FKL transform Key Properties, and Applications to supply-chain analysis

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Abstract

The FKF transform is introduced as a two-variable integral transform that combines the Fourier kernel in a temporal or longitudinal variable with the Kontorovich–Lebedev kernel involving the Macdonald function $K_{iq}(x)$in a positive spatial, scale, or intensity variable. Formulated within a distributional framework on a suitable testing-function space over the half-plane $\Omega = \{(t، x)، : -\infty < t < \infty\ x > 0\}$, the transform admits a rigorous analytic continuation in the Fourier spectral variable and supports operator identities that convert differential structure in both variables into algebraic factors in the dual variables $(s، q)$. Fundamental properties are established, including linearity, time-shift and modulation theorems, differentiation and multiplication rules, the spectral representation of the modified Bessel operator, analyticity on strips in the complex plane, and distributional extension. These properties are then mapped onto supply-chain signals that jointly depend on time and a nonnegative state variable (inventory level, capacity intensity, disruption magnitude, transportation distance, etc.). Spectral signatures in the $(s، q)$-domain are shown to characterize periodicity, lead-time delays, scale-dependent risk, multi-echelon propagation, and transient regime changes. Conceptual applications are developed for inventory-risk analysis, production-capacity dynamics, multi-echelon networks, Monte-Carlo spectral uncertainty quantification, and real-time digital-twin monitoring. The resulting framework supplies a mathematically coherent bridge between classical integral-transform methods and contemporary data-rich, multi scale supply chain problems, while remaining fully compatible with digital-twin architectures, resilience analysis, and hybrid AI quantum decision systems

Keywords: FKF transform; spectral analysis; supply chain management; inventory risk; safety stock; multi-echelon systems; digital twins; supply chain resilience; lead-time analysis; Monte Carlo simulation; production capacity; anomaly detection

1. Introduction

The Fourier–Kontorovich–Lebedev (FKF) transform is a two-variable integral transform formed by combining the Fourier kernel in a temporal or longitudinal variable with the Kontorovich–Lebedev (KL) kernel in a positive spatial, scale, or intensity variable. It is useful when a system contains both oscillatory or temporal behavior and a positive state variable whose natural basis is represented by the modified Bessel (Macdonald) function $K_{iq}(x)$. The construction allows both dimensions to be analysed simultaneously rather than applying two transforms successively.

The formulation below follows the distributional FKF framework developed for generalized functions. In particular, the transform is considered on a testing-function space over the half-plane $\Omega = \{(t، x)، : -\infty < t < \infty\ x > 0\}$, and its dual contains distributions. Foundational contributions to the theory of distributional integral transforms, including LS spaces of Gelfand–Shilov type, the distributional LK transform and its action on impulsive signals, structure formulae for generalised Laplace–Meijer transforms, and the analytic behaviour of the LK transform of generalised functions, have been developed by Gudadhe [21–24]. Complementary investigations of topological creative spaces, exponential growth properties of conventional topological spaces with different kernels, duality spaces connecting distinct optical-form transforms, and inverse Fourier–Stieltjes transforms have been carried out by [25–28]. A unifying treatment of transforms for singular Cauchy problems arising in quantum logistics, supply-chain resilience, and energy systems further extends this mathematical lineage [29].

The analytic character of the FKF transform is especially important for contour methods, spectral representations, inverse problems, and uncertainty propagation. These features become particularly relevant for modern supply-chain and logistics systems, which are inherently multi dimensional: observables typically vary with time while simultaneously depending on nonnegative quantities such as inventory level, transportation distance, demand magnitude, production capacity, safety-stock scale, or disruption intensity.

By providing a single transform that jointly encodes Fourier frequency content and Kontorovich–Lebedev scale information, the FKF framework offers a mathematically coherent bridge between classical integral-transform theory and the data rich, multi-scale environment of contemporary logistics, supply-chain analytics, and related technological systems. The subsequent sections develop the formal definition, principal operator properties, and a series of conceptual applications that illustrate how spectral signatures in the $(s، q)$-domain can inform inventory risk analysis, capacity dynamics, multi-echelon propagation, Monte-Carlo uncertainty quantification, and real time digital-twin monitoring.

