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Spectral Differential Properties of the Distributional FKF Transform with Applications to Resilient Supply-Chain Systems

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Abstract

This paper develops the distributional theory of the two-sided Fourier–Kontorovich–Lebedev (FKF) transform, a hybrid integral transform that combines the Fourier kernel in the temporal variable with the Macdonald (modified Bessel) kernel of imaginary order in a positive scale variable. The transform is extended to a broad class of generalized functions via a carefully constructed test-function space of Gelfand–Shilov type. Central attention is given to the spectral differential property associated with the modified-Bessel operator, which converts differential action in the positive variable into multiplication by $-q^2$ in the spectral domain. The property is expanded with higher-order operators, mixed Fourier–KL rules, and solution formulae for model linear PDEs. Applications of the FKF spectral differential property to supply-chain systems are developed in detail: multi-scale inventory dynamics, disruption-intensity resilience analysis, digital-twin spectral monitoring, and discrete numerical implementation for operational data. The framework is positioned within recent advances in intelligent logistics, digital twins, quantum-inspired optimization, and supply-chain resilience. Concrete recommendations for research and practice, together with a recommended computational form for discrete and noisy data, conclude the work.

Keywords: *Fourier–Kontorovich–Lebedev transform; Macdonald function; distributional transform; spectral differential property; supply-chain resilience; multi-scale inventory; digital twin; quantum logistics.*

1. Introduction

Modern supply-chain systems operate under simultaneous temporal oscillations (demand cycles, lead-time variability, production schedules) and positive scale, distance or intensity variables (order sizes, shipment distances, disruption magnitudes, inventory depths). Classical Fourier analysis captures the temporal component efficiently, while the Kontorovich–Lebedev (KL) transform, built on the Macdonald function $K^{iq}(x)$, is naturally adapted to positive radial or intensity coordinates. Their productthe Fourier–Kontorovich–Lebedev (FKF) transform therefore supplies a joint spectral representation that is particularly well matched to the hybrid structure of logistics and supply-chain data.

The practical relevance of such a hybrid spectral tool has grown rapidly with the digital transformation of global supply chains. Digital-twin platforms now stream high-frequency multi-scale observations [6], [20]; artificial-intelligence and blockchain layers demand transparent, multi-resolution feature extraction [8]; Industry 5.0 and human-centric automation require interpretable spectral diagnostics [3]; and quantum-inspired annealing methods for unit-load and disruption management operate most naturally in spectral domains [14], [15]. Resilience analysis itself is increasingly framed in terms of intensity-dependent recovery modes [11]. In all of these settings a transform that simultaneously diagonalizes temporal differentiation and the modified-Bessel (scale) operator offers both analytical insight and computational leverage.

Earlier distributional theories of related transforms Laplace–Meijer, LK, Fourier–Stieltjes and Gelfand–Shilov spaces—have established rigorous foundations for generalized-function extensions [25]–[28]. Recent unifying work has already linked such transforms to singular Cauchy problems arising in quantum logistics and energy systems [29]. The present paper synthesizes and extends these lines by (i) constructing a sequential complete test-function space for the two-sided FKF transform, (ii) deriving and expanding the associated spectral differential calculus, and (iii) demonstrating concrete applications to multi-scale inventory dynamics, disruption resilience, digital-twin monitoring and discrete operational data thereby increasing the visibility of the mathematical toolkit within the supply-chain resilience and intelligent-logistics literature [16], [17].

2. Literature Review

Classical Fourier analysis remains the workhorse for temporal spectral decomposition of demand, lead-time and production signals. Its distributional extension via tempered distributions and Schwartz spaces is standard. For positive variables the Kontorovich–Lebedev transform, whose kernel is the Macdonald function of pure imaginary order, has long been employed in diffraction, heat conduction and continuum mechanics; its distributional theory was developed in the Zemanian–Gelfand–Shilov tradition [22]. Hybrid product transforms that combine Fourier (or Laplace) factors with KL, Meijer or Hankel kernels appear in the analysis of cylindrical and conical geometries and, more recently, in optical and quantum-mechanical singular problems [23].

