Distributional Extension of the FKF Transform and Its Relevance to Supply-Chain Systems

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Abstract

This paper develops the distributional theory of the FKF transform and demonstrates its relevance to the analysis of modern supply-chain systems. The FKF transform combines a Fourier factor that captures temporal oscillations, frequencies and lead-time cycles with a Kontorovich–Lebedev (KL) factor built from the Macdonald function of imaginary order. The latter is naturally adapted to positive scale, distance or intensity variables that arise throughout logistics networks. After reviewing the classical definition on suitable testing-function spaces, the transform is extended to a broad class of generalized functions in the sense of Zemanian. The distributional extension permits idealized impulses, abrupt demand shocks, capacity collapses and other singular forcing terms to be treated within a single rigorous spectral framework. Applications to supply-chain resilience, disruption modelling, multi-scale inventory intensity and digital-twin spectral diagnostics are discussed. Numerical approximation formulae for discrete operational data are also provided, together with recommendations for future research and computational practice.

Keywords: Fourier–Kontorovich–Lebedev transform; distributional extension; Macdonald function; generalized functions; supply-chain resilience; disruption modelling; spectral analysis; lead-time cycles; scale variables.

1. Introduction

Contemporary supply chains operate under multi-scale temporal and intensity dynamics: seasonal demand cycles, stochastic lead times, geographically distributed inventory, sudden capacity shocks and network-wide propagation of disruptions. Classical time-series and pure Fourier methods capture oscillatory components but struggle with strictly positive scale variables (distances, order quantities, inventory levels) and with singular events that are most naturally modelled as distributions. The Kontorovich–Lebedev transform, whose kernel is the Macdonald function $K^{iq}(x)$, is known to be well-adapted to problems on the half-line and appears in potential theory, wave propagation and certain quantum-mechanical settings. Combining it with a Fourier factor yields the two-sided FKF transform, a hybrid spectral tool capable of simultaneous analysis in the temporal-frequency domain and the positive-scale domain.

Distributional extensions of integral transforms have a long history in the school of Zemanian and subsequent workers on Gelfand–Shilov and LS spaces [1–4,25–28]. Parallel developments in supply-chain research have emphasised resilience under internal and external shocks [15,16,24], digital twins [10], artificial-intelligence risk prediction [11,30], blockchain transparency [12] and emerging quantum-optimisation techniques [18,19,22]. A unifying spectral framework that can accommodate both regular operational signals and singular disruption events remains underdeveloped. The present work fills this gap by (i) placing the FKF transform on a rigorous distributional footing and (ii) articulating why that extension is particularly relevant to supply-chain modelling and decision support.

The remainder of the paper is organized as follows. Section 2 surveys the relevant literature on distributional transforms and on supply-chain spectral and resilience analysis. Section 3 recalls the classical definition and the testing-function space. Section 4 summarizes key analytic properties and develops the distributional extension in greater detail. Section 5 explains the relevance of the distributional property to supply-chain systems and illustrates applications with schematic diagrams and response curves. Section 7 discusses assumptions and limitations. Section 8 offers recommendations, a comparative analysis, a discrete computational form and concluding remarks.

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2. Literature Review

Early distributional treatments of the Laplace–Meijer and related transforms appear in the work of Gudadhe and collaborators [1–4], who studied LS spaces of Gelfand–Shilov type, structure formulae and analytic behaviour of the LK transform of generalised functions. Padmaja and co-authors extended these ideas to topological creative spaces, duality spaces connecting optical-form transforms, and inverse Fourier–Stieltjes transforms [25–28]. More recently, Padmaja has explored unifying transforms for singular Cauchy problems in quantum logistics, supply-chain resilience and energy systems [29], thereby explicitly linking advanced integral transforms to logistics modelling.