2. Literature Review

Recent literature has extensively examined the technological and managerial foundations required for resilient, transparent, and adaptive supply chains. Digital-twin technology has been reviewed as a key enabler of resilient and adaptive global supply chains [6]. Artificial-intelligence applications in sustainable logistics and green supply-chain management have been systematically mapped [7], while the integration of artificial intelligence with blockchain has been shown to enhance transparency, traceability, and resilience [8]. Industry 5.0 perspectives emphasise human-centric automation in intelligent logistics [3], and convergent frameworks combining the Internet of Things, artificial intelligence, and quantum computing have been proposed for smart logistics ecosystems [2]. Quantum-computing approaches to logistics optimisation, unit-load-device configuration, disruption management, and transportation systems have received growing attention [14, 15, 18]. Broader analyses of supply-chain resilience under digital transformation, together with studies of internal and external complexities in modern supply chains, further underscore the need for advanced analytical tools [11, 12, 20]. Complementary work on artificial-intelligence methods for supply-chain risk prediction and mitigation [30], as well as digital-twin and AI applications in sustainable processing systems [34], reinforces the same research trajectory. Related technological developments in smart mobility and intelligent transportation systems [16], electric-vehicle battery technologies [4, 17], solar-assisted electric mobility architectures [5, 19], and energy-efficiency improvements in industrial systems [1] illustrate the wider multi-domain context in which scale-dependent and time-dependent phenomena interact.

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 $s$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 pairing with the FKF kernel and is defined on an open region $\Omega_f$in the (s, q)-plane.

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. The Macdonald function satisfies the modified Bessel equation. With $\nu = iq$ this yields the spectral relation

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

which underpins the differential properties of the transform in the positive variable.

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

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

The resulting space is a sequentially complete, countably multinormal, locally convex Hausdorff space that contains the compactly supported smooth functions. Its dual therefore contains the ordinary distributions (in the Zemanian sense), allowing the FKF transform to be extended to a wide class of generalized functions.

4. Key Characteristics of the FKF Transform

The FKF transform is important because it enables the simultaneous analysis of temporal dynamics and positive-valued system variables within a single mathematical framework [21–24, 29]. Its key characteristics allow researchers to identify recurring patterns, dominant frequencies, characteristic scales, and interactions between time and system intensity [6, 7, 8]. This makes the FKF transform particularly valuable for modeling complex multidimensional systems such as supply chains, logistics networks, transportation, and production systems, where both time-dependent behavior and positive operational variables influence overall performance and resilience [3, 11, 12, 14, 15, 18, 20, 30, 34]

4.1 Shift in the t-Domain

A time delay t_0 produces a phase shift in the Fourier variable. The time-shift property states that shifting a function by t_0 in the time domain introduces only a phase factor in the Fourier dimension, for a time-shifted function $f(t - t_0, x)$,

$$FKF[f(t - t_0, x)](s, q) \;=\; e^{-is\, t_0}\, F(s, q)$$

A delay in demand, transportation, replenishment, or production therefore appears as a phase factor in the Fourier dimension. This means that a delay in a supply-chain process, such as demand arrival, transportation, replenishment, or production, does not alter the magnitude of the FKF spectrum; instead, it changes its phase [6, 11, 20]. Therefore, the FKF transform can distinguish between the original process and a delayed process while preserving its underlying frequency characteristics. This is useful for analyzing lead-time delays, delivery lags, inventory replenishment delays, and propagation of disruptions through a supply chain [8, 12, 30].

4.2 Exponential Modulation

The exponential modulation property describes the effect of multiplying a time dependent function by a complex exponential. It produces a corresponding shift in the Fourier variable, if the input is multiplied by $e^{i s_0 t}$, the Fourier variable is shifted:

$$FKF[e^{i s_0 t} f(t,x)](s,q) = F(s - s_0, q)$$

This is useful conceptually for separating periodic supply-chain components and for analysing frequency bands associated with seasonal or cyclic demand. Thus, modulation in the time domain results in a frequency translation in the FKF domain. This property is particularly useful for identifying specific frequency components associated with seasonal demand, periodic ordering, production cycles, transportation schedules, or recurring supply-chain disruptions [6, 7, 8, 11, 20, 30]. By shifting the spectrum, different frequency bands can be isolated and examined separately, making it easier to understand the dominant periodic patterns within a supply-chain system [3, 12, 14, 15, 18].

4.3 FKF/Spectral Differential Property

The FKF kernel is associated with the modified Bessel operator. Define the differential operator

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

From the modified-Bessel equation for $K_{iq}(x)$, the kernel satisfies

$$L_x K_{iq}(x) = -q^2 K_{iq}(x)$$

Subject to boundary conditions that eliminate the integration-by-parts terms, the corresponding operator acting on f can therefore be represented spectrally in q:

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

This is the FKF analogue of the Fourier rule in which differentiation becomes multiplication by the spectral variable.

