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Hybrid Quantum-Classical Computing: Benchmarking Algorithm Performance on Near-Term Quantum Processors for Optimization Problems

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ABSTRACT

This paper presents a qualitative analysis of hybrid quantum-classical computing approaches aimed at solving complex optimization problems using near-term quantum processors. Hybrid algorithms leverage the strengths of quantum and classical computing to tackle computationally intensive tasks often constrained by current quantum hardware limitations. Through an extensive literature review and synthesis of recent empirical studies, we benchmark various hybrid algorithms, such as the Quantum Approximate Optimization Algorithm (QAOA) and Variational Quantum Eigensolver (VQE), focusing on their performance, scalability, and practical applicability on noisy intermediate-scale quantum (NISQ) devices. The study highlights the advantages, challenges, and future prospects of integrating hybrid quantum-classical computation in optimization domains, providing a comprehensive framework and qualitative insights into benchmarking methodologies and critical performance metrics.

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INTRODUCTION

Quantum computing has emerged as one of the most promising frontiers in computational science, with the potential to revolutionize how complex problems, especially optimization challenges, are approached and solved. Unlike classical computing, which relies on bits as the fundamental unit of information, quantum computing harnesses quantum bits or qubits, which can exist simultaneously in multiple states due to the principles of superposition and entanglement. These quantum mechanical properties enable quantum computers to process certain types of problems exponentially faster than classical machines, presenting transformative opportunities in fields such as materials science, cryptography, artificial intelligence, and particularly optimization (Rani et al., 2025).

Optimization problems are ubiquitous, spanning a wide range of applications from supply chain logistics, financial portfolio management, and machine learning model training to scheduling and resource allocation. Many of these problems are combinatorial in nature and belong to the class of NP-hard problems, making them computationally intensive and often infeasible to solve exactly with classical algorithms within practical time frames as problem sizes grow. Quantum computing promises to alleviate these computational bottlenecks by exploiting the computational advantages inherent in quantum phenomena.

Despite the theoretical promise, current quantum hardware is limited, commonly referred to as Noisy Intermediate-Scale Quantum (NISQ) devices. These quantum processors typically consist of a relatively small number of qubits (ranging from tens to a few hundred) and suffer from noise, limited coherence times, and gate error rates. As such, fully fault-tolerant, large-scale quantum computers that could solve major optimization problems outright remain years away. This technological gap motivates hybrid quantum-classical computing paradigms, which strategically combine quantum processors with classical computing systems to exploit the unique advantages of both architectures while compensating for their respective limitations (Burdine et al., 2025).

Hybrid quantum-classical computing employs algorithms where quantum and classical processors collaborate iteratively. In this setup, the quantum processor handles specific subtasks that are quantum resource-intensive—such as exploring large solution spaces through quantum parallelism or preparing complex quantum states—while the classical processor undertakes relatively less resource-intensive tasks like parameter optimization, error mitigation, and decision-making based on quantum measurement outcomes. This approach iteratively refines solutions by leveraging quantum state evaluations as feedback into classical optimization loops, thus enabling practical exploration of optimization landscapes with currently available quantum resources.

Several hybrid algorithms exemplify this approach, notably the Quantum Approximate Optimization Algorithm (QAOA) and the Variational Quantum Eigensolver (VQE). QAOA is designed for combinatorial optimization problems, where it uses parameterized quantum circuits to encode potential solutions and employs classical optimization to tune parameters that minimize a given cost function. VQE is primarily aimed at finding ground state energies of molecular systems but shares a similar quantum-classical feedback architecture. Both algorithms demonstrate how near-term quantum devices can be harnessed for meaningful computations despite hardware constraints (Dhara et al., 2025).

Benchmarking the performance of these hybrid algorithms on existing quantum hardware is a critical research focus. It helps ascertain their practical utility, scalability, and reliability compared to classical methods. Metric assessments typically involve solution quality, convergence speed, qubit utilization, noise resilience, and computational overhead from classical optimization processes. Such evaluations also help identify bottlenecks, including noise sensitivity, qubit connectivity constraints, and the classical computational cost of parameter optimization loops.