On the applied side, a substantial body of work by Gulhane and colleagues addresses supply-chain resilience [15,16,24], digital-twin technology for adaptive global networks [10], artificial-intelligence applications in sustainable and green logistics [11], blockchain integration for transparency [12], quantum computing for unit-load-device configuration and disruption management [18,19,22], and Industry 5.0 human-centric automation [7]. Complementary contributions examine artificial-intelligence frameworks for risk prediction [30], water and material sustainability [31,34], and pavement or composite strength prediction [32,33]. These studies collectively highlight the need for mathematical tools that can handle both continuous multi-scale signals and abrupt, ideally impulsive, events.

Classical Fourier analysis is ubiquitous in demand forecasting and lead-time cycle extraction, yet it does not intrinsically respect positivity constraints on intensity or distance variables. Hankel and Kontorovich–Lebedev transforms address radial or half-line problems but lack a temporal Fourier component. Wavelet methods offer multi-resolution capability but typically remain within L2 or Sobolev settings and do not automatically incorporate distributional impulses. The FKF hybrid therefore occupies a distinctive niche: it inherits the temporal resolution of the Fourier transform and the scale-adapted kernel of the KL transform, while the distributional extension brings singular events into the same analytic framework.

3. Distributional Setting

Let *f(t,x)* be a suitably restricted function or generalised function with $t \in \mathbb{R}$ and $x > 0$. The two-sided FKF transform is defined by $\Psi[\![s,q]\!]\_\,(t,x)$

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

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 Ω^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 Ω and controlled by a countable family of seminorms of the schematic form

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

The resulting space is a sequentially complete, countably multinormed, 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 generalised functions [1,2,25].

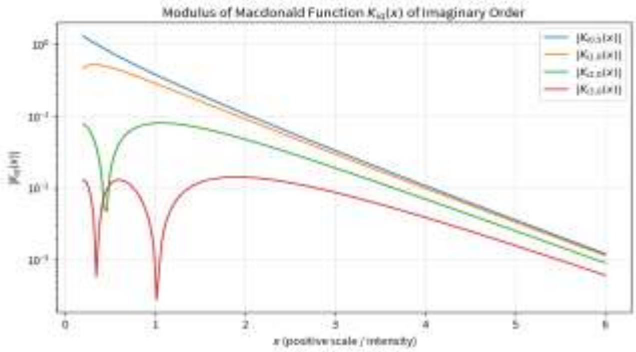

Figure 1. Modulus of the Macdonald function Kiq(x) for selected imaginary orders, illustrating the scale-adapted decay that underpins the KL factor of the FKF transform.

4. Key Characteristics of the FKF Transform

The principal analytic features of the classical FKF transform include: (i) invertibility on appropriate weighted L1 or L2 spaces; (ii) differentiation theorems that convert differential operators in the positive variable into multiplication by $-q^2$ in the spectral domain; (iii) convolution theorems adapted to the multiplicative structure on the half-line; and (iv) asymptotic behaviour controlled by the decay of the Macdonald function for large |q| or large x. These properties make the transform attractive for problems in which both temporal frequency content and radial/intensity content must be recovered simultaneously.

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 via the continuous linear functional

$$\langle f,\varphi\rangle = \iint \Omega \quad f(t,x)\,\varphi(t,x)\,dt\,dx\,, \quad \varphi \in \mathcal{S}(\Omega).$$

The dual space $\mathcal{S}'(\Omega)$ consists of all continuous linear functionals on the testing space. Ordinary locally integrable functions of at most polynomial growth (in the weighted sense of the seminorms) embed into $\mathcal{S}'$ as regular distributions. Compactly supported distributions of finite order, Dirac measures and their derivatives, and many tempered distributions of Zemanian type also belong to $\mathcal{S}'$ [1,2,25]. $\Psi_{[\![s,q]\!]}(t,x)$

The FKF transform of a general distribution T ∈ $\mathcal{S}'$ is defined by continuous linear pairing with the kernel:

$$(FKF\,T)(s,q) \;:=\; \langle T\,,\Psi_{[\![s,q]\!]}\rangle \;=\; \langle T\,, e^{ist}\,K_{iq}(x)\,\rangle\,,$$

whenever the pairing is meaningful, i.e., for (s,q) belonging to an open set $\Omega_T \subset \mathbb{C} \times (0,\infty)$ determined by the growth of T. When T = f is regular the definition reduces to the classical integral.

