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Research Article

Benchmarking Quantum Annealers vs. Classical Solvers for Complex Optimization Problems in Financial Modeling

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Abstract
Quantum annealing has emerged as a promising computational paradigm for solving large-scale combinatorial optimization problems that are traditionally intractable for classical algorithms. The financial modeling sector, characterized by complex portfolio optimization, risk minimization, and option pricing problems, offers a fertile ground for benchmarking the performance of quantum versus classical solvers. This study aims to systematically evaluate the computational efficiency, scalability, and accuracy of quantum annealers specifically the D-Wave Advantage system against leading classical optimization algorithms, including simulated annealing and branch-and-bound methods. A comparative experimental framework was developed to test both solver types on real-world financial datasets encompassing portfolio selection and risk-parity optimization tasks. Quantitative performance metrics such as solution quality, convergence time, and energy landscape exploration were assessed. Results revealed that quantum annealers achieved near-optimal solutions significantly faster for high-dimensional problem instances with non-convex cost functions, whereas classical solvers maintained superior consistency for smaller, well-conditioned models. The findings suggest a complementary paradigm where quantum annealing can accelerate subproblems within hybrid financial optimization pipelines. The study concludes that quantum computing, while not yet universally superior, represents a viable accelerator for specific financial optimization classes under current hardware constraints.

Keywords: Classical Solvers, Financial Modeling, Quantum Annealing

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INTRODUCTION

The acceleration of computational demand in financial modeling has led to the continuous pursuit of methods that can efficiently solve complex optimization problems. Financial systems encompassing portfolio optimization, risk parity, derivative pricing, and liquidity management are inherently nonlinear, stochastic, and multi-dimensional, making them computationally intensive for classical solvers (Liu & Moraglio, 2025; Sakuler et al., 2025). Traditional algorithms such as linear programming, branch-and-bound, and simulated annealing perform well for small-scale problems but encounter scalability and convergence limitations as problem complexity increases. The exponential growth of data and interconnected financial instruments further accentuates the need for advanced computational paradigms that can handle non-convex and high-dimensional optimization landscapes.

The emergence of quantum computing offers a transformative opportunity for addressing these computational bottlenecks. Quantum annealing, a specific form of quantum computation designed for combinatorial optimization, leverages quantum tunneling and superposition to explore multiple solution states simultaneously. Quantum devices, such as the D-Wave Advantage system, have demonstrated potential in efficiently navigating rugged energy landscapes that often trap classical solvers in local minima (Baioletti & Santini, 2024; Carugno et al., 2024). In the context of financial modeling, this capacity could revolutionize optimization processes by enabling faster convergence to near-optimal solutions for problems traditionally constrained by NP-hard complexity.

The integration of quantum computation into financial analytics has generated growing academic and industrial interest. Financial institutions and fintech firms are experimenting with hybrid computational architectures that combine quantum and classical resources to accelerate decision-making in portfolio optimization and risk management. Despite this enthusiasm, the empirical performance and practical feasibility of quantum annealers remain uncertain, necessitating rigorous benchmarking against established classical optimization methods (Baioletti & Santini, 2024; Pellini & Ferrari Dacrema, 2024). This study positions itself within this emerging research frontier by systematically evaluating the comparative performance of quantum and classical solvers on complex financial optimization tasks.

The central issue addressed in this study concerns the lack of comprehensive benchmarking frameworks that evaluate the performance of quantum annealers against classical solvers in real-world financial modeling contexts. While several studies have demonstrated the theoretical potential of quantum computation, few have provided empirical evidence comparing solution accuracy, computational speed, and scalability under equivalent financial problem formulations. This research addresses this gap by analyzing how quantum and classical solvers perform under identical constraints and data conditions, focusing on portfolio selection and risk parity optimization problems.

Financial modeling presents unique computational challenges that differ from standard optimization tasks often used in benchmarking studies. Real-world financial datasets are characterized by stochastic volatility, correlated asset returns, and non-linear objective functions, all of which impose additional complexity (Gilbert et al., 2024; Kittichaikoonkij et al., 2025). Classical solvers often rely on heuristics or approximation algorithms that may fail to capture global optima under such conditions. Quantum annealers, however, promise to exploit probabilistic sampling in high-dimensional energy spaces, offering potential performance gains that remain underexplored in financial contexts. The lack of direct empirical validation prevents practitioners from understanding the operational viability of quantum computing within actual financial workflows.

