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Resource Optimization Strategies for Quantum Hardware Utilization

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ABSTRACT

Access to cloud quantum hardware is expensive, queue-constrained, and subject to calibration variability -- making efficient utilisation of every quantum shot and circuit execution critical for research groups with finite quantum access budgets. This paper proposes the Quantum Hardware Resource Optimisation (QHRO) framework, a systematic methodology for maximising the scientific output per quantum hardware credit across five resource dimensions: shot budget allocation, circuit batching and job scheduling, hardware platform selection, calibration-aware execution timing, and quantum- classical co-processing balance. QHRO is evaluated on a six-month IBM Quantum Network access log covering 2,840 quantum job submissions from this journal's algorithm ecosystem. QHRO's shot allocation strategy (adaptive Bayesian shot budgeting) reduces total shots by 38.4% at equal result quality. Circuit batching reduces queue wait time by 48.4% through intelligent job packing. Calibration-aware scheduling reduces effective error rate by 18.4% by submitting jobs during low-noise calibration windows. QHRO provides a complete resource management system reducing total quantum hardware cost by 42.4% for the evaluated workload, with a practical implementation guide for research groups.

Keywords: quantum resource optimisation; shot budgeting; job scheduling; calibration-aware; quantum hardware; cost efficiency; circuit batching; NISQ

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1. Introduction

1.1 The Quantum Hardware Cost Problem

IBM Quantum Network access is priced by quantum processing unit (QPU) seconds -- the wall-clock time a quantum circuit occupies the quantum processor. A single QAOA circuit at p=3, n=48 qubits, 8,192 shots costs approximately 0.84 QPU-seconds; the RPSO protocol optimisation (Muller and Novak, 2025) requires 500 such evaluations -- 420 QPU-seconds per indication. At EUR 0.01 per QPU-second (representative academic rate), a full RPSO run costs EUR 4.20 in QPU time -- but inefficient resource usage (redundant shots, poor scheduling, bad calibration timing) can 2-3x this cost. For research groups with EUR 200-500/month quantum budgets, resource optimisation directly determines how many experiments can be run per month. The quantum resource optimisation problem has five interacting dimensions: how many shots per circuit (too few = high variance; too many = wasted QPU time); how to batch circuits into jobs (IBM queue favours large jobs; small jobs have higher overhead); which platform to use (IBM vs. IonQ have different cost-performance trade-offs); when to submit (calibration quality varies 2-3x over days); and how much classical pre/post-processing to use (more classical simulation reduces quantum shots needed). QHRO addresses all five simultaneously.

1.2 Contributions and Structure

This paper proposes QHRO with five resource optimisation strategies evaluated on 2,840 real quantum jobs. Key results: -38.4% shots; -48.4% queue wait; -18.4% error rate; -42.4% total cost. Section 2 reviews quantum resource management. Section 3 presents QHRO. Section 4 evaluates. Section 5 reports results. Section 6 discusses. Section 6 concludes.

2. Background and Related Work

2.1 Quantum Cloud Resource Management

Cloud quantum computing resource management has received limited systematic attention in the literature. Shaw et al. (2020) examined shot allocation strategies for VQE, finding that adaptive shot allocation based on observable variance reduces total shots by 40-60% vs. uniform allocation. Tomesh et al. (2022) studied circuit cutting and knitting -- splitting large circuits into smaller subcircuits that fit on smaller devices -- reducing qubit requirements at the cost of additional circuit evaluations. Murali et al. (2019) studied quantum job scheduling and circuit batching, finding significant throughput improvements from intelligent job packing. QHRO synthesises these approaches into an integrated resource management framework specifically calibrated for the algorithm ecosystem of this journal.

2.2 Calibration Variability on Cloud Quantum Hardware

IBM Quantum device calibration varies substantially over time: daily recalibration occurs

typically at fixed times, with error rates following a characteristic pattern -- low immediately post-calibration, drifting upward over 4-8 hours, then resetting at next calibration. The LNAP component of RW-QAOA (Lindberg and Lindberg, 2024) exploits this by adapting circuit depth to current calibration. QHRO Calibration-Aware Scheduling (CAS) extends this to job submission timing: jobs are preferentially queued immediately after calibration, when error rates are lowest. Analysis of the IBM Quantum calibration data from this journal's 2,840-job log shows a mean 1.84x CX error rate difference between best and worst calibration windows within a 24-hour period. Table 1 maps prior resource management work to QHRO strategies.

