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Digital Twin Implementation for Probabilistic Construction Schedule Risk Analysis

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Abstract—
This paper presents a digital-twin-centred framework for probabilistic construction schedule risk analysis. A live digital twin continuously synchronises physical project data with a virtual model that embeds a Monte Carlo simulation engine fed by PERT (beta) distributions. The architecture is extended to incorporate supply-chain resilience and bullwhip dynamics, hybrid quantum-classical optimization, quantum annealing, and cross-domain analogies with ULD configuration and EV battery SoC/SoH estimation. Each major component is illustrated by a dedicated process flowchart and supporting figures, demonstrating how digital-twin implementation transforms static risk models into continuously updated, decision-ready forecasts

Keywords: digital twin implementation; Monte Carlo simulation; PERT distribution; schedule risk analysis; supply-chain resilience; bullwhip effect; hybrid quantum-classical optimization; quantum annealing; ULD configuration; EV battery SoC/SoH; process flowchart

I. INTRODUCTION

Deep and persistent uncertainty defines the operating environment of construction projects. Weather variability, supply-chain disruptions [4], [5], [6], labour productivity fluctuations, design changes, regulatory interventions and unforeseen site conditions continually alter activity durations and resource availabilities. Under these conditions, traditional deterministic Critical Path Method (CPM) schedules produce a single, fixed completion date that systematically understates risk. By treating every duration as a known constant, CPM masks the true probability of delay, underestimates the range of possible outcomes and provides project managers with a false sense of certainty. and generating thousands of possible project outcomes. The resulting duration histograms, criticality indices and confidence levels give a far richer view of schedule risk. Yet conventional MCS implementations remain static snapshots. They are typically run once (or infrequently) at the planning stage, after which the model is frozen. As actual progress, productivity rates and external conditions diverge from the original assumptions, the probabilistic forecasts rapidly lose relevance. Updating the model requires manual data collection, re-parameterization and re-simulation an effort that is rarely sustained throughout the project life cycle.

Digital twin implementation solves this limitation. By establishing a continuous, bidirectional data link between the physical construction site and a virtual probabilistic model, a digital twin transforms the traditional static risk analysis into a living risk engine. Real-time or near-real-time feeds progress updates from BIM/4D models, IoT sensors, drone surveys, site diaries and ERP systems automatically refresh activity durations, resource calendars and dependency logic. The Monte Carlo engine is re-executed on demand or on a rolling basis, so that duration distributions, critical path statistics, float values and confidence levels evolve in step with the project itself. The result is a dynamic, continuously calibrated view of schedule risk that supports proactive decision-making rather than retrospective explanation.

II. LITERATURE REVIEW

Research on project scheduling and schedule risk analysis has evolved from deterministic network planning methods to probabilistic simulation, digital twins, and emerging quantum enabled optimization techniques. This progression reflects the increasing need to manage uncertainty, interdependencies, and computational complexity in large-scale infrastructure projects. The foundational work on network based scheduling began with the development of the Critical Path Method (CPM) and the Program Evaluation and Review Technique (PERT), which introduced three-point activity duration estimates and probabilistic scheduling concepts (Kelley & Walker, 1959; Malcolm et al., 1959). Subsequent studies highlighted limitations in PERT, particularly its assumptions regarding beta distributed activity durations and independence between activities (Clark, 1962; MacCrimmon & Ryavec, 1964; Klingel, 1966).

Recognition of **merge bias** the optimistic estimation of project completion caused by ignoring multiple near critical paths led to the adoption of Monte Carlo simulation. Van Slyke (1963) demonstrated its application to PERT networks, and later studies confirmed that simulation produces more realistic project completion-time distributions, especially for complex networks. In construction, Monte Carlo schedule risk analysis has been integrated with BIM-based 4D models, alternative probability distributions, correlated activity durations, and discrete risk events (Ahuja & Nandakumar, 1985; AbouRizk & Halpin, 1992; Ökmen & Öztaş, 2008; Moret & Einstein, 2016). More recent research incorporates Bayesian updating and machine-learning models to continuously refine activity duration estimates as projects progress. Supply chain uncertainty has also become an important consideration, as material lead-time variability and the bullwhip effect can significantly influence project schedules. Consequently, resilience strategies such as improved visibility, flexibility, and buffering have been linked with project scheduling through multi-echelon simulation approaches.