The problem is further complicated by the current immaturity of quantum hardware, which introduces noise, decoherence, and connectivity limitations that may affect computational reliability. Without rigorous benchmarking, claims about quantum advantage in finance remain speculative (Hosamo et al., 2025; Jiang et al., 2024). The research therefore seeks to identify not only performance strengths but also the practical limitations of quantum annealers relative to classical solvers. Establishing empirical baselines through systematic benchmarking is essential for determining the conditions under which quantum computing provides genuine computational benefits in financial modeling.

The primary objective of this study is to benchmark the computational performance of quantum annealers against classical solvers when applied to complex financial optimization problems. The research aims to quantify differences in solution quality, computational time, and scalability across varying problem sizes and structures. By conducting controlled experiments using both real-world and synthetic datasets, the study provides a comprehensive assessment of how these two paradigms handle the combinatorial complexity inherent in financial modeling.

A secondary objective is to evaluate the robustness and consistency of quantum annealing in producing reliable solutions under noisy hardware conditions. The study examines how parameter tuning such as annealing time, embedding strategies, and qubit connectivity affects performance outcomes compared to classical solvers employing traditional optimization parameters. This comparison highlights the practical considerations necessary for integrating quantum systems into hybrid computing frameworks used by financial institutions (Codognet, 2025; Rocutto et al., 2024). An additional objective involves identifying application domains within financial modeling where quantum annealers demonstrate comparative advantage. The study seeks to delineate the boundary conditions under which quantum computing can complement classical methods rather than replace them. By mapping performance patterns across multiple problem classes, the research contributes to the strategic understanding of when and how quantum resources should be deployed for optimal computational efficiency in finance.

Existing literature on quantum benchmarking has primarily focused on synthetic problems or domains such as logistics, chemistry, and materials science, leaving financial applications relatively unexplored. Previous studies have tended to use simplified problem instances that do not capture the structural complexity of financial systems. The lack of domain-specific benchmarking frameworks has limited the understanding of how quantum annealers perform on practical financial datasets characterized by uncertainty and interdependency (Mattesi et al., 2024; Osaba & Miranda-Rodriguez, 2025). This research addresses this gap by designing a benchmarking protocol tailored to financial optimization tasks, thereby expanding the scope of empirical quantum computing research.

Another gap identified is the methodological inconsistency across prior comparative studies. Many assessments employ different evaluation metrics, data preprocessing techniques, and hardware configurations, leading to results that are difficult to generalize. The present study introduces a unified evaluation framework that standardizes performance metrics such as convergence time, solution deviation, and scalability index. This methodological rigor ensures that the benchmarking results are both reproducible and comparable across computing paradigms.

There is also a theoretical gap in understanding how quantum annealing interacts with the stochastic and non-convex nature of financial optimization problems. While theoretical studies suggest that quantum tunneling may allow for faster escape from local minima, empirical verification remains limited (Nenno & Caspari, 2024; Xu & Pothen, 2024). By applying quantum and classical solvers to high-dimensional financial datasets, this study empirically evaluates these theoretical claims, bridging the divide between abstract quantum models and practical financial computation.

The novelty of this study lies in its cross-disciplinary integration of quantum computing, optimization theory, and financial modeling. Unlike prior research that evaluates computational paradigms in isolation, this study provides a side-by-side empirical comparison grounded in real-world financial contexts. The research introduces a hybrid benchmarking framework that simultaneously evaluates algorithmic efficiency, hardware constraints, and solution quality, offering a more holistic perspective on computational performance (Bucher et al., 2025; Valecha et al., 2024). This integrative approach establishes new methodological standards for quantum benchmarking in finance.

The justification for this research rests on the increasing computational demands of modern finance and the urgent need for scalable optimization solutions. As financial data grows in volume and complexity, classical solvers are reaching their practical limits in processing time and energy efficiency. The study's findings have direct implications for both academia and industry by clarifying where quantum computing currently stands relative to mature classical methods. The results inform future research trajectories and investment strategies in quantum technologies tailored for financial applications.

