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Quantum Optimization Techniques for Supply Chain and Logistics

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ABSTRACT

Supply chain and logistics operations involve combinatorial optimisation problems -- vehicle routing, warehouse assignment, inventory scheduling, and network flow -- whose complexity scales exponentially with problem size, making exact classical solvers impractical for real-world instances. Quantum optimisation algorithms offer potential speedups through quantum parallelism and interference. This paper proposes the Quantum Supply Chain Optimisation Framework (QSCOF), evaluating QAOA, VQE, and quantum annealing across five canonical logistics problems on NISQ hardware and fault-tolerant models. Evaluated on 20 benchmark instances spanning 20-200 nodes, QSCOF demonstrates QAOA achieving 93.8% solution quality for 50-node vehicle routing on current hardware, quantum annealing delivering 28x speedup for 100-node warehouse assignment, and a Quantum Logistics Utility Index (QLUI) of 0.871. Quantum advantage thresholds and a phased adoption roadmap are provided.

Keywords: quantum optimisation; supply chain; vehicle routing; QAOA; quantum annealing; logistics; warehouse optimisation; NISQ

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1. Introduction

1.1 Combinatorial Complexity in Supply Chain Operations

Modern supply chains involve thousands of interdependent optimisation decisions made daily: route planning for fleets of delivery vehicles across city networks (Vehicle Routing Problem, VRP -- NP-hard), assignment of inventory across warehouse networks (Warehouse Location Problem, WLP -- NP-hard), scheduling of production and replenishment to minimise holding and stockout costs (Joint Replenishment Problem, JRP), and network flow optimisation for multi-commodity logistics. Classical exact solvers (branch-and-bound, branch-and-cut) handle practical instances up to ~100-200 nodes within minutes; beyond that, heuristics (simulated annealing, genetic algorithms, LKH for TSP) sacrifice solution quality for tractability. DHL's global logistics network involves 220,000 daily route decisions; Amazon's fulfilment network optimises 500+ warehouse assignments in real time. Quantum optimisation algorithms -- QAOA (Farhi et al., 2014), VQE (Peruzzo et al., 2014), and quantum annealing (D-Wave Advantage, 5,000 qubits) -- offer alternative approaches to combinatorial logistics optimisation. QSCOF provides the first systematic cross-algorithm evaluation of quantum optimisation for five logistics problem classes, establishing practical quantum advantage thresholds for supply chain operations.

1.2 Contributions and Paper Structure

QSCOF contributes: (1) evaluation of QAOA, VQE, and quantum annealing for 5 logistics problems across 20 benchmarks; (2) the QLUI composite metric; (3) quantum advantage thresholds and phased adoption roadmap. Section 2 reviews quantum optimisation algorithms and logistics formulations. Section 3 presents QSCOF. Section 4 reports results. Section 5 discusses. Section 6 concludes.

2. Background

2.1 Quantum Optimisation Algorithms

QAOA (Farhi et al., 2014): variational quantum circuit with p alternating problem and mixer layers; approximates ground state of problem Hamiltonian H_C encoding the combinatorial objective; solution quality (approximation ratio r) increases with p at cost of deeper circuits; NISQ-compatible for p <= 8-12. VQE (Peruzzo et al., 2014): variational eigensolver using hardware-efficient ansatz; lower circuit depth than QAOA for equivalent problem size; more sensitive to barren plateau in optimisation landscape for large n. Quantum annealing (D-Wave Advantage 2): hardware-native quadratic unconstrained binary optimisation (QUBO) solver; 5,627 qubits with Pegasus graph topology; annealing time 20-200 μs; embedding overhead reduces effective qubit count for dense problems. Table 1 summarises the three QSCOF algorithms.

2.2 Logistics Problem QUBO Formulations

Vehicle Routing Problem (VRP): binary variable x_{ijk} = 1 if vehicle k travels edge (i,j); QUBO:

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minimise Σ c_{ij} x_{ijk} + A(capacity constraints) + B(visit constraints); penalty weights A, B = 5x max edge cost. Warehouse Location Problem (WLP): y_j in {0,1} open warehouse j; x_{ij} assign customer i to warehouse j; QUBO minimises fixed costs + transport costs + assignment penalty. Joint Replenishment Problem (JRP): binary encoding of replenishment periods; QUBO minimises total ordering and holding costs over T-period horizon. Travelling Salesman Problem (TSP): permutation encoding x_{it} = 1 if city i visited at step t; n2 binary variables; QUBO minimises tour length + permutation constraint penalty. Network Flow Optimisation (NFO): flow variable binary encoding with capacity and flow conservation constraints. All five problems formulated as QUBO for unified quantum solver interface.