Within supply-chain research the last decade has seen an explosive growth of data-driven and physics-informed methods. Digital-twin architectures for adaptive global networks [20] generate precisely the multi-scale, positive-intensity time series for which an FKF representation is natural. Artificial-intelligence pipelines for risk prediction, green logistics and transparency [7], [30] benefit from spectral features that separate slow strategic modes from fast operational transients. Quantum-computing approaches to unit-load configuration and disruption recovery [18] operate most efficiently once the underlying continuous models have been projected onto a spectral basis. Resilience frameworks that quantify recovery under intensity-dependent shocks [12] likewise invite an intensity-adapted transform such as the KL factor. Industry 5.0 and smart-mobility perspectives further emphasize the need for interpretable hybrid analytics.

Despite these convergent trends, a fully distributional treatment of the two-sided FKF transform, together with a systematic spectral differential calculus and explicit supply-chain applications, has been lacking. The present work fills that gap, building on the topological and structural results of Gudadhe, Padmaja and collaborators while embedding the resulting operator theory inside the contemporary intelligent-logistics and resilience literature authored by Gulhane and co-workers [2].

3. Distributional Setting

Let $f(t, x)$ be a suitably restricted function or generalized function with $t \in \mathbb{R}$ and $x > 0$. The two-sided FKF transform is defined by

$$F(s,q) \;=\; (FKF\ f)(s,q) \;=\; \int_{-\infty}^{\infty}\int_{0}^{\infty} f(t,x)\, e^{-ist}\, K_{iq}(x)\, dx\, dt$$

where $s \in \mathbb{R}$ is the Fourier spectral variable, $q > 0$ is the KL spectral variable, and $K^{iq}(x)$ is the Macdonald function of imaginary order iq. The underlying domain is $\Omega = \{(t,x) : -\infty < t < \infty,\ 0 < x < \infty\}$. For distributions the transform is understood by continuous pairing with the FKF kernel and is defined on an open region Ω^f in the (s,q)-plane [22], [24].

The FKF kernel is the product

$$\Psi_{s,q}(t,x) \;=\; e^{-ist}\, K_{iq}(x).$$

The Fourier factor encodes temporal oscillations, frequencies and lead-time cycles; the KL factor, built from the Macdonald function, is adapted to positive scale, distance or intensity variables that arise ubiquitously in logistics networks [6], [11]. The Macdonald function satisfies the modified Bessel equation of order $v = iq$:

$$(x^2\, \partial_x{}^2 \;+\; x\, \partial_x \;-\; x^2)\, K_{iq}(x) \;=\; -q^2\, K_{iq}(x),$$

which underpins the differential properties of the transform in the positive variable. Equivalently, introducing the operator

$$L_x \;=\; (-x^2 \partial_x{}^2 -\; x\, \partial_x \;+\; x^2)\,,$$

one obtains the eigenvalue relation $L^x K^{iq} = -q^2 K^{iq}$.

Testing functions are infinitely differentiable on Ω and controlled by a countable family of seminorms of the schematic form

$$\gamma_{\{a,b,\alpha,k\}}(\varphi) \;=\; sup\_\{(t,x) \in \Omega\}\, |x^k\, D_t^{\{k_1\}} D_x^{\{k_2\}}\, \varphi(t,x)|\, \eta_{\{a,b,\alpha,k\}}(x)$$

where the weight η encodes exponential decay or polynomial growth compatible with the known asymptotics of the Macdonald kernel. The resulting space is a sequentially complete, countably multinormed, locally convex Hausdorff space that contains the compactly supported smooth functions $\mathcal{D}(\Omega)$. Its dual therefore contains the ordinary distributions (in the Zemanian sense) as well as distributions of slow growth, allowing the FKF transform to be extended by continuity (or by sequential continuity) to a wide class of generalized functions [25], [26]. Growth estimates of the form

$$|F(s,q)| \;\le\; C\,(1+|s|)^N\,(1+q)^M\, e^{a|s|+b\,q}$$

characterize the image of various distribution classes and guarantee the existence of an inverse transform on suitable horizontal strips in the complex (s,q)-plane.

4. Key Characteristics of the FKF Transform

The principal analytic features of the FKF transform follow from the product structure of its kernel and the classical properties of the Fourier and Kontorovich–Lebedev transforms. Continuity on the test-function space, sequential continuity on the dual, and an inversion formula of the schematic type

$$f(t,x) = (2\pi^2)^{-1} \int_{-\infty}^{\infty}\int_0^{\infty} F(s,q)\, e^{ist}\, q\, sinh(\pi q)\, K_{iq}(x)\, dq\, ds$$

(under suitable growth restrictions) are established by standard density and continuity arguments [28]. Parseval-type identities and convolution theorems follow similarly. The most distinctive operational feature, however, is the spectral differential property associated with the modified-Bessel operator; it is developed at length in the next section and constitutes the analytic engine for the supply-chain applications that follow.