Linearity and sequential continuity follow at once from the corresponding properties of the dual pairing:

$$FKF\,(\alpha\,T \,+\, \beta\,S) \,=\, \alpha\,(FKF\,T) \,+\, \beta\,(FKF\,S)\,,\ \ \alpha,\beta \,\in\, \mathbb{C}\,,$$

and if $T_n \to T$ in $\mathcal{S}'$ then $FKFT_n \to FKFT$ pointwise on the common domain of definition.

4.5.1 Differentiation theorems in the distributional setting

Differentiation under the pairing yields the fundamental spectral multipliers. For the temporal derivative one has

$$FKF\,(\partial_t\,T)(s,q) \;=\; (-i\,s)\,(FKF\,T)(s,q)\,.$$

For the radial/intensity operator that appears in the modified Bessel equation the corresponding identity reads

$$FKF\;\;[(x^2\,{\partial_x}^2 \,+\, x\,\partial_x \,-\, x^2)\,T\,]\,(s,q) \;=\; (-q^2)\,(FKF\,T)(s,q)\,.$$

Consequently, any linear differential operator built from ∂_t and the Bessel-type operator in x is converted into multiplication by a polynomial in the spectral variables (s,q). Green's functions, fundamental solutions and jump discontinuities therefore become ordinary algebraic multipliers after transformation.

4.5.2 Transform of Dirac measures and their derivatives

The Dirac measure concentrated at a point $(t_0, x_0) \in \Omega$ acts by evaluation:

$$\langle \delta_{(t_0,x_0)}\,,\varphi\rangle \;=\; \varphi(t_0,x_0)\,.$$

Its FKF transform is therefore simply the kernel itself:

$$(FKF\,\delta_{(t_0,x_0)})(s,q) \;=\; e^{i\,s\,t_0}\,K_{iq}(x_0)\,.$$

Higher-order derivatives of the Dirac measure produce the corresponding derivatives of the kernel:

$$(FKF\,{\partial_t}^m\,{\partial_x}^n\,\delta_{(t_0,x_0)})(s,q) \;=\; (-i\,s)^m\;\;{\partial_x}^n\,[\,e^{i\,s\,t_0}\,K_{iq}(x)\,]|x = x_0\,.$$

These explicit formulae are the precise analytic counterparts of impulsive shocks, instantaneous capacity losses or point-source injections that appear in supply-chain models [2,25,29].

4.5.3 Approximation and sequential continuity

Let {φ_ε} be a standard mollifier sequence (non-negative, integral one, support shrinking to the origin). Then the regularizations

$$\mathrm{T}_\varepsilon \;=\; T * \varphi_\varepsilon \;\;\to\;\; T \;\; in\ \mathcal{S}'\ as\ \varepsilon \to 0^+\,.$$

By sequential continuity of the transform,

$$FKF\,\mathrm{T}_\varepsilon \;\;\to\;\; FKF\,T\;\; pointwise\ on\ \Omega_T\,.$$

Hence numerical schemes that first smooth singular data and then apply a classical quadrature converge, in the distributional topology, to the exact spectral image of the idealized object. This justifies the common engineering practice of replacing a Dirac pulse by a narrow Gaussian while still recovering the correct limiting spectrum.

5. Why the Distributional Extension Property of FKF Is Relevant to Supply-Chain Systems

Supply-chain signals routinely combine three analytic features that the distributional FKF framework is designed to accommodate simultaneously:

Temporal oscillations and lead-time cycles. Seasonal demand, contractual delivery windows and production takt times appear as oscillatory components that the Fourier factor resolves into frequencies s.