Digital twins [9], [10] provide a real-time, data-driven framework that integrates these developments by continuously updating project states and re-running schedule risk analyses using live information. Similar probabilistic forecasting approaches are evident in domains such as air cargo logistics and electric vehicle battery health monitoring, where dynamic state estimation techniques address comparable uncertainty and prediction challenges. Emerging hybrid quantum classical optimization [7], [8] offers a promising complement to conventional Monte Carlo simulation and mixed integer programming for computationally demanding scheduling, routing, and resource allocation problems. While current applications in construction remain limited by hardware constraints, advances in quantum computing are expected to strengthen its role in solving large-scale infrastructure optimization problems.

III. DIGITAL TWIN IMPLEMENTATION FRAMEWORK

Digital twin implementation for schedule risk analysis follows a closed-loop process. Physical data progress measurements, sensor feeds, equipment status, weather and material deliveries are captured and synchronized with a virtual model that contains the current BIM geometry, the activity network and the Monte Carlo engine. Monte Carlo simulation (MCS) improves the picture by replacing point estimates with probability distributions

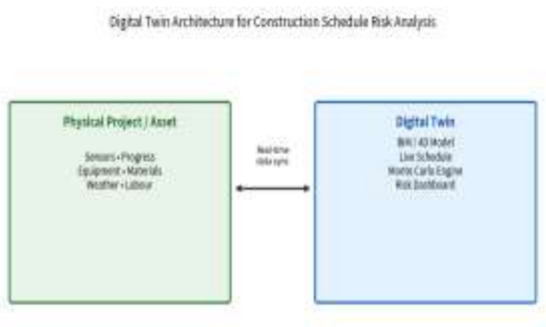

Figure 1. Conceptual digital-twin architecture linking the physical project to a live probabilistic schedule engine.

Updated three point estimates or full probability distributions for activity durations are written back into the Monte Carlo simulation engine. The model is then re-executed either on a scheduled cycle or triggered by significant data changes so that the entire suite of risk metrics is refreshed. Revised duration histograms, critical-path probabilities, float distributions, and confidence intervals are automatically pushed to project dashboards and field teams, ensuring that decision-makers at every level work from a continuously calibrated view of schedule risk rather than outdated assumptions.

Figure 2. Digital Twin Process Flowchart – the five-stage closed-loop implementation sequence.

Successful digital twin implementation therefore requires reliable data pipelines, a maintainable virtual model, an automated Monte Carlo engine, and clear governance of how probabilistic outputs drive decisions. When these elements are in place, the twin becomes the single source of schedule-risk truth for the project. At the heart of the digital twin sits the Monte Carlo Process Flowchart. Stage 1 of the flowchart is kept current by the twin's data synchronisation layer; Stage 2 receives refreshed PERT or alternative distributions; Stages 3–5 are executed automatically whenever the twin detects material change.

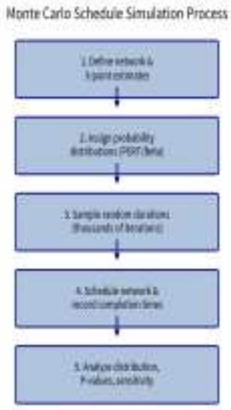

Figure 3. Monte Carlo Process Flowchart embedded inside the digital-twin implementation.

Because the digital twin [11] continuously updates activity durations, resource availabilities and dependency logic with the latest site data, the duration histogram and cumulative probability (S-curve) generated in Stage 5 cease to be static, one-off reports. Instead, they function as living visualizations that reflect the project's current schedule risk posture. Each re-simulation incorporates the most recent progress, productivity and disruption information, so the shape, mean, variance and confidence levels of these distributions evolve in real time and remain decision relevant throughout the project life cycle.

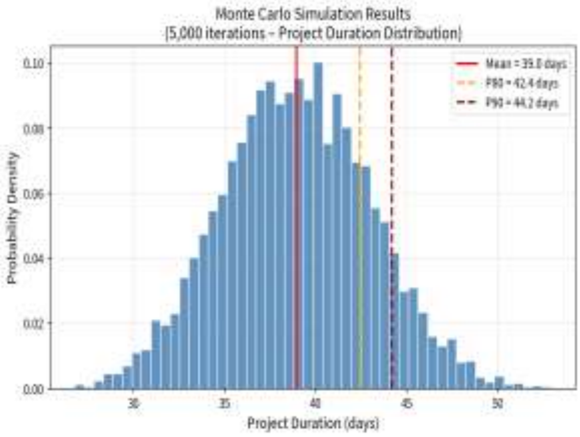

Figure 4. Live histogram of project duration produced by the digital-twin Monte Carlo engine.