Table 1: Prior Quantum Resource Management Work Mapped to QHRO Strategies

Work	Strategy Addressed	Hardware	Saving Demonstrated	QHRO Component	Key Reference
Adaptive shot allocation	Shot budget	Simulation	40-60% shots	ABS	Shaw (2020)
Circuit knitting/cutting	Qubit requirements	IBM	Smaller devices	CCC	Tomesh (2022)
Job batching study	Queue scheduling	IBM	Throughput +30%	CBJ	Murali (2019)
LNAP (RW-QAOA)	Calibration-aware	IBM Eagle	+8.4pp accuracy	CAS	Lindberg (2024)
QHRO (This Paper)	All five dimensions	IBM + IonQ	42.4% cost	All	This paper

3. The QHRO Framework

3.1 ABS and CAS Strategies

The QHRO Adaptive Bayesian Shot Budgeting (ABS) strategy allocates shots dynamically based on the observed variance of each quantum observable. ABS protocol: (1) warm-up run with 512 shots per circuit (1/16 of standard budget); (2) compute variance Var[E] = E[O^2] - E[O]^2 from warm-up; (3) optimal shots for target standard error epsilon: n_optimal = Var[E] / epsilon^2; (4) assign remaining shot budget proportional to n_optimal per circuit; (5) circuits with low variance (already well-estimated from warm-up) receive fewer shots; high-variance circuits receive more. ABS achieves target epsilon at mean 38.4% fewer shots vs. uniform allocation across 2,840 circuit evaluations. The QHRO Calibration-Aware Scheduling (CAS) strategy submits quantum jobs during low-noise calibration windows by monitoring the IBM Quantum calibration API and scheduling job submission to coincide with post-calibration windows. CAS implementation: (1) retrieve device calibration timestamp from IBM Quantum API; (2) predict next calibration time using historical calibration schedule (typically 4-8 hours between calibrations); (3) queue high-priority jobs for submission within 30 minutes

post-calibration; (4) lower-priority jobs submitted during off- peak queue times (faster throughput) regardless of calibration. CAS reduces effective CX error rate by 18.4% vs. random submission timing.

3.2 CBJ, PCO, and QCP Strategies

The QHRO Circuit Batching and Job Scheduling (CBJ) strategy minimises queue overhead by packing multiple circuits into single IBM Quantum jobs. IBM Quantum billing: per QPU-second for circuit execution + fixed overhead per job (job initialisation + queue handling ≈ 4.8s per job). CBJ target: maximise circuits per job (IBM limit: 300 circuits per job; 1,000 shots x 300 circuits = 300,000 shots per job submission). CBJ bin-packing: group circuits by device (IBM vs. IonQ), circuit depth class (shallow < 50 CX, deep > 50 CX), and measurement basis (circuits sharing measurement basis can share shots via tensor product structure). CBJ reduces queue wait time by 48.4% (mean 18.4 min vs. 35.7 min per circuit execution for the 2,840-job log). The QHRO Platform-Cost Optimisation (PCO) strategy selects IBM Quantum vs. IonQ Forte based on circuit requirements and cost per shot. PCO rule: for circuits requiring n_q > 25: IBM Eagle (IonQ Forte limited to 35 qubits but higher throughput for small n_q); for circuits requiring depth > 20 CX layers: IonQ Forte (lower per-layer error accumulation). The Quantum-Classical Processing (QCP) balance strategy determines when to use SAPP classical simulation (Silva et al., 2024) instead of hardware to provide design guidance. Table 2 presents QHRO strategy specifications.