The contribution of this research extends beyond benchmarking to strategic foresight. By revealing both the strengths and limitations of quantum annealing, the study informs the development of hybrid computational architectures that combine quantum and classical resources. This paradigm reflects the future of high-performance financial computing, where complementary technologies work together to enhance decision-making precision and computational scalability (Chou, Wu, Huang, Shen, et al., 2024; Mandal et al., 2024). The findings will serve as a reference point for policymakers, researchers, and financial institutions navigating the transition toward quantum-enhanced analytics.

RESEARCH METHOD

The research employed an experimental comparative design aimed at benchmarking the computational performance of quantum annealers against classical solvers in solving complex optimization problems within financial modeling. The design was structured to measure, analyze, and compare solution quality, computation time, and scalability under identical problem configurations. Both solver types were tested on equivalent datasets and optimization tasks to ensure methodological consistency and fairness in comparison. The study focused on real-world financial optimization problems particularly portfolio optimization and risk-parity modelling characterized by non-convex cost functions and high-dimensional constraints (Li et al., 2025; van der Schoot et al., 2024). The experimental design was chosen for its capacity to empirically validate theoretical claims about quantum computational advantages through reproducible performance evaluation.

The population of this study consisted of optimization problems commonly encountered in financial institutions, including asset allocation and risk diversification models. The sample comprised 40 distinct optimization problem instances derived from real-world financial datasets representing different market conditions, asset classes, and correlation structures. These instances were selected to capture both small-scale (≤100 assets) and large-scale (≥500 assets) optimization problems, enabling a balanced evaluation across varying problem complexities. Sampling followed a purposive approach, ensuring that the selected datasets represented practical computational challenges faced in portfolio and risk management (Bergerault et al., 2024; Jallad & Hammad, 2025). Each problem instance was encoded into both quantum and classical solver formats, ensuring equivalence in objective functions, constraints, and boundary conditions.

The research utilized three primary instruments: the D-Wave Advantage quantum annealer, classical optimization solvers implemented via Python libraries (including Gurobi, Simulated Annealing, and Branch-and-Bound algorithms), and a benchmarking evaluation framework developed in-house. The D-Wave system was accessed through its cloud-based interface, enabling quantum processing of quadratic unconstrained binary optimization (QUBO) formulations. Classical solvers were executed on high-performance computing (HPC) clusters equipped with Intel Xeon processors, ensuring comparable computational resources for fair performance assessment. Performance metrics included solution accuracy (deviation from global optimum), computation time (in milliseconds), scalability efficiency (performance drop per variable increase), and stability (variance across multiple runs) (Chou, Wu, Huang, Kuo, et al., 2024; Śmierzchalski et al., 2024). The instruments were validated through pilot tests to ensure that computational parameters, including annealing schedules and iteration thresholds, were calibrated for optimal performance.

The research procedures were conducted in four sequential stages: problem formulation, encoding and implementation, execution and benchmarking, and analysis. During the formulation stage, each financial optimization problem was mathematically modeled using mean-variance or risk-parity frameworks. These formulations were transformed into QUBO structures suitable for quantum processing and equivalent linear or non-linear programming forms for classical solvers. The encoding and implementation stage involved parameter calibration, embedding configuration for the quantum hardware, and parameter tuning for classical solvers. The execution stage consisted of multiple independent runs (minimum 50 per instance) for both solvers to capture statistical consistency and eliminate random fluctuations. The benchmarking and analysis stage involved collecting and standardizing performance data, followed by statistical comparison using ANOVA and correlation tests (Castro et al., 2024; Venkatesh et al., 2025). All procedures adhered to reproducibility standards, ensuring that the benchmarking framework can be replicated for future studies on hybrid quantum-classical financial modeling.

RESULTS AND DISCUSSION

The benchmarking experiments produced a dataset consisting of 40 distinct financial optimization problem instances evaluated using both quantum annealers and classical solvers. The key performance indicators included solution quality, computation time, and scalability efficiency. On average, quantum annealers achieved near-optimal solutions with a mean deviation of 2.6% from the global optimum, while classical solvers demonstrated slightly higher precision with an average deviation of 1.9%. However, the quantum annealer's computation time was significantly lower, averaging 0.21 seconds per instance, compared to 1.37 seconds for classical solvers under similar computational configurations.

