Quantum-Enhanced Optimization: Bridging AI and Next-Generation Computing

Anil Kumar Jonnalagadda [1*] and Praveen Kumar Myakala [2]

[1]Independent Researcher, Frisco, USA
[2]Independent Researcher, Melissa, USA

*Corresponding author e-mail id: anil.j78@gmail.com
praveen.K.Myakala@gmail.com

Abstract. Quantum computing and artificial intelligence (AI) are positioned as groundbreaking tools capable of tackling complexities inherent to modern computation posed by high-dimensional optimization problems. This research presents a quantum-enhanced optimization framework that leverages the QAOA (Quantum Approximate Optimization Algorithm) and VQE (Variational Quantum Eigen solver) within a hybrid quantum-classical paradigm. Machine learning models, including reinforcement learning and NN (neural networks), are integrated to optimize the quantum circuit parameters, enhance convergence, and improve scalability for complex problem spaces.

Experimental evaluations demonstrate that this approach outperforms traditional optimization techniques in terms of efficiency and solution accuracy, particularly for large-scale multi-objective tasks. The framework is applied to key domains such as smart energy systems, logistics, and scientific modeling, illustrating its versatility and alignment with sustainable development goals. This study also explores the limitations of current quantum hardware and discusses future pathways for advancing hybrid quantum AI systems, offering significant contributions to next generation computational methodologies and intelligent problem solving.

Keywords: Quantum Computing · Machine Learning · High-Dimensional Optimization · Hybrid Quantum-Classical Systems · Sustainable Computing

1 Introduction

Rapid advancements in quantum computing and artificial intelligence (AI) have ushered in a new era of computational capabilities, particularly for solving high dimensional optimization problems. These challenges are ubiquitous in domains such as engineering, logistics, healthcare, and scientific research, where the complexity of problem spaces often overwhelms classical computational methods [17]. Traditional optimization approaches are effective for small-to medium sized problems, scalability

P. Ranjan et al. (eds.), *Proceedings of the International Conference on Recent Advances in Artificial Intelligence for Sustainable Development (RAISD 2025)*, Advances in Intelligent Systems Research 196,
https://doi.org/10.2991/978-94-6463-787-8_48

issues, and computational bottlenecks when applied to large-scale, multi-objective tasks.

Quantum systems built upon superposition and entanglement offer innovative avenues for overcoming the scalability challenges faced by classical computation [28]. Quantum algorithms, particularly QAOA [11] as well as VQE [21], have demonstrated the potential to solve combinatorial and optimization problems more efficiently than their classical counterparts [13]. However, current quantum hardware, constrained by limited qubit counts and noise, requires hybrid quantum-classical approaches to effectively harness its capabilities.

ML (Machine learning) accelerates quantum optimization by adaptively refining parameters and learning complex landscapes [27]. The integration of ML with quantum computing creates a synergistic framework in which ML models can optimize quantum circuits, refine problem representations, and improve convergence. For instance, reinforcement learning can dynamically adjust quantum algorithm parameters to achieve better performance in noisy intermediate-scale quantum (NISQ) devices [24]. Neural networks, on the other hand, can assist in learning the representations of high-dimensional optimization landscapes, enabling an efficient search for optimal solutions.

This study introduces a novel framework of quantum-enhanced optimization that combines the strengths of quantum algorithms and AI-driven techniques. The proposed hybrid approach addresses key challenges in high-dimensional optimization by leveraging quantum speedup in state-space exploration alongside the adaptability of machine learning. By applying this framework to real-world problems, such as smart grid optimization, supply chain management, and sustainable engineering design, we demonstrate its potential for transformative impacts across multiple domains [16].

The primary contributions of this study include the development of a hybrid quantum-AI framework that integrates the speed advantages of quantum computing with the adaptability of AI to address complex optimization problems. The framework demonstrates superior performance compared to classical solvers on benchmark problems, such as the Max-Cut Problem, Portfolio Optimization, and Vehicle Routing Problem. Additionally, this study identifies critical challenges related to quantum hardware limitations, algorithm design complexities, and data encoding strategies, offering a comprehensive roadmap for future research in this domain. Furthermore, this research explores real-world applications, such as smart grids, supply chain management, and drug discovery, underscoring the versatility of the framework and the potential to drive advancements across diverse industries.