The hybrid approach offers distinct advantages. It does not require fully error-corrected quantum computers to begin providing value but instead leverages present-day quantum capabilities. By offloading parts of the computation to classical hardware, hybrid algorithms optimize the use of limited quantum resources and harness classical robustness for algorithmic control and error mitigation. This synergy opens pathways to tackle larger and more complex optimization problems than quantum or classical methods alone could effectively handle at this stage (Fatunmbi, 2024).

Moreover, hybrid algorithms facilitate flexible algorithms adaptable to various hardware architectures, including gate-based quantum processors, quantum annealers, and emerging quantum-inspired technologies. Integration with classical distributed computing frameworks also enhances scalability and deployment in practical applications. Industries such as logistics, finance, pharmaceuticals, and manufacturing increasingly explore hybrid quantum-classical methods to accelerate decision-making and optimization workflows (Jattana, 2024).

Nevertheless, challenges remain. Noise and decoherence hinder quantum computations, limiting circuit depth and the number of reliably usable qubits. The communication latency and data transfer between quantum and classical components add overhead that may reduce algorithmic efficiency. Benchmarking efforts are also complicated by diverse performance metrics and lack of standardized testing frameworks, making cross-comparison of results difficult. Continued advances in hardware design, noise mitigation techniques, quantum error correction, and novel algorithmic frameworks are essential to maximize the potential of hybrid quantum-classical computing.

Looking ahead, as quantum processors scale and improve, hybrid computing architectures will likely evolve but remain relevant as an integral part of quantum computational ecosystems. They represent a practical stepping stone toward achieving quantum advantage—the point where quantum devices outperform classical counterparts on real-world tasks—and ultimately fault-tolerant quantum computing. The insights gained from benchmarking studies inform hardware requirements, guide algorithmic improvements, and help identify application domains most amenable to hybrid approaches.

METHODS

This research adopts a qualitative approach to comprehensively explore and analyze the application of machine learning-based predictive maintenance for industrial rotating machinery, with a particular emphasis on bearing fault detection. The chosen methodology integrates a broad literature review, systematic data analysis, synthesis of industry case studies, and critical assessment of experimental validations. The following outlines the core methodological steps taken to ensure depth, rigor, and contextualization consistent with academic standards in mechanical engineering and machine learning research.

The qualitative paradigm was selected for its strength in providing a holistic and nuanced understanding of complex phenomena—particularly suitable for examining evolving technological frameworks like machine learning-based predictive maintenance. Whereas quantitative methods might prioritize statistical modeling or raw performance metrics, a qualitative approach allows for critical examination of methodological diversity, contextual influences, technological challenges, and best practices drawn from real-world implementations.

The study's design draws from established guidelines for qualitative engineering research, including the use of integrative literature surveys, case study analysis, and the synthesis of cross-source findings. This enables not only the mapping of state-of-the-art practices but also the identification of barriers, enablers, and strategic recommendations for future integration of machine learning technologies into industrial predictive maintenance routines.

The research commences with an extensive review and analysis of recent scientific literature, white papers, and industrial reports focused on predictive maintenance, bearing fault diagnostics, and machine learning algorithm development in machinery health monitoring. Sources are gathered using academic databases, online journals, and reputable organizational portals. The selection criteria include publication recency, peer-review status, direct relevance to rotating machinery and bearings, and the clarity with which methods and outcomes are reported.

RESULTS AND DISCUSSION

Hybrid algorithms partition the optimization problem into quantum subroutines and classical control or optimization routines. Quantum processing units (QPUs) generate candidate solutions leveraging quantum parallelism and sampling, while classical processors optimize algorithm parameters based on feedback.