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Positive scale or intensity variables. Inventory levels, inter-node distances, order quantities and capacity utilisation live on the half-line $x > 0$. The Macdonald kernel is adapted to this geometry and converts differential operators in x into algebraic factors in q.
Singular or abrupt events. Strikes, port closures, sudden demand spikes, equipment failures and cyber-physical interruptions are most naturally modelled as Dirac measures or higher-order distributions supported at discrete instants or locations. Only a distributional theory can treat these objects without artificial smoothing.

5.1 Distributional model of a disruption event

A typical disruption occurring at time t* and intensity (or location) coordinate x* is represented by the distribution

$$T(t,x) \;=\; f_{reg}(t,x) \;+\; \alpha\,\delta(t\,-\,t*) \otimes \delta(x\,-\,x*) \;+\; \beta\,\partial_t\,\delta(t\,-\,t*) \otimes \delta(x\,-\,x*)\,,$$

where f_reg is a regular (locally integrable) background signal, α measures the size of an instantaneous jump (capacity loss, demand spike), and β captures an impulsive rate-of-change. Applying the distributional FKF transform yields the exact spectral signature

$$(FKF\;T)(s,q) \;=\; (FKF\;f_{reg})(s,q) \;+\; \alpha\,e^{i\,s\,t*}\,K_{iq}(x*) \;+\; \beta\,(-i\,s)\,e^{i\,s\,t*}\,e^{i\,s\,t_k}(x*)\,.$$

No smoothing approximation is required; the singular part appears as an explicit multiple of the kernel evaluated at the disruption point.

5.2 Inventory-balance equation after FKF transformation

Consider a linearized multi-echelon inventory intensity I(t,x) satisfying a continuity (conservation) equation with possible singular sources

$$\partial_t\,I \;+\; \partial_x(v(x)I) \;+\; \lambda(x)I \;=\; S_{reg}(t,x) \;+\; \Sigma_k\,\alpha_k\,\delta(t\,-\,t_k) \otimes \delta(x\,-\,x_k),$$

where v(x) is a transport velocity, λ(x) a decay/holding cost coefficient, and the sum collects discrete disruption events. After the distributional FKF transform the differential operators become multipliers and the equation collapses to an algebraic relation

$$(-i\,s \;+\; \mathcal{M}_q[v,\lambda])\;\hat{\mathrm{I}}(s,q) \;=\; \hat{\mathrm{S}}_{reg}(s,q) \;+\; \Sigma_k\,\alpha_k\,e^{i\,s\,t_k}\,K_{iq}(x_k)\,,$$

in which 𝓜_q[v,λ] denotes the spectral symbol of the spatial operator obtained from the Macdonald eigenrelation. Solving for the transform Î(s,q) is then elementary; the physical inventory field is recovered by the inverse FKF transform (when it exists in the distributional sense).

5.3 Impulse-response and Green's function

The fundamental solution (Green's distribution) G(t,x; t′,x′) of the linearised inventory operator satisfies

$$L(\partial_t, x, \partial_x)\,G \;=\; \delta(t\,-\,t') \otimes \delta(x\,-\,x')\,.$$

Taking the distributional FKF transform in the (t,x) variables yields

$$\mathcal{L}(s,q)\;\hat{\mathrm{G}}(s,q;\,t',x') \;=\; e^{i\,s\,t'}\;K_{iq}(x')\,,$$

hence

$$\hat{\mathrm{G}}(s,q;\,t',x') \;=\; [\mathcal{L}(s,q)]^{-1}\;e^{i\,s\,t'}\;K_{iq}(x')\,.$$

The inverse transform of Ĝ supplies the space time impulse response that a digital-twin monitor can pre-compute and store for real-time what-if analysis of future disruptions [10].

