Quantum Algorithm Analysis Framework

Forty studies present Python-based quantum analysis methods, with over half using Qiskit and IBM systems, covering statistical analysis, error mitigation, and advanced techniques like quantum tomography, while providing concrete implementations for algorithms such as QAOA and VQE.

Abstract

Forty studies report methods for analyzing quantum algorithm performance with Python. IBM quantum systems appear in 25 studies, and Qiskit is used in 21. Papers detail statistical techniques that measure fidelity, success and error probabilities, and distribution patterns. For example, one study applies a normalized Wasserstein distance to assess QAOA performance, while another reports fidelity improvements from 23% up to 234.6% via symmetry verification and Bayesian mitigation. Several works describe automated error mitigation workflows that reduce sampling overhead from more than 80 to about 5 and, in one case, achieve over 1000× improvement compared with alternative methods.

Advanced approaches extend to quantum tomography, volumetric benchmarking, and machine learning–based prediction. Studies on QAOA and VQE illustrate quantitative gains—improvements of 1.3–3× or 1.51–2.24× in fidelity—and underscore the benefits of concrete Python implementations and open-source tools for circuit analysis and visualization.

Paper search

Using your research question "I'm searching for research papers that describe methods for analyzing quantum algorithm results using Python and Qiskit. Specifically, I'm interested in: Papers that demonstrate statistical analysis techniques for quantum circuit execution results, including metrics like success rates, error rates, and distribution patterns. Research that shows how to compare quantum simulation results with real quantum hardware execution, particularly focusing on noise models and error mitigation strategies. Studies that propose frameworks or libraries for automated analysis of quantum algorithm performance, including visualization techniques and benchmarking methodologies. Papers that demonstrate advanced analysis techniques beyond basic statistics, such as fidelity measures, quantum tomography, or other quantum-specific metrics. Research focusing on how to analyze the results of specific quantum algorithms (like QAOA, VQE, or Grover's) with concrete Python implementation examples. The goal is to develop a comprehensive analysis framework that incorporates best practices from the literature, building on existing tools in Qiskit while adding specialized analysis capabilities tailored to specific quantum algorithms. I'm particularly interested in papers published within the last 3-5 years that include open-source code repositories or Jupyter notebooks demonstrating their analysis techniques.", we searched across over 126 million academic papers from the Semantic Scholar corpus. We retrieved the 490 papers most relevant to the query.

Screening

We screened in papers that met these criteria:

- **Implementation Methods**: Does the study present analysis methods for quantum algorithm results with concrete implementation examples using Python and/or Qiskit?
- **Analysis Techniques**: Does the research present quantum-specific metrics or statistical analysis techniques specifically designed for quantum circuit execution results?

- **Hardware Validation**: Does the study include comparison between quantum simulation results and real quantum hardware execution, OR present error mitigation and noise analysis methods?
- **Analysis Tools**: Does the paper describe frameworks, libraries, or tools for quantum algorithm analysis with demonstrated practical applications?
- **Algorithm Analysis**: Does the research involve specific quantum algorithms (such as QAOA, VQE, or Grover's) with clearly described analysis methodology?
- **Methodology Documentation**: Does the study include clear methodology descriptions AND experimental validation of the proposed methods?
- **Quantum Context**: Does the paper present analysis methods specifically designed for quantum computing (not solely classical computing methods)?

We considered all screening questions together and made a holistic judgement about whether to screen in each paper.

Data extraction

We asked a large language model to extract each data column below from each paper. We gave the model the extraction instructions shown below for each column.

- **Quantum Computing Framework Used**:

  Identify and list all quantum computing frameworks mentioned in the study (e.g., Qiskit, PennyLane, TensorFlow Quantum).

- If multiple frameworks are used, list them all in order of primary usage
- Include version numbers if explicitly stated
- If no specific framework is mentioned, write "Not specified"
- Note any unique features or specific implementations of the framework in this study

- **Quantum Algorithm Type and Specific Implementation**:

  Describe the specific quantum algorithm(s) studied:

- Name of the algorithm (e.g., QAOA, VQF, VQC, QSVM)
- Number of qubits used
- Circuit depth
- Specific encoding method (if applicable, e.g., Amplitude Encoding, Angle Encoding)
- Any unique ansatz or circuit design details If multiple algorithms are discussed, list each separately

- **Quantum Hardware and Simulation Environment**:

  Capture details about the computational environment:

- Type of quantum hardware used (e.g., superconducting processor, trapped ion processor)
- Specific hardware model or processor name
- Classical computing specifications (if provided):
  - Processor type
  - RAM
  - GPU details
- Simulation vs. actual hardware execution breakdown
- Noise models or error mitigation strategies employed

- **Performance Metrics and Analysis Techniques**:

  List and describe all performance metrics used:

- Quantum-specific metrics (e.g., success probability, fidelity, error rates)
- Statistical analysis techniques
- Visualization methods
- Benchmarking approaches
- Specific quantum error characterization methods

For each metric:

- Provide the exact value if reported
- Note the section of the paper where the metric is discussed
- Highlight any novel or unique analysis techniques

- **Key Quantitative Findings**:

  Extract the most significant quantitative results:

- Precise numerical outcomes
- Statistical significance (p-values, confidence intervals)
- Comparative performance metrics
- Improvements over classical approaches

Format requirements:

- Use exact numbers from the paper
- Include units and statistical significance indicators
- If multiple key findings exist, list them in order of importance
- Note any limitations or caveats mentioned by the authors

Results

Characteristics of Included Studies

Study	Study Focus (Analysis Type)	Hardware Platform	Implementation Framework	Key Contributions	Full text retrieved
Aseguinolaza et al., 2023	Error estimation in quantum computers	IBM quantum computers	Qiskit	Tool for estimating total error probability in quantum circuits	Yes

Study	Study Focus (Analysis Type)	Hardware Platform	Implementation Framework	Key Contributions	Full text retrieved
Baker and Radha, 2022	Quantum Approximate Optimization Algorithm (QAOA) performance analysis	Trapped ion quantum processor	No mention found	Wasserstein distance as a performance metric for QAOA	No
Ball et al., 2020	Quantum control and error suppression	Trapped-ion and superconducting hardware	Python, TensorFlow, Qiskit, pyQuil, Cirq	Software tools for quantum control optimization	Yes
Blunt et al., 2023	Statistical phase estimation and error mitigation	Rigetti's superconducting processors	No mention found	Statistical phase estimation with error mitigation techniques	No
Bultrini et al., 2021	Quantum error mitigation techniques	Trapped-ion quantum computer	No mention found	Unified framework for error mitigation (UNITED)	Yes
Buonaiuto et al., 2024	Variational quantum learning algorithms	IBM quantum computers	Qiskit	Analysis of hardware properties on Variational Quantum Algorithm (VQA) performance	Yes
Cîrstoiu et al., 2022	Volumetric benchmarking of error mitigation	IBM superconducting processors	Qermit, Mitiq	Qermit framework for error mitigation benchmarking	Yes
Dahlhauser and Humble, 2020	Modeling noisy quantum circuits	Superconducting transmon devices	No mention found	Test-driven approach for characterizing Noisy Intermediate-Scale Quantum (NISQ) programs	No

Study	Study Focus (Analysis Type)	Hardware Platform	Implementation Framework	Key Contributions	Full text retrieved
Kakkar et al., 2022	Error mitigation in QAOA	Superconducting and IonQ trapped ion processors	No mention found	Symmetry verification for error mitigation in QAOA	Yes
Karamlou et al., 2020	Variational quantum factoring analysis	IBM superconducting processor	No mention found	Analysis of Variational Quantum Factoring (VQF) algorithm performance on real hardware	Yes
Khan et al., 2024	Quantum machine learning frameworks	IBM Quantum's Falcon r5.11 processor	PennyLane, TensorFlow Quantum, Qiskit	Comparative analysis of Quantum Machine Learning (QML) frameworks	No
Khare et al., 2023	Parallelizing quantum-classical workloads	IBM Quantum Cloud	Qiskit	Techniques for splitting and parallelizing quantum workloads	Yes
Kharkov et al., 2022	Automated benchmarking for quantum compilers	No mention found	IBM Qiskit, CQC Tket, Google Cirq, Rigetti Quilc, PyZX	Arline Benchmarks for quantum compiler evaluation	No
Lao and Browne, 2021	Quantum compiler for Hamiltonian simulation	Google Sycamore, IBM Quantum Experience Montreal, Rigetti Aspen	t	ket, Qiskit, Cirq	Yes
Li et al., 2020	Low-level quantum benchmark suite	IBM Quantum Experience, Rigetti, IonQ	Qiskit, Cirq, Scaffold, ProjectQ	QASMBench for NISQ device evaluation	Yes

Study	Study Focus (Analysis Type)	Hardware Platform	Implementation Framework	Key Contributions	Full text retrieved
Lubinski et al., ”Quantum Algorithm Exploration”	Application-oriented performance benchmarks	No mention found	No mention found	QED-C suite of application-oriented benchmarks	No
Ma et al., 2020	Adaptive circuit learning for quantum metrology	IBM quantum computer ”Paris”	No mention found	Variational algorithm for optimizing quantum sensing circuits	Yes
Maciejewski et al., ”Modeling and Mitigation of Readout Noise”	Modeling and mitigating readout noise	IBM's and Rigetti's devices	Qiskit, pyQuil	Correlated measurement noise model and mitigation	No
McDonough et al., 2022	Automated quantum error mitigation	Rigetti Aspen-11	Qiskit, PyGSTi, Mitiq	Automated framework for probabilistic error reduction	Yes
Mesman et al., 2023	Profiling quantum control stacks	Qblox Cluster (simulated)	Quantify, Qiskit	Q-Profile tool for profiling quantum control stacks	Yes
Mundada et al., 2022	Automated deterministic error-suppression	IBM hardware	No mention found	Workflow for deterministic error suppression	No
Peters et al., 2021	Machine learning on noisy quantum processor	Google Sycamore processor	TensorFlow Quantum (TFQ)	Quantum kernel classifier for high-dimensional data	Yes
Ravi et al., 2022	Dynamic noise landscape navigation	IBM Quantum Experience machines	Qiskit	QISMET for mitigating transient errors in VQAs	Yes
Rogers et al., 2021	Error mitigation in Variational Quantum Eigensolver (VQE)	IBM Quantum Experience	Qiskit	Tailored probabilistic machine learning for VQE error mitigation	Yes

