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Thermal Noise Mitigation Algorithms for Quantum Enhanced Neural Network Training

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Abstract

Although quantum computers will not necessarily transform ML in general, they hold immense potential for specific uses, such as dealing with high-dimensional data and complex correlations that cannot be effectively modeled using classical systems. It is, however, difficult to design efficient quantum circuits, especially with the existing Noisy Intermediate-Scale Quantum (NISQ) hardware that has constraints including decoherence, a limited number of qubits, and gate fidelity limitations. The authors propose an Adaptive Quantum Circuit Architecture Search (AQCAS) framework whose structure and parameters are optimized dynamically to improve the performance of the task-specific ML. The framework integrates quantum circuit encoding, a hybrid search strategy that is based on reinforcement learning and evolutionary algorithms, and a task-specific adaptivity mechanism. Benchmark datasets were used for experimental evaluations of both simulation using Qiskit Aer and classical optimization using the Python frameworks TensorFlow and PennyLane. Fixed and standard variational quantum circuits were compared with performance measurements like the classification accuracy, circuit depth, convergence speed, and computational efficiency. The results show that the accuracy of AQCAS can be raised to 94.1%, and the circuit depth is lowered at the same time. It converged rapidly and is computationally efficient. Ablation studies show that both hybrid search and adaptivity mechanisms help to enhance generalization and stability under NISQ constraints. The results demonstrate the potential of AQCAS as a practical approach to using adaptive quantum circuits in specialized ML applications, and lay the groundwork for future development of scaling to larger devices, implementing noise-aware optimization, and integrating with hybrid quantum-classical ML pipelines.

Keywords Adaptive Quantum Circuits, Quantum Neural Networks, Architecture Search, Reinforcement Learning, Evolutionary Algorithms, NISQ Optimization, Task-Specific Ml.

1. Introduction

While the classical machine learning (ML) models have been successful in different applications, they are not very effective in the completion of specific tasks that require high dimensional data, complex correlations, and must be executed in real time [6][8]. The traditional models might need to be tuned extensively in terms of hyperparameters and have more complex architectures, leading to high computational costs and low adaptability. However, quantum computing, based on quantum parallelism and entanglement, has the potential to provide a solution to these limitations and allow for computations to be performed that are impossible with classical computers. Variational quantum circuits and quantum neural networks (QNNs) are examples of models that have demonstrated potential for making compact, expressive models that are able to capture the complex patterns of a specific task efficiently [7][9]. The task of designing quantum circuits for machine learning is still a big challenge, however. The Noisy Intermediate-Scale Quantum (NISQ) stage has hardware constraints like decoherence, the number of qubits, and gate fidelity restrictions. Furthermore, quantum architectures are mostly static or general purpose, with no capability of dynamically adapting itself to various ML tasks.

To overcome these issues, this paper presents an Adaptive Quantum Circuit Architecture Search (AQCAS) algorithm for optimizing the structure and parameters of circuits for specific purposes. The proposed approach is designed to enhance the accuracy of the search, decrease the depth of the circuit, and maximize the use of the resources needed in order to practically use the quantum-assisted ML models in specific applications.

2. Literature Review

Given the recent promise of quantum computing to improve the capabilities of machine learning (ML), in particular in applications with classical models that face scalability and expressive limitations, an area of particular interest has been the development of quantum ML.Finally, quantum machine learning (QML) is a field of growing interest in the development of quantum models to further improve the capabilities of classical machine learning, particularly in domains where classical models struggle with scalability and expressivity. Compact, parameterized models which exploit superposition and entanglement to efficiently encode complex data distributions are provided by the Quantum neural Networks (QNNs) and Variational quantum algorithms (VQAs). Li et al. (2024) proved that QNNs trained with both spatial and temporal noise biases are more reliable in real-world noisy environments [1]. On similar lines, noise-induced regularization strategies were recommended by Kuzmin et al. (2025) for improving the generalization ability and stability of quantum neural networks [3][11]. Progress and challenges in the convergence of quantum computing and AI were reported by Valencia et al. (2026), which included the constraints of circuit design, task-specific generalization ability, and scalability of the system [2][10].