4.4 Analyticity

A central result of the distributional FKF theory is that if f belongs to the relevant dual space and F(s, q) = FKF[f](s, q) is defined on Ω_f, then F is analytic in its admissible complex-s region under the stated hypotheses. In the source formulation, Ω_f is represented as a strip in s together with q > 0:

$$\Omega_f = \{(s,q): \sigma_1 < Re(s) < \sigma_2, 0 < q < \infty\}$$

Analyticity permits differentiation with respect to the transform variable and supports contour deformation and residue calculations. This property is particularly valuable when analyzing transient supply-chain responses or constructing inverse representations.

4.5 Distributional Extension

If f is locally integrable and satisfies the weighted integrability condition required by the testing space, it generates a regular distribution:

$$\langle f, \varphi \rangle = \iint f \varphi$$

The FKF transform can then be defined through distributional action on the FKF kernel. This extends the method beyond ordinary smooth functions and allows idealized impulses, abrupt events, and generalized forcing terms to be treated within one framework.

4.6 Convergence in the FKF Testing Space

A sequence $\{\varphi_m\}$ converges to φ when every defining seminorm of the testing space tends to zero:

$$\gamma_k(\varphi_m - \varphi) \to 0 \; for\ every\ k$$

This topological formulation is important because convergence of generalized functions is stronger than pointwise convergence and provides a rigorous basis for passing limiting operations through the transform.

Summary Table of Principal Properties

Property	Mathematical form	Interpretation
Linearity	$FKF[af+bg] = a\,FKF[f] + b\,FKF[g]$	Decompose complex supply-chain signals.
Time differentiation	$FKF\left[\frac{\partial f}{\partial t}\right] = is\,F$	Dynamic rates become algebraic spectral factors.
Time shift	$FKF[f(t-t_0,x)] = e^{\{-ist_0\}}F$	Represents delays and lead times.
Time multiplication	$FKF[tf] = i\,\partial F/\partial s$	Links time moments to spectral derivatives.
Modulation	$FKF\left[e^{\{is_0t\}}f\right] = F(s-s_0,q)$	Shifts periodic/frequency components.
KL operator	$FKF[L_xf] = -q^2F$	Positive-state differential structure becomes spectral.
Analyticity	$F(s,q) analytic\ on\ \Omega_f$	Supports complex analysis and contour methods.
Distributional extension	$\langle f,\varphi\rangle = \iint f\,\varphi$	Handles generalized/impulsive signals.

5. Why FKF Is Relevant to Supply-Chain Systems

Supply chains are inherently multidimensional systems in which operational variables evolve simultaneously across time and a positive-valued state or scale variable [6, 11, 20]. For example, a supply-chain signal may vary with time $t$while also depending on a positive quantity x, representing inventory level, transportation distance, demand magnitude, production capacity, safety-stock scale, disruption intensity, or another operational measure [7, 8, 12]. The FKF transform is therefore useful for capturing the coupled temporal and scale-dependent characteristics of such systems [29]. For a supply-chain function $f(t, x)$, the Fourier component resolves variations along the temporal variable t, while the KL component represents the behaviour associated with the positive variable x. The resulting transformed function $F(s, q)$describes the supply-chain signal in terms of a Fourier frequency variable $s$and a KL spectral variable q.

This representation enables different operational characteristics to be examined in the spectral domain. Concentrated peaks in $F(s, q)$may indicate dominant periodic or recurrent patterns, while ridges can reveal interactions between temporal frequencies and operational scales. The decay characteristics of the transform can provide information about transient or rapidly diminishing effects, whereas shifts in spectral concentration or phase behaviour may indicate structural changes, regime transitions, or disruptions within the supply-chain system [3, 14, 15, 18, 30]. Consequently, the FKF transform offers a unified mathematical framework for analyzing temporal dynamics together with scale-dependent behaviors in complex supply-chain processes [6, 8, 20, 29, 34]

5.1 Inventory Risk and Safety-Stock Analysis

Let x denote a positive inventory or demand-risk magnitude. A probability-weighted signal p(t, x) can be transformed as

$$P_F(s,q) = FKF[p](s,q)$$

The q coordinate can then be used as a scale coordinate for analyzing how uncertainty changes with inventory magnitude. For example,

