# A Scale Frequency Spectral Framework Based on the FKF Transform for Resilient Supply Chains

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Abstract—

Modern supply chains operate as distributed, partially observed stochastic systems in which demand, lead times, quality, custody, energy state, and disruption information are revealed with delay and may be distorted across organizational boundaries. The supplied mathematical manuscript develops a distributional-transform perspective around Laplace and K-type kernels, modified Bessel functions, Meijer G-function representations, and second-order differential operators. This reconstruction extends that foundation toward intelligent and resilient supply-chain analysis by integrating the FKF spectral viewpoint with artificial intelligence, digital twins, trusted data exchange, Internet of Things sensing, sustainable mobility, and quantum-enabled logistics optimization. The FKF representation separates temporal oscillation from scale- or intensity-dependent behavior and provides a basis for studying multi-echelon lead-time dynamics, delayed information, resonance, and nonstationary disturbances. Distributional extension is particularly useful when operational signals are irregular, impulsive, incomplete, or generated by heterogeneous sensing systems. Artificial-intelligence models can consume spectral features for prediction and anomaly detection, while digital twins provide continuously updated operational context. Blockchain-oriented trusted records can preserve provenance and state consistency, and quantum optimization can address selected combinatorial logistics decisions.

**Keywords—** Sustainable Logistics; Green Supply Chain Management; Artificial Intelligence; Smart Transportation; Digital Twins; Blockchain; swipe controller; Energy-Efficient Logistics; Quantum Computing; Supply Chain Resilience; FKF Analysis.

## I. INTRODUCTION

Supply-chain systems increasingly combine physical flows with information flows, digital platforms, autonomous decision support, and heterogeneous sensing. Digital twins provide dynamic virtual representations of assets and processes and have been reviewed as instruments for resilient and adaptive global networks **[7]**. Artificial intelligence supports prediction, anomaly detection, optimization, and adaptive decision-making in sustainable logistics and green supply-chain management **[8]**. Blockchain and related trusted-data mechanisms address provenance, traceability, and shared-state requirements when they are coupled with AI **[9]**. Earlier work on intelligent interfaces and embedded control, including swipe-controller designs for human–machine interaction, already illustrated the broader progression from isolated automation toward connected operational decision systems **[10]**.

The logistics environment is additionally affected by electric mobility, battery constraints, sustainable transportation, quantum optimization, and Industry 5.0 requirements. Quantum methods are now discussed as a practical layer for selected combinatorial logistics decisions **[11]**. Battery materials, management systems, and sustainability constraints reshape vehicle-energy trajectories **[12]**. Solar-assisted and hybrid vehicle architectures further couple energy state with routing and dispatch **[22], [24], [28]**. Smart mobility and intelligent transportation systems supply the sensing and control context for last-mile and line-haul operations **[26]**. At the ecosystem level, Internet of Things (IoT), AI, and quantum computing are treated as convergent components of smart logistics **[20]**, while Industry 5.0 emphasizes human-centric automation of supply-chain operations **[21]**. Resilience under digital transformation remains an organizing research agenda **[29]**.

These developments create signals that are multiscale and nonstationary: orders fluctuate, lead times shift, vehicle energy states evolve, disruptions create transient peaks, and information may arrive asynchronously. Conventional time-domain indicators can describe such behavior, but they do not always expose frequency-dependent or scale-dependent structure. A family of FKF-centered studies has therefore been developed for multi-scale spectral analysis and residue-based resonance extraction **[13]**, shift-invariant analysis of multi-echelon lead times **[14]**, spectral frameworks for dynamics and resilience **[15]**, and spectral differential properties of the distributional FKF transform **[16]**. Closely related work on the FKL transform provides complementary kernel properties for supply-chain analysis **[17]**. Expanded treatments of the time-shift property **[18]** and exponential-modulation property **[19]** complete the operational calculus needed for delayed and amplified signals. Distributional extension and sequential convergence supply the functional-analytic justification for irregular telemetry **[30, 31]**.

The present reconstruction uses those ideas to formulate an FKF-centered spectral framework for intelligent supply-chain analysis. The framework links temporal dynamics with scale behavior and provides a route from raw operational telemetry to spectral features, AI inference, digital-twin synchronization, and resilience-oriented decisions. A central premise is that a supply-chain signal $x(t)$ should not be treated solely as a forecastable scalar sequence. Instead, it can be represented as a generalized signal whose spectral structure contains information about periodic demand, lead-time modulation, disruption transients, and scale-dependent operational effects. This perspective is consistent with the cited work on multi-scale spectral analysis, shift invariance, exponential modulation, spectral differential properties, distributional extension, and sequential convergence **[30], [31]**.

