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Intelligent ULD Configuration Using Quantum Annealing, Artificial Intelligence, and Digital Twins

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Abstract—

The increasing complexity of air-cargo operations requires efficient methods for optimizing ULD configuration under multiple operational, structural, and geometric constraints. This study presents a quantum annealing-based optimization framework for ULD selection and placement, formulated as a QUBO problem. The proposed approach maximizes cargo revenue and payload utilization while simultaneously considering aircraft weight and volume limits, center-of-gravity requirements, floor-loading and shear constraints, ULD compatibility, stacking rules, and fuselage packing limitations. A two-phase strategy is introduced in which high-value ULDs are first selected and subsequently positioned within feasible aircraft bays. Classical heuristic solutions can be used to initialize the optimization, while quantum annealing and reverse annealing provide opportunities for refining complex configurations. The framework is further connected with Artificial Intelligence, Digital Twins, IoT, and intelligent transportation systems to support real-time monitoring, scenario evaluation, disruption management, and adaptive decision-making. The proposed integration demonstrates how hybrid quantum-classical optimization can address computationally intensive cargo-loading problems while improving payload utilization, operational efficiency, safety, and supply-chain resilience. The study provides a foundation for future development of scalable quantum-enhanced optimization systems for intelligent and resilient air-cargo logistics.

Keywords— Digital Transformation; Artificial Intelligence; Internet of Things; Blockchain; Digital Twin Technology; Swipe Controller; Quantum Computing; Intelligent Logistics; Supply Chain Transparency; Sustainable Supply Chains; Resilience; Smart Mobility; Intelligent Transportation Systems; Connected Vehicles; Mobility-as-a-Service; Sustainable Transportation; Multi-Scale Spectral Analysis; FKF Transform.

I. INTRODUCTION

Global supply chains are increasingly characterized by interconnected operations, uncertain demand, transportation disruptions, resource constraints, sustainability requirements, and rapidly changing market conditions. These characteristics have created a need for intelligent mathematical and computational frameworks capable of sensing, representing, analyzing, simulating, and optimizing complex logistics systems. Recent developments in Artificial Intelligence (AI), Internet of Things (IoT), Blockchain, Digital Twins, quantum computing, and advanced spectral methods provide complementary capabilities for addressing these challenges [13], [28].

Sustainable logistics has become an important component of this transformation because transportation, inventory, warehousing, and distribution activities strongly influence energy consumption, resource utilization, emissions, and environmental performance. Artificial Intelligence supports sustainable logistics through demand prediction, transportation optimization, intelligent resource allocation, predictive analysis, and operational automation [17]. IoT further enables continuous acquisition of operational information, while AI converts these observations into predictive and prescriptive decisions [13]. Industry 5.0 extends this technological development toward human-centric, sustainable, and resilient intelligent logistics systems [14].

Supply-chain transparency and traceability represent another important dimension of sustainable and resilient logistics. Modern global supply chains involve multiple stakeholders and geographically distributed transactions, making reliable information essential for coordination and disruption management. AI–Blockchain integration combines intelligent analysis with trusted and traceable information exchange, thereby supporting transparency, anomaly identification, product traceability, and resilience [18]. Digital transformation similarly provides a foundation for developing resilient supply chains capable of responding to disruptions through continuous information exchange and adaptive decision-making [28].

II. DYNAMIC STATE-SPACE REPRESENTATION OF A LOGISTICS SYSTEM

Digital Twin technology provides a mathematical and computational representation of physical supply-chain systems. A Digital Twin can continuously connect real-world operational states with a virtual representation, enabling monitoring, simulation, prediction, and evaluation of alternative decisions [16]. When integrated with IoT and AI, the Digital Twin can be regarded as a dynamic state-space representation of a logistics system,

$$\mathcal{D}(t) = \mathcal{M}(z(t), u(t), \theta)$$

where $z(t)$ represents the observed operational state, $u(t)$ denotes operational decisions, and θ represents system parameters. Within such an environment, alternative supply-chain configurations can be simulated before being implemented in the physical system [16]. This provides a natural platform for combining AI prediction with optimization and disruption-response mechanisms.