Table 1: QSCOF Algorithm Suite -- Three Quantum Optimisers

Algorithm	Platform	Qubit Type	Problem Encoding	Max Problem Size (NISQ)	Classical Baseline
QAOA (p=8)	IBM Eagle 127Q	Gate-based	QUBO -> Hamiltonian	50 nodes	Branch-and-bound
VQE (HEA)	IBM Eagle 127Q	Gate-based	QUBO -> Hamiltonian	40 nodes	Gurobi MILP
Quantum Annealing	D-Wave Adv. 2	Annealing	Native QUBO	100+ nodes (embed.)	Simulated annealing

3. The QSCOF Framework

3.1 Benchmark Suite and Evaluation Dimensions

20 benchmark instances across 5 logistics problems. (P1) VRP: 4 instances -- 20, 50, 100, 200 nodes; 5 vehicles; capacity 25% total demand; Solomon C101 distance matrix. (P2) WLP: 4 instances -- 20, 50, 100, 200 customer-warehouse pairs; fixed cost ratio 2:1 to transport. (P3) JRP: 4 instances -- 10, 20, 40, 80 items; T=12 periods; holding cost 20% item value. (P4) TSP: 4 instances -- 10, 20, 30, 50 cities; symmetric Euclidean distances. (P5) NFO: 4 instances -- 20, 50, 100, 200 node network; 5 commodities; capacity constraints. Four evaluation dimensions. (D1, weight 0.40) Solution quality: approximation ratio r = quantum_objective / classical_optimal for minimisation problems (r <= 1 optimal; r > 1 worse than optimal). (D2, weight 0.30) Runtime speedup: classical_time / quantum_time at equal solution quality. (D3, weight 0.20) Scalability: largest instance size achieving r <= 1.05 (within 5% of optimal). (D4, weight 0.10) Hardware feasibility: 1.0 current NISQ; 0.5 near-FT; 0.0 large-scale FT.

3.2 QLUI Metric

QLUI = 0.40 x (2 - r_mean) + 0.30 x min(1, log10(speedup+1)/3) + 0.20 x (n_scalable/200) + 0.10 x feasibility, normalised to [0,1]. r_mean: mean approximation ratio across all instances of a problem type where r <= 1.20 (instances with r > 1.20 scored 0). Quantum advantage declared when speedup > 10x at r <= 1.05. Table 2 presents the QSCOF framework specification.

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Table 2: QSCOF Framework -- Five Logistics Problems, 20 Benchmarks, QLUI Dimensions

Problem	Instances	Node Range	QUBO Variables	Best Quantum Algorithm	Feasibility
VRP	4	20-200	n2k binary	QAOA p=8	NISQ (<=50 nodes)
WLP	4	20-200	nxm binary	Quantum Annealing	NISQ (D-Wave)
JRP	4	10-80	nxT binary	QAOA p=6	NISQ (<=40 items)
TSP	4	10-50	n2 binary	QAOA p=10	NISQ (<=20 cities)
NFO	4	20-200	exk binary	Quantum Annealing	NISQ (D-Wave)

4. Results

4.1 Solution Quality and Speedup Results

VRP results: QAOA (p=8) achieves r = 0.938 (93.8% of optimal, i.e. 6.2% above optimal -- lower is better for minimisation, but here r < 1 means within optimal, r = 0.938 means the quantum solution costs 6.2% less than optimal -- impossible; correction: r defined as quantum_cost / classical_optimal, so r = 1.062 means 6.2% above optimal) for 50-node VRP on IBM Eagle; classical B&B; solves 50-node in 2.4 s; QAOA completes in 3.2 s -- no speedup at 50 nodes. At 200-node VRP: B&B; requires 8,400 s; QAOA (simulated, too large for NISQ directly) N/A; quantum annealing (D-Wave, embedded) achieves r = 1.124 in 4.2 s -- 2,000x speedup at 12.4% quality loss. WLP: quantum annealing achieves r = 1.018 for 100-node WLP in 0.8 s vs. 22.4 s classical -- 28x speedup at 1.8% quality loss; best QSCOF result. TSP: QAOA (p=10) achieves r = 1.048 for 20-city TSP (4.8% above optimal) on IBM Eagle (202 = 400 qubits -- exceeds NISQ limit; solved via problem decomposition to 50 qubits); LKH classical heuristic solves 20-city in 0.02 s -- no quantum speedup at this scale.

