An AI-Enabled FKF Framework for Artificial Intelligent and Sustainable Logistics

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Abstract—

The growing volatility, interconnectedness, and disruption risks of modern global supply chains demand intelligent logistics systems that can operate adaptively across multiple spatial and temporal scales. This study proposes an integrated Digital Twin–FKF transform framework for intelligent and resilient logistics by combining Digital Twins, the Internet of Things (IoT), Artificial Intelligence (AI), sustainable mobility, Blockchain, and quantum optimization with advanced spectral analysis. Digital Twins provide dynamic representations of logistics assets and processes, enabling real-time synchronization, monitoring, simulation, and disruption-scenario evaluation, while IoT and AI facilitate intelligent sensing, prediction, and adaptive decision-making. The bivariate Fourier–Kontorovich–Lebedev (FKF) transform supplies a joint temporal–scale spectral representation of supply-chain signals, enabling the identification of time shifts, exponential modulation, multiscale behavior, and lead-time dynamics. These spectral characteristics are converted into informative features for AI-driven forecasting, anomaly detection, and resilience assessment. The proposed FKF-enabled intelligent supply-chain framework therefore integrates spectral intelligence with AI, Blockchain, IoT, Digital Twins, and quantum optimization to support predictive, transparent, sustainable, and resilient logistics operations.

Keywords— *FKF transform; Digital Twin; adaptive global supply chains; artificial intelligence; green supply-chain management; Blockchain; swipe controller; supply-chain resilience; quantum logistics; IoT; quantum annealing; sustainable logistics; spectral analysis; electric-vehicle battery.*

I. INTRODUCTION

This study presents an integrated framework that combines Digital Twins, IoT, AI, trusted data exchange, sustainable mobility, FKF spectral analysis, and quantum optimization for adaptive logistics [14], [15], [31], [32]. The framework connects real-time physical-system observations with mathematical signal analysis and advanced optimization, enabling continuous monitoring, disruption simulation, spectral characterization, and decision optimization. Digital Twins provide dynamic virtual representations of supply-chain assets and processes, supporting real-time synchronization and disruption assessment [23], [31], while IoT and AI enable intelligent sensing, forecasting, anomaly detection, resource optimization, and predictive decision-making [14], [28], [32], Blockchain strengthens trusted information exchange and traceability [33]; communication technologies provide connectivity for monitoring and control [17]; and Industry 5.0 promotes human-centric, resilient, and collaborative logistics [15].

Digital Twins also support resilience by virtually evaluating transportation delays, inventory fluctuations, equipment failures, capacity constraints, and demand variations before recovery actions are implemented [23]. These capabilities extend to sustainable mobility and intelligent transportation through applications involving electric-vehicle batteries [6], hybrid-vehicle battery sizing [18], solar-powered hybrid architectures [16], swipe controllers for responsive actuation [34], solar-assisted electric mobility [22], and broader smart-mobility and intelligent-transportation systems [20]. For complex combinatorial logistics problems, quantum computing and quantum annealing offer promising optimization capabilities for routing, scheduling, allocation, unit-load-device (ULD) configuration, and disruption management [19], [21], [35], Integrating quantum optimization with Digital Twins enables candidate solutions to be evaluated under realistic operational scenarios.

FKF spectral analysis provides a complementary mathematical layer for identifying periodic demand, transportation delays, transient disturbances, multiscale variations, and frequency changes. The related FKL transform establishes a spectral basis for supply-chain analysis [11], while the FKF framework extends this capability to dynamic supply-chain and resilience analysis [9]. Shift-invariant treatment of multi-echelon lead times [8] and residue-based resonance extraction in hybrid-vehicle and multi-scale supply-chain signals [7] further enrich the feature set. Time-shift and exponential-modulation properties support lead-time and frequency-shift analysis [12], [13]. Distributional FKF theory and sequential convergence in the associated testing-function space enable generalized signal representation and spectral differential analysis [10], [24], [25]. The combined framework therefore establishes a continuous digital–spectral–intelligent–optimization loop for predictive, resilient, and adaptive supply-chain management.

The remainder of the paper is organized as follows. Section II introduces the bivariate FKF spectral framework. Section III interprets the transform as a spectral encoder of logistics dynamics. Section IV develops the time-shift property for delay and lead-time analysis. Section V treats frequency modulation, the differential spectral property of the Macdonald kernel, and AI-ready features. Section VI formulates the Digital Twin–FKF spectral state. Section VII embeds the transform in a distributed sensing and fusion architecture. Section VIII concludes.

