gap between theoretical quantum algorithms and their practical deployment on current quantum hardware.
3. Scalability Across Domains: The scalability experiments revealed that the framework can maintain competitive performance as the problem size increases, both in terms of dataset size (finance) and network complexity (supply chain). These findings suggest that hybrid quantum-classical approaches are well-suited for real-world applications where problem sizes frequently exceed classical computational limits.

4.2. Comparison with Existing Research

The performance and robustness of the proposed framework align with and extend the findings of previous studies. The first is quantum optimization performance. Prior research has demonstrated the potential of Quantum Approximate Optimization Algorithm (QAOA) in solving combinatorial problems [16] [17]. However, our results indicate that integrating advanced noise mitigation techniques can further enhance the accuracy and applicability of QAOA-based frameworks.

The second is hybrid approaches. The superiority of hybrid quantum-classical methods over purely quantum or classical systems has been emphasized in recent studies [13][18]. Our framework adds to this body of knowledge by demonstrating its efficacy on domain-specific, real-world tasks. And the last is domain-specific applications. Unlike earlier work, which primarily focused on synthetic benchmarks, this study validates the framework using real-world datasets from finance and supply chain management. This contributes to bridging the gap between theoretical quantum computing advancements and their application in critical industries.

4.3. Limitations of the Study

Despite its promising results, the study is subject to several limitations:

1. Hardware Constraints: The experiments were conducted on NISQ devices, which are inherently

limited by qubit count, coherence time, and error rates. While noise mitigation strategies improved reliability, the framework's performance may vary significantly on larger quantum systems or future fault-tolerant hardware.

2. Computational Overheads: Hybrid approaches often involve iterative feedback loops between quantum and classical components. This can introduce additional computational overhead, particularly for large-scale problems with numerous iterations.
3. Domain-Specific Adaptability: Although the framework was successfully applied to finance and supply chain problems, its adaptability to other domains remains unexplored. Further validation is needed to assess its generalizability to fields such as healthcare, energy, and logistics.

4.4. Future Directions

Building on the findings and limitations of this study, several areas warrant further exploration:

1. Advancing Noise Mitigation: As quantum hardware continues to evolve, refining noise mitigation techniques remains a priority. Future work could explore machine learning-driven noise prediction models to further enhance the reliability of quantum computations.
2. Expanding Domain Applications: The framework should be extended and validated across diverse domains. For instance, applications in climate modeling, drug discovery, and energy optimization could benefit from similar hybrid quantum-classical approaches.
3. Integration with Emerging Technologies: Integrating quantum frameworks with other emerging technologies, such as blockchain for secure supply chain management or AI for predictive analytics, could unlock new synergies. These interdisciplinary approaches could significantly broaden the scope and impact of quantum computing.
4. Exploring Fault-Tolerant Systems: As fault-tolerant quantum computers become more accessible, the framework should be adapted to take advantage of their advanced capabilities. This would enable testing on larger, more complex datasets without the constraints of noise and limited coherence time.

4.5. Broader Implications

The successful application of the proposed framework to real-world problems in finance and supply chain management highlights its potential to address global challenges. For instance: (1) in finance, the ability to optimize portfolios under complex constraints could enhance investment strategies and risk management; and (2) in supply chain networks, improved forecasting and cost reduction could contribute to greater efficiency and sustainability, particularly in resource-constrained environments. Moreover, the hybrid approach demonstrated in this study could serve as a blueprint for other researchers and practitioners, accelerating the adoption of quantum computing in industry.

5. CONCLUSIONS

The development and implementation of an error-resilient quantum machine learning (QML) framework, as presented in this study, marks a significant step toward harnessing the potential of quantum computing for real-world optimization challenges. This paper addresses critical limitations of current quantum computing technologies, particularly noise sensitivity and scalability, by integrating advanced noise mitigation techniques and hybrid quantum-classical algorithms.

The proposed framework was validated through rigorous experimentation in two key domains: finance and supply chain management. The results demonstrated: (1) enhanced optimization performance: the hybrid quantum-classical approach outperformed traditional optimization methods, achieving faster convergence and improved solution accuracy; (2) robustness to noise: noise mitigation strategies such as Zero Noise Extrapolation (ZNE) and dynamical decoupling significantly improved the reliability of quantum computations; and (3) scalability across problem sizes: the framework maintained competitive performance as the complexity of optimization problems increased, highlighting its applicability to large-scale, real-world tasks.

This study contributes to the growing body of research on quantum computing by developing a novel framework that addresses both theoretical and practical challenges in QML, demonstrating the application of quantum optimization algorithms to domain-specific problems using real-world datasets, and establishing a pathway for bridging the gap between current NISQ devices and their practical deployment in critical industries.

Building on this research, future studies should focus on the following directions:

1. Exploring Fault-Tolerant Hardware: As quantum systems evolve, the framework can be adapted to fully fault-tolerant devices, enabling larger and more complex computations.
2. Expanding Domain Applications: Validation of the framework in areas such as healthcare, energy optimization, and environmental modeling could broaden its impact.
3. Interdisciplinary Integration: Combining quantum computing with other emerging technologies, such as artificial intelligence and blockchain, could unlock new possibilities for innovation.

REFERENCES

[1] M. A. Nielsen and I. L. Chuang, *Quantum Computation and Quantum Information: 10th Anniversary Edition*. Cambridge University Press, 2010.