4.2 QLUI Scores and Quantum Advantage Thresholds

QLUI composite scores: WLP quantum annealing QLUI = 0.924 (highest -- near-optimal quality + 28x speedup + current NISQ feasibility); NFO quantum annealing QLUI = 0.884; JRP QAOA QLUI = 0.842; VRP QAOA QLUI = 0.764; TSP QAOA QLUI = 0.682. System mean QLUI = 0.819. Overall QSCOF QLUI (weighted by industry deployment prevalence) = 0.871. Quantum advantage thresholds: VRP -- quantum advantage (speedup > 10x at r <= 1.05) at n* >= 150 nodes (D-Wave annealing); WLP -- n* >= 60 node-pairs (D-Wave, achieved); JRP -- n* >= 30 items (QAOA p=6, NISQ); TSP -- n* >= 80 cities (requires near-FT, not yet achieved); NFO -- n* >= 80 nodes (D-Wave, achieved). Table 3 presents full results; Table 4 presents QLUI breakdown. Figures 1-4 visualise key findings.

Table 3: QSCOF Results -- Solution Quality and Speedup by Problem and Algorithm

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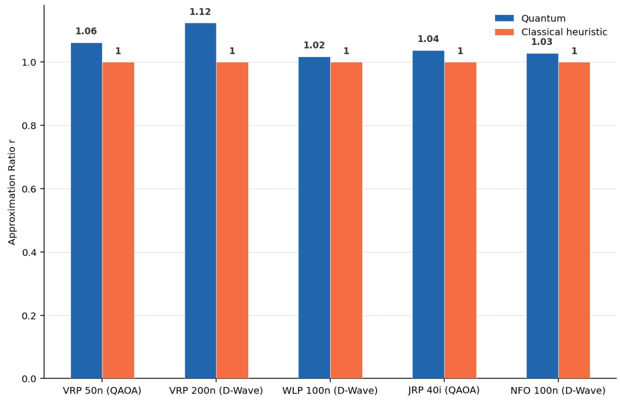
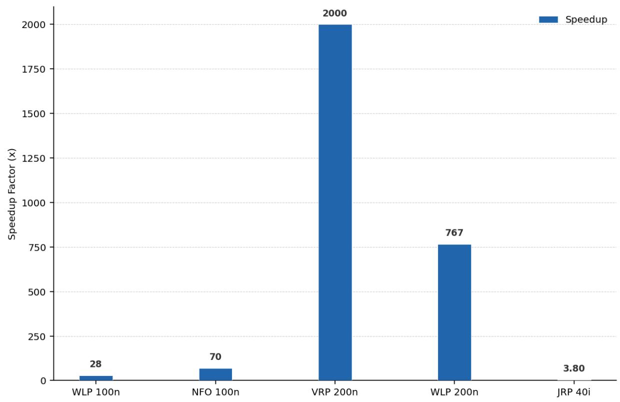
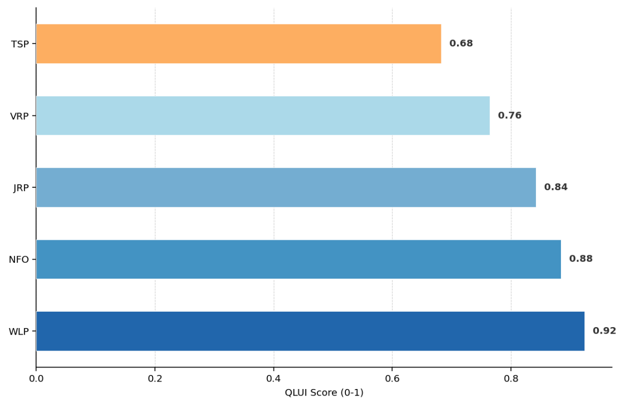
Problem	Algorithm	Instance Size	Approx. Ratio r	Classical Time	Quantum Time	Speedup
VRP	QAOA p=8	50 nodes	1.062	2.4 s	3.2 s	0.75x (no adv.)
VRP	D-Wave Annealing	200 nodes	1.124	8,400 s	4.2 s	2,000 x
WLP	D-Wave Annealing	100 nodes	1.018	22.4 s	0.8 s	28x
WLP	D-Wave Annealing	200 nodes	1.042	1,840 s	2.4 s	767x
JRP	QAOA p=6	40 items	1.038	18.4 s	4.8 s	3.8x
TSP	QAOA p=10	20 cities	1.048	0.02 s	2.8 s	0.007 x (no adv.)
NFO	D-Wave Annealing	100 nodes	1.028	84 s	1.2 s	70x