Study	Study Focus (Analysis Type)	Hardware Platform	Implementation Framework	Key Contributions	Full text retrieved
Rudolph et al., ”ORQVIZ”	Visualizing VQA landscapes	No mention found	No mention found	ORQVIZ package for visualizing VQA landscapes	No
Saib et al., 2021	Noise effects on variational algorithms	IBM superconducting processor	Qiskit	Analysis of hardware efficient ansatze under noise	Yes
Saki et al., ”Hypothesis Testing for Error Mitigation”	Evaluating error mitigation techniques	IBM quantum computers	No mention found	Hypothesis testing framework for error mitigation	No
Shaydulin and Galda, 2021	Error mitigation in quantum optimization	IBM Quantum Falcon processors	Qiskit	Symmetry-based error mitigation for QAOA	Yes
Stein et al., ”Quantum Bayesian Error Mitigation”	Quantum Bayesian error mitigation	IBM Quantum Experience quantum processors	No mention found	Q-Beep approach for Bayesian error mitigation	No
Stein et al., 2022	Quantum Bayesian error mitigation	IBM Quantum Experience quantum processors	No mention found	Q-Beep framework for error mitigation	No
Stein et al., 2024	CUDA-accelerated QAOA simulation	Simulation only	CUAOA (custom CUDA implementation)	CUAOA framework for fast QAOA simulation	Yes
Sturm, 2023	QAOA theory and implementation	IBM quantum computer (ibmq_ehningen)	Qiskit	Comprehensive guide to QAOA implementation	No
Sud et al., 2021	Noise characterization framework	Rigetti's Aspen-9 and Aspen-11	Rigetti PyQuil, HybridQ, QuTiP	Dual-map framework for noise characterization	Yes
Tan et al., 2023	Quantum circuit analysis framework	Custom superconducting devices	Qiskit	QuCT framework for quantum circuit analysis	Yes

Study	Study Focus (Analysis Type)	Hardware Platform	Implementation Framework	Key Contributions	Full text retrieved
Wang et al., 2021	Noise-adaptive quantum circuit search	IBM Quantum Experience quantum computers	TorchQuantum, Qiskit, PennyLane	QuantumNAS framework for robust circuit design	Yes
Wang et al., 2022	Robust quantum circuits case study	IBM superconducting processors	TorchQuantum	TorchQuantum for quantum circuit fidelity prediction	Yes
Woerner and Egger, 2018	Quantum risk analysis	IBM Quantum Experience	Qiskit	Quantum algorithm for financial risk analysis	Yes
Woodrum et al., 2024	Machine learning for quantum phase estimation	IBM Quantum Experience_perth	Qiskit	Machine Learning models for improving Quantum Phase Estimation (QPE) accuracy	Yes
Zhang et al., ”Comparative Analysis of Error Mitigation”	Comparative error mitigation analysis	IBM quantum system	No mention found	Comparison of error mitigation techniques for VQE	No
Zhang et al., 2023	Dynamic iteration skipping for VQAs	IBM Quantum Processing Units (QPUs)	Qiskit	DISQ framework for handling noise drift in VQAs	Yes

Our analysis of 40 studies on quantum computing implementations revealed:

- Hardware Platforms :
  - We found IBM quantum systems mentioned in 25 of the 40 studies, making them the most frequently cited hardware platform in our analysis.
  - Superconducting processors were mentioned in 9 studies.
  - Rigetti and trapped ion systems were mentioned in 6 and 4 studies, respectively.
  - We found 2 studies each mentioning Google systems or simulations.
  - We didn't find mention of the hardware platform in 3 studies.
- Implementation Frameworks :

  - Qiskit was the most frequently mentioned framework, appearing in 21 studies.
  - Cirq and pyQuil were mentioned in 4 and 3 studies, respectively.
  - We didn't find mention of the implementation framework in 14 studies.
  - 21 studies mentioned other frameworks, including custom implementations and less common tools.

- Key Contributions :
  - Error mitigation was the most common focus, addressed in 15 studies.
  - Benchmarking techniques were developed in 4 studies.
  - Performance analysis and machine learning applications were each found in 3 studies.
  - 2 studies focused on circuit analysis or design.
  - The remaining studies covered a wide range of topics, including optimization, visualization, financial analysis, and profiling of quantum systems.

Our analysis revealed a diverse range of hardware platforms and implementation frameworks, with a notable emphasis on error mitigation strategies across various quantum computing applications. The prevalence of IBM quantum systems and the Qiskit framework in the studies we examined suggests their significant role in current quantum computing research.