Asset-level security and field sensing also belong in the same architecture. Power-line carrier communication for anti-theft monitoring is an early example of embedding integrity sensing in physical infrastructure **[23]**; such channels are conceptually analogous to the custody and provenance signals later handled by IoT and blockchain layers **[9, 20]**. Quantum annealing studies for unit-load-device configuration and disruption response, together with broader surveys of quantum computing in transportation, close the decision layer **[25, 27]**.

## II.MATHEMATICAL FOUNDATION

Let $x(t)$ denote an operational signal such as demand, replenishment delay, vehicle energy consumption, inventory deviation, or delivery-time error. A two-sided FKF representation may be written schematically as the composition of a Fourier kernel in the temporal coordinate and a Kontorovich–Lebedev-type kernel in a positive scale variable **[14], [15], [17], [30]**.

*Table 1. Principal notation (OMML symbols).*

| Symbol | Meaning |
|---|---|
| $x(t), z(t)$ | Scalar operational signal; vector of observed operational variables |
| $S(\omega,\nu), S_e(\omega,\nu)$ | Joint FKF spectrum; echelon-indexed lead-time spectrum |
| $\omega, \nu, r$ | Temporal frequency; scale parameter; positive radial/scale coordinate |
| $K_{i\nu}(r)$ | Macdonald function (modified Bessel K) of imaginary order |
| $L_e(t), \tau$ | Lead time at echelon e; time shift / information delay |
| $\Phi_{FKF}(z)$ | Spectral feature map consumed by AI models |
| $A(t), R_{FKF}$ | Anomaly score; spectral resilience indicator |
| $q_a(t), E_a(t)$ | Digital-twin state of asset a; synchronization error |
| $E_b(t), P(t)$ | Battery energy; net power demand |
| $x \in \{0,1\}^n$ | Binary decision vector in the QUBO layer |

The Kontorovich–Lebedev kernel is carried by the Macdonald function of imaginary order, which also admits Meijer G-function representations used in the source manuscript.

$$S(\omega,\nu) = \iint x(t,r)\, e^{-i\omega t}\, K_{i\nu}(r)\, \frac{dt\, dr}{r} \qquad (1)$$

Here $\omega$ denotes temporal frequency, $\nu$ denotes the spectral scale parameter, and $K_{i\nu}(r)$ is a modified Bessel function of the third kind (Macdonald function) of imaginary order. The transform therefore provides a joint spectral description of oscillatory and scale-dependent behavior. The supplied manuscript and the distributional FKF paper explicitly connect K-type kernels with modified Bessel functions and generalized-function representations **[30]**. The related FKL transform shares inversion and operational-calculus structure and is used here as a consistency check on kernel identities **[17]**.

For a signal represented in a distributional testing-function setting, let $\varphi$ belong to a suitable space of infinitely differentiable compactly supported test functions. A generalized functional $T$ acts on $\varphi$ through the dual pairing $\langle T,\varphi\rangle$. This allows impulsive, discontinuous, or otherwise irregular supply-chain observations to be handled without requiring classical pointwise smoothness **[30], [31]**.

$$\langle T_{FKF}, \varphi \rangle = \langle T, \Phi_{FKF}[\varphi] \rangle \qquad (2)$$

A second-order differential operator of the form used in the source manuscript characterizes the spectral behavior of the K-type kernel **[16], [30]**:

$$L_r[u] = r^2 u'' + r u' - r^2 u \qquad (3)$$

The corresponding modified Bessel equation is satisfied by the Macdonald function $K_{iv}(r)$. This operator viewpoint is important because differential operations in the physical domain can be mapped into structured operations in the spectral domain. Spectral differential properties of the distributional FKF transform develop this direction for resilient supply-chain signals **[16]**.