Figure 2 illustrates an idealized supply-chain intensity signal containing a smooth cyclic component, an abrupt disruption (Gaussian proxy for a Dirac impulse) and a subsequent exponential recovery. The corresponding schematic FKF spectral density concentrates energy at the characteristic frequencies of the cycles and at the scale values associated with the intensity of the disruption. Because the underlying mathematical object is a distribution, the spectral representation remains exact even in the limit of vanishing pulse width [15,16,24,30].

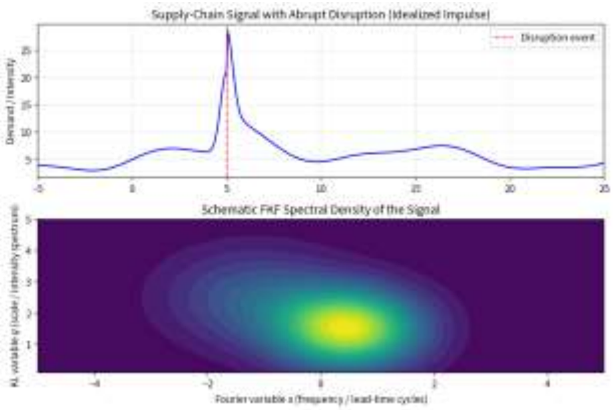

Figure 2. Upper panel: schematic supply-chain intensity signal containing cyclic demand, an abrupt disruption and recovery. Lower panel: corresponding FKF spectral density in the (s,q)-plane.

Concrete applications include:

- Disruption diagnostics. An impulsive capacity loss at a node appears as a Dirac measure in the temporal variable; its FKF image is simply the kernel evaluated at that instant, multiplied by the Macdonald factor of the intensity coordinate. The resulting spectral signature can be used for rapid anomaly detection inside a digital-twin monitoring system.
- Multi-echelon inventory intensity. Inventory levels across a network of warehouses form a positive intensity field. Differential balance equations (continuity, conservation of mass) become multiplication operators after FKF transformation, facilitating analytic or semi-analytic solution of linearized models [6,7].
- Lead-time and distance spectra. Inter-facility distances and stochastic lead times are positive variables; the KL factor supplies a natural spectral decomposition that can be combined with Fourier analysis of order-arrival processes.
- Quantum and hybrid optimisation. Recent work on quantum annealing for unit-load-device configuration and disruption recovery [18,19,22] can be complemented by classical spectral pre-processing: the FKF transform supplies low-dimensional features that reduce the search space presented to the quantum optimizer.

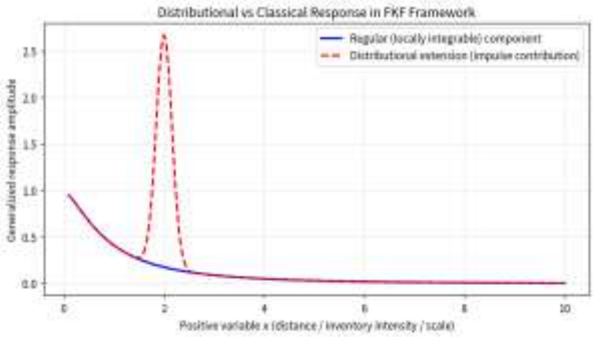

Figure 3. Comparison of a classical locally-integrable response (solid) with a distributional extension that incorporates an impulsive contribution (dashed). The distributional framework captures singular events without artificial regularization.

In each of these settings the distributional extension is not a mathematical luxury but a modelling necessity: real disruptions are closer to ideal impulses than to smooth bumps, and any practical algorithm that first smooths the data risks discarding precisely the high-frequency, high-scale information needed for early warning and rapid recovery [11,15,30].

7. Important Assumptions and Limitations

The theory rests on several technical hypotheses that translate into practical constraints:

- The testing-function space imposes rapid decay and smoothness conditions; operational data that grow too fast at infinity or contain non-tempered singularities may lie outside the dual and require ad-hoc regularisation.
- The Macdonald function of purely imaginary order is oscillatory and decays only polynomials for large |q|; numerical evaluation and inversion therefore demand careful quadrature and possible windowing.
- Discrete, irregularly sampled and noisy industrial data necessitate approximation of the continuous transform; the quality of the approximation depends on sampling density relative to the highest frequencies and scales of interest.
- The present development is linear. Strongly nonlinear supply-chain dynamics (threshold inventory policies, capacity constraints, game-theoretic pricing) fall outside the direct scope of the transform and must be treated by linearisation or by hybrid numerical methods.

