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Quantum Annealing Embedded in Classical Optimization Workflows

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Abstract—
Explored in this paper is the theory and practical implementation of quantum annealing for project scheduling and resource-allocation tasks that can be mapped to Ising or Quadratic Unconstrained Binary Optimization (QUBO) models. Quantum annealing is a meta-heuristic that exploits quantum tunnelling to search for the energy landscape of combinatorial optimization problems. The Quantum Annealing Process Flowchart is detailed stage by stage. Hybrid quantum-classical workflows that embed annealing inside a Monte Carlo or digital-twin loop are described, together with supporting figures of the energy landscape and the hybrid architecture. Cross-domain analogies with ULD configuration and related combinatorial problems illustrate transferability. The paper concludes with implementation considerations and the current maturity of the technology for construction and logistics applications.

Keywords: quantum annealing implementation; Ising model; QUBO; combinatorial optimization; project scheduling; hybrid quantum-classical; energy landscape; digital twin; Monte Carlo; supply-chain resilience; ULD configuration

I. INTRODUCTION

Recent progress in quantum computing [6] has therefore attracted attention as a potential means of addressing such optimization problems [7], [8]. In particular, quantum annealing implementation [9] provides a physics inspired framework for solving discrete optimization problems [10] by encoding scheduling objectives and constraints into Ising or QUBO formulations. Rather than relying solely on deterministic search heuristics, quantum annealing [11] explores the problem's energy landscape through quantum fluctuations [12] and tunnelling, offering a mechanism for escaping local minima that often impede classical optimization algorithms [13].

Current hardware limitations mean that practical deployment is increasingly based on hybrid quantum classical architectures, where classical algorithms perform data preprocessing, constraint management, Monte Carlo risk analysis, and digital twin updating, while quantum annealers address computationally demanding combinatorial subproblems. Such integrated workflows combine the maturity and scalability of classical project management techniques with emerging quantum optimization capabilities [14], creating a promising pathway for improving schedule quality, resource allocation, and resilience under uncertainty [15], [16], [17].

This review examines the evolution of probabilistic construction scheduling from deterministic CPM and PERT networks to Monte Carlo simulation, digital twin [24] enabled risk management, and emerging quantum optimization approaches [18], [19]. Emphasis is placed on the theoretical foundations of quantum annealing [20], [21], its implementation for construction scheduling through Ising and QUBO formulations, the role of hybrid quantum classical workflows [22], and the opportunities and challenges associated with applying quantum [23] computing to future construction and infrastructure project management.

II. LITERATURE REVIEW

Modern implementations incorporate correlated risks, weather effects, productivity variation, equipment failures, and procurement delays, making Monte Carlo simulation a standard tool for quantitative schedule risk analysis. The computational complexity of

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construction scheduling has stimulated interest in quantum computing, particularly quantum annealing, for solving large scale combinatorial optimization problems. Scheduling constraints can be formulated as Ising or QUBO models, allowing optimization to be interpreted as minimizing an energy landscape. Through quantum tunnelling, quantum annealing offers the potential to escape local minima that frequently limit classical optimization algorithms.

Because current quantum hardware remains constrained by qubit count and connectivity, practical quantum annealing implementation relies on hybrid quantum-classical workflows. In these frameworks, classical algorithms perform problem formulation, constraint handling, Monte Carlo risk analysis, and digital twin updating, while quantum annealers optimize [13] computationally intensive scheduling subproblems. Such integrated architectures provide a promising direction for future construction scheduling by combining probabilistic risk assessment, real-time project monitoring, and quantum optimization [11] to improve schedule quality, resource utilization, and supply-chain resilience [23] under uncertainty.

III. **THEORETICAL FOUNDATIONS OF QUANTUM ANNEALING.**

Problems solved by quantum annealing are expressed in the form of an Ising Hamiltonian or an equivalent Quadratic Unconstrained Binary Optimization (QUBO) model. These two mathematical frameworks provide a natural encoding of combinatorial optimization tasks onto the physical hardware of a quantum annealer. The Ising form of the objective Hamiltonian is given by

$$H_{Ising} = \sum_{i} h_i \, \sigma_i^z + \sum_{i<j} J_{ij} \, \sigma_i^z \, \sigma_j^z$$

