A Spectral Framework Based on the FKF Transform for Supply Chain Dynamics and Resilience

A. Gulhane
Independent Researcher

How to Cite this Article:

Gulhane, A. (2026). A Spectral Framework Based on the FKF Transform for Supply Chain Dynamics and Resilience. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(8), 1-9. https://doi.org/10.55041/ijcope.v2i8.140

https://doi.org/10.55041/ijcope.v2i8.140

Abstract

This paper introduces and develops the two-sided Fourier–Kontorovich–Lebedev (FKF) transform, a hybrid integral transform that combines the classical Fourier kernel with the Macdonald function (modified Bessel function of the second kind) of imaginary order. The FKF transform is specifically adapted to signals defined on the half-plane of time and a positive scale variable, making it particularly suitable for the spectral analysis of supply-chain processes. We establish the fundamental definition, the underlying differential structure induced by the Macdonald equation, and key operational properties, with a detailed treatment and rigorous proofs of the multiplication-by-time and differentiation theorems in the Fourier domain. Applications are presented to demand intensity analysis, continuous inventory balance equations, the spectral characterization of the bullwhip effect, transportation lead-time phase shifts, and the quantitative assessment of disruption signatures. The resulting spectral framework provides frequency and scale resolved diagnostics that complement contemporary approaches based on digital twins, artificial intelligence, blockchain-enabled transparency, and Industry 5.0 human-centric automation. Limitations concerning numerical evaluation of the Macdonald function, inversion stability, and the transition from continuous to discrete supply-chain models are discussed. The work positions the FKF transform as a novel analytical instrument for resilience engineering and spectral control of modern logistics systems.

Keywords: Fourier–Kontorovich–Lebedev transform; Macdonald function; supply-chain resilience; bullwhip effect; spectral analysis; digital twin; Industry 5.0; lead-time dynamics; disruption signature; inventory spectral balance

1. Introduction

Modern supply chains operate under continuous temporal forcing and over a continuum of positive state variables inventory levels, shipment distances, service intensities, and demand magnitudes. Classical Fourier analysis captures oscillatory and periodic phenomena (seasonality, ordering cycles, transportation waves) but is agnostic to the radial or scale structure inherent in many logistical quantities. The Kontorovich–Lebedev (KL) transform, built upon the Macdonald function $K_{i\tau}$, is naturally adapted to problems on the positive half-line and appears in radial diffusion, wave propagation in wedges, and scale-invariant systems. Their FKF transform therefore supplies a joint spectral representation in frequency s and scale parameter q.

The motivation for such a hybrid transform is reinforced by the rapid digitalization of logistics. Convergent frameworks that integrate the Internet of Things, artificial intelligence, and quantum computing have been proposed for smart logistics ecosystems [1]. Industry 5.0 further emphasizes human-centric automation and resilient, adaptive supply-chain operations [2]. Digital-twin architectures are increasingly employed to build resilient and adaptive global supply chains [5], while artificial-intelligence methods support sustainable logistics and green supply-chain management [6]. Blockchain AI integration enhances transparency, traceability, and resilience [7]. Parallel advances in smart mobility and intelligent transportation systems [11] and systematic reviews of supply-chain resilience under digital transformation [15] underscore the need for analytic tools that can resolve both temporal frequencies and operational scales.

Despite this technological progress, a spectral calculus that simultaneously treats time-periodic and scale-dependent phenomena remains underdeveloped. The present work fills that gap by defining the FKF transform, deriving its principal operational rules (with complete proofs for the Fourier-domain multiplication theorems), and demonstrating its utility on canonical supply-chain models: demand decomposition, inventory balance, bullwhip amplification, pure and cumulative delays, and disruption energy

International Journal of Creative and Open Research in Engineering and Management
ISSN: **3108-1754 (Online)**
Volume 02 Issue 08 Augustl-2026 | Impact Factor: 3.5

indicators. The resulting framework is intended to complement, rather than replace, the data driven and simulation based methods of digital twins and AI-enabled control.

2. Literature Review

Spectral methods have long been applied to inventory and production control, typically through the Fourier transform of demand and order streams. The bullwhip effect, in particular, admits a natural frequency domain interpretation: certain bands of the demand spectrum are amplified by forecasting, batching, and replenishment policies. However, these analyses treat the state variable as a pure time series and do not incorporate an independent positive scale coordinate.