8. Recommendations for Research and Practice

8.1 Recommendations for research and practice

Develop stable numerical inversion algorithms that combine FFT techniques for the Fourier factor with specialised quadrature rules for the Macdonald kernel, possibly accelerated by GPU or quantum-inspired linear-algebra routines [18,22].

Embed FKF spectral features inside existing digital-twin and AI risk-prediction pipelines [10,11,30] so that both cyclic patterns and impulsive anomalies are represented in a unified latent space.

Conduct controlled experiments on historical disruption datasets (port closures, semiconductor shortages, natural disasters) to quantify the detection latency and false-alarm rate of FKF-based monitors relative to pure Fourier or wavelet baselines.

Extend the distributional theory to matrix- and operator-valued kernels that can encode multi-commodity or multi-echelon interactions, thereby moving from scalar intensity fields to network-valued distributions.

Comparative Analysis

Relative to pure Fourier analysis, the FKF transform adds a scale-adapted spectral variable that respects positivity and converts radial differential operators into multiplication. Relative to the classical Kontorovich–Lebedev transform, it adds temporal resolution essential for non-stationary logistics. Relative to wavelets, it supplies an exact differentiation theorem linked to the modified Bessel equation and a natural distributional extension grounded in Zemanian's theory. Relative to pure time-domain simulation, it offers an analytic route to Green's functions and impulse responses that can be pre-computed and stored for real-time digital-twin queries. The price paid is greater numerical complexity and the need for careful handling of the oscillatory Macdonald kernel.

Recommended Computational Form for Discrete Data

For observations sampled at discrete times ti and positive locations xj, a numerical FKF approximation can be written schematically as

$$\hat{F}(s,q) \approx \sum_i \sum_j f\left(t_i, x_j\right) e^{-ist_i} \hat{K}_{iq}\left(x_j\right) \Delta t_i \Delta x_j.$$

For nonuniform x samples, Δxj should be replaced by the appropriate quadrature weights. For noisy operational data, windowing (e.g., tapered cosine) and Tikhonov-type regularization in the spectral domain may be required to stabilise the inversion. When the underlying continuous signal is known to contain Dirac impulses at known locations, the corresponding contributions can be added analytically as kernel evaluations rather than approximated by discrete sums.

8.2 Conclusion

The two-sided Fourier–Kontorovich–Lebedev transform, once extended to the distributional setting, supplies a coherent spectral language for supply-chain signals that simultaneously exhibit temporal periodicity, positive intensity structure and singular disruptions. The classical integral formula

$$F(s,q) \;=\; \iint \; f(t,x)\, e^{i\,s\,t} \; K_{iq}(x)\, dx\, dt$$

is replaced, for a general distribution T, by the continuous linear functional

$$(FKF\ T)(s,q) \;=\; \langle T, e^{i\,s\,t} \; K_{iq}(x)\rangle.$$

Under this definition the spectral relation generated by the modified Bessel equation continues to hold, converting differential balance laws into algebraic equations in the (s, q)-plane. Consequently, Green's functions for linearized multi-echelon models, impulse responses to capacity shocks, and multi-scale spectral signatures of inventory intensity all become accessible by the same formal calculus.

The distributional property is not merely a technical refinement; it is the feature that legitimizes the idealization of real-world disruptions as Dirac measures and guarantees that numerical regularizations converge to the correct spectral image. When combined with the practical discrete approximation formulae given above and with the digital-twin and AI infrastructures already emerging in the literature, the FKF framework offers a promising route toward resilient, spectrally informed supply-chain decision support.