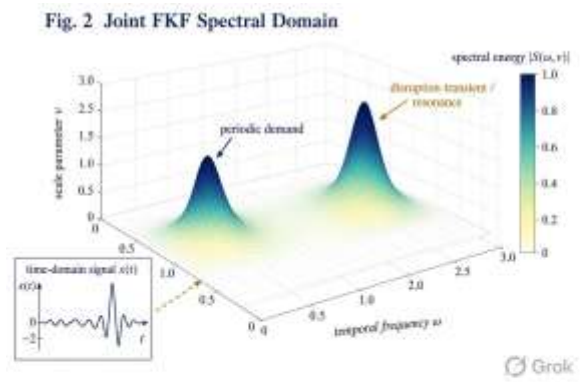


*Figure 1. Joint FKF spectral domain $S(\omega, \nu)$. Periodic demand concentrates at moderate frequency and lower scale; disruption transients appear as resonance peaks at higher frequency and scale [13], [15].*

## III. SPECTRAL REPRESENTATION OF SUPPLY-CHAIN DYNAMICS

Consider a multi-echelon lead-time signal $L_e(t)$, where $e$ indexes an echelon. Its spectral representation can be expressed as **[14], [15], [18]**:

$$S_e(\omega, \nu) = FKF[L_e(t, r)] \qquad (4)$$

Changes in $S_e(\omega, \nu)$ reveal whether a disturbance is concentrated in particular temporal frequencies, scales, or both. A shift in the operational signal, $L_e(t - \tau)$, produces a phase modification in its Fourier component. Thus the spectral representation can distinguish a genuine change in system dynamics from a simple time displacement. This is aligned with the shift-invariant FKF research direction **[14]** and the expanded time-shift treatment **[18]**.

$$FKF[x(t - \tau)](\omega, \nu) = e^{-i\omega\tau} FKF[x](\omega, \nu) \quad (5)$$

Similarly, exponential modulation can be represented as a spectral translation under appropriate conditions. Such behavior is useful for identifying accelerating or attenuating demand and disruption components, and it connects with the exponential-modulation treatment developed for secure digital supply-chain networks **[19]**.

$$FKF[e^{\alpha t} x(t)](\omega, \nu) = FKF[x](\omega + i\alpha, \nu) \quad (6)$$

Residue-based resonance extraction is used when concentrated poles in the joint spectrum correspond to recurring operational disturbances, including hybrid-vehicle load cycles that couple logistics timing with energy draw **[13]**. Figure 2 illustrates how supplier, distribution-center, and last-mile echelons occupy different $(\omega, \nu)$ neighborhoods even when their time-domain traces look only moderately different.

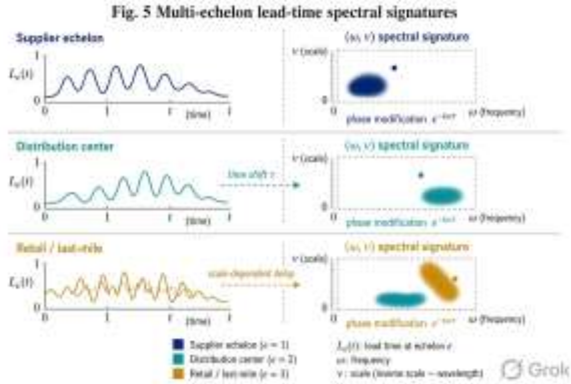


*Figure 2. Multi-echelon lead-time signals $L_e(t)$ and their FKF signatures. A pure delay appears as a phase factor $e^{-i\omega\tau}$; scale-dependent last-mile congestion spreads energy across $\nu$ [14], [18].*

## IV. SEQUENTIAL CONVERGENCE

Operational data are rarely ideal mathematical functions. Missing observations, sudden demand shocks, sensor spikes, discrete events, and abrupt lead-time changes create generalized signals. The distributional extension of the FKF transform provides a principled way to define transform action on such objects. The representation theorem uses bounded measurable coefficient functions, weighted test spaces, higher-order derivatives, continuity, Hahn–Banach extension, and duality **[30]**.

Sequential convergence is equally important for digital-twin environments because data arrive as a sequence of increasingly refined measurements **[7], [31]**. If $\{\varphi_n\}$ converges to $\varphi$ in the testing-function topology, continuity of the distributional transform implies convergence of the corresponding spectral action. Sequential convergence in the testing-function space of the two-sided FKF transform is established in **[31]**.

$$\varphi_n \to \varphi \quad \Rightarrow \quad \langle T_{FKF}, \varphi_n \rangle \to \langle T_{FKF}, \varphi \rangle \qquad (7)$$

This continuity statement is the reason the architecture can ingest irregular IoT streams including custody tags, energy meters, and integrity sensors descended from earlier power-line monitoring concepts **[20], [23]** without first forcing those streams into classically smooth interpolants.