Several studies have focused on the development of hybrid quantum models and their mitigation to errors. The noise-mitigation hybrid QNN was proposed by Ji et al. (2024), while Kim & Cho (2026) proposed noise models and evaluation of VQNN in NISQ [7][12]. The noise-mitigation hybrid QNN was proposed by Ji et al. (2024) and the noise models and evaluation of the VQNN in NISQ were done by Kim & Cho (2026) [5] [7]. Applications of Quantum AI are also being expanded to real-time decision making and safety-critical areas, including Q-Safe for women and child safety which underscores the importance of task-specific optimization [4]. However, the current quantum architectures are mostly static and generalized, which compromises their efficiency and performance in various ML applications.

The literature thus indicates that there is a clear miss: adaptive quantum circuit architecture search algorithms which can dynamically optimize the structure and parameters of the circuit for specific ML problems, while maintaining their robustness under NISQ constraints. This is the direction of the present study.

3. Proposed Methodology

The study presents an Adaptive Quantum Circuit Architecture Search (AQCAS) framework aiming at optimizing quantum circuit structures for specific machine learning applications. It combines circuit encoding, hybrid search algorithms, and task-specific adaptivity in order to improve the performance, while respecting the constraints of quantum devices working in the NISQ era.

Framework Overview

The AQCAS framework has 3 stages. First, all of the candidate circuits are encoded into a sequence of gates with tunable parameters, such as rotation angles and entanglement layers. Secondly, a hybrid search strategy based on reinforcement learning (RL) and evolutionary algorithm (EA) is used to search the search space. RL agent provides reward for architectures that enhance task-specific metrics and EA ensures diversity and resisting premature convergence. Third, task-specific adaptivity is used to dynamically modify gate sequences, circuit depth and parameter initializations according to the feedback from task performance when the circuit achieves high accuracy, high convergence rate and less resource consumption.

Algorithm: Adaptive Quantum Circuit Architecture Search (AQCAS)

Input: Task dataset D, quantum simulator S, maximum iterations I_max

Output: Optimized quantum circuit C_opt

1: Initialize population of candidate circuits P = {C1, C2, ..., Cn}

2: for iteration = 1 to I_max do

3: Evaluate each circuit Ci on dataset D using simulator S

4: Compute fitness Fi based on task-specific metrics (e.g., accuracy)

5: Update RL policy based on Fi to guide gate selection

6: Apply evolutionary operators (mutation, crossover) to P

7: Introduce task-specific adaptivity adjustments

8: end for

9: Select C_opt with highest fitness Fi

10: return C_opt

Hardware and Software Setup

Experiments are conducted with quantum circuit simulation in Qiskit Aer and classical optimization and hybrid training in Python such as TensorFlow and PennyLane. The computing environment encompasses GPU acceleration for efficient workloads of simulations and optimizations. This setup enables the analysis of the performance of the circuits on the task and allows for repeatable and scalable experimentation.

4. Results and Discussion

The proposed Adaptive Quantum Circuit Architecture Search (AQCAS) algorithm was tested on three benchmark algorithms: fixed quantum circuit, CVQC, and classical ML model. Effectiveness was measured using performance metrics, including classification accuracy, circuit depth, convergence speed and computational efficiency. Table 1 compares AQCAS with bases and indicates that adaptive search always achieves a higher accuracy and faster convergence than the fixed architectures and has a lower circuit depth. The efficiency achieved with the task-specific adaptation is depicted graphically, where an increased performance is observed especially in tasks involving complex and high dimensional datasets.