Analysis Frameworks and Methods

Statistical Analysis Techniques

Analysis Method	Application Context	Implementation Approach	Performance Metrics
Wasserstein distance	QAOA performance evaluation	Quantum Alternating Operator Ansatz	Normalized and Complementary Wasserstein Distance ( )
Total error probability estimation	General quantum circuits	Custom tool (TED-qc)	Fidelity, success probability
Volumetric benchmarking	Error mitigation techniques	Qermit framework	Absolute error, relative error of mitigation
Bayesian error mitigation	General quantum circuits	Q-Beep framework	Circuit execution fidelity
Machine learning-based prediction	Quantum kernel methods	TensorFlow Quantum	Classification accuracy, fidelity
Hypothesis testing	Error mitigation evaluation	Custom framework	Resource requirement, mitigation efficiency
Quantum tomography	Noise characterization	Dual-map framework	Fidelity, correlations in Pauli expectation values
Graph-based circuit analysis	Quantum circuit optimization	QuCT framework	Fidelity prediction accuracy
Probabilistic error reduction	Automated error mitigation	Custom software package	Expectation values, sampling overhead
Dynamic iteration skipping	Variational quantum algorithms	DISQ framework	Fidelity improvement, noise detection speed

Our analysis identified 10 different analysis methods for quantum computing performance evaluation across the studies we examined:

- Analysis Methods :
  - We found 10 distinct analysis methods, each appearing in one study.
  - These methods ranged from mathematical approaches (e.g., Wasserstein distance) to machine learning-based techniques and custom frameworks for error mitigation and circuit analysis.
- Application Contexts :
  - We found 3 studies focusing on error mitigation.
  - 2 studies addressed general quantum circuits.
  - 5 other contexts were each addressed by 1 study: QAOA, quantum kernel methods, noise characterization, circuit optimization, and variational quantum algorithms.
- Implementation Approaches :
  - We found 5 studies using frameworks for implementation.
  - 4 studies used custom implementations.
  - 1 study used an existing platform (TensorFlow Quantum).
- Performance Metrics :
  - Fidelity was the most commonly mentioned metric, appearing in 6 studies.
  - Accuracy was mentioned in 2 studies.
  - We found 9 other metrics each mentioned in 1 study: error, probability, distance-based measures, expectation values, overhead, resource requirements, efficiency, correlation, and speed.

Our analysis revealed a diverse range of approaches in evaluating quantum computing performance, with no clear standardization across studies. This diversity suggests a field still in active development, with researchers exploring various methods to address the challenges of quantum computing performance evaluation.

Error Characterization and Mitigation

Study	Error Characterization Method	Mitigation Strategy	Reported Improvement
Aseguinolaza et al., 2023	Total error probability estimation	Error mitigation techniques in Qiskit	Analysis satisfactory in >99% of cases
Blunt et al., 2023	Statistical phase estimation	Zero-noise extrapolation, readout error mitigation	1-2 orders of magnitude improvement in accuracy
Bultrini et al., 2021	Unified error mitigation framework	Zero-noise extrapolation, Clifford data regression, virtual distillation	Most accurate mitigation for largest shot budget (10^10)
Cîrstoiu et al., 2022	Volumetric benchmarking	Zero-noise extrapolation, Clifford data regression	Varied performance across circuit sizes and devices

Study	Error Characterization Method	Mitigation Strategy	Reported Improvement
Kakkar et al., 2022	Symmetry verification	Leveraging problem symmetries	Up to 19.2% improvement in QAOA objective
McDonough et al., 2022	Probabilistic error reduction	Automated error mitigation workflow	Reduced sampling overhead from >80 to about 5
Mundada et al., 2022	Deterministic error suppression	Automated workflow for gate-level to circuit execution	>1000X improvement over alternative techniques
Rogers et al., 2021	Tailored probabilistic machine learning	Gaussian process regression in active learning framework	Fidelity improvement from 0.888 to 0.945
Shaydulin and Galda, 2021	Symmetry-based error mitigation	Leveraging global bit-flip symmetry	23% average improvement in quantum state fidelity
Stein et al., 2022	Quantum Bayesian error mitigation	Iterative algorithm over Bayesian network state-graph	Up to 234.6% fidelity improvement on certain circuits

Our analysis of error characterization and mitigation strategies revealed:

- Error Characterization Methods :
  - We identified 10 different error characterization methods across the 10 studies we examined, with no method appearing in more than one study.
  - These methods ranged from statistical approaches to machine learning-based techniques and custom frameworks.
- Mitigation Strategies :
  - Zero-noise extrapolation was the most frequently mentioned strategy, appearing in 3 studies.
  - Clifford data regression and automated workflows were each mentioned in 2 studies.
  - We found 8 other strategies each mentioned in 1 study, including symmetry-based approaches and machine learning techniques.
- Reported Improvements :
  - 3 studies reported fidelity improvements, ranging from 23% to 234.6%.
  - 1 study reported >1000X improvement over alternative techniques.
  - 1 study reported 1-2 orders of magnitude improvement in accuracy.
  - Other improvements included reduced sampling overhead, up to 19.2% improvement in QAOA objective, and >99% satisfactory analysis.
  - 1 study reported varied performance across circuit sizes and devices.

Our analysis revealed a wide range of approaches to error characterization and mitigation in quantum computing, with researchers exploring diverse strategies to address the challenges of quantum noise and errors.

The lack of standardized metrics for comparing improvements across studies presents a challenge in assessing the relative effectiveness of different approaches. This diversity in methods and reported improvements suggests a field still in active development, with ongoing efforts to establish best practices for error mitigation in quantum computing.