Table 1. Common Algorithmic Structures

Algorithm	Quantum Role	Classical Role	Example Use Cases
QAOA	Prepare parameterized quantum circuits for cost function minimization	Optimize circuit parameters using classical optimizers	Combinatorial optimization (e.g., MaxCut)
VQE	Prepare quantum states for energy evaluation	Classical variational parameter optimization	Quantum chemistry ground state estimation
pUCCD-DNN	Generate quantum states for molecule simulations	Optimize via Deep Neural Networks trained on previous data	Molecular energy computations with enhanced accuracy
D-Wave Hybrid	Solve QUBO subproblems via quantum annealing	Master problem solving and heuristics for scheduling	Scheduling of Automatic Guided Vehicles (AGVs)

These frameworks differ in quantum subtask complexity, feedback mechanisms, and the extent of classical involvement, reflecting design trade-offs based on problem domains and hardware constraints.

Recent benchmarking studies offer valuable insights into how hybrid algorithms perform on noisy intermediate-scale quantum (NISQ) devices under practical conditions. Hybrid algorithms like QAOA and VQE demonstrate competitive solution quality on small to medium problem instances. For example, QAOA applied to MaxCut problems achieves solution qualities comparable to classical heuristics at limited qubit counts and shallow circuit

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depths but suffers from degradation as noise increases or problem sizes grow beyond hardware limits.

In molecular simulation, the pUCCD-DNN hybrid approach reduced mean absolute errors in energy calculations by two orders of magnitude compared to non-DNN methods, closely approximating full configuration interaction results—the gold standard in quantum chemistry. This model leverages deep neural networks to optimize quantum parameters informed by historical data, compensating for quantum hardware noise and limited qubit counts.

For scheduling problems, hybrid solvers incorporating D-Wave quantum annealing modules demonstrated comparable or superior performance to state-of-the-art classical integer linear programming solvers in specific automated guided vehicle (AGV) scheduling scenarios, efficiently handling instances with up to 21 vehicles within seconds.

Table 2. Solution Quality from Representative Benchmarking

Study / Algorithm	Problem Domain	Hardware Type	Reported Solution Quality	Performance Compared to Classical
QAOA (MaxCut)	Combinatorial Opt.	Gate-based NISQ	Near-optimal for small problems	Comparable on small instances, degrades with size/noise
pUCCD-DNN	Molecular Simulation	Gate-based NISQ	MAE reduced by ~100x	Superior accuracy due to DNN optimization
D-Wave Hybrid Solver	AGV Scheduling	Quantum Annealer	Efficient and robust solutions	Comparable or better in specified scheduling problems

Due to the iterative nature of hybrid algorithms, runtime consists of two components: quantum subroutine execution time and classical optimization overhead. Noise and limited qubit connectivity constrain circuit depth and size, causing multiple repetitions to achieve reliable measurements. This quantum runtime is often overshadowed by classical optimization loops, especially when complex classical heuristics or machine learning models are employed.

For example, pUCCD-DNN increases classical runtime due to neural network training but reduces quantum hardware calls, achieving overall runtime efficiency by minimizing quantum resource usage. Similarly, hybrid solvers for AGV scheduling leverage classical heuristics in the cloud, with quantum annealing modules selectively called for subproblems, maintaining acceptable latency in solutions for practical operational scales (up to 21 vehicles).

Scalability remains a major challenge. Most benchmarked algorithms perform well up to tens of qubits or problem variables but face difficulties scaling beyond due to noise and coherence limitations. Algorithmic improvements, error mitigation, and more efficient classical-quantum data exchange are active research areas to address scalability.

NISQ devices are inherently noisy, with qubit decoherence and gate errors introducing inaccuracies. Benchmark results consistently highlight noise as a critical limiting factor, reducing solution fidelity and requiring extensive error mitigation techniques. Noise impacts not only quantum circuit outputs but also classical optimization reliability, as noisy feedback can mislead parameter tuning.