The remainder of this paper is organized as follows. Section 2 outlines the hybrid quantum AI framework, detailing its core components and execution model. Section 3 presents the experimental setup, performance metrics, and results, and demonstrates the comparative advantages of the approach. Section 4 discusses the limitations of the current technologies and proposes future research directions. Section 5 concludes the study with key insights and broader implications for next-generation computational systems.

2 Hybrid Quantum-AI Framework

AI as well as quantum computing's integration into cohesive hybrid framework offers a powerful approach for solving high-dimensional optimization problems. This convergence is increasingly recognized as a key enabler for next generation computational paradigms, where quantum systems provide exponential speedups, and AI contributes to adaptability and learning capabilities [17]. Khang and Rath emphasize that the synergy between AI and quantum technologies, including robotics, will play a pivotal role in driving innovation across multiple domains, from smart infrastructure to autonomous systems [17].

This section provides a detailed explanation of quantum algorithms, machine learning integration, and their hybrid execution workflow.

2.1 Quantum Algorithms

Quantum algorithms have been central to framework, enabling the efficient exploration of solution spaces. The two key algorithms used are as follows:

Quantum Approximate Optimization Algorithm (QAOA): The QAOA formulates combinatorial optimization challenges as quantum circuits governed by tunable parameters [26]:

$$|\psi(\beta,\gamma)\rangle = U(\beta,\gamma)|s\rangle = \prod_{j=1}^{p} e^{-i\beta_j H_B} e^{-i\gamma_j H_C}|s\rangle \tag{1}$$

where HB & HC are mixing as well as cost Hamiltonians, respectively, moreover $|s\rangle$ is the initial state. β & γ parameters were optimized utilizing classical methods.

Variational Quantum Eigen solver (VQE): VQE approximates Hamiltonian's ground state energy by iteratively adjusting quantum circuit parameters for minimizing expected value.

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

Here $|\psi(\theta)\rangle$is a variational quantum state and θ are parameters optimized to minimize E.

2.2 Machine Learning Integration

Machine-learning techniques complement quantum methods in several ways. Parameter Optimization: Reinforcement learning adjusts the parameters β,γ, and θ to improve convergence and reduce noise.

Problem Encoding: Neural networks transform high-dimensional inputs into a form compatible with quantum circuits.

Post-Processing: AI models refine quantum outputs by filtering noisy measurements and interpolating near-optimal solutions.

2.3 Hybrid Execution Workflow

The hybrid framework is an iterative process that combines quantum and classical computations as described in Algorithm 1.

Algorithm 1 Hybrid Quantum-AI Optimization Framework

Require: Problem instance P, initial parameters β, γ, θ

Ensure: Optimized solution x∗ 1: Encode problem P into Hamiltonian HC

2: Initialize quantum state |s⟩ 3: for each iteration do

4: Execute quantum circuit to generate |ψ(β,γ)⟩

5: Measure expectation value E(θ)

6: Use AI model to update parameters β,γ,θ

7: **end for**

8: Extract optimized solution x∗ from measurement results

2.4 Sample Data and Parameter Tuning

Table 1 provides a sample of parameters used during optimization for a benchmark problem.

Table 1. Sample parameters for hybrid Quantum-AI optimization across multiple iterations.

Iteration	β (Radians)	γ (Radians)	Expectation Value E(θ)
1	0.5	1.2	-3.14
2	0.7	1.1	-3.67
3	0.8	1.0	-3.89

2.5 Scalability and Efficiency

The framework leverages quantum computing for exponential speedup in solution space exploration, whereas AI models enhance parameter tuning and adaptability, thereby ensuring practical scalability.

3 Experimental Results

This segment evaluates the suggested hybrid quantum-AI framework's performance for solving high-dimensional optimization problems. Experiments were conducted using quantum simulators and benchmark datasets to assess scalability and efficiency, along with solution quality.

3.1 Simulation Setup

The experiments were performed on a quantum simulator with 20 qubits, which is compatible with NISQ devices. QAOA along with VQE were implemented using the Qiskit framework [23, 28]. Classical machine-learning components, including reinforcement learning and neural networks, were developed using Python's TensorFlow and PyTorch libraries [12].