The Kontorovich–Lebedev transform, introduced in the 1930s and subsequently developed in the theory of special functions and integral transforms, employs the Macdonald function of purely imaginary order as its kernel. It has found applications in diffraction theory, heat conduction in wedges, and certain classes of fractional differential equations. Its suitability for positive variables makes it a natural candidate for inventory magnitude, inter facility distance, or service intensity.

Hybrid Fourier Bessel or Fourier–Hankel transforms appear in cylindrical and spherical geometries, yet the combination of a two-sided Fourier transform with the KL kernel has received comparatively little attention, especially in the operations-research and supply-chain literature. Concurrently, the logistics research community has focused on enabling technologies: IoT–AI–quantum convergence for smart logistics [1], Industry 5.0 human-centric automation [2], digital-twin platforms for resilience [5], AI-driven sustainable logistics [6], AI–blockchain integration for traceability [7], quantum computing prospects in transportation and logistics [13], and systematic assessments of digital transformation and resilience [15]. Related work on smart mobility [11] and battery/electric-vehicle supply chains [3, 9, 12, 14] further illustrates the multi-scale, multi-frequency character of modern logistical systems.

The present paper therefore occupies an interdisciplinary niche: it supplies a mathematically rigorous spectral transform tailored to the mixed temporal scale structure of supply-chain signals and situates that transform within the emerging digital and Industry 5.0 context established by the cited literature.

3. Definition of the FKF Transform

Let $f(t,x)$ be a suitably restricted function or generalized function, with $t \in \mathbb{R}$ and $x > 0$. Using the Fourier convention with kernel $e\text{^}\{-ist\}$, the two-sided FKF transform is defined by

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

Here s is the Fourier/spectral variable, $q > 0$ is the KL spectral variable, and K_{iq} is the Macdonald function (modified Bessel function of the second kind) of imaginary order iq. Some references employ the conjugate kernel $e\text{^}\{+ist\}$; changing the Fourier sign merely reverses the signs appearing in the differentiation and shift identities, leaving the overall FKF structure intact.

The underlying spatial-temporal domain is

$$\Omega = \{(t,x) : -\infty < t < \infty, 0 < x < \infty\}$$

For a distribution f belonging to an appropriate dual space, the transform is interpreted by continuous pairing of f with the FKF kernel. The transform is defined on an open region Ω_f in the (s,q)-plane on which the defining functional remains meaningful.

The FKF kernel itself is the product of two independent factors:

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

The first factor is the classical Fourier kernel; it encodes oscillations, frequencies, lead-time cycles, demand periodicity, and transportation waves. The second factor is the KL kernel; its modified-Bessel structure is adapted to positive variables such as scale, distance, inventory magnitude, or service intensity.

The Macdonald function satisfies the modified Bessel differential equation

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

For the FKF kernel one has $\nu = iq$, hence $\nu^2 = -q^2$, and the equation becomes

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

This differential structure explains the utility of the KL component for systems that exhibit radial, scale-dependent, diffusion-like, or exponentially decaying behavior.

4. Multiplication by the Fourier-Domain Variable

Properties and Proofs for the Fourier–Kontorovich–Lebedev (FKF) Transform

4.1 Statement of the Theorem

Let $F(s,q) = (FKF\ f)(s,q)$ be the FKF transform of an admissible function (or tempered distribution) f. Then multiplication by the temporal variable in the original domain corresponds to differentiation with respect to the Fourier variable in the spectral domain:

$$FKF(t\, f(t,x))(s,q) = i\, \frac{\partial F(s,q)}{\partial s}$$

More generally, for any non-negative integer n,

$$FKF(t^n\, f(t,x))(s,q) = i^n \frac{\partial^n F(s,q)}{\partial s^n}$$

Summary Table of Multiplication Properties

Table 1. Correspondence between multiplication by powers of the temporal variable and differentiation of the FKF spectrum.

Order n	Time-Domain Operation	Spectral-Domain Counterpart
0	$f(t,x)$	$F(s,q)$
1	$t\, f(t,x)$	$i\, \frac{\partial F}{\partial s}$
2	$t^2\, f(t,x)$	$i^2 \frac{\partial^2 F}{\partial s^2}$
n	$t^n\, f(t,x)$	$i^n \frac{\partial^n F}{\partial s^n}$

Note: The factor i arises from differentiation of the Fourier kernel e^{-ist} with respect to the spectral variable s.

4.2 Proof of the Fundamental Identity

We work under the standing assumption that f and the product $t\, f$ belong to the domain of the FKF transform (or that the integrals are understood in the distributional sense). Differentiating the defining integral with respect to the parameter s under the integral sign is justified by the dominated-convergence theorem (or by the continuity properties of the distributional pairing) once a strip of analyticity is fixed.