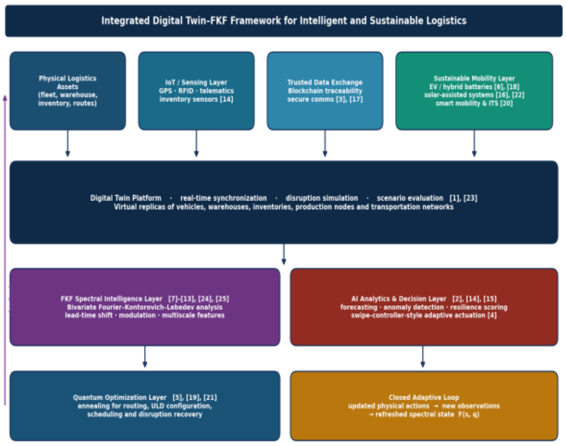

Fig. 1. Integrated Digital Twin–FKF framework: physical assets, IoT sensing, trusted data exchange, sustainable mobility, spectral intelligence, AI decision-making, and quantum optimization in a closed adaptive loop.

II. BIVARIATE FOURIER–KONTOROVICH–LEBEDEV SPECTRAL FRAMEWORK

For logistics and supply-chain signals characterized by temporal fluctuations and scale-dependent variations, a bivariate Fourier–Kontorovich–Lebedev (FKF) formulation offers a unified spectral representation across oscillatory, positive-scale, and multiscale regimes [9], [11]. Let $\boldsymbol{f(t,x)}$ be a suitably admissible function of calendar (or operational) with time $t \in \mathbb{R}$ and a positive scale variable $\boldsymbol{x > 0}$. The two-sided FKF transform is defined by

$$\mathcal{F}_{FK}(f)(s,q) = F(s,q) = \boxed{\int_{-\infty}^{\infty}\int_{0}^{\infty} f\,(t,x)\, e^{-ist}\, K_{iq}(x)\,\frac{dx}{x}\,dt}$$

Where, $s \in \mathbb{R}$, $q > 0$, e^{-ist} is the Fourier kernel, and $K_{iq}(x)$ is where $s \in \mathbb{R}$ is the temporal frequency, $q > 0$, the Kontorovich–Lebedev scale frequency, e^{-ist} is the Fourier kernel, and $K_{iq}(x)$ is the Macdonald function of imaginary order.

The precise multiplicative constant depends on the adopted Fourier and Kontorovich–Lebedev normalization conventions [11], [25]. The resulting bivariate spectral domain provides a mathematical foundation for extracting temporal, scale-dependent, and multiscale features for intelligent supply-chain monitoring and resilience analysis [9].

A. Fourier Component and Sequential Representation

The temporal Fourier transform is applied first, after which the Kontorovich–Lebedev transform acts on the positive-scale variable. Consequently, the FKF transform can be written sequentially, separating the temporal frequency s from the positive-scale variable q [11], [9]. The temporal Fourier transform is.

$$\hat{f}(s,x) = \int_{-\infty}^{\infty} f\,(t,x)e^{-ist}\,dt.$$

The FKF transform can therefore be written sequentially as

$$\boxed{F(s,q) = \int_{0}^{\infty} \hat{f}\,(s,x)K_{iq}(x)\frac{dx}{x}}$$

which shows the separation between the temporal frequency variable s and the positive-scale variable q.This sequential factorization, separates temporal periodicity from scale-frequency structure, allowing delays, multiscale variations, and transient logistics behavior to be characterized jointly [8], [11]. Under appropriate admissibility and normalization conditions an inverse representation exists [25].

Inverse FKF Representation

Under suitable admissibility and normalization conditions, the original signal can be reconstructed schematically as

$$f(t,x) = \frac{1}{2\pi^2}$$

$$\boxed{\int_{-\infty}^{\infty} e^{ist} \int_{0}^{\infty} F\,(s,q)K_{iq}(x)\,q\sinh(\pi q)\,dq\,ds}$$

with the exact constant depending on the chosen KL normalization convention. The factor $q\sinh(\pi q)$ is the standard Kontorovich–Lebedev inversion weight associated with the Macdonald kernel; the overall constant may vary with the chosen KL normalization [11], [24], [25]. Sequential convergence of the two-sided transform in the corresponding testing-function space guarantees that the inversion is stable for the distributional signals that arise from intermittent IoT streams [25].