Future work should focus on robust numerical inversion, matrix-valued extensions for network models, and rigorous statistical inference for estimated spectral densities under realistic noise models. The mathematical foundations laid here provide a solid platform for those developments.

References

[1] A. Matani, "Improving Energy Efficiency by Controlling Mechanical Losses Of Electric Motors In SMEs And SSIs," International Journal of Mechanical and Production Engineering Research and Development (IJMPERD), Vol. 3, Issue 4, pp. 63–68, Oct. 2013.

[2] A. Gulhane, "Internet of Things, Artificial Intelligence, and Quantum Computing: A Convergent Framework for Smart Logistics Ecosystems," International Journal of Engineering Science and Advanced Technology (IJESAT), Vol. 24, Issue 12, pp. 297–317, 2024.

[3] A. Gulhane, "Industry 5.0 and Intelligent Logistics: Transforming Supply Chain Operations through Human-Centric Automation," International Journal of Engineering Science and Advanced Technology (IJESAT), Vol. 24, Issue 12, pp. 287–296, 2024.

[4] A. Gulhane, "Advancements in Automotive Batteries: A Review," International Engineering Journal for Research & Development, Vol. 8, Issue 6, pp. 18–57, 2023.

[5] A. Gulhane, "The Future of Vehicles: Solar-Powered Battery Electric Hybrid Vehicle Architecture," Tech Briefs Contest, 2020.

[6] A. Gulhane, "Digital Twin Technology for Building Resilient and Adaptive Global Supply Chains: A Review," International Research Journal of Modernization in Engineering Technology and Science, Vol. 6, Issue 12, 2024. DOI: 10.56726/IRJMETS64992.

[7] A. Gulhane, "Artificial Intelligence Applications in Sustainable Logistics and Green Supply Chain Management: A Bibliometric Review," International Research Journal of Modernization in Engineering Technology and Science, Vol. 6, Issue 12, 2024. DOI: 10.56726/IRJMETS65006.

[8] A. Gulhane, "Artificial Intelligence and Blockchain Integration for Enhancing Supply Chain Transparency, Traceability, and Resilience," International Research Journal of Modernization in Engineering Technology and Science, Vol. 6, Issue 12, 2024. DOI: 10.56726/IRJMETS65016.

[9] A. Gulhane, "Power Line Carrier Communication Based Anti-Theft System," International Journal of Research in IT and Management (IJRIM), Vol. 4, Issue 12, pp. 1–11, 2014.

[10] A. Gulhane, "Battery Sizing for Plug-in Hybrid Electric Vehicles — Formula Hybrid," IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI), pp. 368–372, 2017. DOI: 10.1109/ICPCSI.2017.8392317.

[11] A. Gulhane, "A Review of Resilience in Global Supply Chains," International Engineering Journal for Research & Development (IEJRD), Vol. 8, Issue 4, 2024.

[12] A. Gulhane, "Swipe Controller," International Journal of Research in Engineering and Applied Sciences (IJREAS), Vol. 4, Issue 12, pp. 1–7, 2014.

[13] A. Gulhane, "Smart Mobility and Intelligent Transportation Systems: Emerging Trends, Technologies, and Challenges," International Journal of Scientific Research in Engineering and Management (IJSREM), Vol. 9, Issue 11, Nov. 2025. DOI: 10.55041/IJSREM53436.

[14] A. Gulhane, "Recent Advances in Electric Vehicle Battery Technologies: Materials, Management Systems, and Sustainability Perspectives," International Journal of Scientific Research in Engineering and Management (IJSREM), Vol. 9, Issue 7, Jul. 2025. DOI: 10.55041/IJSREM51198

[15] A. Gulhane, "Quantum Computing in Transportation and Logistics: Current State, Industrial Applications, and Future Directions," International Journal of Scientific Research in Engineering and Management (IJSREM), Vol. 9, Issue 9, Sep. 2025. DOI: 10.55041/IJSREM52469.