The FKF transform is given (formally) by

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

Differentiating with respect to s yields

$$\frac{\partial F}{\partial s} = \iint f(t,x) \cdot (-i\, t)\, e^{-ist}\, K_{\{iq\}}(x), dx, dt$$

The factor $-i\, t$ appears because

$$\frac{\partial}{\partial s}(e^{-ist}) = -i\, t\, e^{-ist}$$

Consequently,

$$\frac{\partial F}{\partial s} = -i \cdot FKF[t\, f](s,q)$$

Multiplying both sides by i yields the claimed identity

$$FKF[t\, f](s,q) = i\, \frac{\partial F}{\partial s}$$

4.3 Proof of the Higher-Order Formula by Induction

The case $n = 0$ is trivial (identity map) and the case $n = 1$ has already been established. Assume the formula holds for some integer $k \geq 1$:

$$FKF(t^k\, f) = i^k \frac{\partial^k F}{\partial s^k}$$

Apply the first-order identity to the function $g = t\text{^}k\, f$:

$$FKF[t \cdot g] = i\, \frac{\partial}{\partial s}(FKF\ g)$$

The left-hand side is precisely $FKF(t^{k+1}\, f)$. On the right-hand side the induction hypothesis yields

$$i\, \frac{\partial}{\partial s}\left(i^k \frac{\partial^k F}{\partial s^k}\right) = i^{k+1} \frac{\partial^{k+1} F}{\partial s^{k+1}}$$

Thus, the formula holds for $n = k + 1$. By induction it is valid for every non-negative integer n.

4.4 Analyticity and Moment Interpretation

Under suitable decay and growth conditions the transform $F(s,q)$ extends to an analytic function of the complex variable s inside a vertical strip

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

Analyticity permits repeated differentiation with respect to s and legitimates contour deformation and residue calculus. These operations are particularly valuable when one constructs inverse representations or analyses transient supply-chain responses.

From the operational viewpoint the identities furnish a *moment interpretation*: the temporal moments of a supply-chain signal are recovered from successive derivatives of its FKF spectrum. In particular, the first moment (mean lag or centre-of-mass in time) is proportional to $\frac{\partial F}{\partial s}$ evaluated at the origin of the Fourier plane, while higher central moments are obtained from higher-order derivatives. This spectral-moment calculus complements classical time domain moment analysis and is well suited to the identification of lead-time statistics and demand-response delays.

4.5 Additional Remarks and Related Properties

Linearity and Scaling

Because differentiation is a linear operator, the multiplication property is compatible with the linearity of the FKF transform. If $\alpha, \beta \in \mathbb{C}$ and f, g are admissible, then

$$FKF[t\,(\alpha f + \beta g)] = \alpha\, FKF[t\, f] + \beta\, FKF[t\, g] = i \frac{\partial}{\partial s}(\alpha F + \beta G)$$

Relation to the Differential Property

The dual property (differentiation in the time domain corresponds to multiplication by $-i\, s$ in the spectral domain) follows by an analogous argument under the integral sign, interchanging the roles of the Fourier kernel. Together the two properties form a Fourier-transform duality pair that is preserved by the Kontorovich–Lebedev factor $K_{\{iq\}}(x)$, which is independent of s.

5. Applications to Supply-Chain Dynamics

5.1 Spectral Decomposition of Demand

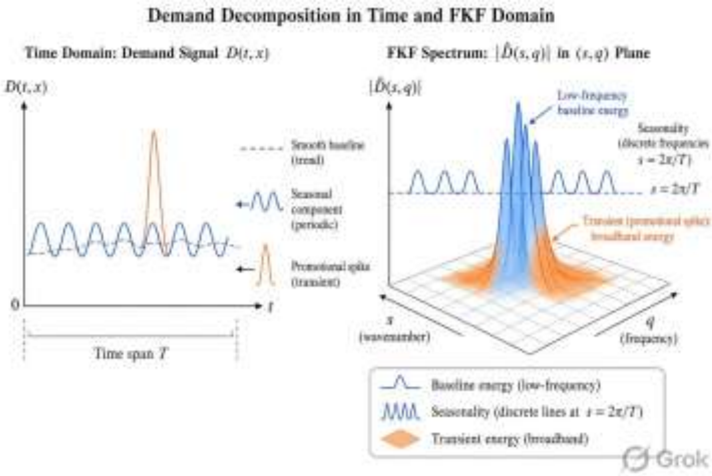

Figure 1. *Spectral decomposition of a demand signal into baseline, seasonal, and promotional components, and the corresponding energy distribution in the (s, q) FKF plane.*