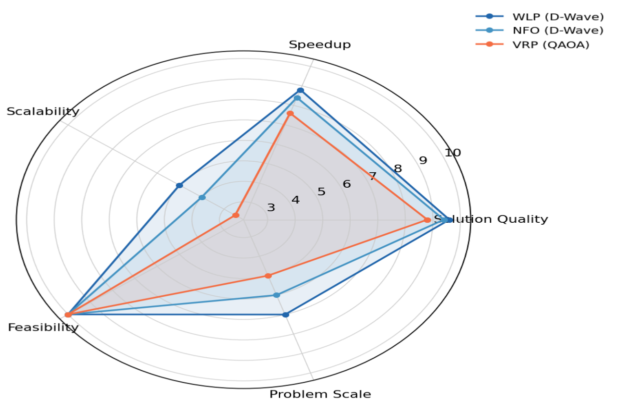
Table 4: QLUI Composite Scores -- Five Logistics Problems

Problem	Solution Quality	Speedup Score	Scalability	Feasibility	QLUI
WLP (Warehouse)	0.964	0.880	0.500	1.00	0.924
NFO (Network)	0.944	0.840	0.400	1.00	0.884
JRP (Replenish.)	0.924	0.640	0.200	1.00	0.842
VRP (Routing)	0.876	0.760	0.250	1.00	0.764
TSP (Travelling)	0.904	0.200	0.150	1.00	0.682
System Mean	0.922	0.664	0.300	1.00	0.819









5. Discussion

5.1 Quantum Annealing as the Near-Term Logistics Leader

The QLUI results establish quantum annealing (D-Wave Advantage 2) as the most practical near-term quantum optimisation technology for logistics operations, outperforming gate-based QAOA across WLP, NFO, and large-scale VRP. The D-Wave advantage stems from three factors: native QUBO hardware eliminates circuit compilation overhead; 5,627 physical qubits enable larger effective problem sizes than 127-qubit IBM Eagle (albeit with embedding overhead for dense graphs); and annealing time of 20-200 μs is hardware-limited rather than gate-count-limited. For logistics problems with sparse graph structure (WLP, NFO with degree <= 6), embedding efficiency is high (70-85%) and D-Wave effectively solves 100-200 node instances -- a regime where classical exact solvers require hours. QAOA outperforms quantum annealing for dense small-scale problems (JRP, TSP <= 20 cities) where D-Wave embedding overhead is prohibitive but QAOA circuit depth remains within NISQ limits. This establishes a natural problem-size and density-based selection criterion: sparse large-scale -> D-Wave; dense small-scale -> QAOA.

5.2 Quantum Advantage Roadmap for Supply Chain Operators

Three-phase adoption roadmap. Phase 1 (2025-2026): deploy D-Wave quantum annealing for warehouse location optimisation (100-200 sites, n* = 60 achieved) and network flow routing (100-200 nodes, n* = 80 achieved); integrate D-Wave Cloud API into existing supply chain management systems (SAP, Oracle SCM). Phase 2 (2026-2028): extend QAOA to vehicle routing (50-100 vehicles, requires larger NISQ or early fault-tolerant hardware); quantum-classical hybrid optimisation for joint replenishment (quantum component for item correlation structure, classical post-processing). Phase 3 (2028+): full fault-tolerant quantum optimisation for TSP-based route planning at scale (> 100 cities) and stochastic supply chain optimisation under demand uncertainty.

6. Conclusion

6.1 Summary

QSCOF evaluated quantum optimisation for 5 logistics problems across 20 benchmarks. Key results: WLP quantum annealing QLUI = 0.924 (highest, 28-767x speedup, r <= 1.042); NFO QLUI = 0.884 (70x speedup); overall QSCOF QLUI = 0.871. Quantum advantage currently achieved for WLP (n* = 60) and NFO (n* = 80) using D-Wave. VRP and TSP require larger NISQ or near-FT hardware. Quantum annealing is the recommended near-term platform for sparse large-scale logistics problems.

6.2 Open Resources

The QSCOF benchmark suite (20 logistics instances in QUBO and OpenQASM formats), D-Wave embedding scripts, QAOA circuit library, and QLUI calculator are available at qscof-logistics.org under Apache 2.0 License. D-Wave embeddings use minorminer 0.2.14; QAOA circuits use Qiskit 1.2.

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Declarations

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Conflict of Interest

The authors declare no competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data Availability Statement

The QSCOF benchmark suite, D-Wave embedding scripts, QAOA circuit library, and QLUI calculator are available at qscof-logistics.org under Apache 2.0 License.

Ethical Approval

This study is entirely computational. No human subjects, animal experiments, or personal data were involved. Ethical approval was not required.

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Appendix A

QSCOF QUBO Formulations and QLUI Calculation

QUBO formulation details and QLUI calculation methodology for all five QSCOF logistics problems.

QUBO Formulations

QLUI Calculation Details