Advanced Metrics and Measurements

Study	Advanced Metric	Measurement Technique	Application
Baker and Radha, 2022	Wasserstein distance	Quantum circuit evaluation	QAOA performance assessment
Li et al., 2020	Circuit width, depth, gate density, retention lifespan	QASMBench suite	NISQ device evaluation
Ma et al., 2020	Signal-to-Noise Ratio, Classical/Quantum Fisher Information	Adaptive circuit learning	Quantum metrology
Peters et al., 2021	Quantum kernel classifier accuracy	Machine learning on quantum processor	High-dimensional data classification
Rudolph et al., "ORQVIZ"	High-dimensional landscape visualization	ORQVIZ package	Variational quantum algorithm analysis
Saib et al., 2021	Expressibility	Parameterized quantum circuit evaluation	Variational algorithm performance prediction
Sud et al., 2021	Marginal noise channel characterization	Dual-map framework	Quantum computer noise analysis
Tan et al., 2023	Contextual and topological features	QuCT framework	Quantum circuit analysis and optimization
Wang et al., 2021	Noise-adaptive circuit performance	QuantumNAS framework	Robust quantum circuit design
Woodrum et al., 2024	Machine learning model accuracy for QPE	Classical Machine Learning models	Quantum Phase Estimation improvement

Our analysis of advanced metrics and measurements in quantum computing research revealed:

- Advanced Metrics :
  - Our analysis identified 11 different advanced metrics across the 10 studies we examined, with no metric appearing in more than one study.
  - These metrics ranged from mathematical distances (e.g., Wasserstein distance) to circuit characteristics, information-theoretic measures (e.g., Fisher Information), and machine learning model accuracies.
- Measurement Techniques :
  - We identified 10 distinct measurement techniques, each used in one study.
  - These techniques included various frameworks (e.g., QuCT, QuantumNAS), suites (QASMBench), and approaches such as adaptive circuit learning and classical machine learning models.

- Applications :
  - We found 10 different applications across the 10 studies we examined.
  - These applications covered various aspects of quantum computing, including algorithm performance assessment (e.g., QAOA, VQA), device evaluation (NISQ), quantum metrology, data classification, circuit design and optimization, and noise analysis.

Our analysis revealed a wide range of advanced metrics and measurement techniques being explored in quantum computing research. The diversity of approaches suggests a field still in active development, with researchers exploring various methods to evaluate and analyze quantum computing systems and algorithms. This lack of standardization in metrics and measurement techniques presents both opportunities for innovation and challenges in comparing results across different studies and hardware platforms.

Algorithm-Specific Analysis Patterns

Quantum Approximate Optimization Algorithm (QAOA) and Variational Quantum Eigensolver (VQE) Analysis Methods

Study	Algorithm	Analysis Method	Key Findings
Baker and Radha, 2022	QAOA	Wasserstein distance metric	Peak solution quality at specific circuit depths; variability in performance as a benchmark
Buonaiuto et al., 2024	VQE	Hardware property impact analysis	Influence of quantum hardware topology on VQA performance
Kakkar et al., 2022	QAOA	Symmetry verification	Up to 19.2% improvement in QAOA objective on IonQ processor
Ravi et al., 2022	VQE	Dynamic noise landscape navigation (QISMET)	1.3x-3x fidelity improvement over traditional VQA baselines
Rogers et al., 2021	VQE	Tailored probabilistic machine learning	Fidelity improvement from 0.888 to 0.945
Saib et al., 2021	VQE	Hardware efficient ansatz analysis	Weak correlation between expressibility and VQE performance
Shaydulin and Galda, 2021	QAOA	Symmetry-based error mitigation	23% average improvement in quantum state fidelity
Stein et al., 2024	QAOA	CUDA-accelerated simulation (CUAOA)	Multiple orders of magnitude speedup in runtime for small to medium problems

Study	Algorithm	Analysis Method	Key Findings
Zhang et al., ”Comparative Analysis of Error Mitigation”	VQE	Comparative error mitigation analysis	Effectiveness of different error mitigation techniques for VQE
Zhang et al., 2023	VQE	Dynamic iteration skipping (DISQ)	1.51-2.24× fidelity improvement over traditional baseline

Our analysis of QAOA and VQE studies revealed:

- Algorithms Studied :
  - Our analysis identified two main algorithms studied across the 10 papers we examined:
    * Variational Quantum Eigensolver (VQE) in 6 studies
    * Quantum Approximate Optimization Algorithm (QAOA) in 4 studies
- Analysis Methods :
  - We found 9 different approaches across the studies:
    * Error mitigation was the most frequently mentioned, appearing in 2 studies
    * Other methods (e.g., Wasserstein distance, hardware impact analysis, symmetry verification) were each mentioned in 1 study
- Key Findings :
  - Fidelity improvement was the most commonly reported finding, mentioned in 4 studies
  - Other findings included QAOA improvement, runtime speedup, and impacts of hardware topology
  - We found quantitative improvements ranging from 19.2% for QAOA objective to 1.3x-3x and 1.51-2.24× for fidelity improvements
- Comparison Challenges :
  - We didn't find consistent metrics or benchmarks across studies, making direct comparisons challenging
  - This lack of standardization suggests a need for more unified evaluation methods in QAOA and VQE research

Our analysis revealed a diverse range of analysis methods and reported improvements for QAOA and VQE algorithms. The variety of approaches and metrics used across studies highlights the complexity of evaluating quantum algorithm performance on different hardware platforms and under various noise conditions. This diversity also presents challenges in comparing results across studies and establishing standardized benchmarks for algorithm performance.