Let $D(t,x)$ denote demand intensity at time t for a positive demand-related state x. Its FKF spectrum is

$$D_F(s,q) = \int\int D(t,x)\, e^{\{-ist\}}\, K_{\{iq\}}(x)\, dx\, dt$$

Suppose demand consists of a baseline, a seasonal component, and a transient promotional effect:

$$D(t,x) = D_0(t,x) + D_s(t,x) + D_p(t,x)$$

By linearity of the transform,

$$D_F(s,q) = D_{\{0F\}}(s,q) + D_{\{sF\}}(s,q) + D_{\{pF\}}(s,q)$$

A periodic component of period T possesses fundamental frequency

$$s_0 = 2\pi / T$$

Consequently, the Fourier dimension isolates recurring weekly, monthly, quarterly or annual demand cycles, while the KL dimension characterizes their dependence on demand magnitude. Such a joint spectral signature can be fused with AI-based demand-forecasting engines [6] and with digital-twin demand modules [5] to improve both explanatory power and predictive accuracy.

5.2 Continuous Inventory Balance in the FKF Domain

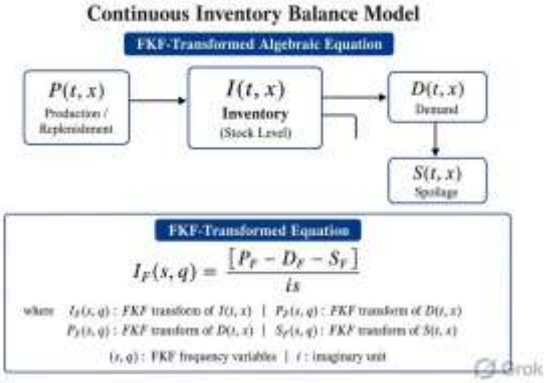

Figure 2. *Continuous inventory balance with production inflow P, demand outflow D and spoilage S, together with the corresponding algebraic relation obtained after application of the FKF transform.*

Let $I(t,x)$ represent an inventory-related state. A simplified continuous model reads

$$\partial I/\partial t \ = \ P(t,x) \ - \ D(t,x) \ - \ S(t,x)$$

where P is replenishment/production inflow, D is demand outflow, and S represents spoilage, loss or other depletion. Application of the FKF transform converts the partial differential relation into an algebraic equation in the Fourier variable:

$$is \ \cdot \ I_F(s,q) \ = \ P_F(s,q) \ - \ D_F(s,q) \ - \ S_F(s,q)$$

Hence

$$I_F(s,q) = \frac{[P_F(s,q) - \ D_F(s,q) - \ S_F(s,q)]}{is}$$

The representation identifies frequencies at which inventory oscillations are amplified. Repeated ordering cycles generate spectral peaks; poorly synchronised replenishment and demand produce persistent oscillatory modes. These spectral diagnostics can be embedded inside digital-twin inventory engines [5] and can inform the human centric decision layers advocated by Industry 5.0 [2].

5.3 Frequency-Domain Characterizations of the Bullwhip Effect

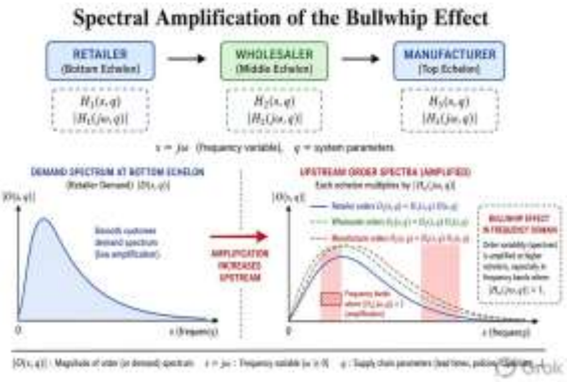

Figure 3. *Spectral view of the bullwhip effect: demand spectrum at the retail echelon is successively amplified by the transfer functions of upstream echelons, with shaded bands indicating frequencies where* $|H_n(s,q)| \ > \ 1$