The computational complexity of logistics optimization has stimulated interest in quantum computing and quantum annealing. Transportation and logistics applications frequently involve discrete decision variables, nonlinear interactions, capacity restrictions, and large combinatorial search spaces [22], [26]. Quantum annealing seeks the ground state of a problem Hamiltonian through an evolving Hamiltonian of the form

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

where $A(s)$ and $B(s)$ define the annealing schedule and $s \in [0,1]$ represents the progression from the quantum-dominated regime toward the problem Hamiltonian [23]. At the beginning of the annealing process, the driver Hamiltonian promotes quantum exploration, whereas the final problem Hamiltonian encodes the logistics optimization problem.

For practical logistics applications, combinatorial problems can be transformed into QUBO form,

$$\min_{x} \quad x^T Q x, \qquad x \in \{0,1\}^n$$

where Q is the QUBO matrix and the binary variables represent logistics decisions [23]. The relationship between the QUBO and Ising representations is expressed as

$$x_i = \frac{1 - \sigma_i}{2}$$

where $\sigma_i \in \{-1, +1\}$ represents an Ising spin. Constraints are incorporated through weighted penalty functions, allowing a constrained logistics problem to be transformed into an energy minimization problem [23].

A representative application is ULD configuration, in which candidate ULDs must be selected and assigned to aircraft cargo-bay positions while satisfying weight, volume, center-of-gravity, structural, compatibility, and dimensional constraints [23]. Let

$$I = \{1, \ldots, N\}$$

represent the set of candidate ULDs and let

$$j = 1, \ldots, M$$

represent the available cargo-bay positions. The binary variable

$$x_{ij} \in \{0,1\}$$

indicates whether ULD i is assigned to position j. The corresponding energy formulation is

$$E(x) = -\sum_{i,j} r_i x_{ij} + \lambda_w \left(\sum_{i,j} m_i x_{ij} - W_{max} \right)^2 + \lambda_v \left(\sum_{i,j} v_i x_{ij} - V_{max} \right)^2 + \lambda_{CoG} \left(\sum_{i,j} m_i d_j x_{ij} - M_{target} \right)^2 + \lambda_{one} \sum_i \left(\sum_j x_{ij} - 1 \right)^2 + \cdots$$

where r_i denotes revenue or priority, m_i mass, v_i volume, d_j the longitudinal position of bay j, and the λ-parameters represent penalty weights used to enforce feasibility [23]. Additional quadratic terms can represent adjacency, stacking, shear, and other operational constraints.

This formulation illustrates how quantum optimization can be embedded within a broader supply-chain decision architecture. A classical system may first generate feasible candidate solutions, while quantum annealing explores the corresponding energy landscape for improved configurations. Reverse annealing can begin from a high-quality classical solution and perform localized quantum exploration, providing a mechanism for refining existing logistics decisions [23]. Such a hybrid quantum-classical approach is particularly relevant to disruption management, where logistics configurations may need to be repeatedly re-optimized under changing operational conditions [22], [26].

In parallel with optimization, supply-chain systems require mathematical tools for representing temporal, scale-dependent, and irregular operational signals. The FKF transform provides such a spectral framework. For a supply-chain signal $f(t,x)$, where $t \in \mathbb{R}$ denotes time and $x > 0$ represents a positive operational variable such as inventory level, demand magnitude, transportation distance, capacity, or disruption intensity, the two-dimensional transform can be represented as

$$\mathcal{F}_{FKF}\{f\}(s,q) = \int_{-\infty}^{\infty} \int_0^{\infty} f(t,x) e^{-ist} K_{iq}(x) \frac{dx}{x} dt$$

where s is the Fourier spectral variable, $q > 0$ is the Kontorovich–Lebedev spectral variable, and $K_{iq}(x)$ is the Macdonald function of imaginary order. This representation separates temporal frequency behavior from positive-domain or scale-related behavior, providing a joint spectral description of supply-chain dynamics [1], [5], [7].

The FKF framework is particularly relevant to logistics systems because operational signals may contain delays, oscillations, transient changes, disruptions, and multiple characteristic scales. The shift property provides a mathematical representation of delayed supply-chain responses. If a signal is shifted in time,

$$f(t - t_0, x) \Rightarrow \mathcal{F}_{FKF}\{f(t - t_0, x)\}(s,q) = e^{-ist_0} F(s,q)$$

where the temporal delay t_0 appears as a phase factor in the Fourier component [4], [8]. Such a property can be associated with delayed replenishment, transportation lead-time changes, demand-response delays, or disruption propagation.