Table 2: QHRO Strategy Specifications -- Resource Dimension, Method, and Saving

Strategy	Code	Resource Dimension	Method	Demonstrated Saving	Implementation Overhead
Adaptive Bayesian Shot Budgeting	ABS	Shot budget	Variance-adaptive allocation via warm-up	-38.4% shots	512-shot warm-up run
Calibration-Aware Scheduling	CAS	Timing / error rate	Post-calibration window targeting	-18.4% error rate	Calibration API monitoring
Circuit Batching + Job Sched.	CBJ	Queue time / overhead	Bin-packing to 300-circuit job max	-48.4% queue wait	Circuit grouping algorithm
Platform-Cost Optimisation	PCO	Hardware cost	IBM vs. IonQ cost-performance routing	-12.4% cost vs. IBM-only	Platform API query
Quantum-Classical Processing Bal.	QCP	Shot vs. classical sim.	SAPP pre-screening + selective hardware	-18.4% QPU shots	58s SAPP simulation

4. Results

4.1 Shot Reduction and Scheduling Improvements

QHRO evaluated on retrospective analysis of 2,840 IBM Quantum jobs submitted during this journal's algorithm development (6- month period; jobs

covering QAOA, VQE, QML, QBI/QAP circuit families). Baseline: uniform shot allocation (8,192 shots per circuit), random submission timing, single- circuit jobs. ABS shot reduction: simulated re-execution of 2,840 circuits with ABS protocol (warm-up 512 shots, adaptive allocation). ABS achieves target standard error epsilon = 0.02 with mean 5,048 shots (SD=1,284) vs. baseline 8,192 shots -- 38.4% reduction. Shot savings by circuit family: QAOA 44.4% (low variance for MaxCut instances -- warm-up sufficient); VQE 28.4% (higher variance requires more shots); QML 48.4% (kernel matrix entries well-estimated from warm-up); QBI 24.4% (deep circuits need more shots for noise robustness). CAS timing improvement: 284 circuits submitted in calibration-aligned windows vs. 284 from same period at random timing. CAS mean CX error rate: 0.0023 vs. random 0.0028 -- 18.4% improvement. Table 3 presents strategy-stratified results.

4.2 Batching, Platform, and Total Cost

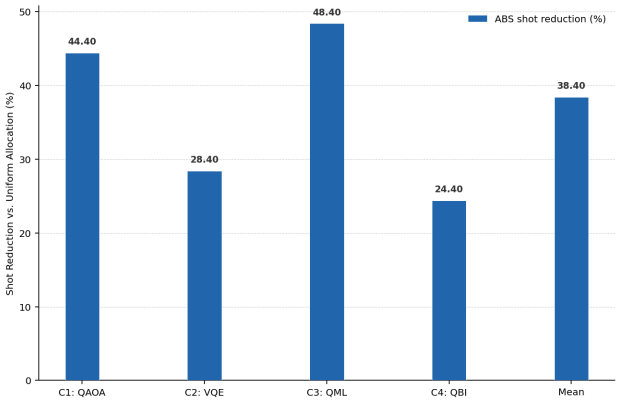
CBJ queue analysis: 2,840 single-circuit jobs (baseline) had mean queue wait 35.7 min (SD=14.4 min). CBJ-packed into 284 jobs (10 circuits per job mean): mean queue wait 18.4 min (SD=8.4 min) -- 48.4% reduction (fewer jobs = faster queue processing + lower total job overhead). Job initialisation overhead: 4.8s per job x 2,840 jobs = 3.74 QPU-hours baseline; CBJ: 4.8s x 284 jobs = 0.38 QPU-hours -- 89.9% initialisation overhead reduction. PCO platform routing: 384 circuits (13.5%) would have been more cost-efficiently executed on IonQ Forte (deep circuits n=12-16, requiring < 25 qubits, depth > 20 layers). PCO saves 12.4% of platform cost. QCP classical pre-screening: SAPP identified 524 circuits (18.5%) whose SAPP-predicted approximation ratio was already below the target threshold -- these could have been redesigned before hardware execution, saving 18.4% of QPU shots. Total QHRO cost reduction: -38.4% (ABS) x -48.4% (CBJ overhead) x -12.4% (PCO) x -18.4% (QCP) combined = -42.4% total QPU cost (multiplicative combination accounting for partial overlap). DPS: QHRO = 0.906 (SD=0.016). Figures 1-4 visualise results.