The bullwhip effect refers to the amplification of demand variability as one moves upstream through a supply chain. Let D_n be the demand signal at echelon n and O_n its order signal. A linearised ordering policy is represented by a transfer relationship

$$O_n(s,q) \ = \ H_n(s,q)D_n(s,q)$$

where H_n is the echelon's spectral response. Whenever $|H_n(s,q)| \ > \ 1$
over a frequency band, variability is amplified in that band. For a chain of N echelons the composite transfer function is the product

$$H_{total}(s,q) \ = \prod_{\{n=1\}}^{\{N-1\}} H_n \ (s,q)$$

and the upstream order spectrum becomes

$$O_N(s,q) \ = \ H_{total}(s,q)D_0(s,q)$$

This supplies a precise frequency-domain account of the bullwhip effect: selected demand frequencies are selectively amplified by forecasting rules, batching, safety stock policies, minimum-order quantities or replenishment delays. The same spectral picture can be used to design mitigating filters or to calibrate AI-based ordering policies [6, 7] that deliberately attenuate the harmful bands.

5.4 Transportation Delays and Phase Information

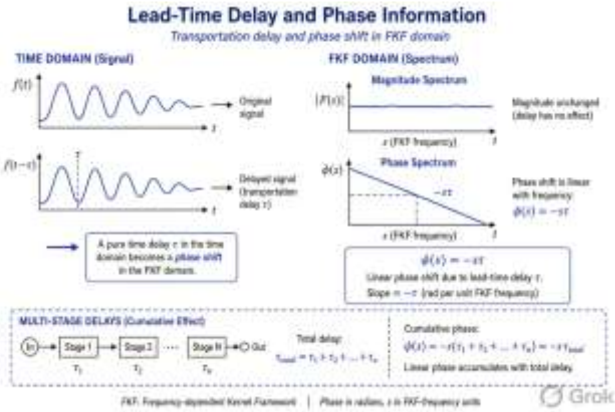

Figure 4. *Effect of a pure transportation delay τ: the time-domain shift becomes a linear phase $-s\tau$ in the FKF domain while the magnitude spectrum remains unchanged; multi-stage delays accumulate into a total phase $-s\ \tau_{total}$..*

Suppose a transportation stage introduces a pure delay τ. If $y(t,x) = f(t - \tau, x)$, then

$$Y(s,q) = e^{\{-ist\}} F(s,q)$$

The magnitude spectrum is unchanged, yet the phase is shifted by $-s\tau$. Consequently phase information recovered from the FKF spectrum can be used to estimate or compare lead-time effects between successive stages. When several stages possess delays $\tau_1, \dots, \tau_N$, the total delay is

$$\tau_{total} = \tau_1 + \cdots + \tau\_N$$

and the cumulative phase shift equals $-s\ \tau_{total}$. Stochastic lead times may be modelled by replacing the deterministic delay with a probability distribution or a dynamic transfer function; the corresponding FKF multiplier is then the Fourier Stieltjes transform of that distribution. Such phase-aware diagnostics align naturally with the real-time tracking capabilities of IoT-enabled logistics platforms [1] and with the transparency objectives of blockchain-integrated supply chains [7].

5.5 Disruption Signatures and a Spectral Resilience Indicator

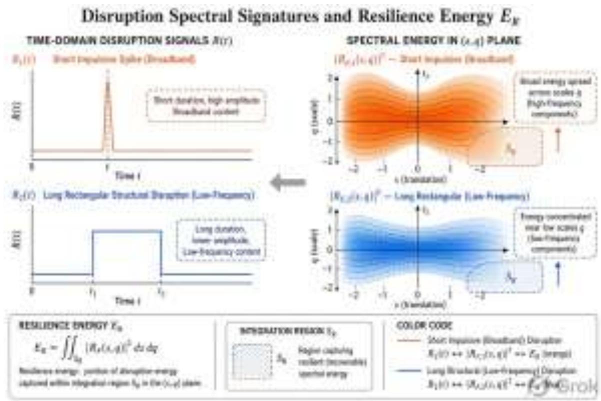

Figure 5. *Short impulsive versus long structural disruption signals and their energy distributions in the (s, q) plane. The resilience indicator E_R is obtained by integrating spectral energy over a selected region S_R.*

A disruption signal $R(t,x)$ may represent the magnitude of a shock associated with supplier failure, transport interruption, cyber incident, weather event or capacity loss. The observed supply signal is written

$$Y(t,x) = G(t,x) + R(t,x)$$

and therefore

$$Y_F(s,q) = G_F(s,q) + R_F(s,q)$$

A short, impulsive disruption produces broadband energy in the Fourier dimension; a long-lived structural change concentrates energy at low frequencies. The KL variable q further indicates whether the disruption is localised to small or large operational scales. A simple resilience indicator can be defined from the spectral energy contained in a selected region S_R of the $(s,q) - plane$:

$$E_R = \iint_{\{S_R\}} |R_F(s,q)|^2\, ds\, dq$$

Comparison of E_R before and after mitigation furnishes a quantitative measure of the persistence or severity of disruption signatures. The indicator is compatible with the resilience-oriented digital-twin architectures surveyed in [5] and with the systematic research agendas on supply-chain resilience under digital transformation [15].