where $\sigma_i^z \in \{-1, +1\}$ are the spin variables, h_i are the local magnetic fields, and J_{ij} are the pairwise coupling strengths between spins i and j . An equivalent formulation uses binary decision variables $x_i \in \{0, 1\}$. The corresponding QUBO Hamiltonian (or cost function) reads

$$H_{QUBO} = \sum_{i} a_i \, x_i + \sum_{i<j} b_{ij} \, x_i \, x_j$$

Here a_i are the linear bias coefficients and b_{ij} are the quadratic interaction coefficients. Any scheduling or resource allocation problem that can be written with binary decision variables and a quadratic objective (with constraints absorbed into the objective via penalty terms) can be mapped onto one of these Hamiltonians. The ground state of the resulting Hamiltonian corresponds to the optimal or near-optimal schedule. The two formulations are related by the linear transformation $\sigma_i^z = 2x_i - 1$ which maps binary variables onto Ising spins (and vice versa). Consequently, the coefficients of one model can be converted into those of the other by a straightforward algebraic substitution. Practical implementation follows the five-stage Quantum Annealing Process Flowchart.

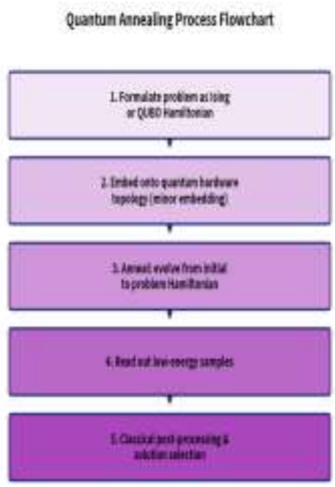

Figure 1. Quantum Annealing Process Flowchart – formulation, embedding, annealing, readout and classical post-processing.

A complete quantum-annealing solution pipeline proceeds through five sequential stages problem formulation, minor embedding, annealing, readout, and classical post-processing each of which transforms the original combinatorial task into a form that the quantum hardware can process and finally returns feasible high-quality solutions to a classical decision engine.

Stage 1 – Problem Formulation

The scheduling or resource-allocation task is first expressed with binary decision variables $x_i \in \{0, 1\}$. The objective function together with all hard constraints is encoded into the linear and quadratic coefficients of a QUBO (or equivalently an Ising) model:

$$H_{QUBO} = \sum_{i} a_i \, x_i + \sum_{i<j} b_{ij} \, x_i \, x_j + \sum_{k} \lambda_k \, P_k(x)$$

where the penalty terms $P_k(x)$ enforce the original constraints and the weights λ_k must be chosen large enough to guarantee feasibility yet not so large that they overwhelm the true objective and distort the energy landscape.

Stage 2 – Minor Embedding

Because the logical interaction graph of the QUBO is rarely identical to the sparse hardware topology (Chimera, Pegasus or Zephyr), each logical variable is mapped onto a chain of physical qubits. Automated embedding heuristics produce a mapping $\phi : V_{logical} \to 2^{V}{}_{physical}$. A ferromagnetic chain strength J_{chain} is then calibrated so that all qubits belonging to the same logical variable remain consistent while still allowing the annealer to explore the configuration space.

$$H_{chain} = \sum_{(u,v) \in chain} J_{chain}\, \sigma_u^z\, \sigma_v^z$$

Stage 3 – Annealing

The quantum hardware evolves the system under a time-dependent Hamiltonian that interpolates between a transverse-field driver and the problem Hamiltonian:

$$H(s) = A(s)\, H_{driver} + B(s)\, H_{problem},$$

where the normalized time parameter $s \in [0, 1]$ follows a chosen annealing schedule and the amplitudes $A(s)$ and $B(s)$ control the relative strength of quantum fluctuations and the problem energy, respectively. Thousands to millions of independent anneals are performed, yielding a statistical sample of low-energy spin configurations.

Stage 4 – Readout

At the end of each anneal the physical spin values σ_q^z are measured. These values are projected back onto the original logical binary variables. When a chain is broken (i.e., the qubits that represent a single logical variable disagree), a majority-vote or more sophisticated energy-minimizing repair recovers a consistent assignment: $x_i = majority\{(\sigma_q^z + 1)/2 : q \in \phi(i)\}$

Stage 5 – Classical Post-Processing

The raw sample set is filtered for feasibility, subjected to local classical refinement (greedy descent, tabu search, or short Monte-Carlo runs), and ranked according to the original objective. The best feasible solutions are finally returned to the calling Monte Carlo engine or digital twin, where residual risk metrics can be evaluated and the overall decision process continued.