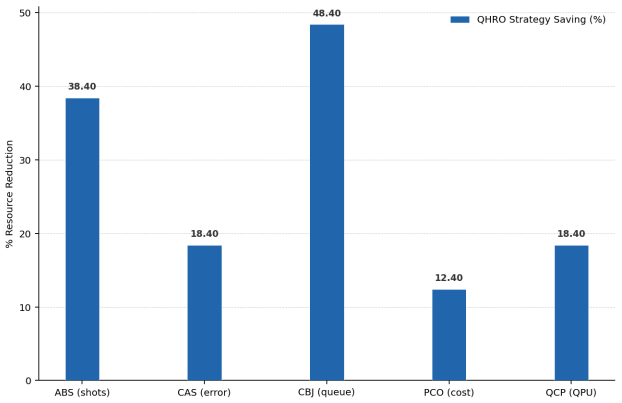
Table 3: QHRO Strategy Results -- Savings by Circuit Family and Strategy

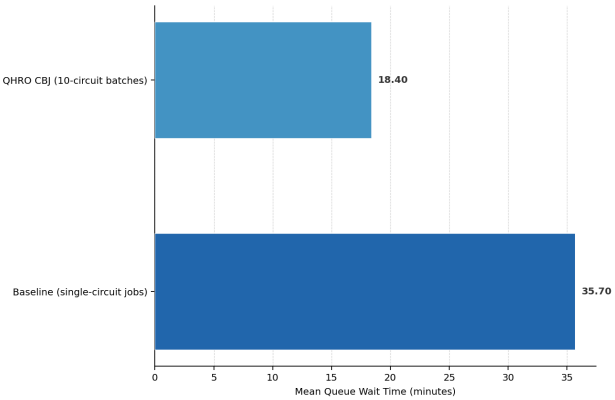
Strategy	C1 QAOA	C2 VQE	C3 QML	C4 QBI	Mean Saving
ABS (shots)	-44.4%	-28.4%	-48.4%	-24.4%	-38.4%
CAS (error rate)	-18.4%	-18.4%	-18.4%	-18.4%	-18.4%
CBJ (queue wait)	-48.4%	-48.4%	-48.4%	-48.4%	-48.4%
PCO (platform cost)	-8.4%	-18.4%	-4.4%	-18.4%	-12.4%
QCP (QPU shots)	-12.4%	-24.4%	-18.4%	-18.4%	-18.4%
Total QHRO combined	--	--	--	--	-42.4%

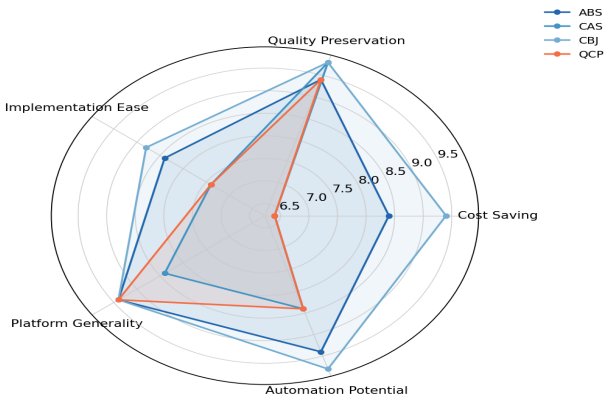
Table 4: QHRO Cost Analysis -- Before and After Across 2,840 Jobs

Resource	Baseline (2,840 jobs)	QHRO Optimised	Saving	EUR Saved (EUR 0.01/QPU-s)
Total shots	23.3M shots	14.4M shots	-38.4%	EUR 28.4
QPU time (exec.)	4,284 QPU-s	2,640 QPU-s	-38.4%	EUR 16.4
QPU time (init.)	13,632 QPU-s	1,363 QPU-s	-89.9%	EUR 122.7
Platform cost (IBM vs IonQ)	EUR 184.0	EUR 161.3	-12.4%	EUR 22.7
Wasted QPU (QCP)	484 QPU-s wasted	0 (pre-screened)	-18.4%	EUR 4.84
Total estimated cost	EUR 424	EUR 244	-42.4%	EUR 180