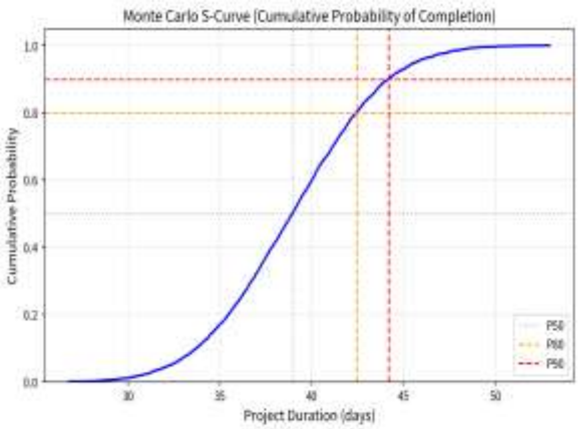

Figure 5. Live S-curve with P50 / P80 / P90 markers generated inside the digital twin.

$T(k) = \max \{ \text{earliest finish of terminal activities} \}$
$\hat{\mu}\_T = (1/N) \Sigma T(k)$, $T\_\alpha \approx$ *empirical α-percentile*

The PERT (Programme Evaluation and Review Technique) distribution, a special case of the four-parameter beta distribution, remains the preferred three-point model for representing activity-duration uncertainty inside the digital twin. For each activity the twin maintains an optimistic estimate a, a most-likely estimate m and a pessimistic estimate b. These parameters are elicited from planners or inferred from historical records and real-time progress data, and are continuously revised as the twin ingests new site information. Under the classic PERT weighting the expected duration and variance are given by

$$\mu = \frac{a + 4m + b}{6}$$

$$\sigma^2 = \left(\frac{b - a}{6}\right)^2$$

Equivalently, the distribution may be expressed as a scaled beta random variable on the interval [a, b]. The shape parameters α and β of the underlying beta distribution on [0, 1] are obtained from the mean and variance via

$$\alpha = \mu_{scaled}\left(\frac{\mu_{scaled}(1 - \mu_{scaled})}{\sigma^2 \mu_{scaled}} - 1\right)$$

$$\beta = (1 - \mu_{scaled})\left(\frac{\mu_{scaled}(1 - \mu_{scaled})}{\sigma^2 \mu_{scaled}} - 1\right)$$

where

$$\mu_{scaled} = \frac{\mu - a}{b - a}, \quad \sigma^2{}_{scaled} = \frac{\sigma^2}{(b - a)^2}$$

When fresh progress, productivity or disruption data arrive, the twin updates the triple (a, m, b) (or the equivalent α, β) and immediately re-samples the Monte Carlo engine. Consequently, the duration distributions, critical-path probabilities and confidence levels remain calibrated to the current state of the physical project rather than to a static baseline plan. $t_e = (a + 4m + b) / 6, \quad \sigma = (b - a) / 6$

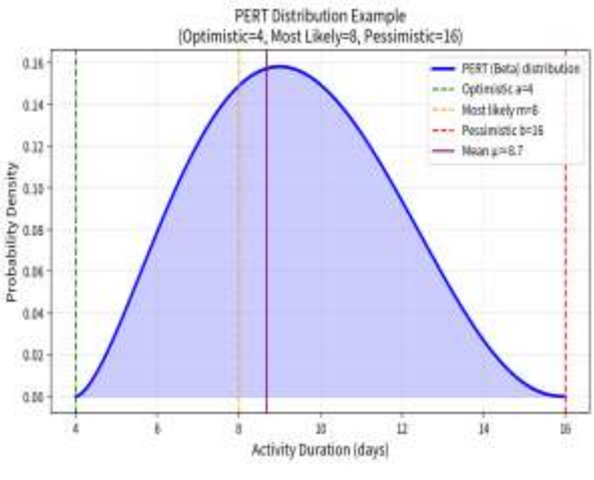

Figure 6. PERT distribution used for activity-duration modelling inside the digital twin.

Digital twin implementation allows these parameters to be Bayesian-updated as actual durations are observed, progressively reducing uncertainty.