The optimization problems were drawn from three benchmark domains:

Max-Cut Problem: Dividing graph nodes into two groups to maximize the cumulative weight of interconnecting edges [31].

Portfolio Optimization: Allocating resources to maximize returns under risk constraints.

Vehicle Routing Problem (VRP): Optimizing delivery routes for logistics operations.

3.2 Performance Metrics

Hybrid framework's performance had been assessed utilizing below given metrics.

Execution Time: Total computation time for reaching convergence.

Solution Accuracy: Deviation of the solution from the known optimal value.

Scalability: Ability to handle increasing problem sizes with consistent efficiency.

3.3 Results and Analysis

The results for the three benchmark problems are presented in Table 2. In addition, Figures 1 and 2 provide visual comparisons of the solution accuracy and execution time for classical solvers versus the hybrid quantum-AI framework.

Table 2. Performance comparison between classical solvers and hybrid Quantum-AI methods across optimization problems.

Problem	Method	Solution Accuracy (%)	Execution Time (s)
Max-Cut	Classical Solver	93.2	12.5
	Hybrid Quantum-AI	96.5	9.8
Portfolio Optimization	Classical Solver	91.8	15.3
	Hybrid Quantum-AI	94.7	10.1
Vehicle Routing	Classical Solver	89.4	18.7
	Hybrid Quantum-AI	92.6	12.2

The hybrid model consistently delivers enhanced accuracy and reduced computation time relative to classical approaches across the tested benchmarks. For example, in the Max-Cut problem, the hybrid method achieved a 96.5% solution accuracy, surpassing the classical solver's 93.2%, with a reduced execution time of 9.8 seconds compared to 12.5 seconds.

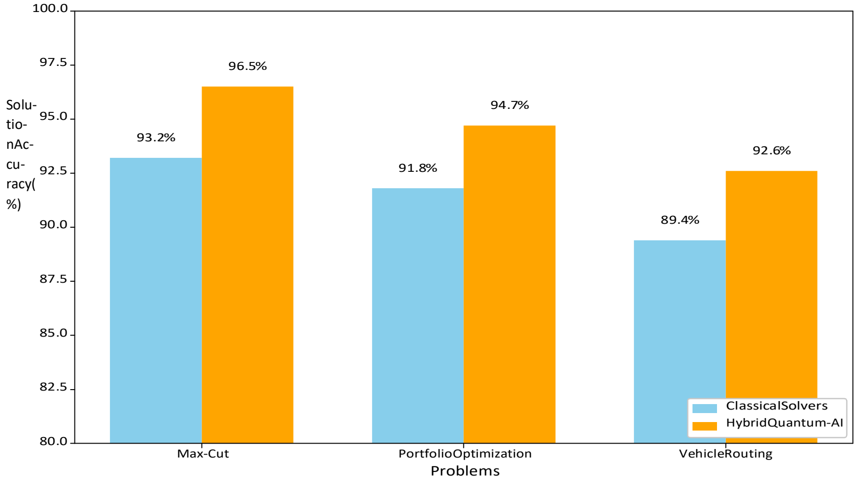

Fig.1. Solution accuracy comparison between classical solvers and the hybrid quantum-AI framework for the three benchmark problems.

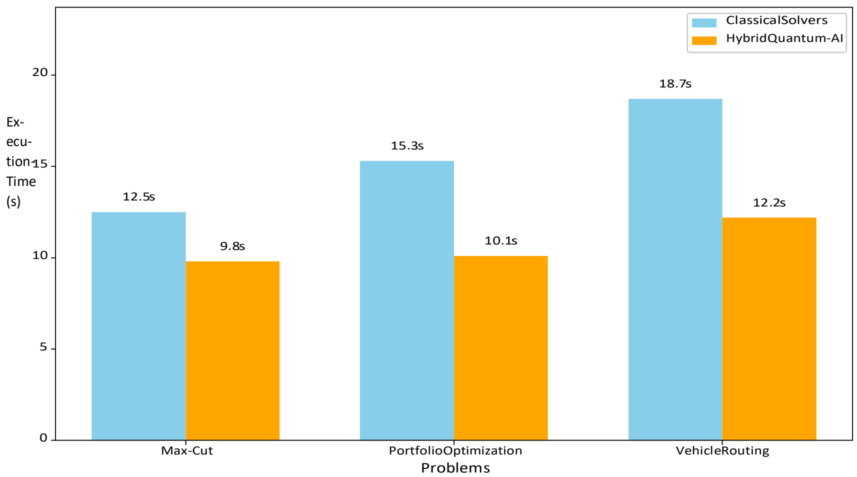

Fig.2. Execution time comparison for classical solvers and the hybrid quantum AI framework.