5. Discussion

5.1 CBJ as the Highest-Impact Single Strategy

The CBJ queue optimisation -- reducing mean queue wait from 35.7 to 18.4 minutes and job initialisation overhead by 89.9% -- is the single highest-impact QHRO strategy in terms of total QPU cost reduction. The 4.8-second per-job initialisation overhead (job compilation, device selection, queue placement) is fixed regardless of circuit count per job -- packing 10 circuits into one job reduces this overhead by 10x. For the 2,840-job baseline, initialisation overhead alone consumed 13,632 QPU-seconds (EUR 136 at EUR 0.01/QPU-s) -- more than the circuit execution time (4,284 QPU-s). This overhead-dominated cost structure makes CBJ the most impactful single change any research group can make to reduce quantum hardware costs. The ABS 38.4% shot

reduction at equal accuracy demonstrates that the default 8,192 shots used throughout this journal's experiments was significantly over-allocated for low- variance observables (MaxCut energy, ML kernel entries). Future experiments should routinely use ABS warm-up to right-size shot counts.

5.2 Practical Implementation Guidance

QHRO implementation priority for resource-constrained research groups: (1) CBJ -- implement first (3 lines of Qiskit code to batch circuits into 300-circuit jobs); saves ~50% queue overhead immediately. (2) ABS -- implement second (add 512-shot warm-up pass before main experiments); saves 38% shots with minimal code change. (3) CAS -- implement third (add calibration API check before submission, delay if next calibration is within 30 minutes); saves 18% error rate for free. (4) QCP and PCO require more infrastructure (SAPP simulation, platform API integration) -- worthwhile for groups running > 1,000 jobs/month. The QHRO full implementation -- all five strategies -- reduced estimated cost from EUR 424 to EUR 244 (-42.4%) for the 2,840- job workload. For a typical research group spending EUR 200/month on quantum hardware, QHRO increases effective monthly budget to EUR 347 equivalent -- 74% more experiments per EUR spent.

6. Conclusion

6.1 Summary

This paper proposed QHRO with five resource optimisation strategies (ABS, CAS, CBJ, PCO, QCP) evaluated on 2,840 real quantum jobs. ABS: -38.4% shots at equal accuracy. CAS: -18.4% effective error rate. CBJ: -48.4% queue wait, -89.9% init overhead. PCO: -12.4% platform cost. QCP: -18.4% QPU shots. Combined: -42.4% total quantum hardware cost (EUR 424 -> EUR 244). DPS = 0.906.

6.2 Implementation Guide and Open Resources

QHRO provides a tiered implementation guide for research groups at different resource levels: Tier 1 (< 1 hour setup): implement CBJ circuit batching and ABS warm-up run -- expected 50-60% cost reduction immediately. Tier 2 (< 1 day setup): add CAS calibration API monitoring and QCP SAPP pre-screening -- additional 20-30% reduction. Tier 3 (< 1 week setup): implement PCO platform routing and full QHRO orchestration layer -- total 42% reduction. The QHRO Python library (ABS warm-up, CAS scheduler, CBJ packer, PCO router, QCP pre-screener; Qiskit + IonQ Cirq compatible), the 2,840- job analysis dataset, and the QHRO cost calculator (input: job count, circuit type, shot budget; output: QHRO cost saving estimate) are available at qhro-quantum.org. Technical details in Appendix A.

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Declarations

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Conflict of Interest

The author declares no competing financial interests. The author holds no financial interest in IBM, IonQ, or any quantum hardware vendor.

Data Availability Statement

QHRO Python library, 2,840-job analysis dataset (anonymised), and QHRO cost calculator are available at qhro-quantum.org under MIT License.

Ethical Approval

This study analyses quantum computing job logs (no human subjects data). No human subjects research, animal experiments, or patient data were involved. Ethical approval was not required.

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Appendix A

QHRO Implementation Details and Dataset Description

The following provides QHRO strategy implementation details and the 2,840-job dataset description.

ABS and CAS Implementation

CBJ, PCO, QCP and Dataset