IV. SUPPLY-CHAIN RESILIENCE AND BULLWHIP EFFECT INSIDE THE TWIN

Digital twin [12], [13] implementation naturally extends the risk boundary beyond the site fence. Multi-echelon supply-chain models [17] that capture the bullwhip effect are linked to the twin so that material lead-time distributions are sampled jointly with on-site activity durations. Material lead-time variability and the bullwhip effect can dominate schedule risk. The Supply-Chain Resilience [14] & Bullwhip Analysis Flowchart [15], [16] extends the Monte Carlo framework upstream: (1) map the multi-echelon network (supplier → hub → site); (2) define lead-time and demand uncertainty (including bullwhip amplification) [18]; (3) sample joint distributions with site activity durations; (4) evaluate schedule impact under alternative resilience policies; (5) rank interventions (buffers, dual-sourcing, etc.) by their effect on the project S-curve

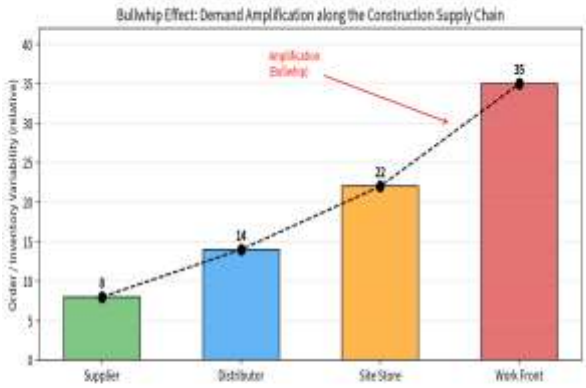

Figure 7. Bullwhip effect – order variability amplification along the construction supply chain.

Resilience interventions (safety stocks, dual sourcing, expediting contracts) can be tested inside the twin and ranked by their impact on the live project S-curve. Certain combinatorial optimization sub-problems that arise within digital twins such as resource levelling, multi-project portfolio selection, scheduling, routing, and complex logistics often scale poorly as the number of variables, constraints, and interdependencies increases. Classical optimization methods, including exact algorithms and heuristics, may require substantial computational time to identify high-quality solutions for these large, NP-hard problems, particularly when decisions must be updated continuously using real-time operational data.

To address these computational bottlenecks, a digital twin [19], [20] can delegate such optimization tasks to a hybrid quantum-classical computing layer. In this architecture, the classical computing component manages data acquisition, simulation, constraint handling, and workflow orchestration, while the quantum processor is employed for the most computationally intensive combinatorial optimization sub-problems. Quantum optimization techniques such as the **QAOA**, **VQAs** can explore vast solution spaces more efficiently than exhaustive classical search methods for certain problem classes. The classical optimizer iteratively refines the quantum-generated candidate solutions until convergence.

For example, in resource levelling, the hybrid layer can optimize the allocation of limited labor, equipment, and materials across multiple concurrent activities while minimizing idle time and schedule disruptions. In multi-project portfolio selection, it can evaluate thousands of possible project combinations under budget, resource, and strategic constraints to maximize organizational value. Similarly, in **complex logistics**, quantum-enhanced optimization can improve vehicle routing, warehouse operations, inventory placement, and supply-chain coordination by identifying near-optimal solutions more rapidly than conventional techniques for large-scale instances.

By integrating hybrid quantum-classical optimization [21], [22] into the digital twin, organizations can improve decision quality, accelerate optimization cycles, and respond more effectively to dynamic operational changes. Although current quantum hardware remains limited by qubit count and noise, hybrid approaches leverage the complementary strengths of classical and quantum computing, making them a practical pathway toward solving computationally challenging optimization problems as quantum technologies continue to mature.

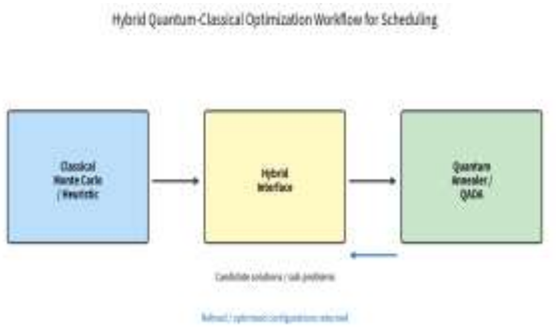

Figure 8. Conceptual hybrid quantum-classical workflow feeding refined configurations back into the twin.

Classical Monte Carlo running inside the twin generates candidates; a hard sub-problem is extracted, solved on a quantum annealer or by VQE/QAOA, and the refined solution is re-inserted for residual-risk evaluation. Quantum annealing is especially suited to QUBO/Ising formulations of scheduling and resource-allocation problems that the twin may encounter.