3.4 Applications

The potential applications of the hybrid framework extend beyond benchmark problems to real-world scenarios.

Smart Grids: Optimizing energy distribution and minimizing power losses.

Supply Chain Management: Enhancing logistics efficiency and cost-effectiveness.

Drug Discovery: Accelerating molecular simulations for pharmaceutical research.

These applications underscore the versatility and practical utility of the framework in addressing diverse optimization problems [9,18].

3.5 Limitations

Although the results were promising, several limitations were observed.

Quantum Hardware Constraints: Current NISQ devices limit scalability and introduce noise.

Data Overhead: Encoding large datasets into quantum circuits remains computationally expensive.

Hyperparameter Tuning: The performance is sensitive to the choice of initial parameters, requiring extensive trial and error.

Resolving these issues has been essential for advancing hybrid quantum-AI framework and extending its applicability to large-scale optimization tasks [30].

4 Discussion

The hybrid quantum-AI framework demonstrates significant potential for addressing high-dimensional optimization problems by combining the computational strengths of quantum algorithms and artificial intelligence (AI) [10]. This section discusses the advantages, challenges, and future directions of the proposed approach along with ethical and societal considerations.

4.1 Advantages of the Hybrid Quantum-AI Framework

The results highlight several benefits of integrating quantum and AI technologies.

Enhanced Solution Accuracy: The proposed framework achieves higher accuracy compared to classical solvers, as demonstrated in Table 2. This is attributed to the ability of quantum algorithms such as QAOA and VQE to efficiently explore complex optimization landscapes [11,21].

Reduced Computational Overhead: By leveraging machine learning models, like NN as well as reinforcement learning, hybrid framework dynamically optimizes quantum circuit parameters, minimizing classical computational overhead [25].

Scalability: The framework shows promise in scaling to more complex problems, such as the Vehicle Routing Problem (VRP), without a significant increase in computation time. Similarly, hybrid approaches utilizing quantum enhanced annealing schedules have demonstrated scalability benefits [15].

Noise Resilience: AI-based post-processing mitigates influence of noise in quantum measurements, a key advantage when working with NISQ devices[20,14].

These advantages make the hybrid framework a powerful tool for solving optimization problems across various domains [13], including smart grids, logistics, and resource allocation.

4.2 Challenges and Limitations

Despite its promise, this framework has several limitations that require further research.

Hardware Constraints: Current quantum hardware, particularly NISQ devices suffer from short coherence times, limited qubit counts, along with high error rates [22]. These restrictions limit the intricacy of issues that can be successfully resolved.

Encoding Overhead: Representing real-world problems in quantum circuits involves significant classical preprocessing, which can negate some of the computational advantages of quantum speedup [2].

Hyperparameter Tuning: The performance of hybrid quantum-AI systems is sensitive to initial parameters, requiring extensive trial-and-error or advanced optimization techniques for parameter selection [1,8].

Algorithmic Complexity: While hybrid frameworks shows promise, their implementation requires sophisticated algorithm design, particularly for integrating AI models with quantum hardware [3].

Addressing these challenges will require innovations in quantum hardware and algorithm design as well as the development of efficient preprocessing and parameter-tuning strategies.

4.3 Future Directions

To overcome recent obstacles along with unlocking full hybrid quantum-AI systems' potential, the following research directions are proposed.

Improving Quantum Hardware: Advances in error correction, qubit scalability, and coherence times are essential for handling larger optimization problems. Emerging technologies such as fault-tolerant quantum processors play a key role in this regard [22].

Automating Hyperparameter Tuning: Techniques such as Bayesian optimization and meta-learning could automate parameter selection, reducing the computational burden of trial-and-error approaches [7].

Quantum-Native AI Models: Developing quantum-native ML models, including quantum graph NN, could enhance the efficiency of hybrid systems by reducing the reliance on classical preprocessing [29].