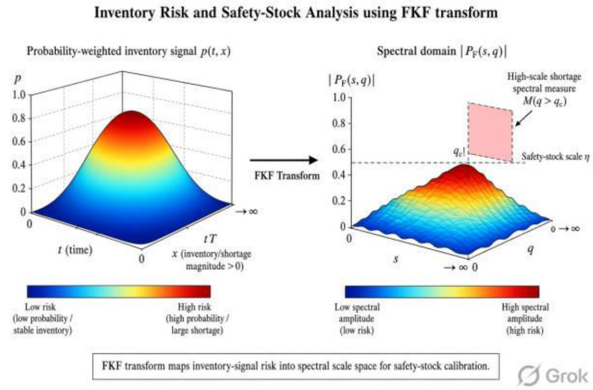

Figure 1. Inventory risk mapped into the FKF spectral domain; high-q region highlights elevated shortage risk relative to a safety-stock scale threshold

if x is a positive shortage magnitude, one can examine a spectral region q > q^c corresponding to higher scale shortage behaviors and define a high-scale spectral measure P_F

$$E_{high} = \int_{-\infty}^{\infty}\int_{q\_c}^{\infty} |P_F(s,q)|^2 \, dq \, ds$$

Such a measure should be treated as an analytical indicator rather than a replacement for conventional probability based service level metrics.

5.2 Production and Capacity Fluctuations

Let C(t, x) denote production capacity or utilization intensity. If its dynamics satisfy a differential model in t, the Fourier property transforms temporal derivatives into powers of is. For example,

$$\frac{\partial C}{\partial t} + a\,C = U(t,x)$$

becomes

$$(is + a)C_F(s,q) = U_F(s,q)$$

and therefore

$$C_F(s,q) = \frac{U_F(s,q)}{is + a}$$

The denominator acts as a frequency dependent response. This provides a compact way of studying how production systems attenuate or amplify different temporal frequencies.

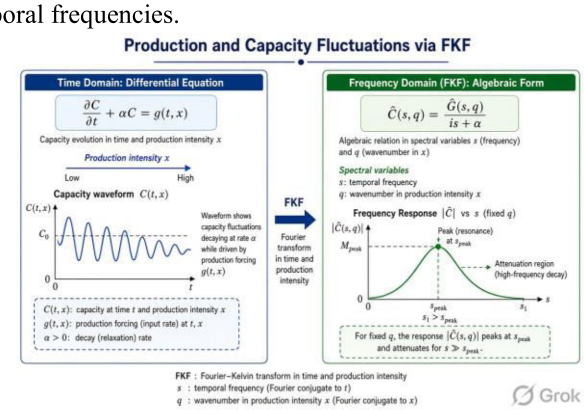

Figure 2. Production/capacity dynamics: time-domain differential equation converted by FKF into a frequency-response representation.

5.3 Supply-Chain Network and Multi-Echelon Analysis

For a multi-echelon chain, let $X_n(t,x)$ denote the state at echelon n. A linearized dynamic relation may be written

$$X_{\{n+1,F\}}(s,q) = H_n(s,q)X_{\{n,F\}}(s,q)$$

Repeated substitution gives

$$X_{\{N,F\}}(s,q) \;=\; \prod_{\{n=1\}}^{\{N-1\}} H_n(s,q)]\, X_{\{1,F\}}(s,q)$$

This equation makes the cumulative effect of forecasting, replenishment, transportation, and production policies explicit in the transform domain.

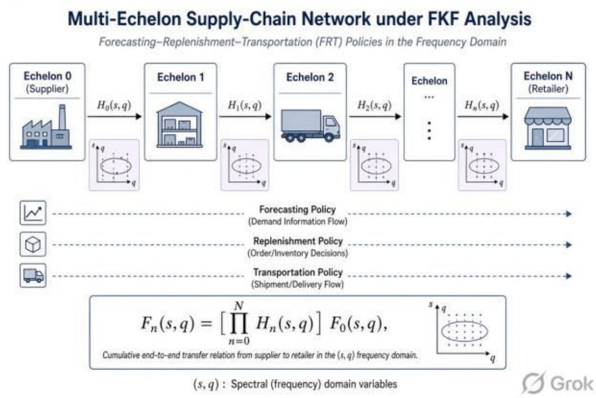

Figure 3. Multi-echelon network with transfer functions $H_n(s,q)$ and the cumulative end-to-end spectral relation