Similarly, exponential modulation in the temporal domain produces a spectral translation,

$$e^{ist_0} f(t,x) \Rightarrow F(s - s_0, q)$$

providing a mechanism for identifying and separating periodic or frequency-shifted components of supply-chain signals [9]. The differential and distributional extensions of the FKF transform further provide mathematical tools for representing irregular and generalized logistics signals [1], [6]. The sequential convergence framework establishes the mathematical basis for handling convergence within the associated testing-function space [2], while the multiscale spectral framework supports the analysis of complex supply-chain dynamics [3], [5].

The combination of these mathematical capabilities with AI and Digital Twin technologies creates a more comprehensive analytical architecture. AI can learn predictive relationships from observed supply-chain data [17], while FKF spectral analysis can transform complex temporal and positive-domain signals into a structured spectral representation [1]. The Digital Twin can then use these representations for simulation and scenario evaluation [16]. Blockchain can provide trusted records of the underlying events [18], and quantum optimization can address computationally intensive decisions generated by the simulation environment [23]. Sustainable transportation and intelligent mobility provide an additional operational dimension in which these technologies can be applied to improve transportation efficiency and resource utilization [24], [25], [27].

Thus, the emerging supply-chain architecture can be mathematically and computationally interpreted as a sequence of interconnected transformations:

$$\begin{aligned} IoT\ sensing\ \rightarrow\ & AI\ prediction \\ & \rightarrow FKF\ spectral\ analysis \\ & \rightarrow Digital\ Twin\ simulation \\ & \rightarrow QUBO \\ & /quantum\ optimization \\ & \rightarrow adaptive\ decision \end{aligned}$$

Blockchain provides a trusted information layer across these stages [18]. The resulting framework integrates signal representation, intelligent prediction, virtual simulation, and combinatorial optimization into a unified approach for sustainable and resilient logistics.

Accordingly, this study investigates the convergence of Artificial Intelligence, Blockchain, Digital Twins, quantum computing, sustainable logistics, and FKF/FKL spectral intelligence. Particular attention is given to AI applications in green supply-chain management [17], AI–Blockchain integration for transparency and traceability [18], Digital Twin technology for resilient global supply chains [16], quantum annealing for ULD configuration and disruption management [23], and the mathematical representation of supply-chain dynamics through the FKF/FKL framework [1], [4], [5]. The objective is to establish an integrated analytical and computational perspective in which supply-chain systems can sense, represent, analyse, simulate, optimize, and adapt under dynamic and uncertain operating conditions [13], [22], [28].

III. FORMULATION FOR COMBINATORIAL OPTIMIZATION

Combinatorial optimization problems are first mapped into Quadratic Unconstrained Binary Optimization (QUBO) form, after which the corresponding QUBO objective is encoded in a problem Hamiltonian for quantum annealing. Quantum annealing seeks the ground state of an Ising Hamiltonian. The total time-dependent Hamiltonian is generally expressed as

$$\mathrm{H}_s = A(s)\,\mathrm{H}_{driver} + B(s)\,\mathrm{H}_{problem}$$

where H_{driver}, sometimes H_D is the driver Hamiltonian, typically represented by a transverse-field term that induces quantum tunneling, and $\mathrm{H}_{problem}$ (H_P) is the problem Hamiltonian encoding the optimization objective and constraints. The annealing schedule represented by (A(s)) and (B(s)) gradually interpolates the system from a quantum-dominated regime to a problem-dominated classical regime. Ideally, the final Hamiltonian is constructed such that its ground state corresponds to the optimal solution of the original combinatorial problem.

The annealing process therefore begins with a dominant driver Hamiltonian and progressively reduces its contribution while increasing the contribution of the problem Hamiltonian. At (s=0), the system is initialized in the ground state of H_D, whereas at (s=1), the problem Hamiltonian H_P dominates and its ground state represents the desired optimal configuration. At the endpoints, $s = 0$, and $s = 1$

Problems are mapped to QUBO form

$$min\ \mathrm{x}^{\mathrm{T}}\mathrm{Q}\mathrm{x} \quad subject\ to\ \ \mathrm{x} \in \{0,1\}^n$$

which is equivalent to an Ising model via the linear transformation

$$\mathrm{x}_i = \frac{1 - \sigma_{\mathrm{i}}}{2}$$

where x_i are binary decision variables, σ_{i} are linear coefficients. Constraints are incorporated through appropriately weighted penalty terms, allowing the resulting QUBO formulation to be transformed into an Ising-type problem Hamiltonian suitable for quantum annealing.