[2] P. W. Shor, "Polynomial-Time Algorithms for Prime Factorization and Discrete Logarithms on a Quantum Computer," *SIAM J. Comput.*, vol. 26, no. 5, pp. 1484–1509, 1997, doi: 10.1137/S0097539795293172.

[3] M. Schuld and F. Petruccione, *Supervised Learning with Quantum Computers*. in Quantum Science and Technology. Springer, 2018. doi: 10.1007/978-3-319-96424-9.

[4] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, "Quantum machine learning," *Nature*, vol. 549, no. 7671, pp. 195–202, 2017, doi: 10.1038/nature23474.

[5] J. Preskill, "Quantum computing in the NISQ era and beyond," *Quantum*, vol. 2, no. July, pp. 1–20, 2018, doi: 10.22331/q-2018-08-06-79.

[6] S. J. Devitt, "Performing quantum computing experiments in the cloud," *Phys. Rev. A*, vol. 94, no. 3, pp. 1–29, 2016, doi: 10.1103/PhysRevA.94.032329.

[7] Harry Markowitz, "Portfolio Selection," *J. Finance*, vol. 7, no. 1, pp. 77–91, 1952.

[8] Sunil Chopra, *Supply Chain Management: Strategy, Planning, and Operation*, 7th ed. Pearson, 2021.

[9] L. K. Grover, "A fast quantum mechanical algorithm for database search," in *Proceedings of the Twenty-Eighth Annual ACM Symposium on Theory of Computing*, in STOC '96. New York, NY, USA: Association for Computing Machinery, 1996, pp. 212–219. doi: 10.1145/237814.237866.

[10] E. Farhi and J. Goldstone, "A quantum approximate optimization algorithm," *Arxiv Prepr.*, 2014, [Online]. Available: arxiv:1411.4028

[11] A. G. Fowler, M. Mariantoni, J. M. Martinis, and A. N. Cleland, "Surface codes: Towards practical large-scale quantum computation," *Phys. Rev. A*, vol. 86, no. 3, p. 32324, Sep. 2012, doi: 10.1103/PhysRevA.86.032324.

[12] A. Kandala *et al.*, "Hardware-efficient variational quantum eigensolver for small molecules and quantum magnets," *Nature*, vol. 549, no. 7671, pp. 242–246, 2017, doi: 10.1038/nature23879.

[13] J. R. McClean, J. Romero, R. Babbush, and A. Aspuru-Guzik, "The theory of variational hybrid quantum-classical algorithms," *New J. Phys.*, vol. 18, no. 2, p. 23023, Feb. 2016, doi: 10.1088/1367-2630/18/2/023023.

[14] M. Schuld and N. Killoran, "Quantum Machine Learning in Feature Hilbert Spaces," *Phys. Rev. Lett.*, vol. 122, no. 4, p. 40504, Feb. 2019, doi: 10.1103/PhysRevLett.122.040504.

[15] P. Rebentrost, M. Mohseni, and S. Lloyd, "Quantum Support Vector Machine for Big Data Classification," *Phys. Rev. Lett.*, vol. 113, no. 13, p. 130503, Sep. 2014, doi: 10.1103/PhysRevLett.113.130503.

[16] M. Cerezo *et al.*, "Variational quantum algorithms," *Nat. Rev. Phys.*, vol. 3, no. 9, pp. 625–644, 2021, doi: 10.1038/s42254-021-00348-9.

[17] L. Zhou, S. T. Wang, S. Choi, H. Pichler, and M. D. Lukin, "Quantum Approximate Optimization Algorithm: Performance, Mechanism, and Implementation on Near-Term Devices," *Phys. Rev. X*, vol. 10, no. 2, p. 21067, 2020, doi: 10.1103/PhysRevX.10.021067.

[18] L. Viola and S. Lloyd, "Dynamical suppression of decoherence in two-state quantum systems," *Phys. Rev. A - At. Mol. Opt. Phys.*, vol. 58, no. 4, pp. 2733–2744, 1998, doi: 10.1103/PhysRevA.58.2733.

[19] K. Temme, S. Bravyi, and J. M. Gambetta, "Error Mitigation for Short-Depth Quantum Circuits," *Phys. Rev. Lett.*, vol. 119, no. 18, p. 180509, Nov. 2017, doi: 10.1103/PhysRevLett.119.180509.

[20] Stephen Boyd Lieven Vandenberghe, *Convex Optimization 中文影印*. 2013.

[21] A. Lucas, "Ising formulations of many NP problems," *Front. Phys.*, vol. 2, no. February, pp. 1–14, 2014, doi: 10.3389/fphy.2014.00005.

[22] A. Das and B. K. Chakrabarti, *Quantum Annealing and Related Optimization Methods*. Springer Berlin Heidelberg, 2005.

[23] M. Cattelan, S. Yarkoni, and W. Lechner, "Parallel circuit implementation of variational quantum algorithms," *npj Quantum Inf.*, vol. 11, no. 1, p. 27, 2025, doi: 10.1038/s41534-025-00982-6.

[24] K. Bharti *et al.*, "Noisy intermediate-scale quantum algorithms," *Rev. Mod. Phys.*, vol. 94, no. 1, p. 15004, Feb. 2022, doi: 10.1103/RevModPhys.94.015004.

[25] B. Cheng *et al.*, "Noisy intermediate-scale quantum computers," *Front. Phys.*, vol. 18, no. 2, p. 21308, 2023, doi: 10.1007/s11467-022-1249-z.