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An FKF–AI–Digital Twin Framework for Intelligent Supply-Chain Management

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Abstract—
Next-generation supply chains can be viewed as distributed, partially observed stochastic systems where demand, lead times, quality, custody, energy conditions, and disruptions are revealed with delay and may be distorted across organizational boundaries. The supplied mathematical manuscript establishes a distributional-transform foundation based on Laplace and K-type kernels, modified Bessel functions, Meijer G-function representations, and second-order differential operators. This framework is extended toward intelligent and resilient supply-chain analysis by integrating the FKF spectral perspective with artificial intelligence, digital twins, trusted data exchange, Internet of Things sensing, sustainable mobility, and quantum-enabled logistics optimization. The FKF representation separates temporal oscillations from scale- or intensity-dependent behavior, enabling analysis of multi-echelon lead-time dynamics, delayed information, resonance, and nonstationary disturbances. Its distributional extension is especially suitable for irregular, impulsive, incomplete, and heterogeneous operational signals. AI models can exploit spectral features for prediction and anomaly detection, while digital twins provide continuously updated operational context. Blockchain-oriented trusted records support provenance and state consistency, and quantum optimization can address selected combinatorial logistics decisions.

Keywords—Distributional FKF Transform; Spectral Analysis; Supply-Chain Resilience; Intelligent Supply Chains; Digital Twins; Swipe Controller; Artificial Intelligence; Trusted Data Exchange; Sustainable Logistics; Quantum Optimization; Industry 5.0.

I. INTRODUCTION

The evolution of supply chains toward intelligent, interconnected, and resilient ecosystems is driven by the convergence of physical operations, digital platforms, autonomous decision support, and heterogeneous sensing. Digital twins provide dynamic virtual representations of assets and processes that support resilient and adaptive networks [11]. Artificial intelligence enables prediction, anomaly detection, optimization, and adaptive decision-making in sustainable logistics and green supply-chain management [12]. Blockchain and trusted-data mechanisms strengthen provenance, traceability, and shared-state consistency when integrated with AI [13]. Earlier intelligent-interface and embedded-control developments, including swipe-controller designs for human–machine interaction [14], illustrate the progression from isolated automation toward connected operational decision systems.

The logistics environment is further shaped by electric mobility, battery constraints, sustainable transportation, quantum optimization, and Industry 5.0. Quantum methods provide opportunities for selected combinatorial logistics decisions [15], [29], [31], while battery technologies and energy-management systems influence vehicle-energy trajectories [16], [28]. Solar-assisted and hybrid vehicles couple energy conditions with routing and dispatch [26], [32], and smart mobility systems provide sensing and control for last-mile and line-haul operations [30]. IoT, AI, and quantum computing increasingly converge within smart logistics [24], while Industry 5.0 promotes human-centric automation and resilience-oriented digital transformation [25], [33].

These developments generate multiscale and nonstationary signals: orders fluctuate, lead times vary, vehicle energy states evolve, disruptions produce transient peaks, and information arrives asynchronously. Conventional time-domain indicators may not fully reveal frequency- and scale-dependent structures. FKF-centered spectral analysis therefore provides a basis for multi-scale characterization, resonance extraction, shift-invariant lead-time analysis, and differential analysis of supply-chain dynamics [17]–[20]. Related FKL formulations offer complementary kernel properties [21], while time-shift and exponential-modulation operations support the analysis of delayed and amplified signals [22], [23]. Distributional extensions and sequential convergence further provide a mathematical basis for handling irregular, impulsive, incomplete, and heterogeneous telemetry [34], [35].

The present reconstruction develops an FKF-centered spectral framework for intelligent supply-chain analysis, linking temporal dynamics and scale behavior with spectral features, AI inference, digital-twin synchronization, trusted data exchange, and resilience-oriented decisions. Rather than treating supply-chain observations solely as forecastable scalar sequences, the framework represents them as generalized signals whose spectral structure captures periodic demand, lead-time modulation, disruption transients, and scale-dependent operational effects. Asset-level sensing, IoT connectivity, blockchain-based provenance, sustainable mobility, and quantum optimization can consequently be integrated within a common architecture, connecting physical operations, spectral intelligence, and adaptive decision-making.