Phase Estimation and Tomography

Study	Technique	Application	Key Results
Blunt et al., 2023	Statistical phase estimation	Chemistry problems	1-2orders of magnitude improvement in energy estimate accuracy
Maciejewski et al., ”Modeling and Mitigation of Readout Noise”	Quantum Overlapping Tomography	Readout noise characterization	Correlated measurement noise model with >22x error reduction
Sud et al., 2021	Dual-map framework	Noise characterization	High fidelity (>95%) reconstruction of non-local noise
Woodrum et al., 2024	Machine learning for QPE	2-5 qubit phase estimation	6x-36x improvement in model performance

Our analysis of phase estimation and tomography studies revealed:

- Techniques :
  - Our analysis identified four different techniques across the studies we examined:
    - Statistical phase estimation
    - Quantum Overlapping Tomography
    - Dual-map framework
    - Machine learning for Quantum Phase Estimation (QPE)
- Applications :
  - We found 2 studies focusing on noise characterization
  - We found 1 study each for chemistry problems and phase estimation
- Key Results :
  - All studies reported significant improvements in their key results:
    - 1 study reported 1-2 orders of magnitude improvement in energy estimate accuracy
    - 1 study showed >22x error reduction
    - 1 study achieved high fidelity (>95%) reconstruction of non-local noise
    - 1 study demonstrated 6x-36x improvement in model performance

Our analysis revealed a diverse range of techniques and applications in phase estimation and tomography research. The significant improvements reported across all studies suggest the potential of these advanced techniques in enhancing the accuracy and reliability of quantum measurements and noise characterization. However, the lack of overlapping techniques or applications across studies presents challenges in directly comparing the effectiveness of different approaches. This diversity highlights the need for more standardized benchmarks and evaluation methods in quantum phase estimation and tomography research.

Search and Optimization Algorithms

Study	Algorithm Type	Analysis Requirements	Error Mitigation Strategy	Implementation Tools
Karamlou et al., 2020	Variational Quantum Factoring (VQF)	Success rate analysis, energy surface optimization	Characterization of incoherent and coherent errors	No mention found
Khare et al., 2023	Variational Quantum Eigensolver (VQE), Quantum Support Vector Machine (QSVM)	Energy level, accuracy, resource footprint	Circuit cutting, data parallelization	Qiskit
Lao and Browne, 2021	2-local qubit Hamiltonian simulation	SWAP count, gate count, circuit depth	Permutation-aware optimization	t
Peters et al., 2021	Quantum kernel classifier	Classification accuracy, fidelity	Error mitigation techniques (not reliably improving performance)	TensorFlow Quantum
Wang et al., 2021	QuantumNAS	Classification accuracy, expectation values	Noise-adaptive circuit search	TorchQuantum, Qiskit, PennyLane
Woerner and Egger, 2018	Quantum Amplitude Estimation	Success probability, estimation error bound	No mention found	Qiskit

Our analysis of search and optimization algorithms revealed:

- Algorithm Types :
  - Our analysis identified 7 different algorithm types across the 6 studies we examined, with no algorithm type appearing in more than one study.
  - These included Variational Quantum Factoring (VQF), Variational Quantum Eigensolver (VQE), Quantum Support Vector Machine (QSVM), Hamiltonian simulation, quantum kernel classifiers, and Quantum Amplitude Estimation.
- Analysis Requirements :
  - We found a wide range of analysis requirements across studies:
    * Classification accuracy was the most frequently mentioned, appearing in 2 studies.
    * We found 11 other analysis requirements each mentioned in 1 study, including energy-related measures (optimization, level), resource measures (footprint, SWAP count, gate count, circuit depth), and performance measures (success rate, accuracy, fidelity, expectation values, error bound).
- Error Mitigation Strategies :
  - We found error mitigation strategies mentioned in 5 out of 6 studies:

    - Each study used a different approach, including error characterization, circuit cutting, data parallelization, permutation-aware optimization, and noise-adaptive circuit search.
    - For 1 study, we found that error mitigation techniques were used but not specified to reliably improve performance.
    - We didn't find information on error mitigation strategies for 1 study.

- Implementation Tools :
  - Implementation tools were specified in 4 out of 6 studies:
    - Qiskit was the most frequently mentioned, appearing in 3 studies.
    - TensorFlow Quantum and PennyLane were each mentioned in 1 study.
    - We didn't find implementation tool information for 2 studies.

Our analysis revealed a diverse range of search and optimization algorithms being explored in quantum computing research. The variety of algorithm types, analysis requirements, and error mitigation strategies suggests a field still in active development, with researchers exploring various approaches to address the challenges of quantum search and optimization. The lack of standardization in analysis requirements and error mitigation strategies presentsboth opportunities for innovation and challenges in comparing results across different studies and algorithms.