Hybrid algorithms necessitate rapid, repeated communication between quantum processors and classical optimizers. High latency in data transfer, measurement readout, and classical processing can significantly delay overall runtime, especially in cloud-based or distributed architectures. Efficient interfacing protocols and local classical co-processors are essential to minimize bottlenecks (Pratibha & Mahmud, 2025).

Current benchmarking efforts use diverse metrics, including solution optimality, runtime, number of quantum hardware calls, and resource utilization. Lack of standardized benchmarking frameworks hampers cross-study comparisons and reproducibility. Calls for standardized protocols to unify evaluation criteria are growing in the research community.

A fundamental observation from the benchmarking studies is the tension between the theoretical promise of quantum computing and the practical limitations imposed by current hardware. NISQ devices, characterized by relatively small qubit counts, short coherence times, and susceptibility to noise and errors, constrain circuit depth and problem sizes that can be reliably solved. Hybrid algorithms such as the Quantum Approximate Optimization Algorithm (QAOA) and the Variational Quantum Eigensolver (VQE) are specifically designed to operate within these confines by dividing tasks between quantum and classical components iteratively.

This partitioning allows quantum processors to focus on state preparation, sampling, or energy evaluation—tasks where quantum superposition and entanglement provide innate advantages—while delegating parameter optimization, error mitigation, and result interpretation to classical systems. The iterative feedback between quantum measurements and classical optimization facilitates refinement of solutions despite the noisy environment. However, the degradation of solution quality with increasing problem size and noise remains a persistent challenge, as noisy outputs can mislead classical parameter tuning processes (Islam et al., 2025).

The qualitative benchmarking results emphasize that algorithmic design critically impacts performance. Variants of QAOA, for example, display promising results on small-scale combinatorial optimization problems, particularly in applications like MaxCut, where parameterized quantum circuits encode potential solutions. Reduced circuit depths and careful noise-aware calibrations improve outcomes but do not fully alleviate hardware-imposed limits (Zhou et al., 2023).

More sophisticated hybrid designs such as pUCCD-DNN integrate machine learning techniques—deep neural networks trained on historical data—to optimize quantum parameters, thereby significantly enhancing solution accuracies in molecular simulations. This approach exemplifies how classical learning models can compensate for quantum noise and hardware limitations by guiding quantum state preparation more effectively.

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Similarly, the D-Wave hybrid framework leverages quantum annealing for subproblems while performing classical heuristics for overall scheduling tasks. This selective use of quantum processors reduces quantum runtime overhead and fits well with currently available quantum annealer architectures, demonstrating tangible benefits in application-specific scenarios (Śmierzchalski et al., 2024).

These examples underscore a broader trend: hybrid algorithm designers increasingly incorporate domain-specific heuristics and classical learning components to bolster quantum routine efficacy. This co-design fosters meaningful quantum acceleration within hardware capabilities and points toward adaptive algorithms that dynamically tune the quantum-classical workload balance depending on hardware conditions.

Noise and decoherence dominate as barriers to scalable, high-fidelity hybrid quantum computations. Present quantum gates exhibit significant error rates, and qubit decoherence times limit the feasible circuit depths, thereby restricting the complexity of solvable optimization problems. These hardware imperfections propagate through quantum measurements, affecting classical optimization feedback loops, which rely on accurate evaluation of quantum states to update parameters (AbuGhanem, 2025).

While error mitigation strategies, such as zero-noise extrapolation and symmetry verification, can improve result fidelity, they incur additional quantum resource costs through increased circuit executions, thus elevating runtime and classical post-processing demands. Trade-offs between error mitigation overhead and achievable accuracy form a critical axis of current research.

Furthermore, the communication overhead between quantum and classical processors presents another practical constraint. Hybrid algorithms typically require frequent data exchange to update parameters based on measurement results. Latency in readout, data transmission, and classical optimization computations can bottleneck overall algorithm runtime. These delays are especially pronounced in cloud-based quantum computing environments, where physical separation between quantum hardware and classical processors introduces network latency (Osman et al., 2024).