II. DISTRIBUTIONAL REPRESENTATION AND SUPPLY-CHAIN SPECTRAL

Let denote an operational signal such as demand, replenishment delay, vehicle energy consumption, inventory deviation, or delivery-time error. A two-sided FKF representation can be formulated schematically as the composition of a Fourier kernel in the temporal coordinate and a Kontorovich–Lebedev-type kernel in a positive scale variable. This joint representation enables operational signals to be characterized simultaneously according to temporal frequency and scale-dependent behavior [18], [19], [34]. The principal notation used in the framework is as follows. The scalar signal $\boldsymbol{x(t)}$ and the vector of observed operational variables $\boldsymbol{x(t)}$ describe physical and informational supply-chain states. Their joint FKF spectrum is denoted by $\boldsymbol{X(\omega,\lambda)}$, while an echelon-indexed lead-time spectrum can be represented by $\boldsymbol{X_e(\omega,\lambda)}$. Here, $\boldsymbol{\omega}$ denotes temporal frequency, $\boldsymbol{\lambda > 0}$ represents the spectral scale parameter, and $\boldsymbol{r > 0}$ denotes a positive radial or scale coordinate. The Macdonald function $\boldsymbol{K_{i\lambda}(r)}$, namely the modified Bessel function of the third kind with imaginary order, forms the principal Kontorovich–Lebedev kernel. The variables $\boldsymbol{\tau_e}$ and $\boldsymbol{\delta}$ represent the lead time at echelon $\boldsymbol{e}$ and the corresponding time shift or information delay. A spectral feature map $\boldsymbol{\Phi(X)}$ can be supplied to AI models for prediction and anomaly detection, while $\boldsymbol{A(X)}$ denotes an anomaly score and $\boldsymbol{R_s}$ a spectral resilience indicator. Digital-twin variables may be represented by $\boldsymbol{z_a^{DT}}$ for the state of asset $\boldsymbol{a}$ and $\boldsymbol{\varepsilon_{DT}}$ for synchronization error. Energy-related variables include battery energy $\boldsymbol{E_b}$ and net power demand $\boldsymbol{P_n}$, while the quantum optimization layer uses a binary decision vector $\boldsymbol{q}$ within the QUBO formulation.

The FKF transform may therefore be expressed schematically as

$$\boldsymbol{\mathcal{F}_{FKF}\{x\}(\omega,\lambda) = \int_{-\infty}^{\infty}\int_{0}^{\infty} x\,(t,r)\, e^{-i\omega t}\, K_{i\lambda}(r)\, \frac{dr}{r}\, dt}$$

Here, $\boldsymbol{\omega}$ denotes temporal frequency, $\boldsymbol{\lambda}$ the spectral scale parameter, and $\boldsymbol{K_{i\lambda}(r)}$ the Macdonald function of imaginary order. The transform consequently provides a joint spectral description of oscillatory and scale-dependent behavior. The K-type kernel also admits representations through the Meijer G-function, providing an alternative analytical form for generalized spectral calculations. For distributional signals, let $\boldsymbol{\mathcal{D}(\Omega)}$ denote a suitable space of infinitely differentiable compactly supported test functions, and let $\boldsymbol{T \in \mathcal{D}'(\Omega)}$ be a generalized functional. Its action on a test function $\boldsymbol{\varphi \in \mathcal{D}(\Omega)}$ is represented by the dual pairing

$$\boldsymbol{\langle T,\varphi\rangle}.$$

This distributional formulation allows impulsive, discontinuous, incomplete, noisy, or otherwise irregular supply-chain observations to be incorporated without requiring classical pointwise smoothness [34].