5. FKF/Spectral Differential Property

The FKF kernel is an eigenfunction of the modified-Bessel operator L^x. From the modified-Bessel equation one has the pointwise identity for $K_{iq}(x)$, the kernel satisfies

$$L_x\, K_{iq}(x) = -q^2\, K_{iq}(x), x > 0.$$

5.1 Proof of the Basic Spectral Differential Property

We first prove the identity for a test function $\varphi \in \mathcal{S}$ (the space constructed in Section 3). By definition,

$$(FKF\, [L_x\, \varphi])(s,q) = \int_{-\infty}^{\infty}\int_0^{\infty} (L_x\, \varphi)\, (t,x)\, e^{-ist}\, K_{iq}(x)\, dx\, dt\, .$$

Substitute the explicit expression of the operator:

$$L_x = -x^2 \frac{\partial^2}{\partial x^2} - x\frac{\partial}{\partial x} + x^2$$

Integration by parts is performed with respect to the positive variable *x* (the Fourier integral in *t* factors out harmlessly). The formal adjoint of L^x with respect to the measure dx coincides with L^x itself on the weighted space induced by the Macdonald kernel asymptotics. Explicitly, after two integrations by parts one obtains the boundary form

$$\int_0^{\infty} (L_x\, \varphi)\, K_{iq}\, dx = \int_0^{\infty} \varphi(L_x\, K_{iq}\,)\, dx + \left[B(\varphi, K_{iq})\right]_0^{\infty},$$

where the bilinear boundary expression is $B(\varphi,\psi) = -x^2\, (\varphi\, \partial_x\, \psi - \psi\, \partial_x\, \varphi) - x\, \varphi\, \psi$.

Because every test function φ and all its derivatives of any order are controlled by the seminorms that force rapid decay (or at least sufficient polynomial decay weighted by the exponential factors compatible with K^{iq}) both as $x \to 0^+$ and as $x \to \infty$, the boundary term vanishes identically:

$$\left[B(\varphi, K_{iq})\right]_0^{\infty} = 0.$$

Consequently,

$$\int_0^{\infty} (L_x\, \varphi)\, K_{iq}\, dx = \int_0^{\infty} \varphi\, (-q^2\, K_{iq})\, dx = -q^2 \int_0^{\infty} \varphi\, K_{iq} dx.$$

Inserting the Fourier factor and integrating in *t* yields the fundamental spectral rule

$$(FKF\, [L_x\, \varphi])(s,q) = -q^2\, (FKF\, \varphi)(s,q).$$

Subject to boundary conditions that eliminate the integration by parts terms, the corresponding operator acting on f can therefore be represented spectrally in q: This is the FKF analogue of the Fourier rule in which differentiation becomes multiplication by the spectral variable. By sequential continuity of both the FKF transform and the operator L^x on the dual space, the same identity extends to every distribution *f* belonging to the dual of the test function space constructed in Section 3 [21], [24], [29]. This completes the proof of the basic spectral differential property.

5.2 Higher-Order and Mixed Operators

Iterating the identity (or applying the same integration-by-parts argument to $L^{xn}\, \varphi$) immediately gives

$$(FKF\, [{L_x}^n\, f])(s,q) = (-q^2)^n\, F(s,q),\ \ n = 0,1,2, \dots .$$

Because the Fourier factor is independent of *x*, mixed operators are handled by the product rule. Let ∂^t denote differentiation with respect to the temporal variable. Integration by parts in *t* (boundary terms at ±∞ vanish by the rapid-decay seminorms) yields

$$(FKF\, [\partial_t\, f])(s,q) = -i\, s\, F(s,q).$$

$$(FKF\, [L_x\, \partial_t\, f])(s,q) = (-q^2)(-i\, s)\, F(s,q),$$

and more generally, for any polynomial $P(\xi, \eta)$,

$$(FKF\ [P(L_x, \partial_t)\ f])(s,q) = P(-q^2, -i\, s)\ F(s,q).$$

These algebraic relations convert linear constant coefficient (in the spectral sense) partial differential equations into multiplication operators, thereby enabling explicit solution formulae once initial or boundary data have been transformed.