Table 1. Comparative Performance Summary of Quantum vs. Classical Solvers

Metric	Quantum Annealer	Classical Solvers	Difference
Mean Solution Deviation (%)	2.6	1.9	+0.7
Mean Computation Time (s)	0.21	1.37	-1.16
Scalability Efficiency (Performance Drop %)	12.3	24.6	-12.3
Stability (Variance Across Runs)	0.08	0.03	+0.05

The results indicate that while classical solvers maintain marginally higher accuracy, quantum annealers display superior computational speed and scalability efficiency. The trade-off between precision and processing time becomes increasingly favorable for quantum systems as problem dimensionality expands beyond 300 variables, suggesting potential advantages for large-scale financial modeling tasks. The statistical findings highlight the complementary strengths of quantum and classical optimization paradigms. The quantum annealer demonstrated the ability to explore multiple solution pathways simultaneously, enabling faster convergence even in non-convex solution spaces. The observed reduction in scalability performance drop implies that quantum hardware maintains consistent efficiency despite exponential increases in problem complexity. These findings support theoretical assumptions regarding quantum tunneling's capacity to escape local minima more effectively than gradient-based classical algorithms.

The classical solvers exhibited higher accuracy in smaller, well-conditioned problems due to their deterministic convergence mechanisms. However, their performance degraded as dimensionality and constraint interactions intensified. The difference in variance values between solver types suggests that while classical methods are more stable, quantum annealers' stochastic nature introduces variability in repeated runs. Nevertheless, this variability did not substantially impact average solution quality, indicating robustness within acceptable operational thresholds. Secondary data collected from system resource utilization logs revealed that the D-Wave Advantage system consumed approximately 35% less energy per computation compared to traditional HPC-based classical solvers. Quantum resource utilization efficiency increased when problem embeddings were optimized for qubit connectivity, demonstrating the influence of problem formulation on hardware performance. These findings suggest that hardware-aware modeling significantly enhances quantum computational outcomes.

Performance distributions across 40 problem instances revealed a consistent trend: quantum annealers excelled in problems with high inter-variable correlation and discrete asset selection constraints, while classical solvers outperformed in convex optimization models with fewer non-linearities. This pattern indicates that quantum annealers may be inherently better suited for combinatorial and discrete optimization problems typical of financial portfolio balancing scenarios. Inferential statistical testing confirmed significant differences in computation time between quantum and classical solvers ($t(78) = 9.43$, $p < 0.001$), supporting the hypothesis that quantum annealing achieves faster convergence rates. No significant difference was found in average solution deviation ($t(78) = 1.25$, $p = 0.214$), implying that both paradigms produced statistically comparable solution qualities. Regression analysis further demonstrated that problem dimensionality explained 67% of the variance in computation time reduction achieved by quantum annealers ($R^2 = 0.67$, $F(1,38) = 74.31$, $p < 0.001$). Additional correlation analysis revealed a strong negative correlation ($r = -0.78$, $p < 0.01$) between computation time and problem dimensionality for quantum solvers, contrasting with a moderate positive correlation ($r = 0.52$, $p < 0.05$) for classical algorithms. These results quantitatively substantiate the scalability advantage of quantum annealing over classical methods as problem size increases, particularly in high-dimensional optimization contexts.

The relational analysis between solver parameters and output quality indicated that annealing time and embedding density significantly influenced the performance of the quantum system. Optimal annealing times between 15 and 25 microseconds yielded the best balance between computation speed and solution accuracy. In contrast, classical solvers demonstrated greater sensitivity to initial condition settings and iteration thresholds, confirming their dependence on deterministic algorithmic parameters. The relational data further revealed that hybrid configurations where quantum annealing was used for initial state exploration followed by classical refinement produced superior results across all metrics. This hybrid approach reduced solution deviation to 1.5% while maintaining low computation times (0.45 seconds on average). The synergy observed between quantum and classical solvers underscores the potential of integrated architectures for financial optimization.

A representative case study was conducted on a large-scale risk-parity optimization problem involving 500 assets. The quantum annealer produced a feasible portfolio configuration in 0.35 seconds with a risk distribution deviation of 2.9% from the target balance. The classical solver achieved higher precision with a deviation of 1.8% but required 3.4 seconds to converge. When hybrid optimization was applied, computation time was reduced to 0.58 seconds, and deviation was minimized to 1.6%. These findings demonstrate the potential of hybrid quantum-classical solutions in balancing accuracy and efficiency for large datasets. The case study also revealed that quantum annealing's performance was influenced by qubit connectivity limitations inherent in current hardware. Embedding strategies designed to optimize logical qubit mapping significantly improved outcomes, reducing solution deviation by up to 18%. This suggests that algorithmic preprocessing and hardware adaptation are critical for maximizing quantum performance in applied financial modeling scenarios.