The spectral behavior of the K-type kernel can be characterized through a second-order differential operator of the form

$$\mathcal{L}_r K_{i\lambda}(r) = -\left(\lambda^2 + \frac{1}{4}\right) K_{i\lambda}(r),$$

where represents the corresponding radial differential operator. The associated modified Bessel equation is satisfied by the Macdonald function . This operator perspective is important because differential operations applied to physical-domain signals can be translated into structured operations in the spectral domain. Consequently, the distributional FKF framework provides a mathematical basis for examining lead-time variations, transient disruptions, energy fluctuations, resonance behavior, and other nonstationary supply-chain phenomena [19], [20].

III. FKF SPECTRAL ANALYSIS OF MULTI-ECHELON SUPPLY-CHAIN DYNAMICS

Multi-echelon supply chains exhibit interconnected temporal behavior in which demand propagation, replenishment delays, transportation variability, and downstream disruptions evolve across successive organizational and operational stages. Consider a multi-echelon lead-time signal $x_e(t)$, where $e$indexes the supply-chain echelon. Its FKF spectral representation can be expressed as

$$X_e(\omega, \lambda) = \mathcal{F}_{FKF}\{x_e\}(\omega, \lambda),$$

where represents temporal frequency and denotes the positive spectral scale parameter. The resulting joint spectrum provides a two-dimensional description of the operational signal, allowing variations to be examined simultaneously in time-frequency and scale domains [18], [19]. Changes in $X_e(\omega, \lambda)$ indicate whether an operational disturbance is concentrated within particular temporal frequencies, characteristic scales, or a combination of both. This is especially useful for distinguishing routine demand fluctuations from abnormal lead-time variations, transportation disturbances, and disruption-driven transients. For example, recurring demand cycles may produce localized spectral concentrations, whereas sudden supplier interruptions or transportation bottlenecks can generate broader or high-frequency spectral components.

A time displacement of the operational signal,

$$x_e(t - \tau_e),$$

produces a corresponding phase modification in its Fourier component. The FKF representation therefore provides a mechanism for separating an actual change in system dynamics from a simple temporal displacement:

$$\mathcal{F}_{FKF}\{x_e(t - \tau_e)\} = e^{-i\omega\tau_e} X_e(\omega, \lambda).$$

Here, denotes the delay associated with echelon . The scale component remains structurally separated from the temporal phase factor, making the representation useful for identifying delayed information, replenishment propagation, transportation latency, and synchronization differences among supply-chain stages [18], [22].

Exponential modulation provides another important spectral operation. For a modulated signal of the form $e^{at} x_e(t)$, the corresponding spectral behavior can be represented schematically as a translation in the complex frequency domain:

$$\mathcal{F}_{FKF}\{e^{at} x_e(t)\} = X_e(\omega, +ia\lambda)$$

subject to the appropriate transform and convergence conditions. This property is useful for characterizing accelerating or attenuating demand, rapidly changing disruption effects, and growth or decay patterns in operational signals. It also provides a mathematical mechanism for representing nonstationary behavior that cannot be adequately described by stationary spectral measures alone [23]. Residue-based resonance extraction can further identify concentrated spectral structures associated with recurring or amplified operational disturbances. Such resonances may arise from repeated transportation cycles, synchronized replenishment patterns, warehouse congestion, vehicle-load variations, or hybrid-vehicle energy-demand cycles [17], [28]. When temporal logistics behavior becomes coupled with energy consumption, the resulting spectral peaks can provide additional information for energy-aware routing, fleet management, and sustainable transportation decisions. Across a multi-echelon network, supplier, distribution-center, warehouse, and last-mile signals may occupy different regions of the joint spectral domain even when their time-domain trajectories appear relatively similar. A pure delay primarily modifies the temporal phase, whereas scale-dependent congestion, capacity limitations, or heterogeneous operating conditions can redistribute spectral energy across different scale regions. The FKF representation therefore enables multi-echelon dynamics to be analyzed not only through their observed time histories but also through their frequency- and scale-dependent signatures.