## V. AI-ENABLED SPECTRAL INTELLIGENCE

The spectral representation can be coupled with AI models by treating FKF coefficients as engineered features. Let $z(t)$ denote the vector of observed operational variables and let $\Phi_{FKF}(z)$ denote its spectral feature vector. An AI predictor can then be written as **[8], [13], [15], [20]**:

$$\hat{y}(t+\Delta) = f_{\theta}(\Phi_{FKF}(z(t)), c(t)) \quad (8)$$

where $\theta$ contains model parameters, $c(t)$ represents contextual information from the digital twin **[7]**, and $\Delta$ is the prediction horizon. Spectral features can include dominant frequencies, scale concentrations, spectral energy, shift indicators, and residue-based resonance measures **[13], [15]**. This construction is compatible with the broader integration of AI, spectral analysis, IoT, and intelligent logistics **[8], [20], [21]**.

For anomaly detection, a spectral deviation score may be defined by comparing the current spectral state with a learned baseline **[15], [16]**:

$$A(t) = (\Phi_{FKF}(z(t)) - \mu_{FKF})^T \, W \, (\Phi_{FKF}(z(t)) - \mu_{FKF}) \quad (9)$$

Here $\mu_{FKF}$ is the baseline spectral signature and $W$ is a weighting matrix. Large values of $A(t)$ can indicate abnormal lead-time modulation, inventory oscillation, vehicle-energy behavior, or disruption signatures. Because the features already separate oscillation from scale, the detector can distinguish a pure schedule slip from a genuine change in disturbance intensity **[14], [18], [19]**.

### Spectral Resilience Indicators

Operational resilience is treated here as a dynamic spectral property. Let the current joint spectrum be compared with a baseline signature through the weighted deviation already introduced for anomaly detection. A monotone transformation of that score yields a bounded resilience index that contracts when resonance, lead-time modulation, or energy-scale distortion grows, and that recovers as the spectrum returns toward the baseline [15], [16], [30]. Distributional peaks associated with custody or quality shocks enter the same index without requiring classical smoothness of the raw telemetry [30], [31].

Because the anomaly score already isolates oscillation from scale, it can be read as a spectral resilience indicator rather than as a generic residual. High-frequency, high-scale energy concentrated in disruption bands is interpreted as a loss of resilience, whereas a pure time-shift of an otherwise unchanged spectrum is interpreted as a recoverable delay [14], [15], [16], [18]. Residue-based resonance peaks extracted from the joint spectrum provide event-level flags that can be passed to the digital twin and to the quantum decision layer [13], [25]. The same indicator is compatible with the broader digital-transformation resilience agenda [29] and with Industry 5.0 exception handling [21].

## VI. DIGITAL TWIN, BLOCKCHAIN, AND IOT INTEGRATION

A digital twin can serve as the operational integration layer. IoT devices provide telemetry; the twin synchronizes physical and virtual states; AI transforms observations into predictions and decisions; and trusted data infrastructure preserves provenance and shared-state consistency. Digital-twin resilience and adaptive supply-chain applications are discussed in **[7]**, while AI–blockchain integration is addressed in **[9]**. IoT, AI, and quantum computing are treated as convergent components of smart logistics in **[20]**. Industry 5.0 supplies the human-in-the-loop requirement for exception handling **[21]**.

For an asset $a$, define its digital-twin state as $q_a(t)$. The state can include location, inventory, quality, custody, energy, maintenance status, and transaction metadata. A generic synchronization error is

$$E_a(t) = \| q_a(t) - \hat{q}_a(t) \| \quad (10)$$

The twin should trigger re-estimation when $E_a(t)$ exceeds an application-specific tolerance. Blockchain or other trusted data mechanisms can attach provenance metadata to state transitions, reducing ambiguity about the origin and sequence of critical events **[9]**. Integrity sensing of physical assets historically explored through power-line carrier anti-theft systems **[23]** can feed the same custody field of $q_a(t)$. Sequential FKF convergence then guarantees that as the twin's measurement sequence is refined, the associated spectral features stabilize **[31]**.