References

Abdullah Ash Saki, Amara Katabarwa, Salonik Resch, and George Umbrarescu. "Hypothesis Testing for Error Mitigation: How to Evaluate Error Mitigation," 2023.

Amir H. Karamlou, W. Simon, Amara Katabarwa, Travis L. Scholten, B. Peropadre, and Yudong Cao. "Analyzing the Performance of Variational Quantum Factoring on a Superconducting Quantum Processor." *Npj Quantum Information*, 2020.

Andreas Sturm. "Theory and Implementation of the Quantum Approximate Optimization Algorithm: A Comprehensible Introduction and Case Study Using Qiskit and IBM Quantum Computers," 2023.

Ang Li, S. Stein, S. Krishnamoorthy, and James Ang. "QASMBench: A Low-Level Quantum Benchmark Suite for NISQ Evaluation and Simulation." *ACM Transactions on Quantum Computing*, 2020.

Ashish Kakkar, Jeffrey Larson, A. Galda, and Ruslan Shaydulin. "Characterizing Error Mitigation by Symmetry Verification in QAOA." *International Conference on Quantum Computing and Engineering*, 2022.

Benjamin McDonough, A. Mari, Nathan Shammah, N. Stemen, Misty Wahl, W. Zeng, and P. P. Orth. "Automated Quantum Error Mitigation Based on Probabilistic Error Reduction." *2022 IEEE/ACM Third International Workshop on Quantum Computing Software (QCS)*, 2022.

C. Cîrstoiu, Silas Dilkes, Daniel Mills, Seyon Sivarajah, and Ross Duncan. "Volumetric Benchmarking of Error Mitigation with Qermit." *Quantum*, 2022.

Charles Woodrum, Torrey Wagner, and David Weeks. "Improving 2-5 Qubit Quantum Phase Estimation Circuits Using Machine Learning." *Algorithms*, 2024.

D. Bultrini, Max Hunter Gordon, Piotr Czarnik, A. Arrasmith, M. Cerezo, Patrick J. Coles, and L. Cincio. "Unifying and Benchmarking State-of-the-Art Quantum Error Mitigation Techniques." *Quantum*, 2021.

E. Peters, J. Caldeira, A. Ho, Stefan Leichenauer, M. Mohseni, H. Neven, P. Spentzouris, D. Strain, and G. Perdue. "Machine Learning of High Dimensional Data on a Noisy Quantum Processor." *Npj Quantum Information*, 2021.

Filip B. Maciejewski, F. Baccari, Z. Zimborás, and Michał Oszmaniec. "Modeling and Mitigation of Realistic

Readout Noise with Applications to the Quantum Approximate Optimization Algorithm," 2021.

Giuseppe Buonaiuto, Francesco Gargiulo, G. De Pietro, M. Esposito, and Marco Pota. "The Effects of Quantum Hardware Properties on the Performances of Variational Quantum Learning Algorithms." *Quantum Machine Intelligence*, 2024.

Gokul Subramanian Ravi, Kaitlin N. Smith, Jonathan M. Baker, T. Kannan, N. Earnest, Ali Javadi-Abhari, Henry Hoffmann, and F. Chong. "Navigating the Dynamic Noise Landscape of Variational Quantum Algorithms with QISMET." *International Conference on Architectural Support for Programming Languages and Operating Systems*, 2022.

H. Ball, M. Biercuk, A. Carvalho, Rajib Chakravorty, Jiayin Chen, L. A. Castro, Steven Gore, et al. "Software Tools for Quantum Control: Improving Quantum Computer Performance Through Noise and Error Suppression." *Quantum Science and Technology*, 2020.

Hanrui Wang, Pengyu Liu, Jinglei Cheng, Zhiding Liang, Jiaqi Gu, Zi-Chen Li, Yongshan Ding, et al. "TorchQuantum Case Study for Robust Quantum Circuits (Invited Paper)." *2022 IEEE/ACM International Conference On Computer Aided Design (ICCAD)*, 2022.

Hanrui Wang, Yongshan Ding, Jiaqi Gu, Yujun Lin, D. Pan, F. Chong, and Song Han. "QuantumNAS: Noise-Adaptive Search for Robust Quantum Circuits." *International Symposium on High-Performance Computer Architecture*, 2021.

J. Baker, and Santosh Kumar Radha. "Wasserstein Solution Quality and the Quantum Approximate Optimization Algorithm: A Portfolio Optimization Case Study," 2022.

James Sud, Jeffrey Marshall, Zhihui Wang, E. Rieffel, and F. Wudarski. "Dual-Map Framework for Noise Characterization of Quantum Computers." *Physical Review A*, 2021.

John Rogers, Tao Jiang, Marius S Frank, O. Christiansen, Yongxin Yao, and Nicola Lanatà. "Error Mitigation in Variational Quantum Eigensolvers Using Tailored Probabilistic Machine Learning." *Physical Review Research*, 2021.

Jonas Stein, Jonas Blenninger, David Bucher, Josef Peter Eder, Elif cCetiner, Maximilian Zorn, and Claudia Linnhoff-Popien. "CUAOA: A Novel CUDA-Accelerated Simulation Framework for the QAOA." *International Conference on Quantum Computing and Engineering*, 2024.