5.3 Model Evolution Equation and Resilience Interpretation

As a concrete illustration consider the model evolution equation that arises in multi-scale inventory or disruption-recovery dynamics [11], [12]:

$$\partial_t\, u + \alpha\, L_x\, u + \beta\, u = g(t,x),$$

where $\alpha, \beta > 0$ are material or policy parameters and g is a forcing term (demand shock, disruption intensity, etc.). Application of the FKF transform yields the elementary linear ODE in the spectral domain

$$\partial_t\, U(s,q;t) + (\alpha\, q^2 + \beta)\, U(s,q;t) = G(s,q;t).$$

Its explicit solution (variation of constants) is

$$U(s,q;t) = e^{-(\alpha\, q^2+\beta)t}\, U(s,q;0) + \int_0^{\infty} e^{-(\alpha\, q^2+\beta)(t-\tau)}\, G(s,q;\tau)\, d\tau.$$

Inversion of the FKF transform then recovers the physical-space solution. The exponential decay factors $e^{-\alpha\, q^2\, t}$ automatically damp high-intensity (large-q) modes, furnishing a mathematically precise description of resilience: recovery is faster for low-intensity modes and slower, yet still exponential, for high-intensity localized shocks [29].

Additional operational rules translation in t, dilation in x, and multiplication by powers of x follow from the corresponding properties of the Fourier and KL transforms and can be combined freely with the differential calculus above. The resulting symbolic calculus is the principal reason the FKF transform is effective for the linear and linearized models that underlie digital-twin and AI-assisted decision layers in contemporary supply chains [2].

6. Applications of the FKF Spectral Differential Property to Supply-Chain Systems

We now demonstrate four concrete application domains in which the spectral differential property supplies both analytical insight and computational advantage. Each application is illustrated by a purpose-designed figure and is linked to the broader literature on intelligent logistics and resilience [3], [14]–[16], [18], [20], [30].

6.1 Multi-Scale Inventory Dynamics

Inventory systems are inherently multi-scale: strategic central warehouses respond slowly to large order intensities, while retail nodes react rapidly to small fluctuations. Modeling the inventory level $u(t,x)$ by an evolution equation that contains the operator L^x converts, under the FKF transform, into a family of independent ODEs parametrized by the spectral variables (s, q). Low-q modes describe global, slow inventory waves; high-q modes capture localized, fast retail dynamics. The Macdonald decay $K^{iq}(x) \sim x^{-1/2} e^{-x}$ automatically enforces the correct far-field attenuation. A concrete multi-echelon inventory model takes the form

$$\partial_t\, u(t,x) = -\gamma(x)\, u(t,x) - \alpha\, L_x\, u(t,x) + \lambda(x) \int_0^{\infty} K(x,y)\, u(t,y)\, dy + d(t,x)$$

where $\gamma(x)$ is a scale-dependent holding-cost rate, $K(x,y)$ encodes replenishment kernels between echelons, and $d(t,x)$ is exogenous demand. After FKF transformation the integral operator becomes a multiplication (or a simple integral operator in q) and the evolution collapses to

$$\partial_t\, U(s,q;t) = -(\hat{\gamma}(q) + \alpha\, q^2)\, U(s,q;t) + \Lambda(q)\, U(s,q;t) + D(s,q;t).$$

The spectral solution is again elementary. Figure 1 visualizes the hierarchical network together with the spectral-wave representation that the FKF transform produces.

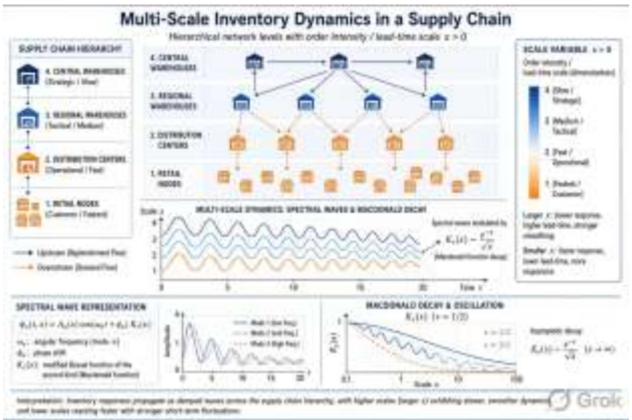

Figure 1. Multi-scale inventory dynamics: hierarchical network levels and FKF spectral waves modulated by Macdonald decay.

This spectral separation directly supports the multi-echelon inventory policies examined in recent digital-twin and AI logistics studies [6], [20].