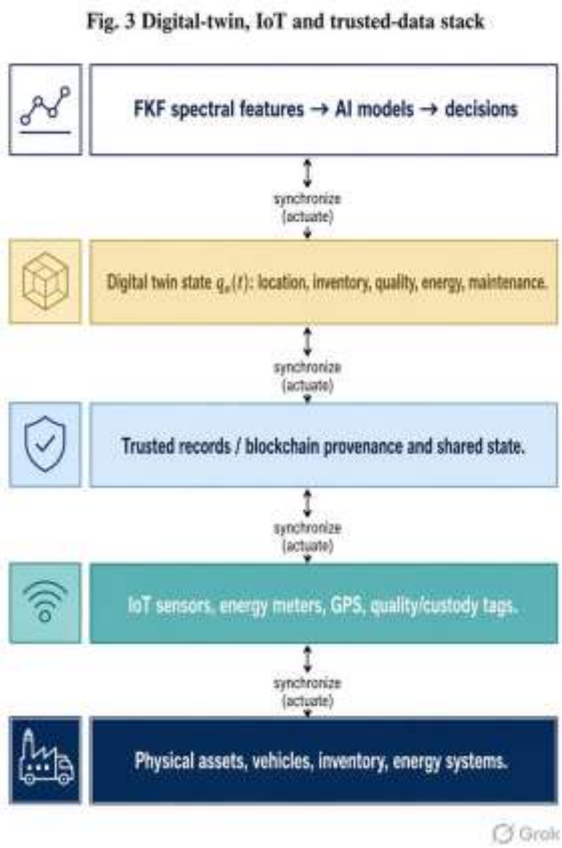


*Figure 3. Layered integration of physical assets, IoT sensing, trusted records, digital-twin state, and FKF–AI decision services [7], [9], [20], [23].*

### Energy-Aware Mobility and Last-Mile Coupling

Last-mile and line-haul operations inject an energy coordinate into the same spectral picture. Battery state and net power demand evolve on timescales that are distinct from order cycles, yet they modulate feasible lead times and disruption response [12], [26]. Scale-dependent spectral energy of the vehicle-energy signal is therefore a first-class feature for charging, dispatch, and recovery decisions.

Hybrid and solar-assisted architectures further couple energy state with routing and dispatch [22], [24], [28]. When energy trajectories are treated as FKF signals, charging windows and last-mile congestion appear as joint (frequency, scale) concentrations rather than as isolated time-series spikes. Smart-mobility sensing supplies the field context for those trajectories [26], and battery-management constraints keep the resulting dispatch decisions physically feasible [12].

### Quantum Optimization Layer with Validation Path

Selected logistics decisions ULD configuration, disruption reallocation, and related assignment problems admit QUBO forms whose decision vector is the binary variable already listed in Table 1 [11], [25]. Spectral features and resilience indicators enter the QUBO as time-varying weights or penalty terms: a resonance flag can forbid a lane, a lead-time shift can reweight a transit arc, and an energy-scale excursion can restrict a vehicle class [13], [14], [25]. Annealing studies for unit-load-device configuration and disruption response provide the immediate operational template [25].

Quantum computing is not proposed as a replacement for the spectral layer. It is a downstream combinatorial engine that consumes spectral and twin-derived constraints. Surveys of quantum methods in transportation and logistics locate annealing and related heuristics in exactly this supporting role [11], [27], while the convergent IoT–AI–quantum ecosystem paper frames the same stacking at the platform level [20].

The displayed relations define a mathematical architecture and candidate indicators, but parameter selection, transform normalization, inversion conditions, AI-model choice, resilience thresholds, and quantum-optimization performance depend on the application and the dataset. These elements should be tested using real multi-echelon demand, lead-time, vehicle-energy, inventory, and disruption records. Sequential convergence supplies the justification for ingesting successively refined twin measurements during such tests. Related-kernel identities from the FKL study [17] and historical control or sensing results [10], [23] should be treated as supporting context rather than as plug-in modules. Empirical work should therefore compare spectral features with conventional time-domain features on the same multi-echelon records before the proposed indicators are treated as operational standards.

## VII. CONCLUSION

This reconstructed study develops a distributional FKF spectral framework for intelligent and resilient supply-chain systems. Beginning with the supplied manuscript's generalized-transform and differential-operator foundations, it connects Fourier temporal behavior with Kontorovich–Lebedev scale behavior and extends the interpretation to multi-echelon lead times, disruption signatures, AI features, digital twins, trusted data exchange, sustainable mobility, and quantum optimization. The resulting architecture treats supply-chain resilience as a dynamic spectral property rather than solely as a static inventory or recovery metric. Future work should establish rigorous normalization and inversion conditions for the selected FKF formulation, develop benchmark datasets, compare spectral features with conventional time-domain features, and experimentally evaluate hybrid AI–quantum decision workflows.

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