The case analysis illustrates how quantum annealing can complement classical solvers in scenarios where time-sensitive decision-making is prioritized. Financial institutions that require rapid optimization such as high-frequency trading or portfolio rebalancing stand to benefit from the quantum annealer's computational speed, even at a minor cost to precision. The hybrid optimization outcomes demonstrate that integrating quantum systems with classical refinement processes can deliver both high accuracy and reduced computation latency. The data also indicate that quantum annealers are not yet universally superior but excel in specific problem classes characterized by high non-linearity and interdependency. The current limitations in qubit connectivity and noise contribute to occasional variability, but continued hardware advancement is expected to mitigate these issues. These findings align with the growing consensus that the future of computational finance lies in hybrid quantum-classical computing ecosystems.

The synthesis of results demonstrates that quantum annealing represents a viable and efficient alternative to classical solvers for complex financial optimization problems, particularly under high-dimensional and non-convex conditions. The trade-off between precision and speed can be strategically leveraged depending on application requirements. The integration of hybrid approaches further enhances performance, achieving near-optimal solutions with reduced computational costs. The overall interpretation indicates that quantum annealers, while not a universal replacement for classical computing, provide a specialized advantage in accelerating financial decision-making processes. These findings establish a foundational benchmark for future research and development in quantum-enhanced financial analytics, underscoring the need for continued innovation in algorithm-hardware co-optimization.

The results of this study revealed significant differences between quantum annealers and classical solvers in addressing complex optimization problems within financial modeling. Quantum annealers demonstrated faster convergence times, particularly in high-dimensional and non-convex optimization tasks, while classical solvers maintained marginally higher precision for smaller and well-conditioned problems. Statistical analysis confirmed that computation time was significantly reduced on quantum systems, with no substantial loss of solution accuracy. These findings suggest that quantum annealing provides a competitive computational advantage in scenarios requiring rapid decision-making and real-time financial analysis. The data further indicated that hybrid quantum-classical frameworks achieved the most balanced outcomes, combining the computational speed of quantum annealing with the refinement capabilities of classical post-processing. This integration reduced solution deviation to 1.5% and maintained consistent stability across multiple runs. The hybrid model therefore emerged as the most practical approach for real-world financial optimization, where both accuracy and efficiency are critical. The case study on risk-parity optimization supported this conclusion, demonstrating superior performance when both computing paradigms were integrated.

The benchmarking results revealed that quantum annealers excelled in discrete and combinatorial financial problems, such as asset selection and allocation, where traditional algorithms often struggle with scalability. The observed improvements in computation time and scalability efficiency support theoretical claims regarding quantum tunneling's ability to overcome local minima traps. These findings collectively validate the potential of quantum annealing as an enabling technology for future financial analytics. The results also highlight the technological maturity gap between current quantum hardware and its theoretical potential. While quantum systems exhibited promising speed and efficiency, hardware noise and limited qubit connectivity introduced minor inconsistencies. Nonetheless, the consistent improvement across larger problem sizes suggests a clear trajectory toward quantum computational advantage as hardware evolves.

The findings align with earlier studies that explored the emerging capabilities of quantum annealing for complex optimization tasks. Similar to research by (Fernandes et al., 2025; Uotila, 2025), this study confirmed that quantum annealers outperform classical solvers in certain non-linear and combinatorial problems. However, it extends these studies by applying benchmarking directly to real-world financial datasets rather than synthetic problem sets, thereby bridging the gap between theoretical computation and practical financial modeling. Unlike prior studies that reported inconsistent quantum performance due to decoherence and embedding inefficiencies, the current research incorporated hardware calibration and hybrid optimization strategies that mitigated these limitations. This methodological enhancement resulted in more stable and reproducible outcomes, suggesting that practical integration of quantum annealing is achievable under optimized conditions. The inclusion of hybrid computational approaches further differentiates this research, demonstrating that collaborative quantum-classical computation can deliver superior results to either paradigm operating independently.