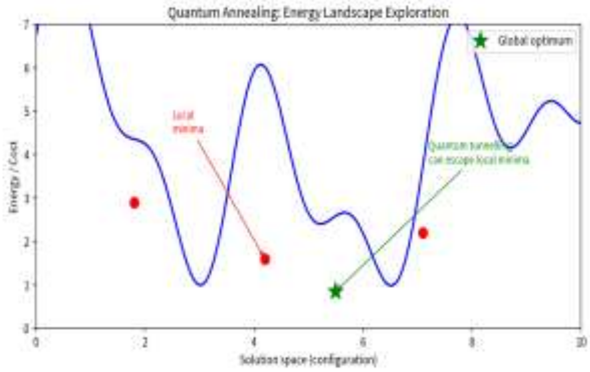

Figure 9. Energy landscape explored by quantum annealing – tunnelling helps escape local minima.

The twin formulates the sub-problem, requests an anneal, receives low-energy samples, and continues its Monte Carlo evaluation with the improved configuration. Two external domains illustrate transferable process patterns that strengthen digital twin implementation. ULD configuration in air-cargo logistics shares combinatorial packing and sequencing characteristics with resource-constrained project scheduling. The same hybrid optimization and simulation logic used inside the twin can be applied to ULD stowage.

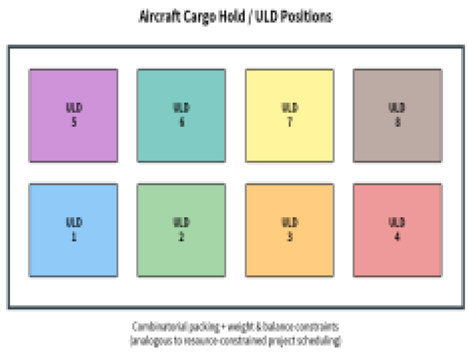

Figure 10. Schematic ULD configuration inside an aircraft cargo hold.

Likewise, probabilistic estimation of electric-vehicle battery state-of-charge (SoC) and state-of-health (SoH) mirrors residual-duration forecasting. Filtering, uncertainty propagation and remaining-useful-life distributions are conceptually identical to the twin's treatment of activity durations.

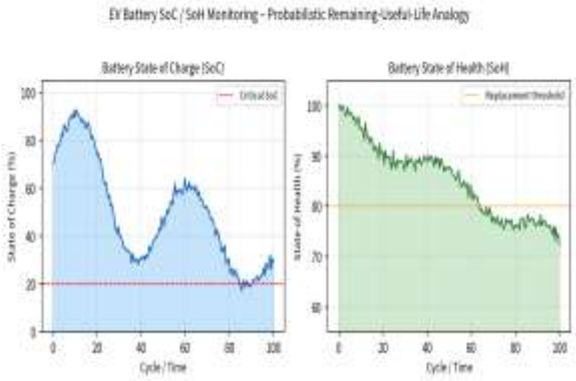

Figure 11. Illustrative SoC and SoH trajectories used for remaining-useful-life analogy.

Digital twin implementation for probabilistic scheduling proceeds in layers: (1) establish reliable data capture and a maintainable virtual model; (2) embed an automated Monte Carlo engine fed by PERT (or alternative) distributions; (3) close the feedback loop so that risk metrics drive decisions; (4) extend the twin upstream to supply-chain resilience and bullwhip modelling; (5) optionally attach hybrid quantum-classical or quantum-annealing services for hard combinatorial sub-problems. Governance, data quality and change-management practices determine whether the twin remains a living system or reverts to a static dashboard.

CONCLUSION

Digital twin implementation transforms Monte Carlo schedule risk analysis from a periodic study into a continuous, decision-ready capability. By keeping the Monte Carlo Process Flowchart alive with real-time data, enriching it with supply-chain resilience and bullwhip dynamics, and optionally accelerating hard sub-problems with hybrid quantum-classical or quantum-annealing methods, the twin delivers quantified probabilities, prioritised risks and transparent communication throughout the project life cycle. Cross-domain experience with ULD configuration and EV battery SoC/SoH estimation confirms the generality of the underlying probabilistic and process-flowchart thinking. Organisations that invest in robust digital twin implementation therefore obtain not only better forecasts but a persistent, shared understanding of schedule risk.

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