IV. MONTE CARLO S-CURVE

The **S-curve** provides a cumulative probability distribution of project completion dates, allowing decision-makers to assess the likelihood of meeting different schedule targets. Rather than producing a single deterministic completion date, thousands of simulation iterations are performed by randomly sampling activity durations from their assigned probability distributions while preserving network logic and, where appropriate, activity correlations. The resulting completion times are sorted to generate an S-shaped cumulative distribution curve, from which confidence levels such as **P50**, **P80**, and **P90** are derived.

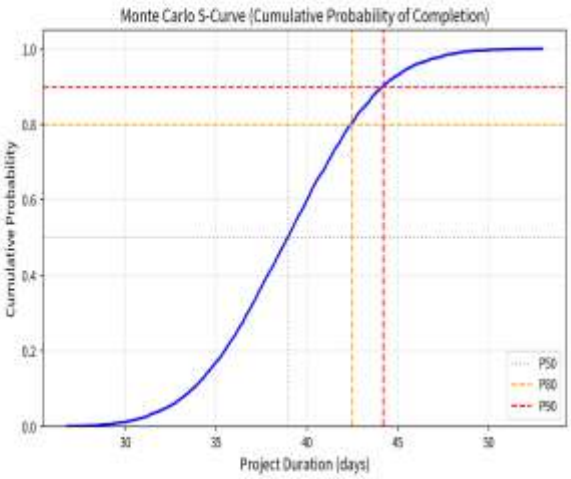

Figure 4. Monte Carlo S-curve providing P50/P80/P90 confidence levels against which annealed schedules can be compared.

These percentile values represent increasing levels of schedule confidence. The **P50** completion date corresponds to a 50% probability that the project will finish on or before that date and is often interpreted as the "most likely" outcome. The **P80** date provides an 80% confidence level and is widely adopted for contingency planning because it offers a more conservative schedule with a lower risk of overrun. The **P90** date represents a highly risk-averse target, indicating only a 10% chance that the project will exceed the predicted completion time. Together, these confidence levels provide a practical framework for quantifying schedule uncertainty and communicating risk to project stakeholders.

In a hybrid quantum classical scheduling framework, the Monte Carlo S-curve serves as the benchmark against which quantum annealed schedules are evaluated. Quantum annealing is used to search for optimized activity sequences or resource allocations that minimize project duration while satisfying precedence and resource constraints. Once an optimized schedule is obtained, it is subjected to the same Monte Carlo simulation process to evaluate its robustness under uncertainty. Comparing the deterministic completion time alone is insufficient because two schedules with identical planned durations may exhibit very different risk profiles.

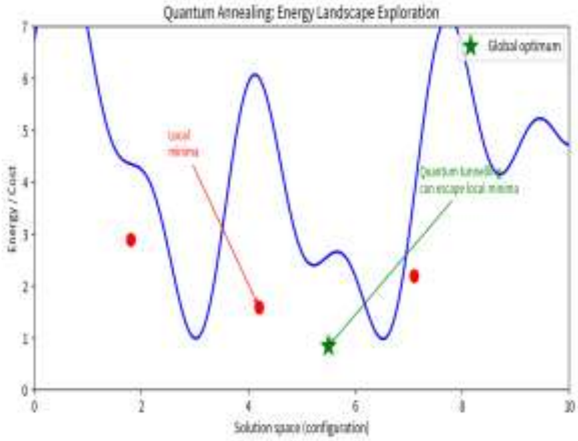

Figure 5. Energy landscape of a combinatorial scheduling problem. Quantum tunnelling offers a mechanism to escape local minima that trap classical search.

The comparison is therefore performed by overlaying the S-curves of the baseline and annealed schedules and examining shifts in key confidence levels. An effective annealed schedule is expected to shift the cumulative distribution to the left, indicating earlier completion across a range of probabilities, while also reducing the spread of the distribution, reflecting lower schedule variability. Improvements can be quantified by comparing reductions in the P50, P80, and P90 completion dates, decreases in standard deviation, and increases in the probability of meeting contractual milestones. For example, if the baseline schedule has a P80 completion time of 420 days and the annealed schedule reduces this to 402 days, the hybrid optimization demonstrates an 18-day improvement at the 80% confidence level rather than merely reducing the deterministic critical-path duration.