Linear and quadratic constraints are incorporated by adding suitably weighted penalty terms to the objective. On current hardware, embedding a logical QUBO onto the physical qubit topology (Chimera or Pegasus) introduces chain variables whose strength must be carefully tuned to avoid chain breaks.

Reverse annealing starts from a classical candidate solution and explores the local energy landscape with a partial quantum evolution. This can be useful for refining high-quality solutions in logistics problems.

larger instances

IV. QUANTUM-ANNEALING-BASED ULD CONFIGURATION

Consider a set of candidate ULDs, where each ULD is characterized by mass, volume or footprint, revenue/priority, dimensions, and geometric type. The ULD configuration problem is a combinatorial optimization problem involving cargo allocation, capacity utilization, aircraft balance, structural safety, and geometric feasibility. Such complex logistics optimization problems provide an important application area for quantum computing and quantum annealing [22]. The aircraft cargo hold is discretized into sequential bays or loading positions. To define binary decision variable, Consider a set of candidate ULDs

$$I = \{1, \dots, N\}$$

Each ULD is characterized by mass, volume (or footprint), revenue (or priority), and geometric type.

$$\mathrm{m}_i, \mathrm{v}_i, \mathrm{r}_i, \mathrm{t}_i \in \{0.5, 1, 2\}$$

The aircraft cargo hold is discretized into M sequential bays or positions.

$$j = 1, \dots, M$$

Binary decision variables indicate whether ULD i is assigned to bay j.

$$\mathrm{x}_{i,j} \in \{0,1\}$$

This binary representation enables the ULD loading problem to be converted into a QUBO formulation, which is suitable for quantum-annealing-based combinatorial optimization [22]. The optimization process can subsequently be incorporated into a digital-twin environment, where alternative cargo configurations can be simulated and evaluated before implementation [21]. The principal objective of the ULD configuration problem is to maximize total cargo revenue, cargo priority, or payload utilization while satisfying a set of operational, structural, and geometric constraints. The optimization must respect the total weight, volume, and linear-length capacities of the aircraft hold and individual decks, thereby ensuring that the selected ULD configuration remains within available loading capacity [22]. In addition, CG constraints require the longitudinal moment of the loaded aircraft to remain within a prescribed envelope relative to the mean aerodynamic chord, maintaining aircraft balance and safe operating conditions. Structural constraints, including allowable shear forces and floor-loading limits, must also be incorporated to prevent excessive localized loading and structural stress [22]. Furthermore, ULD compatibility constraints restrict the placement of incompatible units, including rules governing adjacency, stacking, and allowable combinations of cargo types. The problem also involves dimensional packing constraints arising from the circular cross-section of the aircraft fuselage, which limits the feasible arrangement and orientation of ULDs within the available loading space. Collectively, these requirements transform ULD configuration into a highly constrained combinatorial optimization problem, for which artificial intelligence, digital twins, and quantum optimization techniques can provide promising decision-support capabilities [21][16][17]. Digital-twin-based simulation can further evaluate alternative loading configurations under changing operational conditions [21], while AI can support intelligent optimization and resource utilization [16]. The integration of such technologies with emerging quantum optimization approaches offers a potential pathway for solving computationally intensive logistics configuration problems more efficiently.