5.4 Monte Carlo and Probabilistic Supply-Chain Risk

FKF analysis can be combined conceptually with Monte Carlo simulation. Let the r-th simulation scenario produce $[f_T](s,q)$, r = 1, …, M. Its transform is

$$F_r(s,q) = \; FKF[f_r](s,q)$$

The empirical mean transform is

$$\bar{F}(s,q) = \left(\frac{1}{M}\right)\sum_{\{r=1\}}^{M} F_r(s,q)$$

and a spectral variance estimate is

$$V_F(s,q) = \left(\frac{1}{M-1}\right)\sum_{\{r=1\}}^{M} |F_r(s,q) - \; \bar{F}(s,q)|^2$$

This creates a bridge between scenario-based risk analysis and spectral analysis. The result can identify frequency scale regions where uncertainty is concentrated, rather than reporting only a single scalar risk measure.

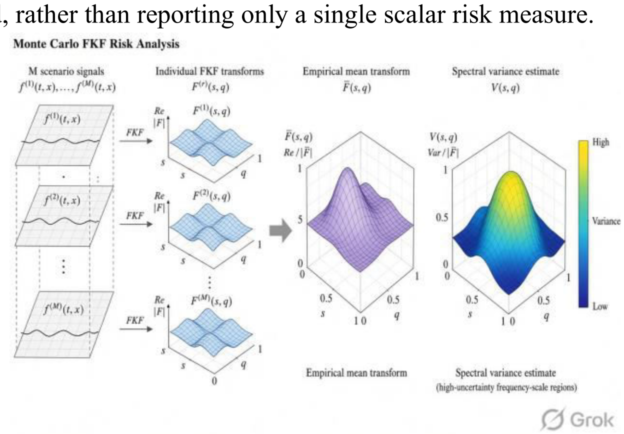

Figure 4. Monte Carlo ensemble of FKF transforms yielding empirical mean and spectral variance surfaces

5.5 Digital Twins and Real-Time Monitoring

In a digital-twin architecture, measurements are collected continuously and transformed over a moving window. For a windowed signal $f_T(t,x)$,

$$F_T(s,q) \;=\; FKF[f_T](s,q)$$

A baseline transform $F_0(s,q)$ can be compared with the current transform. Define a normalized spectral deviation

$$R_F(s,q) \;=\; \frac{|F_T(s,q) \;-\; F_0(s,q)|}{|F_0(s,q)| \;+\; \varepsilon}$$

where ε > 0 prevents division by zero. Large values of R_F indicate spectral changes and can be used as candidate indicators for anomaly detection, supplier deterioration, transportation disruption, or demand regime change.

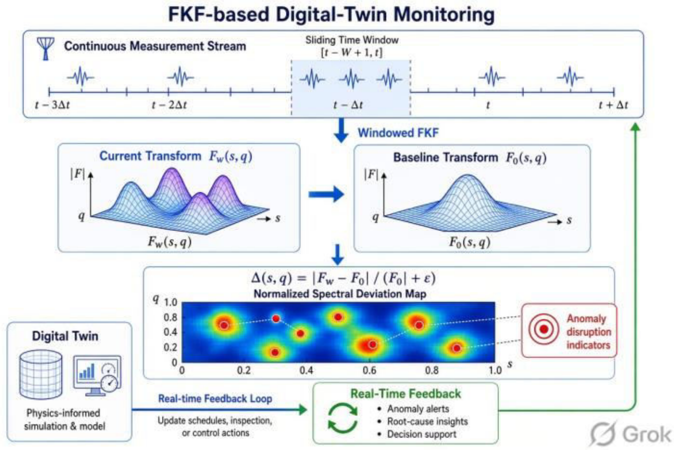

Figure 5. Windowed FKF monitoring inside a digital twin, with spectral deviation map highlighting anomalies.

6. Conceptual FKF-Based Supply-Chain Workflow

The Workflow consists of five main stages [1–3]. First, supply-chain data such as demand, inventory, transportation, production, or disruption intensity are represented as a two-dimensional function (f(t,x)), where (t) denotes time and (x>0) represents an operational scale or state variable [4,5]. Second, the Fourier–Kontorovich–Lebedev (FKF) transform converts (f(t,x)) into its joint spectral representation (F(s,q)), where (s) is the Fourier frequency and (q) is the KL spectral variable [6–8]. Third, spectral features such as peaks, ridges, decay rates, and shifts are extracted to identify periodic patterns, transient effects, scale interactions, and structural changes [9,10]. Fourth, these spectral characteristics are interpreted for anomaly detection, forecasting, and supply-chain risk assessment [11–13]. Finally, the extracted information supports decisions concerning inventory control, capacity planning, transportation management, disruption mitigation, and supply-chain resilience [14,15].