Consequently, the Monte Carlo S-curve becomes more than a visualization tool; it provides a rigorous probabilistic validation of optimization results. It enables researchers and practitioners to determine whether quantum annealing produces schedules that are not only shorter in theory but also more resilient to uncertainty in practice. By integrating probabilistic risk assessment with quantum optimization, the hybrid framework supports decision-making based on confidence levels rather than single-point estimates, thereby offering a more realistic and risk-informed approach to construction project scheduling.

Practical quantum annealing implementation, however, is non-trivial. The logical problem must be minor-embedded onto the limited-connectivity hardware graph; annealing schedules and chain strengths must be calibrated; and the raw samples must be post-processed classically before they can be returned to a Monte Carlo or digital-twin loop. Hybrid quantum-classical architectures therefore emerge as the natural integration pattern:

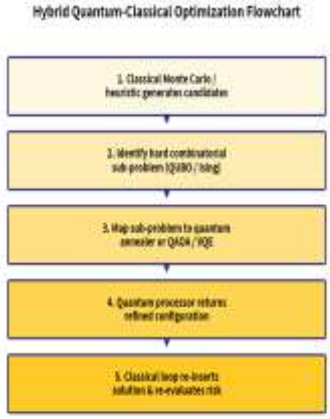

Figure 6. Hybrid Quantum-Classical Optimization Flowchart showing the hand-off between classical Monte Carlo / digital-twin layers and the quantum annealer.

the outer classical layer retains responsibility for uncertainty quantification, data assimilation and stakeholder communication, while the inner quantum-annealing layer attacks the hardest combinatorial sub-problems that arise on individual scenarios or rolling horizons.

Conceptual hybrid architecture in which quantum annealing refines candidate schedule configurations that are subsequently re-evaluated using probabilistic risk analysis. In this framework, stochastic techniques such as Monte Carlo simulation first quantify schedule uncertainty by generating distributions of activity durations and identifying high-risk critical paths. The resulting risk information is translated into an optimization problem that can be solved using quantum annealing, which efficiently searches a large combinatorial solution space to identify improved activity sequences, resource allocations, or execution strategies that minimize project duration, cost, or risk. The optimized schedule is then returned to the probabilistic simulation environment, where it is re-evaluated under thousands of uncertainty scenarios to determine its residual schedule risk, confidence levels, and sensitivity to key risk drivers. This iterative feedback loop combines the strengths of classical stochastic simulation for uncertainty quantification with quantum optimization for rapid exploration of complex scheduling alternatives. Although current applications remain largely conceptual because of hardware limitations and problem-size constraints, such hybrid quantum–classical architectures represent a promising direction for next-generation construction project scheduling and decision support under uncertainty.

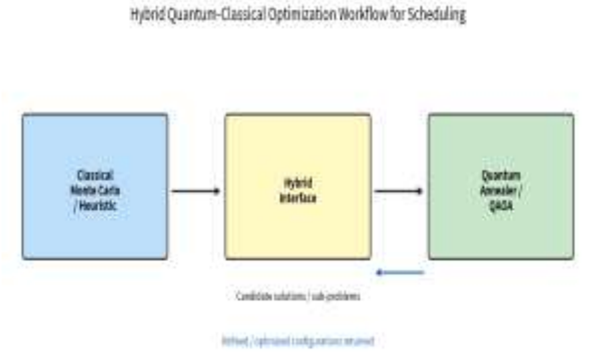

Figure 7. Conceptual hybrid architecture in which quantum annealing refines configurations that are then re-evaluated for residual schedule risk.

The same modelling style and the same hybrid workflow transfer beyond construction. Unit Load Device (ULD) configuration in air-cargo logistics, vehicle routing under capacity constraints, and certain energy-system dispatch problems share the quadratic-binary structure that quantum annealing is designed to exploit. Digital-twin implementations further amplify the value of the approach by keeping the classical data and risk layers continuously current, so that the quantum annealer is always presented with the most relevant sub problem.