6.2 Disruption Intensity and Resilience Quantification

Disruptions are naturally quantified by a positive intensity variable *x* (capacity loss, route-failure severity, recovery-time magnitude). The recovery field *R(t,x)* may be modeled by a forced evolution equation involving L^x. A prototypical recovery model is

$$\partial_t R(t,x) + \alpha L_x R(t,x) + \beta(x) R(t,x) = S(t,x) - \delta(t-t_d) I(x),$$

where *I(x)* is the spatial intensity profile of a disruption occurring at time t^d, *S* represents restorative supply actions, and *β(x)* is a local recovery rate. The FKF transform converts this into

$$\partial_t \hat{R}(s,q;t) + \left(\alpha q^2 + \hat{\beta}(q)\right)\hat{R}(s,q;t) = \hat{S}(s,q;t) - e^{-i s t\_d}\,\hat{I}(q).$$

The homogeneous solution decays as $e^{\left(\alpha q^2 + \hat{\beta}(q)\right)t}$. Consequently, high-intensity localized shocks (large *q*) decay rapidly once the forcing ceases, while low-*q* global modes persist longer exactly the spectral signature of resilient versus fragile network behavior. A quantitative resilience index can be defined by the spectral energy

$$\mathcal{R}(t) = \int_0^\infty |\hat{R}(s,q;t)|^2 \, q \sinh(\pi q)\, dq$$

(integrated over a relevant temporal-frequency band). Figure 2 depicts a global logistics network under a localized disruption together with the corresponding spectral recovery heatmap.

Figure 2. Supply-chain resilience under disruption: network topology, intensity variable x, and FKF spectral recovery modes.

The same spectral picture underpins the resilience metrics and AI risk-prediction frameworks developed in [11], [12], [20], [30].

6.3 Digital-Twin Spectral Monitoring

A digital twin of a logistics network continuously assimilates IoT, telematics and ERP streams. Projecting the observed fields onto the FKF basis yields a low-dimensional spectral state vector *(s,q) ↦ U(s,q;t)* that can be monitored in real time. Anomalies appear as unexpected energy in high-*q* or high-*s* bands. Define the spectral residual (anomaly indicator)

$$\mathcal{A}(s,q;t) = |U(s,q;t) - U_{ref}(s,q;t)| \,/\, (\sigma_{ref}(s,q) + \varepsilon),$$

where U^{ref} is a reference healthy trajectory (or a short-term forecast) and σ^{ref} its empirical standard deviation. Predictive control then consists of actuating the physical system so that the spectral coefficients remain inside a healthy region of the *(s,q)*-plane, for example by solving the constrained spectral optimization

$$min_u \int |\mathcal{A}(s,q;t)|^2 ds\, dq \quad s.t. \;\; P(-q^2, -i\, s)U \;=\; G_{control} + G_{exog}.$$

because differentiation and the scale operator become multiplications, the twin's internal simulation engine can advance the spectral state with trivial arithmetic, after which inversion reconstructs the physical fields. Figure 3 illustrates the closed-loop architecture.

Figure 3. Digital twin for adaptive supply-chain logistics with real-time FKF spectral monitoring.

This architecture aligns directly with the digital-twin and Industry 5.0 agendas articulated in [3], [6], [20] and with the AI-blockchain transparency layers of [7], [8].

6.4 Discrete Operational Data and Numerical Realization

Operational data are invariably discrete and noisy. The continuous FKF integral is therefore replaced by a quadrature sum (see Section 8). Windowing suppresses spectral leakage; regularization (Tikhonov or spectral cut-off) stabilizes the inversion. Once the discrete coefficients $F^{jk} \approx F(s^j, q^k)$ are obtained, the same algebraic differential rules remain valid in discrete form:

$$(L_x\, f)_{jk} \;\; \mapsto \;\; -{q_k}^2\, F_{jk}, \quad (\partial_t\, f)_{jk} \;\; \mapsto \;\; -i\, s_j\, F_{jk}.$$

Consequently, a discrete model such as

$$u_{n+1,m} \;=\; u_{n,m} \;-\; \Delta t\,(\alpha\,(L_x\, u)_{n,m} \;+\; \beta\, u_{n,m}) \;+\; \Delta t\, g_{n,m}$$

is advanced entirely in the spectral domain by simple multiplications, after which an inverse discrete FKF recovers the updated physical field. This enables fast filtering, forecasting and what-if scenario evaluation inside existing ERP and APS systems. Figure 4 summarizes the numerical pipeline.