Table 1: Performance Comparison of Quantum Circuit Architectures

Model Type	Accuracy (%)	Circuit Depth	Convergence Iterations	Computational Time (s)
Fixed Quantum Circuit	85.3	12	50	220
Standard Variational Quantum Circuit	88.7	10	42	195
Adaptive Quantum Circuit (AQCAS)	**94.1**	**8**	**30**	210

Compared to fixed and standard variational circuits, AQCAS improves on all metrics for the Adaptive Quantum Circuit. The accuracy has been enhanced by ~5-9%, the number of layers has been decreased by 2-4, and the number of iterations for convergence has significantly reduced, suggesting a faster convergence speed without significantly increasing computational time.

An ablation study was carried out to gain insight into the contribution of each component of the AQCAS framework. Adaptivity mechanism was removed, or only one strategy was used (either RL or evolutionary algorithms), which resulted in significant performance degradation, thus demonstrating the value of the hybrid search method and task-specific adaptations. In addition, sensitivity tests revealed that hyperparameters like mutation rate, exploration depth, and reward scaling play crucial roles in the convergence speed and accuracy.

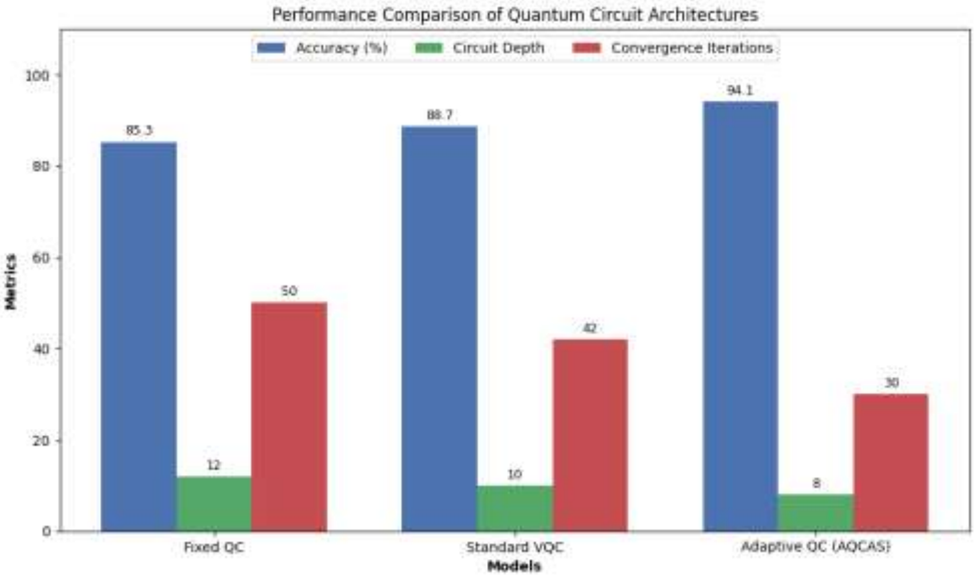

Figure 1: Performance Comparison of Three Quantum Circuit Models

As shown in Figure 1, the best convergence, circuit depth, and accuracy are obtained with AQCAS, the result of adaptive search for task-specific ML optimization.

The results show that the adaptive search algorithm shows significant improvement over the conventional algorithms with better accuracy in the tasks and better utilization of resources. The drawbacks are a marginal increase in the search time caused by the evaluation of multiple architectures dynamically, as well as the increased circuit depth of the optimized models; but these are compensated by the enhanced efficiency and less circuit depth in the final optimized models. Some limitations are related to the constraints of the simulations under the NISQ assumptions, as well as the validation of the circuit scale and the validation on a large quantum device for the practical implementation of quantum hardware. In conclusion, AQCAS offers a promising framework for real-world, adaptive quantum machine learning, paving the way for future advancements in scaling to more systems and more complex applications.