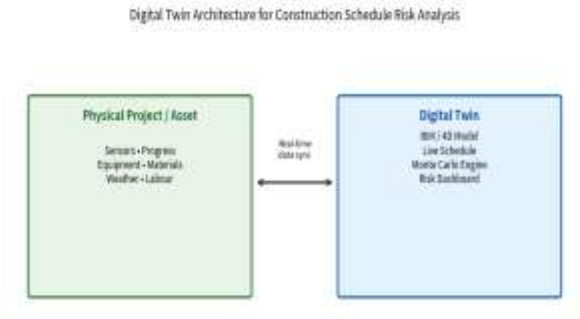

Figure 8. Digital-twin context in which a live probabilistic model can invoke quantum-annealing services for combinatorial sub-problems.

This paper therefore pursues four objectives. First, it reviews the theoretical foundations of quantum annealing Ising and QUBO formulations, the role of quantum tunnelling, and the necessity of minor embedding. Second, it presents a detailed Quantum Annealing Process Flowchart that practitioners can follow from problem formulation through classical post-processing. Third, it situates annealing inside hybrid quantum-classical and digital-twin architectures that also perform Monte Carlo risk analysis. Fourth, it discusses current hardware limitations, implementation best practices, and the transferability of the method to neighboring combinatorial domains. The overarching claim is that quantum annealing implementation is already a viable specialized tool for selected construction and logistics sub-problems and will become progressively more powerful as hardware connectivity and hybrid software mature.

V. HYBRID QUANTUM-CLASSICAL INTEGRATION

Quantum annealing is most powerful when embedded inside a larger classical loop. Classical Monte Carlo or a digital twin generates scenarios and identifies hard combinatorial sub problems; the Quantum Annealing Process Flowchart solves those sub problems; the refined configurations are re-inserted and the residual schedule risk is re-evaluated. This hybrid pattern combines the strengths of probabilistic risk analysis with the combinatorial power of quantum annealing.

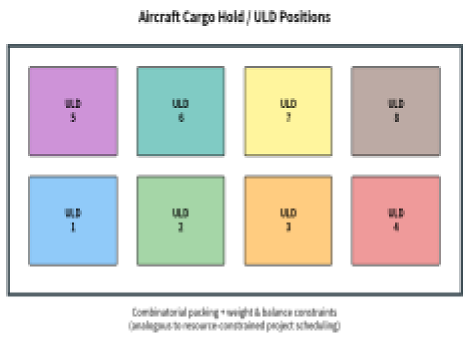

Figure 9. ULD configuration – a cross-domain combinatorial packing problem amenable to the same Ising/QUBO and quantum-annealing treatment.

Resource constrained project scheduling can be formulated with binary variables indicating activity start times. Precedence, resource capacity and time window constraints become quadratic penalty terms. Because current hardware limits problem size, practical implementations decompose the full schedule into rolling-horizon or critical subnetwork sub-problems. Similar QUBO formulations apply to multi project portfolio selection, crew rostering and construction logistics routing.

The same Ising/QUBO modelling style and the same Quantum Annealing Process Flowchart transfer to other combinatorial domains. ULD configuration in air cargo operations three-dimensional packing underweight and balance constraints maps naturally onto quadratic binary models and has been explored with both classical heuristics and quantum-inspired solvers. Successful implementation depends on high quality QUBO formulation, effective minor embedding, sufficient annealing time and reads, robust classical post processing, and seamless integration with the surrounding Monte Carlo or digital-twin workflow. Present-day annealers can already address modest sized scheduling sub problems. Larger instances still require decomposition. Noise, embedding overhead and parameter tuning remain practical challenges, yet improving hardware and hybrid software are steadily expanding the set of viable applications.

VI. CONCLUSION

Managing construction scheduling and resource allocation requires solving complex combinatorial optimization problems that become increasingly challenging as project size, uncertainty, and resource interactions grow. Quantum annealing offers a promising optimization paradigm for addressing these challenges by mapping scheduling problems onto Ising or QUBO Hamiltonians and exploiting quantum tunnelling to efficiently search for low energy solutions. Although current quantum annealers remain constrained by hardware limitations, including limited qubit connectivity, noise, and restricted problem size, they have demonstrated considerable potential for solving practical optimization problems when integrated with classical computational algorithms. Hybrid quantum–classical frameworks that combine quantum annealing with Monte Carlo simulation, digital twins, and artificial intelligence are particularly promising, as they enable simultaneous optimization and probabilistic schedule risk assessment. Continued advances in quantum hardware, embedding techniques, and hybrid optimization methods are expected to further enhance the practical applicability of quantum annealing, making it an increasingly important component of next-generation construction scheduling and schedule risk management systems.

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