Junyao Zhang, Hanrui Wang, Gokul Subramanian Ravi, F. Chong, Song Han, F. Mueller, Yiran Chen, and E. X. P. V. A. l. "DISQ: Dynamic Iteration Skipping for Variational Quantum Algorithms." *International Conference on Quantum Computing and Engineering*, 2023.

Koen J. Mesman, F. Battistel, Edgar Reehuis, D. D. Jong, M. Tiggelman, Jordy Gloudemans, J. V. Oven, and C. C. Bultink. "Q-Profile: Profiling Tool for Quantum Control Stacks Applied to the Quantum Approximate Optimization Algorithm." *2024 IEEE International Conference on Quantum Software (QSW)*, 2023.

L. Lao, and D. Browne. "2QAN: A Quantum Compiler for 2-Local Qubit Hamiltonian Simulation Algorithms." *International Symposium on Computer Architecture*, 2021.

Manuel S. Rudolph, Sukin Sim, A. Raza, Michal Stechly, J. McClean, Eric R. Anschuetz, Luis Serrano, and A. Perdomo-Ortiz. "ORQVIZ: Visualizing High-Dimensional Landscapes in Variational Quantum Algorithms," 2021.

Megan L. Dahlhauser, and T. Humble. "Modeling Noisy Quantum Circuits Using Experimental Characterization." *Physical Review A*, 2020.

Muhammad Jawad Khan, Sumeera Bibi, Muzammil Ahmad Khan, Hozaifah Shahadat Ali, Aysha Ijaz Khan, Rajia Anwar, and Fariha Islam. "Investigating Quantum Machine Learning Frameworks and Simulating Quantum Approaches." *The Asian Bulletin of Big Data Management*, 2024.

N. S. Blunt, Laura Caune, R'obert Izs'ak, E. Campbell, and Nicole Holzmann. "Statistical Phase Estimation and Error Mitigation on a Superconducting Quantum Processor." *PRX Quantum*, 2023.

Pranav S. Mundada, Aaron Barbosa, Smarak Maity, Yulun Wang, Thomas Merkh, T. Stace, Felicity F. Nielson, et al. “Experimental Benchmarking of an Automated Deterministic Error-Suppression Workflow for Quantum Algorithms.” *Physical Review Applied*, 2022.

Ruslan Shaydulin, and A. Galda. “Error Mitigation for Deep Quantum Optimization Circuits by Leveraging Problem Symmetries.” *International Conference on Quantum Computing and Engineering*, 2021.

S. Stein, N. Wiebe, Yufei Ding, James Ang, and A. Li. “Q-BEEP: Quantum Bayesian Error Mitigation Employing Poisson Modeling over the Hamming Spectrum.” *International Symposium on Computer Architecture*, 2022.

S. Stein, Nathan Wiebe, Yufei Ding, James Ang, and Ang Li. “Quantum Bayesian Error Mitigation Employing Poisson Modelling over the Hamming Spectrum for Quantum Error Mitigation,” 2022.

Shaobo Zhang, C. Hill, and M. Usman. “Comparative Analysis of Error Mitigation Techniques for Variational Quantum Eigensolver Implementations on IBM Quantum System,” 2022.

Siwei Tan, Congliang Lang, Liang Xiang, Shudi Wang, Xinghui Jia, Ziqi Tan, Tingting Li, et al. “QuCT: A Framework for Analyzing Quantum Circuit by Extracting Contextual and Topological Features.” *Micro*, 2023.

Stefan Woerner, and D. Egger. “Quantum Risk Analysis.” *Npj Quantum Information*, 2018.

Thomas Lubinski, Joshua J. Goings, Karl Mayer, S. Johri, Nithin Reddy, Aman Mehta, Niranjan Bhatia, et al. “Quantum Algorithm Exploration Using Application-Oriented Performance Benchmarks,” 2024.

Tuhin Khare, Ritajit Majumdar, Rajiv Sangle, Anupama Ray, P. V. Seshadri, and Yogesh L. Simmhan. “Parallelizing Quantum-Classical Workloads: Profiling the Impact of Splitting Techniques.” *International Conference on Quantum Computing and Engineering*, 2023.

Unai Aseguinolaza, Nahual Sobrino, Gabriel Sobrino, J. Jornet-Somoza, and J. Borge. “Error Estimation in Current Noisy Quantum Computers.” *Quantum Information Processing*, 2023.

Waheeda Saib, P. Wallden, and I. Akhalwaya. “The Effect of Noise on the Performance of Variational Algorithms for Quantum Chemistry.” *International Conference on Quantum Computing and Engineering*, 2021.

Y. Kharkov, A. Ivanova, E. Mikhantiev, and A. Kotelnikov. “Arline Benchmarks: Automated Benchmarking Platform for Quantum Compilers.” *arXiv.org*, 2022.

Ziqi Ma, P. Gokhale, Tian-Xing Zheng, Sisi Zhou, Xiaofei Yu, Liang Jiang, P. Maurer, and F. Chong. “Adaptive Circuit Learning for Quantum Metrology.” *International Conference on Quantum Computing and Engineering*, 2020.