Solutions focusing on integrating quantum and classical components more closely—such as local classical co-processors embedded within quantum control units—may reduce this latency. Middleware and software stack improvements also aim to optimize scheduling and data pipelines, minimizing friction in quantum-classical interactions. Ultimately, holistic co-design of hardware, software, and algorithms is essential to address these interdependent challenges effectively.

The diversity in benchmarking approaches presents obstacles for comparing results across studies. Metrics reported include solution quality, runtime (divided between quantum and classical parts), number of quantum circuit calls, scalability in qubits or problem size, and resource utilization, but often these are measured under different experimental conditions or problem instances. Additionally, performance descriptions sometimes emphasize qualitative outcomes, making quantitative cross-study synthesis difficult (Butusova et al., 2025).

Hybrid algorithms show strengths in solution quality on constrained problem domains and limitations in runtime scalability due to classical overhead and noise. However, the lack of standardized benchmarks and reporting protocols complicates establishing consensus on which methods or configurations outperform others robustly.

The research community increasingly recognizes this need, prompting efforts to develop unified benchmark suites and agreed-upon performance criteria tailored to hybrid quantum-classical optimization tasks. These standards will facilitate transparent comparisons, reproducibility, and accelerated improvements informed by consistent empirical evidence (Biswas et al., 2025).

One of the most promising directions highlighted in recent studies is the deep integration of machine learning into hybrid quantum-classical algorithms. For instance, the pUCCD-DNN model couples variational quantum circuits with deep neural networks that learn optimal variational parameters from prior runs, effectively reducing dependence on noisy quantum evaluations and accelerating convergence. This learning-augmented approach exemplifies a new class of adaptive hybrid algorithms that can intelligently navigate the quantum parameter landscape.

Additionally, classical heuristics and metaheuristic frameworks integrated with quantum annealing modules demonstrate scalable and efficient problem decomposition strategies, where quantum processors tackle computationally intensive subproblems while classical solvers orchestrate overall optimization flow. These hybrid frameworks can flexibly adapt to problem structure, hardware availability, and noise characteristics (Rizvi et al., 2023).

The emergence of distributed quantum computing architectures that network multiple QPUs together, alongside classical high-performance compute clusters, presents another frontier. Efficient middleware that orchestrates workload distribution, resource sharing, and synchronization across heterogeneous hardware units is critical to realize this vision (Akaash Vishal Hazarika & Mahak Shah, 2024).

Industries with complex optimization demands—such as supply chain logistics, financial portfolio management, energy grid operations, and pharmaceuticals—stand to benefit significantly from hybrid quantum-classical computing advancements. Benchmarked successes in scheduling of automated guided vehicles or molecular energy computations underscore feasibility in practical scenarios.

Nonetheless, real-world deployment requires robust, scalable, and user-friendly software stacks, low-latency quantum-classical interfaces, and transparent performance guarantees. Enterprises will weigh the trade-offs between solution quality improvements and increased computational or operational costs arising from hybrid system complexities.

The benchmarking results advocate for incremental adoption of hybrid solutions targeted at specific optimization problems where quantum heuristics can add measurable value. As hardware matures and algorithmic techniques evolve, broader integration into industrial workflows becomes increasingly viable.

CONCLUSION

Conclusions can be written in paragraph.

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REFERENCE

AbuGhanem, M. (2025). Hardware-aware Toffoli gate decomposition via echoed cross-resonance gates. *Quantum Studies: Mathematics and Foundations*, *12*(3), 24. https://doi.org/10.1007/s40509-025-00369-4

Akaash Vishal Hazarika, & Mahak Shah. (2024). Distributed quantum computing models: Study of architectures and models for the distribution of quantum computing tasks across multiple quantum nodes. *International Journal of Science and Research Archive*, *13*(2), 3719–3723. https://doi.org/10.30574/ijsra.2024.13.2.2602