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IV. SEQUENTIAL CONVERGENCE

Operational data are rarely ideal mathematical functions. Missing observations, sudden demand shocks, sensor spikes, discrete events, and abrupt lead-time changes create generalized signals. The distributional extension of the FKF transform provides a principled way to define transform action on such objects. The representation theorem uses bounded measurable coefficient functions, weighted test spaces, higher-order derivatives, continuity, Hahn–Banach extension, and duality [34].

Sequential convergence is equally important for digital-twin environments because data arrive as a sequence of increasingly refined measurements [11], [35]. If converges to in the testing-function topology, continuity of the distributional transform implies convergence of the corresponding spectral action. Sequential convergence in the testing-function space of the two-sided FKF transform is established in [35].

$$\varphi_n \to \varphi \quad \Rightarrow \quad \langle T_{FKF}, \varphi_n \rangle \to \langle T_{FKF}, \varphi \rangle$$

This continuity statement is the reason the architecture can ingest irregular IoT streams including custody tags, energy meters, and integrity sensors descended from earlier power-line monitoring concepts [24], [27] without first forcing those streams into classically smooth interpolants.

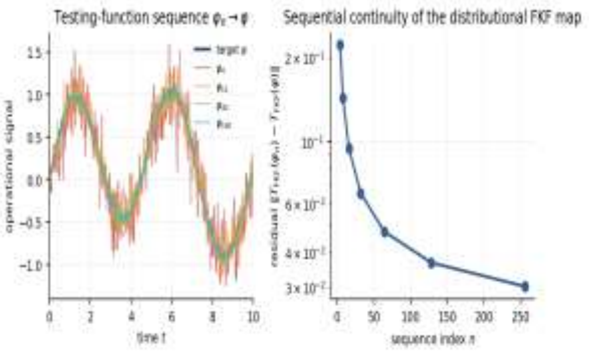

Figure 1. Sequential convergence of irregular operational observations φ_n toward the target signal φ, and decay of the distributional FKF residual [34], [35].

V. DISTRIBUTIONAL CONTINUITY AND SEQUENTIAL CONVERGENCE OF FKF SIGNALS

Modern supply-chain telemetry is inherently irregular, heterogeneous, and continuously updated, making classical smooth-function assumptions inadequate for many operational signals. Missing observations, sudden demand shocks, sensor spikes, discrete events, abrupt lead-time variations, and transient disruptions can naturally be represented as generalized signals. The distributional extension of the FKF transform provides a rigorous framework for defining transform operations on such signals. Its mathematical construction incorporates bounded measurable coefficient functions, weighted test-function spaces, higher-order derivatives, continuity, Hahn–Banach extension, and duality, thereby extending the transform beyond conventional pointwise functions [34].

Sequential convergence is particularly important in digital-twin and IoT environments, where operational measurements arrive as sequences of increasingly refined observations. Let be a sequence in an appropriate testing-function space that converges to in the corresponding testing-function topology. The continuity of the distributional FKF transform then ensures that the associated spectral actions converge consistently [35]. In symbolic form,

$$\varphi_n \to \varphi \implies \langle \mathcal{F}_{FKF}, (T)\varphi_n \rangle \to \langle \mathcal{F}_{FKF}, (T)\varphi \rangle$$

This sequential continuity establishes mathematical stability when progressively updated operational measurements are incorporated into the spectral representation. It is particularly relevant when digital twins continuously assimilate new observations and refine their representations of assets, inventories, transportation states, and network conditions [11], [35].

The distributional formulation also allows irregular IoT streams to be processed without artificially forcing them into classically smooth interpolants. Custody records, energy-meter measurements, vehicle telemetry, integrity sensors, temperature observations, and other heterogeneous data can therefore be incorporated within a common generalized-signal framework. Sudden impulses may represent disruption events, isolated sensor spikes may indicate anomalies, and discontinuities may reflect changes in operational states or supply-chain conditions.