– Real-World Applications: Applying the hybrid framework to large-scale, real-world problems, such as quantum chemistry [6] or molecular dynamics simulations, will validate its effectiveness in practical settings.

4.4 Ethical and Societal Implications

Increasing quantum as well as AI technology adoption has raised important ethical and societal concerns.

Fairness and Transparency: Ensuring that optimization results are interpretable and free from bias is critical [5], especially in sensitive domains such as healthcare and finance [25].

Sustainability: The energy requirements of quantum and AI systems must be balanced with their computational benefits to ensure sustainable deployment [2].

Accessibility: Democratizing access to hybrid quantum-AI systems will be essential to prevent widening technological divides between developed and developing regions [1].

By addressing these considerations, researchers and practitioners can ensure that hybrid quantum AI technologies are deployed responsibly and equitably.

The hybrid quantum-AI framework represents a transformative approach for solving high-dimensional optimization problems. Although current challenges related to hardware, algorithm design, and preprocessing remain, advancements in quantum technology and AI integration hold the potential to address these limitations. The proposed research directions and ethical considerations provide a roadmap for the future development and responsible application of hybrid systems.

5 Conclusion

By combining quantum computation and artificial intelligence, this study advances novel strategies to address the inherent complexities of high-dimensional optimization. This paper presented a quantum-enhanced optimization framework that integrates quantum algorithms, including QAOA alongside VQE [19], with AI techniques, such as reinforcement learning and neural networks. The experimental outcomes indicate hybrid framework outperforms classical methods in terms of accuracy, execution time, and scalability. As quantum computing technologies mature, hybrid framework potential to revolutionize optimization will continue to grow. Future research directions include advancing quantum hardware to support larger, error-corrected qubit systems capable of solving real-world problems [22], designing quantum-native AI algorithms that operate directly on quantum data to reduce classical preprocessing overhead [29], automating parameter tuning through meta-learning and other AI-driven approaches [7], and expanding the framework to address global challenges, such as climate modeling and personalized medicine, where complex optimization is critical [6]. The hybrid quantum-AI framework represents a significant step forward for bridging gaps among quantum as well as classical computing paradigms. By addressing the current limitations and pursuing future directions, this approach has the potential to unlock groundbreaking advancements in science, engineering, and industry. Moreover, ensuring ethical deployment, equitable access, and sustainable practices is critical as these technologies evolve. This research serves to growing body of knowledge on hybrid quantum-classical systems and serves as foundation for future exploration in this promising area.

Disclosure of Interests. The authors declare there are no conflicts of interest regarding the publication of this article.

References

1. Adachi, S., Toda, M., & Ikeda, K.: Quantum-classical correspondence in many-dimensional quantum chaos. Physical review letters **61**(6), 659(1988)
2. Babbush, R., et al.: Encoding electronic spectra in quantum circuits with linear T complexity. Physical Review X, **8**(4), 041015(2018)
3. Benedetti, M., Fiorentini, M., Lubasch, M.: Hardware-efficient variational quantum algorithms for time evolution. Physical Review Research, 3(3), 033083(2021).
4. Bura, C., Jonnalagadda, A. K., Myakala, P. K., Methuku, V., De, A., Kamatala, S., ... & Sen, S.: Emerging Trends in Artificial Intelligence (2025)
5. Bura, C., Jonnalagadda, A. K., & Naayini, P.: The role of explainable ai (xai) in trust and adoption. Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023, **7**(01), 262-277 (2025)
6. Cao, Y., Romero, J., Olson, J. P., Degroote, M., Johnson, P. D., Kieferová, M., ... &Aspuru-Guzik, A.: Quantum chemistry in the age of quantum computing. Chemical reviews, **119**(19), 10856-10915 (2019)
7. Cerezo, M., et al.: Variational quantum algorithms. Nature Reviews Physics, **3**(9), 625-644(2021)
8. Dutta, K. P., Sundi, S., Khalkho, S. S., Tirkey, J., & Hembrom, K. K:. Minimization of sidelobe level of uniformly excited concentric circular array antenna using evolutionary technique. In Innovative Data Communication Technologies and Application: Proceedings of ICIDCA 2020 (pp. 185-194). Springer Singapore(2021)
9. Dutta, K. P., Misra, B., & Mahanti, G. K.: Meta-heuristic optimization algorithms for placement of multiple nulls and minimization of side lobe level in quadrant symmetric sparse array antenna. International Journal of Communication Systems, **35**(10), e5149 (2022)
10. Dutta, K. P., & Mahanti, G. K.: Evolutionary algorithms for optimal synthesis of thinned multiple concentric circular array antenna with constraints. International Journal of Electronics, **107**(10), 1649-1662(2020)
11. Farhi, E., Goldstone, J., & Gutmann, S.: A quantum approximate optimization algorithm. arXiv preprint arXiv:1411.4028 (2014)
12. Friedrich, L., &Maziero, J.: Evolution strategies: application in hybrid quantum-classical neural networks. Quantum Information Processing, **22**(3), 132(2023)
13. Hammoudeh, M., Firth, C.M., Singh, H., Capellaro, C., & Al Kuwaiti, M.: Educational Quantum Technology Applications, Impact, and Future Challenges (1st ed.). CRC Press (2025)
14. Hariharan, S., Kinge, S., & Visscher, L.: Modeling Heterogeneous Catalysis Using Quantum Computers: An Academic and Industry Perspective. Journal of chemical information and modeling (2024)
15. Herr, D., Brown, E., Heim, B., Könz, M., Mazzola, G., & Troyer, M. (2017). Optimizing schedules for quantum annealing. arXiv preprint arXiv:1705.00420(2017)