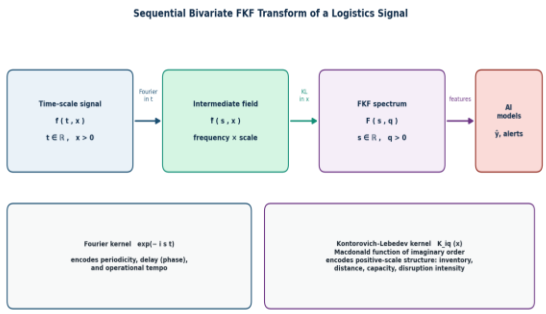

Fig. 2. Sequential FKF pipeline: a time–scale logistics signal is mapped first by a Fourier transform in t and then by a Kontorovich–Lebedev transform in x, yielding features for AI models.

III. SPECTRAL ENCODING OF LOGISTICS DYNAMICS

In a logistics environment the independent variables t and x are associated, respectively, with temporal evolution and an operational scale such as inventory level, demand magnitude, transportation distance, capacity, safety-stock level, or disruption intensity. The FKF representation

$$F(s,q) = \mathcal{F}_{FK}\{f(t,x)\}(s,q)$$

captures both temporal-frequency characteristics and scale-dependent behavior. Peaks and localized spectral features indicate periodic demand, recurring transportation patterns, or operational oscillations, while spectral shifts reveal lead-time variations, delays, and changes in supply-chain dynamics [8], [9], [11]. Residue-based resonance extraction further isolates hybrid-vehicle and multi-scale supply-chain modes that would otherwise remain buried in broadband operational noise [7].

The transformed logistics signal may therefore be read through complementary temporal and scale-related characteristics, as in illustrated in Fig. 3.

$$F(s,q) = \mathcal{F}_{FK}\{f(t,x)\}(s,q)$$

The FKF-transformed logistics signal can be interpreted through complementary temporal and scale-related characteristics.

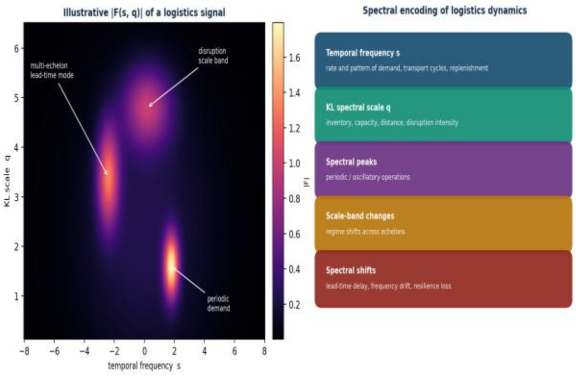

Fig. 3. Illustrative FKF magnitude |F(s, q)| of a logistics signal (left) and the corresponding operational interpretation of spectral coordinates (right).

In this representation:

Temporal frequency represents the rate and pattern of changes occurring over time.

KL spectral scale represents the scale at which operational variations and supply-chain behaviors are observed.

Peaks in the FKF spectrum indicate periodic or oscillatory behavior, such as recurring demand, transportation cycles, or inventory fluctuations.

Changes across spectral scales indicate scale-dependent operational behaviors, including variations in inventory, capacity, demand, and disruption intensity.

Spectral shifts can indicate transportation delays, lead-time variations, disruptions, or changes in overall logistics dynamics.

Residues / resonances Narrowband hybrid-vehicle or multi-scale supply- chain modes [7]

Overall, FKF spectral analysis provides a compact approach for identifying temporal patterns, multiscale variations, recurring behavior, and dynamic changes in complex supply-chain operations [9], [7].

IV. TEMPORAL DELAY AND FREQUENCY MODULATION IN INTELLIGENT LOGISTICS

Time-shift and frequency-modulation properties of the FKF framework provide practical tools for analyzing dynamic changes in logistics and supply-chain signals [12], [13], [8]. When a transportation, replenishment, or delivery process experiences a delay t_0, the corresponding signal is shifted in time and produces a phase factor in the Fourier dimension. This enables lead-time variations and delayed logistics responses to be detected from the spectrum, including in multi-echelon settings [8], [12].