Consequently, sequential convergence provides a mathematical link between continuously evolving physical observations and stable spectral representations. As measurement resolution improves or additional observations become available, the FKF spectral description can evolve consistently rather than requiring complete reconstruction of the underlying signal. This property strengthens the suitability of the distributional FKF framework for real-time digital twins, AI-based anomaly detection, resilience monitoring, and adaptive supply-chain decision systems [34], [35].

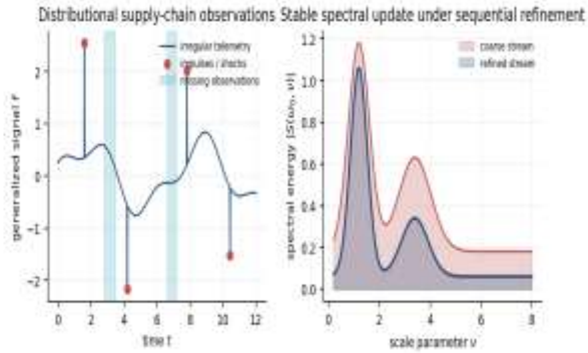

Figure 2. Distributional telemetry with impulses and missing observations, and stable spectral-energy update under sequential refinement [34], [35].

VI. DIGITAL-TWIN ARCHITECTURE FOR TRUSTED AND INTELLIGENT SUPPLY CHAINS

An intelligent supply-chain architecture can use the digital twin as a central integration layer connecting physical assets, sensing systems, analytical models, and trusted information exchange. IoT devices continuously generate telemetry, the digital twin synchronizes physical and virtual states, AI converts observations into predictions and adaptive decisions, and trusted-data infrastructure maintains provenance and shared-state consistency. This integrated structure enables operational information to move continuously between physical processes and their digital representations while supporting monitoring, prediction, anomaly detection, and resilience management. Industry 5.0 further introduces a human-in-the-loop dimension in which operators remain responsible for interpreting critical exceptions and validating high-impact decisions [11], [13], [25].

For an asset a, let its digital-twin state be represented by

$$\boldsymbol{z}_a^{DT}(t) = [p_a,(t), I_a,(t), q_a,(t), c_a(t)E_a(t)m_a(t)\mu_a(t)],$$

where the state may include physical location p_a, inventory I_a, quality q_a, custody c_a, energy E_a, maintenance condition m_a, and associated transaction or provenance metadata μ_a. The corresponding physical state can be represented by $\boldsymbol{z}_a^P(t)$. A generic synchronization error is then defined as

$$\varepsilon_{DT}(t) = \|\boldsymbol{z}_a^P(t) - \boldsymbol{z}_a^{DT}(t)\|.$$

When exceeds an application-specific tolerance, the digital twin can initiate state re-estimation, sensor verification, or model updating. This mechanism is particularly important when observations are delayed, incomplete, noisy, or inconsistent across multiple sensing channels [11].

Trusted-data mechanisms can associate provenance information with individual state transitions, thereby improving confidence in the origin, timing, and sequence of critical operational events. Blockchain-based records or comparable distributed-trust mechanisms can support this function without requiring every operational computation to be performed on-chain. Physical integrity sensing, including earlier power-line communication approaches for asset monitoring, can also contribute information to the custody and integrity components of the digital-twin state [13], [27]. As the sequence of measurements becomes progressively refined, the distributional FKF framework provides a consistent basis for updating the corresponding spectral representation and extracted features.

The resulting architecture can therefore be viewed as a continuous feedback loop: IoT sensing generates observations, the digital twin integrates and contextualizes those observations, FKF analysis extracts temporal and scale-dependent features, AI models perform prediction or anomaly detection, trusted-data mechanisms preserve provenance, and human or automated decision layers initiate appropriate responses [1], [2], [14], [24]. This arrangement connects mathematical signal analysis with practical operational intelligence.