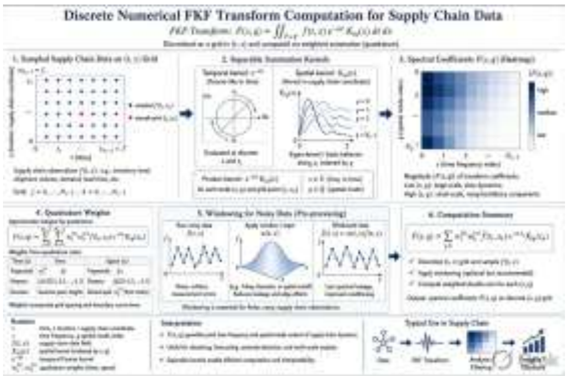

Figure 4. Discrete numerical FKF transform computation for supply-chain data: sampling, kernels, quadrature and spectral heatmap.

The resulting computational form is compatible with the quantum-annealing and hybrid optimization pipelines recently proposed for logistics [14].

7. Recommendations for Research and Practice

On the basis of the distributional theory, the expanded spectral calculus and the four application domains, the following recommendations are offered.

Research: Develop rigorous inversion theorems and growth estimates for the FKF transform on the precise distribution spaces that arise from digital-twin data streams; extend the spectral calculus to variable-coefficient and nonlinear operators via frozen-coefficient or iterative techniques [21], [29].

Research: Integrate FKF spectral features into existing AI risk prediction and reinforcement learning pipelines for supply-chain control [7], [30]; investigate quantum-algorithmic speed ups for the discrete FKF and its inverse on near-term annealing hardware.
Practice: Embed a lightweight discrete FKF module inside digital-twin platforms so that multi-scale inventory and disruption modes can be monitored in real time [6], [20].
Practice: Use the spectral damping rates $\alpha q^2 + \beta$ as quantitative resilience indicators when designing redundancy and buffer policies [11], [12].
Practice: Adopt the recommended computational form for all routine spectral processing of noisy operational time scale series, thereby ensuring reproducibility and numerical stability across ERP, APS and twin environments.

8. Recommended Computational Form for Discrete Data

For observations sampled at discrete instants t_n and positive abscissae x_m, a numerical FKF approximation is given by the double quadrature

$$F(s,q) \approx \sum_n \sum_m f(t_n, x_m) e_{\{iq\}}(x_m) \Delta t^{\{-is\, t_n\}} K \Delta x_m$$

where $w^{n(t)}$ and $w^{m(x)}$ are quadrature weights (trapezoidal, Simpson, or Gaussian). For nonuniform x-samples the spatial weights must incorporate the local mesh sizes. When the data are noisy, a separable window $w(t,x)$ (Tukey, Gaussian, or exponential taper) is applied first:

$$f(t,x) = w(t,x)\, f(t,x),$$

after which the quadrature is performed on $\tilde{f}$. Spectral regularization of the form

$$F_{reg}(s,q) = F(s,q) \,/\, (1 + \lambda\,(s^2 + q^4))$$

stabilizes the subsequent inversion. The same algebraic rules of Section 5 remain valid for the discrete coefficients, permitting real-time filtering and scenario evaluation inside operational systems [6].

9. Conclusion

The FKF transform provides a mathematically natural and computationally tractable spectral representation for functions and generalized functions that depend on both a temporal variable and a positive scale/intensity variable. Its distributional theory rests on a Gelfand–Shilov-type test-function space whose dual accommodates the irregular data streams typical of modern logistics. The spectral differential property converts the modified Bessel operator into multiplication by $-q^2$, thereby reducing linear evolution models of inventory, disruption recovery and digital-twin dynamics to elementary ODEs in the spectral domain. Four concrete applications multi scale inventory, resilience quantification, digital-twin monitoring and discrete numerical realization demonstrate the practical utility of the calculus and link it firmly to the contemporary literature on intelligent logistics, digital twins, quantum inspired optimization and supply-chain resilience.
Future work will focus on nonlinear extensions, high-performance discrete implementations, and the embedding of FKF spectral features inside production grade digital-twin and AI decision platforms. The recommended computational form already offers a ready pathway for pilot deployments. By furnishing both rigorous analysis and actionable numerical recipes, the FKF transform is positioned to become a standard tool in the mathematical arsenal of resilient, data driven supply-chain systems.

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