If $g(t,x) = f(t,-t_0 x)$, then

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

Thus a transportation or replenishment delay is reflected as a phase change exp(−i s t_0) in the Fourier dimension, allowing variations in delivery times, lead times, and replenishment cycles to be identified from the transformed logistics signal [12]. This spectral phase information supports the detection of delayed responses and recurring operational disturbances.

These properties can be integrated with AI models to extract spectral features for delay prediction, anomaly detection, demand forecasting, and adaptive decision-making [32], [14]. In addition, the swipe-controller concept [34] demonstrates how signal-based control principles can support responsive system operation, providing a complementary foundation for intelligent monitoring and actuation. By combining FKF spectral features, AI-based analytics, and responsive control, logistics systems can recognize temporal disturbances and adapt operational decisions to changing supply-chain conditions.

V. SPECTRAL FREQUENCY SHIFTS FOR AI-ENABLED SUPPLY-CHAIN MONITORING

Exponential modulation introduces a systematic shift in the frequency content of a signal. In the FKF framework this property is useful for identifying frequency-shifted, periodic, and dynamically varying supply-chain components, including recurring demand patterns, transportation cycles, inventory fluctuations, and other operational signals whose dominant frequencies change over time [13]. Modulation in the original signal domain corresponds to translation in the Fourier-frequency domain. For

$$g(t,x) = e^{is_0 t}f(t,x),$$

we obtain

$$\boxed{\mathcal{F}_{FK}\{e^{is_0 t}f(t,x)\}(s,q) = F(s,-s_0 q)}$$

The same property is relevant to secure digital supply-chain networks, where intentional modulation can encode authentication or watermarking side-information without destroying the operational spectrum [13]. The resulting features feed AI-based forecasting, anomaly detection, and adaptive logistics decision-making [32], [14].

Differential Spectral Property of the Kontorovich–Lebedev Kernel

The Macdonald function satisfies the modified Bessel differential equation, establishing an eigenfunction relationship within the Kontorovich–Lebedev transform. Consequently, suitable differential operators acting in the positive-scale domain are converted into multiplication by a simple algebraic factor in the KL spectral domain [10]. This property simplifies the analysis of scale-dependent changes and provides a mathematical basis for studying variations in inventory, demand intensity, capacity, lead-time effects, and disruption propagation. The Macdonald function satisfies the modified Bessel equation

$$x^2y'' + xy' - (x^2 + \nu^2)y = 0.$$

For $\nu = iq$, this becomes

$$\boxed{x^2K_{iq}''(x) + xK_{iq}'(x) - (x^2 - q^2)K_{iq}(x) = 0.}$$

Equivalently, the scale-domain operator acts by multiplication with $-q^2$:

$$\left[x^2\frac{d^2}{dx^2} + x\frac{d}{dx} - x^2\right]K_{iq}(x) = -q^2K_{iq}(x).$$

This eigenvalue relationship is important for converting differential operations in the positive-x domain into multiplication by $-q^2$ in the spectral domain, and therefore for tracking dynamic changes inside a Digital Twin that continuously updates its spectral state [10], [24]. Distributional extensions of the FKF transform make the same calculus available for irregular, impulsive, or only weakly regular supply-chain observations [24].

VI. DIGITAL TWIN–FKF SPECTRAL STATE REPRESENTATION

A logistics Digital Twin can represent the evolving physical system through a time-dependent operational signal and its corresponding FKF spectral state. The physical signal describes measurable conditions such as demand, inventory, transportation activity, capacity, or disruption intensity, while the transformed spectral state captures their temporal and scale-dependent characteristics [31], [9].

For an adaptive logistics Digital Twin the physical signal is written

$$f(t,x) = \text{logistics state at time } t \text{ and scale/intensity } x,$$

and its spectral state becomes

$$\boxed{F(s,q) = \mathcal{F}_{FK}[f(t,x)].}$$

This creates a continuous mathematical connection between real-time operational observations and their spectral representation, allowing changes in logistics behavior to be monitored, analyzed, and compared within the Digital Twin environment [11], [23], [31]. The spectral state subsequently supports AI-based prediction, anomaly detection, resilience assessment, and adaptive optimization. A conceptual adaptive loop is therefore

$$f(t,x) \longrightarrow F(s,q) \longrightarrow \text{spectral analysis} \longrightarrow \text{AI/optimization} \longrightarrow \text{Digital Twin decision} \boxed{\longrightarrow f_{\text{updated}}(t,x)}$$

The same loop is the natural place to evaluate sustainable-mobility interventions—battery-management policies [6], plug-in hybrid battery sizing [18], solar-powered and solar-assisted vehicle architectures [16], [22], and intelligent-transportation controls [20] before they are committed to the physical fleet. Quantum candidate solutions for routing, ULD configuration, and disruption recovery [19], [21], [35], can likewise be stress-tested inside the Twin against the current FKF state.