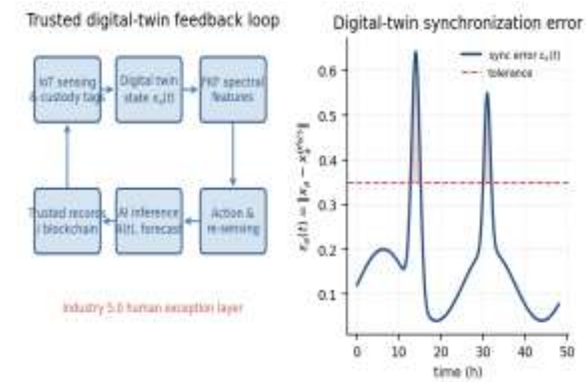

Figure 3. Closed-loop digital-twin architecture and synchronization-error trajectory against an operational tolerance [11], [13], [14], [25].

VII. ENERGY-AWARE MOBILITY AND SPECTRAL ANALYSIS OF LAST-MILE OPERATIONS

Transportation and last-mile logistics introduce energy dynamics that interact directly with lead times, routing decisions, and disruption recovery. Battery state, charging availability, vehicle load, and net power demand evolve on timescales that differ from conventional order and replenishment cycles. Representing these variables as operational signals allows their temporal and scale-dependent behavior to be incorporated into the same FKF spectral framework. Let $E_b(t)$ denote the available battery energy and $P_n(t)$ the net power demand of a vehicle. Their evolution can be represented schematically through an energy state equation such as

$$\frac{dE_b(t)}{dt} = P_c(t) - P_n(t),$$

where represents charging power. Energy feasibility can consequently be incorporated into routing, dispatch, and recovery decisions rather than being treated as an independent vehicle constraint [16], [28].

Hybrid and solar-assisted vehicle architectures further couple energy availability with transportation schedules. When vehicle-energy trajectories are represented through FKF analysis, charging cycles, acceleration patterns, load variations, and last-mile congestion can appear as joint frequency-scale structures rather than isolated time-domain events. Spectral energy concentrations can therefore provide additional features for identifying energy-intensive operating conditions, planning charging windows, and evaluating the effect of congestion on delivery performance [17], [16], [32].

Smart-mobility sensing provides the physical context required to interpret these spectral features, while battery-management constraints ensure that resulting dispatch decisions remain physically feasible. The integration of energy, transportation, and lead-time signals consequently enables a more comprehensive representation of sustainable mobility within resilient supply-chain management [30], [32], [33].

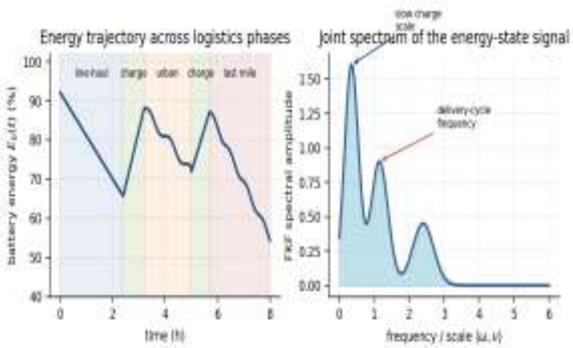

Figure 4. Battery-energy trajectory across line-haul, charging, urban, and last-mile phases, with the corresponding FKF spectral concentrations [16], [26], [28], [30], [32].

VIII. QUANTUM-ENABLED OPTIMIZATION AND DECISION VALIDATION

The final decision layer can employ quantum or hybrid quantum-classical optimization for selected combinatorial logistics problems. Unit-load-device configuration, assignment, disruption-based reallocation, routing selection, and related resource-allocation problems can be formulated using a quadratic unconstrained binary optimization model. Let denote the binary decision vector. A generic QUBO objective can be written as [15], [29], [31]

$$\min_{\boldsymbol{q}\in\{0,1\}^n} Q(\boldsymbol{q}) = \boldsymbol{q}^T Q \boldsymbol{q} + \boldsymbol{c}^T \boldsymbol{q} + C,$$

where Qrepresents interaction and penalty coefficients, $\boldsymbol{c}$ contains linear decision costs, and C is a constant term.