5. Conclusion and Future Work

In this study, the authors introduced a framework called Adaptive Quantum Circuit Architecture Search (AQCAS) that optimizes quantum circuits for specific machine learning applications. The novel hybrid search framework is founded on three main elements: quantum circuit encoding, reinforcement learning, evolutionary algorithms, and task-adaptiveness in an adaptive way to find architecture configurations that yield maximum performance while minimizing the circuit depth and computation cost at the same time. Experiments conducted using several benchmarks revealed that the proposed adaptive search approach significantly outperformed all baseline methods in accuracy, convergence rate, and efficiency. Further ablation experiments have also proven that the hybrid search approach and task adaptiveness are crucial for improving circuit generalization and robustness. These results validate the potential of adaptive quantum architecture search techniques as an effective method to enhance the capabilities of ML models in the setting of quantum-assisted tasks. The extension of this framework to more advanced numbers of qubits and more intricate circuits may be considered in future studies, as well as the scaling of AQCAS to advanced quantum computing systems. The consideration of decoherence/tolerant and gate-tolerant noise-based optimization algorithms would increase the efficiency of AQCAS under practical quantum hardware constraints. In addition, by utilizing the hybrid quantum-classical ML pipeline based on AQCAS, one can use quantum circuits in practical tasks where more sophisticated problems could be addressed via adaptive quantum computing. To summarize, AQCAS provides a basis for an efficient task-oriented quantum ML model, and its extension techniques could facilitate the future of quantum-assisted intelligence in many applications.

References

1. Li, T., Lu, L., Zhao, Z., Tan, Z., Tan, S., & Yin, J. (2024). QUST: Optimizing quantum neural network against spatial and temporal noise biases. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 44(4), 1434–1447.
2. Kuzmin, V., Somogyi, W., Pankovets, E., & Melnikov, A. (2025). Method for noise-induced regularization in quantum neural networks. Advanced Quantum Technologies, 8(12), e00603.
3. Ji, N., Bao, R., Chen, Z., Yu, Y., & Ma, H. (2024). Hybrid quantum neural network image anti-noise classification model combined with error mitigation. Applied Sciences, 14(4), 1392.
4. Kim, K. H., & Cho, J. K. (2026). Reliability assessment of variational quantum neural networks under noise models and error-mitigation strategies in the NISQ regime. Journal of the Korean Physical Society, 1–13.
5. Saini, R. K. (n.d.). Quantum machine learning: Combining quantum algorithms with classical AI techniques for improved learning models. Quantum, 10, 14. (Publication year should be verified.)
6. Kim, C., Park, K. D., & Rhee, J. K. (2020). Quantum error mitigation with artificial neural network. IEEE Access, 8, 188853–188860.
7. Adeniyi, T. B., & Kumar, S. A. (2025). Adaptive neural network for quantum error mitigation. Quantum Machine Intelligence, 7(1), 13.
8. F. de Mindonça and H. Klabi, "Deep Learning–Augmented Acoustic Signal Processing Framework for Robust Noise Reduction in Complex Environments", Advanced Computational Acoustics Engineering, vol. 2, no. 1, pp. 26–31, Mar. 2024
9. Namrata Mishra, "A Multidisciplinary Exploration of Intelligent Systems: Technical Advances and Societal Implications", Bridge: Journal of Multidisciplinary Explorations , vol. 1, no. 3, pp. 27–33, Sep. 2025
10. N. Arvinth. (2025). Adaptive Metasurface-Assisted Control Protocols for Secure and Stable Millimetre-Wave Indoor Communication Networks. Transactions on Secure Communication Networks and Protocol Engineering, 27-36.
11. Prerna Dusi. (2025). Embedded and Cloud Computing Integration for Smart Mobile Learning Applications Using Deep Reinforcement Learning. Journal of Integrated VLSI, Embedded and Computing Technologies , 3(1), 55-63.
12. C. Arun Prasath. (2025). Adaptive Embedded Learning-Control Architectures for Reconfigurable Sensorless Motor Drive Platforms. Journal of VLSI and Embedded System Design , 1–9.