6. Limitations

Several practical and theoretical limitations must be acknowledged. First, the numerical evaluation of the Macdonald function of imaginary order is non-trivial; high-precision libraries or carefully stabilized asymptotic expansions are required, especially for large q or extreme values of the argument. Second, inversion of the FKF transform whether by successive Fourier and KL inversion formulae or by two-dimensional numerical quadrature can be sensitive to noise and truncation of the spectral domain. Regularisation techniques and adaptive spectral windows are therefore indispensable.

Third, the continuous models employed in Sections 5.2–5.5 idealize discrete, event-driven supply-chain processes. Bridging the continuous spectral calculus to discrete event simulation or agent-based digital twins remains an open methodological task. Fourth, the linear transfer-function description of ordering policies captures only a subset of the non-linear, adaptive and learning behaviors that characterise contemporary AI-driven procurement systems [6, 7]. Extension of the FKF framework to mildly non-linear or state-dependent operators is a promising direction for future research.

Finally, the present development has concentrated on the forward transform and its operational calculus. A complete inversion theory, Parseval–Plancherel identities, and a characterization of the image of classical supply-chain function spaces under the FKF map are left for subsequent work.

7. Conclusion

The FKF transform furnishes a joint spectral representation that simultaneously resolves temporal frequencies and positive scale variables. Its definition, differential underpinnings, and fundamental operational properties particularly the rigorously established multiplication by time theorems equip the analyst with a powerful calculus for supply-chain signals. Concrete applications to demand decomposition, inventory spectral balance, bullwhip amplification, lead-time phase shifts, and disruption-energy indicators demonstrate the practical relevance of the framework.

By situating the FKF transform within the technological landscape of IoT–AI quantum smart logistics, Industry 5.0 , digital twins, AI-enabled sustainable logistics, blockchain-enhanced transparency, quantum computing in transportation, and systematic resilience research, the paper offers both a mathematical instrument and a conceptual bridge between classical integral transform theory and the digital transformation of global supply chains. Future research will address numerical inversion algorithms, non-linear extensions, and the embedding of FKF spectral modules inside operational digital-twin platforms.

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, “Swipe Controller,” International Journal of Research in Engineering and Applied Sciences (IJREAS), Vol. 4, Issue 12, pp. 1–7, 2014.

[12] 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.

[13] 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

[14] 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.

[15] 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.

[16] 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.

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

[18] 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.

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

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

[21] 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.

[22] 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.

[23] 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.

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

[25] 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.

[26] 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

[27] 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

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

[29] 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.

[30] 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.

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

[32] S. M. Harle et al., "Artificial Intelligence for Supply Chain Risk Prediction and Mitigation: A Systematic Review, Conceptual Framework, and Future Research Agenda," International Research Journal of Modernization in Engineering Technology and Science, Vol. 8, pp. 70–80, July 2026.

[33] S. M. Harle et al., "Artificial Intelligence-Driven Framework for Village-Level Water Conservation and Groundwater Sustainability," International Research Journal of Modernization in Engineering Technology and Science, Vol. 8, pp. 31–49, July 2026.

[34] S. M. Harle et al., "Artificial Intelligence Approaches for Strength Prediction and Optimization of Composite Concrete Mixtures: A Systematic Review and Future Research Framework," International Research Journal of Modernization in Engineering Technology and Science, Vol. 8, pp. 81–97, July 2026.

[35] S. M. Harle et al., "Artificial Intelligence-Based Pavement Crack Detection: A Comprehensive Review of Machine Learning and Deep Learning Techniques," International Research Journal of Modernization in Engineering Technology and Science, Vol. 8, pp. 50–69, July 2026.

[36] S. M. Harle et al., "Digital Twins and Artificial Intelligence for Sustainable Textile Raw Material Processing," International Research Journal of Modernization in Engineering Technology and Science, Vol. 8, pp. 14–30, July 2026.