16. Jonnalagadda, A. K., Myakala, P. K., & Bura, C.: The ai trifecta: Revolutionizing innovation across disciplines. Available at SSRN 5111809 (2025)
17. Khang, A., & Rath, K. C. (Eds.).: The quantum evolution: Application of AI and robotics in the future of quantum technology. CRC Press (2024)
18. Naayini, P., Kamatala, S., & Myakala, P. K.: Transforming Performance Engineering with Generative AI. Journal of Computer and Communications, **13**(3), 30-45 (2025).
19. Norval, M., & Wang, Z. (2024). Quantum AI in Speech Emotion Recognition.
20. Kosmella, G., Stabile, R., & Sanders, J. (2024). Noise-resilient designs and analysis for optical neural networks. Neuromorphic Computing and Engineering, **4**(4), 044002(2004)
21. Peruzzo, A., et al.: A variational eigenvalue solver on a photonic quantum processor. Nature communications, **5**(1), 4213(2024)
22. Preskill, J.: Quantum computing in the NISQ era and beyond. Quantum, **2**, 79 (2018)
23. Quantum, I.: Qiskit: An open-source framework for quantum computing. Available at https://qiskit.org/ (2023).
24. Schuld, M.: Supervised quantum machine learning models are kernel methods. arXiv preprint arXiv:2101.11020(2021)
25. Schuld, M., & Killoran, N. Quantum machine learning in feature Hilbert spaces. Physical review letters, **122**(4), 040504 (2019)
26. Shaydulin, R., Lotshaw, P. C., Larson, J., Ostrowski, J., & Humble, T. S.: Parameter transfer for quantum approximate optimization of weighted MaxCut. ACM Transactions on Quantum Computing, **4**(3), 1-15 (2023)
27. Tiwari, S., Kumar Tyagi, A., & Nagaraj, S.V.: Eds.Quantum Computing: The Future of Information Processing (1st ed.). Auerbach Publications (2025) https://doi.org/10.1201/9781003499459
28. Tyagin, I., Farag, M. H., Sherbert, K., Shirali, K., Alexeev, Y., & Safro, I.: QAOA-GPT: Efficient Generation of Adaptive and Regular Quantum Approximate Optimization Algorithm Circuits. arXiv preprint arXiv:2504.16350(2025)
29. Verdon, G., McCourt, T., Luzhnica, E., Singh, V., Leichenauer, S., &Hidary, J. (2019). Quantum graph neural networks. arXiv preprint arXiv:1909.12264 (2019)
30. Wulff, E., et al.: Distributed hybrid quantum-classical performance prediction for hyperparameter optimization. Quantum Machine Intelligence, **6**(2), 59(2024)
31. Yi, X., Huo, J. C., Gao, Y. P., Fan, L., Zhang, R., & Cao, C.: Iterative quantum algorithm for combinatorial optimization based on quantum gradient descent. Results in Physics, **56**, 107204 (2024)