[16] A. Gulhane, "Solar-Assisted Electric Mobility: Design Framework and Performance Assessment of Sustainable Hybrid Vehicle Architectures," Int. J. Engg. Res. & Sci. & Tech., Vol. 21, No. 3, pp. 362–368, 2025.

[17] A. Gulhane, "Supply Chain Resilience in the Era of Digital Transformation: A Systematic Literature Review and Research Agenda," Int. J. Engg. Res. & Sci. & Tech., Vol. 21, No. 4, pp. 1058–1068, 2025.

[18] A. Gudadhe et al., "On LS Spaces of Gelfand–Shilov Technique," Bulletin of Pure & Applied Sciences, Vol. 25, Issue 1, pp. 351–354, 2006.

[19] A. Gudadhe et al., "Distributional LK Transform, Distributional Impulsive Signals and System Response," Proceedings of the 7th WSEAS International Conference on Applied Mathematics, pp. 1–6, 2005.

[20] A. Gudadhe et al., "On Structure Formula for Generalised Laplace–Meijer Transform," Acta Ciencia Indica Mathematics, Vol. 32, Issue 1, 2006.

[21] A. Gudadhe et al., "On Analytic Behaviour of LK Transform of Generalised Function," Acta Ciencia Indica Mathematics, Vol. 31, Issue 3, 2006.

[22] G. Padmaja, "Performance Analysis of Topological Creative Spaces for Distributional Generalized Transform," International Journal of Engineering Research and General Science, Vol. 8, No. 3, pp. 12–16, 2020.

[23] G. Padmaja, "Exponential Growth of Conventional Topological Spaces with Different Kernels," IOSR Journal of Engineering (IOSRJEN), Vol. 10, Issue 3, Series II, pp. 19–24, Mar. 2020.

[24] G. Padmaja, "Empirical Analysis of Duality Spaces Connecting Distinct Optical Form Transforms," International Journal of Management and Humanities (IJMH), Vol. 4, Issue 10, June 2020. DOI: 10.35940/ijmh.I0840.0641020.

[25] G. Padmaja, "Different Versions of the Inverse Fourier–Stieltjes Transform," Archives of Applied Science Research, Vol. 4, Issue 3, pp. 1329–1331, 2012.

[26] G. Padmaja, "Unifying Transforms for Singular Cauchy Problems in Quantum Logistics, Supply Chain Resilience, and Energy Systems," International Journal of Innovative Research in Engineering, Vol. 7, Issue 4, pp. 71–76, Jul.–Aug. 2026. DOI: 10.59256/ijire.20260704010.

[27] Harle, SM, & et al , "Investigation of Mechanical Behavior of Steel Fiber-Reinforced Geopolymer Concrete Under ulti-Axial Stress Conditions," Hydraulic and Civil Engineering Technology IX: Proceedings of the 9th International Technical Conference on Frontiers of HCET, Sanya, China, SAGE Publications, 25-27 September pp 555-561 , 2024

[28] Harle, SM, & et al , "Comparison," Global Journal of Current Research in Urban Architecture and Regional Planning, Global Journal of Current Research in Urban Architecture and Regional Planning, vol 1, 2018/6, Issue 1, Pages 1-15

[29] Harle, SM, & et al, "White Topping In Roads: Review", Journal of Structural and Transportation Studies, Volume 1, Issue 3, 2016.

[30] Harle, SM, & et al (2024, February). Durability and long-term performance of fiber reinforced polymer (FRP) composites: A review. In Structures (Vol. 60, p. 105881). Elsevier. 15.

[31] Harle, SM, & et al (2024). Advancements and challenges in the application of artificial intelligence in civil engineering: a comprehensive review. Asian Journal of Civil Engineering, 25(1), 1061-1078. 16.

[32] Harle, SM, & et al (2024, August). Advancing seismic resilience: Focus on building design techniques. In Structures (Vol. 66, p. 106432). Elsevier.