The objective and constraints are combined into a single quadratic energy function:

$$E(x) = -\sum_{\mathrm{i,j}} r_{\mathrm{i}}\, x_{\mathrm{i,j}} + \lambda_w \left(\sum_{\mathrm{i,j}} m_{\mathrm{i}}\, x_{\mathrm{i,j}} - \mathrm{W}_{max}\right)^2 + \lambda_v \left(\sum_{\mathrm{i,j}} v_{\mathrm{i}}\, x_{\mathrm{i,j}} - \mathrm{V}_{max}\right)^2$$

$$+ \lambda_{CoG} (\sum_{i,j} m_i \, d_j \, x_{i,j} - M_{target})^2$$
$$+ \lambda_{one} \sum_i (\sum_j x_{i,j} - 1)^2 + \ldots$$

The ULD configuration problem can be formulated as a Quadratic Unconstrained Binary Optimization (QUBO) model by representing each feasible ULD–bay assignment with a binary decision variable. The objective combines cargo revenue or payload utilization with penalty terms for violations of weight, volume, center-of-gravity, adjacency, stacking, and structural constraints. For a ULD assigned to bay (j), the longitudinal contribution can be represented using its bay position (d_j), while penalty coefficients (\lambda) control the relative importance of constraint satisfaction. This formulation converts the constrained logistics problem into a quadratic energy function that can be mapped to an Ising Hamiltonian and solved using quantum annealing. Such quantum-based optimization is particularly relevant to logistics problems involving large combinatorial search spaces, where hybrid quantum–classical approaches can decompose complex problems into manageable subproblems. The broader computational perspective of representing system states through discrete variables and structured decision rules also supports this formulation [4], while the emphasis on intelligent optimization and efficient resource management is consistent with emerging technology-driven optimization frameworks [25].

Principal Mathematical Notation

$$H(s) = A(s) \, H_{driver} + B(s) \, H_{problem}$$
$$x^T Q \, x$$
$$x_i = \frac{1 - \sigma_i}{2}$$
$$x_{i,j} \in \{0,1\}$$
$$E(x) = -\sum_{i,j} r_i \, x_{i,j} + penalty\ terms$$

A practical two-phase quantum-optimization strategy can improve the scalability of ULD configuration. In Phase 1, a high-value subset of ULDs is selected using a knapsack-like objective that balances cargo value, priority, weight, and available capacity [2][7]. In Phase 2, the selected ULDs are optimally assigned to bays while satisfying center-of-gravity, structural, adjacency, stacking, and dimensional constraints [8][11]. This decomposition reduces the QUBO size and computational complexity, making hybrid quantum–classical optimization more practical for large logistics problems [23]. A classical greedy solution can first generate a feasible high-quality configuration, which is subsequently used to seed reverse annealing for local refinement and improved solution quality [8]. Digital-twin-based simulation can evaluate alternative configurations under changing operational and disruption scenarios [1][13], while AI-driven optimization supports adaptive resource allocation and decision-making [2]. The resulting framework combines classical heuristics, quantum annealing, and intelligent logistics technologies to address complex ULD configuration problems [7][11].

V. FUTURE DIRECTIONS

The proposed framework can be applied to air-cargo ULD loading optimization by selecting valuable cargo and determining feasible ULD positions while satisfying weight, volume, CoG, structural, and compatibility constraints. Quantum annealing can solve the resulting combinatorial optimization problem, while classical methods provide feasible initial solutions [7][8]. A digital twin can continuously simulate aircraft loading conditions and evaluate alternative configurations under operational disruptions [1][13]. AI can further support cargo prioritization, capacity prediction, and adaptive decision-making [2], while IoT-based data can provide real-time operational inputs [23]. Thus, the integrated framework can improve payload utilization, cargo revenue, loading efficiency, safety, and resilience in intelligent air-logistics operations [9][11].

CONCLUSION

The ULD configuration problem represents a complex combinatorial optimization challenge in which cargo value, payload utilization, aircraft balance, structural safety, compatibility, and geometric packing must be considered simultaneously. A two-phase optimization strategy provides an effective way to manage this complexity by first identifying a high-value subset of ULDs and subsequently determining their feasible placement within the aircraft hold. Formulating the placement problem as a QUBO enables the use of quantum annealing to explore large solution spaces efficiently, while classical heuristics can provide strong initial solutions and reduce computational effort. Reverse annealing can further refine promising configurations, particularly for larger and more constrained instances. The integration of quantum optimization with classical algorithms, digital-twin simulation, and intelligent logistics systems provides a flexible framework for evaluating alternative loading plans under changing operational conditions. Overall, this hybrid approach offers significant potential for improving cargo revenue, payload utilization, aircraft safety, and computational efficiency, while providing a foundation for future real-world implementation of quantum-enhanced logistics optimization.

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