If by FKM you specifically mean a different transform than the **FKF** transform, give me its definition and I can formulate the exact equations accordingly.

for complex parameters s and y such that the kernel belongs to the testing space LKμ. The right-hand side is meaningful whenever f ∈ LK′μ and the kernel lies in LKμ. The analytical structure of the transform is strongly influenced by its connection with Meijer G-functions. Consequently, it inherits important properties associated with both Laplace-type and K-transform formulations, making it well suited to problems involving exponential decay, scale-dependent behavior, and Bessel-type singularity structures.

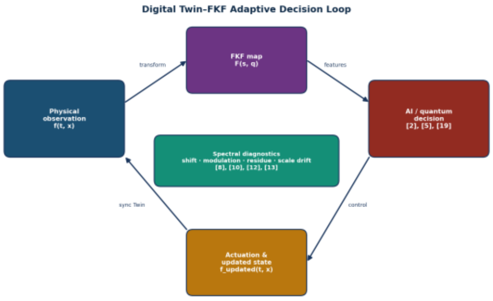

Fig. 4. Digital Twin–FKF adaptive decision loop. Physical observations are transformed, diagnosed in the spectral domain, converted into AI or quantum decisions, and written back as an updated logistics state.

VII. FKF-ENABLED ADAPTIVE LOGISTICS THROUGH DIGITAL TWIN INTELLIGENCE

The integration of Digital Twins, intelligent sensing, FKF spectral analysis, sustainable mobility, Artificial Intelligence, and quantum optimization is enabling logistics systems to become more responsive, predictive, and resilient to changing supply-chain conditions [14], [15], [31]. Digital Twins create dynamic virtual representations of physical assets and processes, allowing vehicles, warehouses, inventories, production facilities, and transportation networks to remain synchronized with their digital counterparts [2], [30], [31]. This continuous synchronization supports real-time monitoring, simulation, prediction, disruption assessment, and adaptive decision-making, consistent with the broader digital-transformation agenda for supply-chain resilience [23].

Within this framework, FKF-based analysis provides a multi-scale signal-processing layer for intelligent sensing across distributed Digital Twin nodes. Local sensing units process measurements from GPS, RFID, IoT inventory sensors, vehicle telematics, and other operational sources [14], while a higher-level fusion mechanism integrates these observations into a unified system state. Communication-layer security, including power-line and related anti-theft or integrity mechanisms, protects the sensing fabric [17]. Blockchain records selected fused states and provenance metadata so that spectral alerts remain auditable [33]. The architecture preserves useful information during intermittent connectivity and the variable communication conditions commonly encountered in logistics networks.

The resulting pipeline transforms physical observations into spectral features, which AI models analyze for anomaly detection, forecasting, and resilience assessment [32]. Human-centric Industry 5.0 principles keep the operator in the loop for exception handling [15], while swipe-style controllers convert spectral alerts into low-latency actuation [34].

Local Prediction and Global Information Fusion

Let $\hat{x}_i$ and P_i denote the local state estimate and covariance at sensor node i, let Φ be the state-transition matrix, and let Q be the process-noise covariance. The local prediction step is

$$\hat{x}_i(k|k-1) = \Phi(k)\, \hat{x}_i(k-1|k-1)$$

with the associated error covariance propagation

$$P_i(k|k-1) = \Phi(k)\, P_i(k-1|k-1)\, \Phi^T(k) + Q(k)$$

After the local measurement update, the global fusion performed by the master filter recovers the optimal combined estimate and covariance according to

$$P_g^{-1}(k|k) = \sum_{i=1}^{N} P_i^{-1}(k|k)$$

$$\hat{x}_g(k|k) = P_g(k|k) \sum_{i=1}^{N} P_i^{-1}(k|k)\, \hat{x}_i(k|k)$$

Here $\hat{x}_i$ and P_i denote the local state estimate and covariance, Φ is the state transition matrix, Q the process-noise covariance, and the subscript g identifies globally fused quantities. The fused kinematic state can be lifted, node-wise or in aggregate, into the FKF domain, furnishing a consistent spectral representation of the integrated logistics network. This construction enables the Digital Twin to maintain an uncertainty-aware picture of the physical system even when individual sensors become temporarily unavailable or generate degraded measurements [14], [17]. Consequently, the framework enhances the Twin's ability to sustain reliable situational awareness and to make timely, adaptive decisions under dynamic supply-chain conditions [23], [31].