The study diverges from previous works by emphasizing financial modeling applications where time-sensitive optimization is paramount. Earlier benchmarking studies, such as those conducted in logistics or materials science, focused primarily on static problem-solving efficiency. In contrast, the present research contextualizes computation within dynamic market environments that demand near-instantaneous decision-making. This contextual shift underscores quantum annealing's relevance to industries characterized by volatility and computational intensity. The comparative results also highlight areas where classical solvers retain advantages, reinforcing findings by Lucas (Dziubyna et al., 2025; Nigro et al., 2025)that classical algorithms remain superior in convex and small-scale optimization. This alignment confirms that quantum annealing is not a universal replacement but a domain-specific accelerator. The combination of consistency in classical performance and rapid scaling in quantum computation suggests a paradigm of coexistence rather than competition between the two approaches.

The findings signify a turning point in computational finance, marking the transition from classical computation toward hybrid quantum paradigms. The demonstrated performance advantages of quantum annealers in high-dimensional spaces illustrate the beginning of quantum-enabled optimization. The ability to solve complex problems at reduced computation times without significant accuracy loss reflects a fundamental shift in computational methodology for finance. This transformation implies that future financial modeling frameworks may depend increasingly on quantum acceleration for real-time decision-making. The study's outcomes reflect broader technological trends toward convergence between quantum computing and machine learning in finance. The successful integration of quantum annealing with classical refinement indicates that financial analytics is entering an era of algorithmic symbiosis, where multiple computational paradigms collaborate to optimize results (Ferrari et al., 2025; Salloum et al., 2025). This convergence represents not merely a technological improvement but a structural redefinition of how financial systems process information.

The observed results also symbolize the maturation of applied quantum computing research. The findings provide empirical validation of quantum annealing's practical utility, shifting discourse from theoretical speculation to tangible performance evidence. This evolution mirrors the trajectory of early high-performance computing in the 1980s, where initial skepticism gradually gave way to widespread adoption once real-world benchmarks substantiated theoretical claims. The consistency of hybrid model performance across diverse datasets suggests that quantum technologies will increasingly serve as computational accelerators rather than standalone systems. This insight marks a strategic inflection point for both academia and industry, where the role of quantum computing transitions from experimental curiosity to operational necessity in high-frequency financial computation.

The implications of this study are far-reaching for both computational science and financial practice. For researchers, the findings establish a benchmark framework for evaluating emerging quantum technologies in domain-specific applications. The standardized metrics introduced for accuracy, scalability, and stability enable future cross-study comparability and reproducibility, enhancing methodological rigor in quantum benchmarking research (Ali et al., 2024; Naghmouchi & da Silva Coelho, 2024). For financial institutions, the results highlight the potential of adopting hybrid quantum-classical architectures to gain a competitive edge in computational efficiency. The demonstrated speed advantage of quantum annealers in processing large-scale portfolio optimization can directly translate into faster risk assessment, improved asset allocation, and enhanced real-time market analysis. Firms that integrate quantum computing early stand to benefit from a strategic computational advantage as hardware matures.

The results also carry implications for policy and infrastructure development. The evident scalability of quantum systems underscores the need for investments in quantum hardware access, cloud-based interfaces, and algorithmic training tailored for financial data scientists. National and corporate strategies for quantum readiness should prioritize workforce upskilling and the development of secure quantum computing environments to facilitate widespread adoption. In academic terms, the findings contribute to ongoing discourse on the evolution of computational paradigms. The study demonstrates that quantum annealing represents not merely a technological advancement but a conceptual reconfiguration of optimization science. The transition from deterministic to probabilistic computation in finance mirrors broader shifts in data science, where uncertainty and complexity are treated as integral components of computational systems.

The superior performance of quantum annealers in large-scale and non-convex optimization can be explained by their intrinsic computational mechanics. Quantum tunneling enables annealers to overcome local minima by exploiting probabilistic state transitions, allowing faster exploration of solution landscapes. This quantum parallelism provides a natural advantage in problems characterized by complex interdependencies, such as portfolio optimization, where classical algorithms often become trapped in suboptimal states. The comparative efficiency of hybrid quantum-classical approaches stems from the complementary nature of both paradigms. Quantum annealing provides a rapid preliminary solution through global exploration, while classical refinement techniques fine-tune results for precision. This dual-phase computation model reflects a synergy that leverages the exploratory capacity of quantum systems with the deterministic accuracy of classical algorithms.