7. Important Assumptions and Limitations

- The FKF integral must exist in the ordinary or distributional sense appropriate to the selected function space.
- Boundary terms must vanish, or be handled explicitly, when deriving differentiation and operator identities by integration by parts.
- The Fourier sign convention must be fixed consistently. This note uses e^{-ist}.
- The positive variable x must be compatible with the KL kernel and its required integrability conditions.
- The q-domain and the normalization of the KL transform depend on the precise convention adopted in a given mathematical reference.
- Supply-chain applications presented here are analytical extensions: they show how the FKF framework can be mapped to supply-chain variables, but empirical validation is required before treating a spectral indicator as an operational KPI.
- For discrete supply-chain data, numerical quadrature, discretization, windowing, and sampling effects must be addressed carefully.

8. Conclusion and Recommendations

The FKF transform provides a promising framework for analyzing complex supply-chain systems in which operational variables evolve simultaneously over time and positive-valued scales. By combining Fourier and KL spectral representations, the FKF transform can capture periodicity, transient behavior, scale effects, anomalies, and structural changes within multidimensional supply-chain signals. Its application can enhance supply-chain visibility and support forecasting, risk assessment, inventory management, capacity planning, and resilience analysis.

Further research should validate FKF based models using real world supply-chain datasets and compare their performance with conventional Fourier, wavelet, and time series methods. Future studies should also investigate integration with artificial intelligence, machine learning, digital twins, and optimization techniques. Particular attention should be given to computational efficiency, parameter selection, noise handling, spectral feature interpretation, and real-time implementation. Such developments could strengthen the practical applicability of the FKF transform as an analytical tool for resilient and data-driven supply-chain management.

8.1 Recommendations for research and practice:

Real-World Performance Assessment Apply the FKF framework to real-world supply-chain datasets covering demand, inventory, transportation, production, and disruption events, thereby testing the practical utility of spectral indicators against established operational metrics [6, 11, 20, 30].

Comparative Analysis Systematically compare FKF-based analysis with classical Fourier, wavelet, Laplace, and conventional time-series methods in order to quantify its relative advantages for jointly capturing temporal dynamics and scale-dependent behaviour [21–24, 29].

AI and Machine Learning Integration Combine FKF spectral features with machine-learning models to enhance forecasting accuracy, anomaly detection, and risk prediction, building on recent advances in artificial-intelligence applications for sustainable logistics and supply-chain risk mitigation [7, 8, 30].

Digital Twin Integration Incorporate FKF analysis into supply-chain digital twins to enable continuous spectral monitoring and early detection of operational regime changes, aligning with emerging digital-twin architectures for resilient and adaptive global supply chains [6, 34].

Real-Time Implementation Develop computationally efficient discrete FKF algorithms suitable for real-time supply-chain monitoring and decision support, leveraging convergent frameworks that integrate IoT, artificial intelligence, and quantum-inspired methods [2, 3, 15, 18].

Resilience and Risk Management Investigate the use of FKF spectral indicators for identifying disruption patterns, quantifying uncertainty concentration, and evaluating overall supply-chain resilience under both internal and external complexities [8, 11, 12, 20, 30].

Future Research Directions Further examine parameter selection, noise sensitivity, boundary conditions, numerical stability, and the physical interpretation of the Kontorovich–Lebedev spectral component in order to strengthen both the theoretical foundations and the practical applicability of the FKF framework in logistics and related multi-scale systems [21–29].

Recommended Computational Form for Discrete Data

For observations sampled at t_n and x_m, a numerical FKF approximation can be written schematically as

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

For nonuniform x samples, Δx_m should be replaced by the appropriate quadrature weights. For noisy operational data, windowing and regularization may be required.

8.2 Conclusion

The Fourier–Kontorovich–Lebedev (FKF) transform offers a unified framework for analysing multidimensional supply-chain dynamics involving both temporal variation and positive-valued operational scales. By combining Fourier and KL spectral representations, it enables the identification of periodic patterns, transient behaviour, scale-dependent effects, anomalies, and structural changes that may be difficult to detect in the original data. The framework therefore has potential applications in demand analysis, inventory management, transportation planning, disruption detection, forecasting, and supply-chain resilience. Although further empirical validation is required, the FKF approach provides a promising mathematical foundation for advanced supply-chain analytics.

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