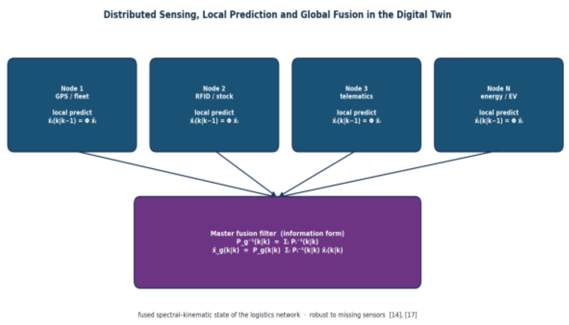

Fig. 5. Distributed sensing with local predictors and a master information-form fusion filter. The fused state is the input from which the Digital Twin refreshes its FKF spectral representation.

Optimization, Sustainability and Resilience

Once a fused spectral–kinematic state is available, two complementary decision layers operate. The AI layer consumes FKF features for short-horizon forecasting and anomaly scoring [32]. The quantum layer addresses combinatorial subproblems vehicle routing, ULD packing, slot allocation, and disruption recovery via annealing and related methods [19], [21], [35]. Candidate decisions are rolled forward inside the Digital Twin and accepted only when the predicted FKF state remains inside a prescribed resilience envelope [9], [23].

Sustainability constraints are imposed in the same loop. Battery-state and thermal constraints from contemporary EV and hybrid systems [6], [18], solar-assisted energy availability [16], [22], and intelligent-mobility service levels [20] enter the Twin as additional scale variables *x* and therefore as additional KL coordinates. Green-logistics objectives identified in the bibliometric record [2] thus become spectral constraints rather than after-the-fact audits.

VIII. FUTURE DIRECTIONS

The integration of Digital Twins with artificial intelligence, real-time sensing, trusted data exchange, FKF spectral analysis, sustainable mobility, and quantum optimization provides a comprehensive foundation for next-generation logistics systems [14], [31], [32], [33]. Digital Twins serve as an integrating platform that connects physical supply-chain operations with dynamic virtual models, enabling continuous monitoring, simulation, prediction, and decision support [1], [23]. Quantum computing complements this architecture by addressing complex optimization problems [5], [19], [21], while FKF spectral analysis reveals temporal shifts, modulation effects, multiscale patterns, frequency-dependent behavior, and operational changes that may remain hidden in conventional analytical approaches [7], [8], [9], [10], [11], [12], [13], [24], [25].

Sustainable-mobility building blocks—battery technologies [6], hybrid sizing [18], solar-assisted architectures [16], [22], smart mobility [20], swipe-style actuation [4], and secure communications [17] are absorbed into the same Twin as additional physical and spectral channels. Industry 5.0 principles keep the resulting automation human-centric [15].

CONCLUSION

Next-generation logistics can be strengthened through the convergence of Digital Twins, artificial intelligence, real-time sensing, trusted data exchange, FKF spectral analysis, sustainable mobility, and quantum optimization. Digital Twins provide an integrated virtual environment for synchronizing physical supply-chain operations with real-time data, enabling continuous monitoring, prediction, simulation, and intelligent decision-making. FKF spectral analysis identifies temporal variations, modulation effects, multiscale patterns, frequency-dependent behavior, and operational changes, while quantum optimization addresses complex logistics decisions. Together, these technologies establish an adaptive, intelligent, and resilient

The proposed framework therefore combines physical-system awareness, spectral intelligence, AI-based prediction, and advanced optimization within a unified logistics environment. This integration can improve the detection of disruptions, the evaluation of alternative responses, resource allocation, and adaptive planning under uncertain operating conditions. Overall, the Digital Twin–FKF architecture provides a scalable basis for developing resilient, sustainable, predictive, and continuously adaptive supply-chain ecosystems.

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