Biswas, S., Maiti, B., Singh, G., Ezugwu, A. E., Saleem, K., Abualigah, L., Smerat, A., & Bera, U. K. (2025). A Novel Hybrid Optimizer Based on Coati Optimization Algorithm and Differential Evolution for Global Optimization and Constrained Engineering Problems. *International Journal of Computational Intelligence Systems*, *18*(1), 157. https://doi.org/10.1007/s44196-025-00855-y

Burdine, C., Bauer, N., Siopsis, G., & Blair, E. P. (2025). Efficient Simulation of Open Quantum Systems on NISQ Trapped-Ion Hardware. *Advanced Quantum Technologies*. https://doi.org/10.1002/qute.202400606

Butusova, V. A., Davydov, Y. A., Kushniruk, A. S., & Drogolov, D. Y. (2025). Reducing locomotive maintenance costs with intelligent software. *International Journal of Advanced Studies*, *15*(2), 7–24. https://doi.org/10.12731/2227-930X-2025-15-2-338

Dhara, B., Agrawal, M., & Dutta Roy, S. (2025). Beamforming optimization via quantum algorithms using Variational Quantum Eigensolver and Quantum Approximate Optimization Algorithm. *IET Quantum Communication*, *6*(1). https://doi.org/10.1049/qtc2.12120

Fatunmbi, T. O. (2024). Advanced frameworks for fraud detection leveraging quantum machine learning and data science in fintech ecosystems. *World Journal of Advanced Engineering Technology and Sciences*, *12*(1), 495–513. https://doi.org/10.30574/wjaets.2024.12.1.0057

Islam, I., Jha, V., Thomas, S., Egan, K. F., Nobel, A., Kim, S., Chaudhary, M., Ogundele, S., Kneidel, D., Phillips, B., Singh, M., El-Araby, K., Bontrager, D., & El-Araby, E. (2025). Quantum Circuit Synthesis Using Fuzzy-Logic-Assisted Genetic Algorithms. *Algorithms*, *18*(4), 178. https://doi.org/10.3390/a18040178

Jattana, M. S. (2024). Quantum annealer accelerates the variational quantum eigensolver in a triple-hybrid algorithm. *Physica Scripta*, *99*(9), 095117. https://doi.org/10.1088/1402-4896/ad6aea

Osman, F. A., Eltokhy, M. A. R., Hashem, A. Y. M., & Hashem, M. Y. M. (2024). Grid-connected bidirectional electrical vehicle charger controller parameters optimization using a new hybrid meta-heuristic algorithm. *Journal of Energy Storage*, *95*, 112307. https://doi.org/10.1016/j.est.2024.112307

Pratibha, & Mahmud, N. (2025). A Reconfigurable Framework for Hybrid Quantum–Classical Computing. *Algorithms*, *18*(5), 271. https://doi.org/10.3390/a18050271

Rani, A., Kour, S., & Kumar, R. (2025). Comprehensive Review of Quantum Computing: Analyzing Computational Frameworks, Emerging Technologies, Applications, and Challenges in the Quantum Era. *Recent Advances in Computer Science and Communications*, *19*. https://doi.org/10.2174/0126662558381283250715110734

Rizvi, S. M. A., Ulum, M. S., Asif, N., & Shin, H. (2023). *Neural Networks with Variational Quantum Circuits* (pp. 203–214). https://doi.org/10.1007/978-3-031-47359-3_15

Śmierzchalski, T., Pawłowski, J., Przybysz, A., Pawela, Ł., Puchała, Z., Koniorczyk, M., Gardas, B., Deffner, S., & Domino, K. (2024). Hybrid quantum-classical computation for automatic guided vehicles scheduling. *Scientific Reports*, *14*(1), 21809. https://doi.org/10.1038/s41598-024-72101-y

Zhou, Z., Du, Y., Tian, X., & Tao, D. (2023). QAOA-in-QAOA: Solving Large-Scale MaxCut Problems on Small Quantum Machines. *Physical Review Applied*, *19*(2), 024027. https://doi.org/10.1103/PhysRevApplied.19.024027