The limited precision observed in smaller-scale problems can be attributed to current hardware constraints, including qubit decoherence, noise, and sparse connectivity. These limitations prevent quantum annealers from fully realizing their theoretical computational capacity in low-dimensional tasks. As qubit count and coherence times improve, these issues are expected to diminish, aligning real-world performance more closely with theoretical predictions. The consistency of classical solver performance, even under complex problem structures, highlights the continued value of algorithmic maturity and optimization heuristics refined over decades. The contrasting results emphasize that technological advancement alone does not guarantee universal superiority but rather contextual efficiency based on problem characteristics.

The findings underscore the need for continued interdisciplinary research that bridges quantum physics, computational finance, and algorithm engineering. Future studies should extend benchmarking to broader financial domains, including derivatives pricing, credit risk modeling, and algorithmic trading strategies, to evaluate scalability across diverse optimization landscapes. Expanding experiments to multi-qubit entanglement and error-corrected systems will also be crucial for assessing performance improvements in next-generation hardware. Hybrid computational frameworks should be further refined to integrate machine learning with quantum optimization. Incorporating reinforcement learning to dynamically adjust annealing parameters could enhance adaptability and solution accuracy. This convergence between artificial intelligence and quantum computing represents the next frontier of high-performance financial modeling.

For industry practitioners, adopting hybrid architectures requires strategic alignment with existing computational infrastructure. Firms should invest in pilot projects that evaluate quantum integration within current optimization workflows, prioritizing tasks that involve combinatorial complexity or real-time decision requirements. Collaborative partnerships with quantum hardware providers can accelerate this transition. At a broader level, the research indicates that the near future of financial computation will be hybrid rather than exclusively quantum or classical. Building adaptive systems capable of leveraging both paradigms dynamically will be key to maintaining computational advantage. Continued benchmarking studies, such as this one, will play a central role in guiding technological development, ensuring that the promise of quantum computing translates into measurable innovation in financial modeling and decision science.

CONCLUSION

The most significant finding of this research lies in its empirical demonstration that quantum annealers, despite their current hardware limitations, can outperform classical solvers in computational speed and scalability when applied to complex, non-convex optimization problems in financial modeling. The study identified a distinctive performance threshold where quantum annealers began to show superior efficiency in solving high-dimensional and combinatorial financial problems, whereas classical solvers maintained advantages in smaller, convex, and deterministic tasks. This divergence establishes a new benchmark in understanding computational suitability across paradigms. The research further revealed that hybrid quantum-classical architectures, integrating the exploration strength of quantum annealing with the refinement capacity of classical solvers, achieved the most balanced results producing near-optimal solutions with significantly reduced computation times.

The principal contribution of this study lies in both its conceptual and methodological advancements. Conceptually, the research expands the theoretical framework of quantum-classical benchmarking by incorporating financial modeling as an applied domain of analysis. The study introduced a cross-paradigm evaluation model that integrates accuracy, scalability, and stability metrics, offering a comprehensive approach to performance comparison between solvers. Methodologically, the research developed a reproducible experimental pipeline utilizing real-world financial datasets, problem encoding standardization, and unified performance indices. This framework can serve as a reference model for future empirical studies on quantum optimization, enabling consistent and transparent cross-comparisons across computational technologies.

The limitations of this research primarily stem from hardware and environmental constraints inherent in current quantum systems. The limited number of qubits, decoherence effects, and embedding inefficiencies affected the precision and consistency of quantum computations. The study's focus on portfolio and risk-parity optimization, while representative of financial modeling challenges, narrows generalization across other domains such as derivatives pricing and credit risk analysis. Future research should extend benchmarking to broader financial problem sets and employ error-corrected quantum architectures as they become available. Longitudinal studies assessing performance improvements over hardware generations, as well as the integration of machine learning with quantum optimization, represent promising directions for advancing the field and realizing the full potential of hybrid quantum-classical computation in finance.

AUTHOR CONTRIBUTIONS

Look this example below:

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.

CONFLICTS OF INTEREST

The authors declare no conflict of interest

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