FKF-derived spectral features and digital-twin indicators can be incorporated into these coefficients as time-dependent weights or operational constraints. For example, a resonance indicator may increase the penalty associated with a disrupted transportation lane, a detected lead-time shift may modify the cost of a transit connection, and an energy-scale excursion may restrict the selection of a particular vehicle class. In this manner, spectral intelligence can influence the optimization problem without requiring the quantum layer to reproduce the underlying signal-processing operations [17], [18], [29].

Quantum computing is therefore positioned as a downstream combinatorial decision engine rather than as a replacement for FKF analysis, AI inference, or digital-twin synchronization. A hybrid workflow can first transform raw telemetry into spectral features, use AI and digital-twin models to estimate operational states, construct an optimization problem from the resulting constraints, and then employ classical, quantum, or hybrid optimization to identify feasible decisions [15], [24], [29], [31].

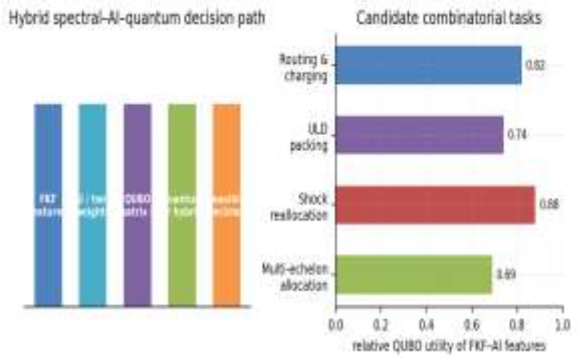

Figure 5. Hybrid FKF–AI–quantum decision path and relative utility of spectral–AI features for candidate QUBO logistics tasks [15], [24], [29], [31].

IX. VALIDATION, LIMITATIONS, AND EXPERIMENTAL PATHWAY

The proposed mathematical relations define a conceptual architecture and candidate operational indicators, but their practical effectiveness depends on parameter selection, transform normalization, inversion conditions, AI-model configuration, resilience thresholds, and optimization performance. These components should therefore be evaluated using real multi-echelon demand, lead-time, inventory, vehicle-energy, transportation, and disruption datasets [19], [33].

Experimental validation should compare FKF-derived features with conventional time-domain and frequency-domain features using identical operational records. Performance can be assessed through forecasting accuracy, anomaly-detection capability, synchronization error, disruption-recovery time, energy efficiency, and optimization quality. Sequential convergence provides the mathematical basis for incorporating progressively refined digital-twin measurements during these experiments [11], [35].

Related transform identities and earlier sensing or control architectures can provide supporting theoretical and historical context, but they should not automatically be interpreted as ready-to-deploy modules. The proposed framework should instead be treated as an extensible analytical architecture whose individual components require empirical calibration and validation. Such a validation pathway can determine whether FKF spectral indicators provide measurable advantages for intelligent, sustainable, and resilient supply-chain decision-making [9], [33].

X. CONCLUSION

The proposed framework provides a unified mathematical and computational approach for intelligent, sustainable, and resilient supply-chain analysis. Extending the distributional FKF transform to multi-echelon logistics enables demand fluctuations, lead-time variations, disruption transients, energy trajectories, and irregular sensor observations to be represented through both temporal frequency and scale-dependent behavior.

Integrating FKF analysis with AI, digital twins, IoT sensing, trusted data exchange, and sustainable mobility creates a continuous pathway from operational observation to prediction and adaptive decision-making. Distributional formulation and sequential convergence support the treatment of incomplete, impulsive, discontinuous, and continuously updated telemetry, while digital twins provide operational context and trusted-data mechanisms strengthen provenance and state consistency.

Energy-aware mobility further couples’ vehicle-energy conditions with routing, dispatch, and recovery decisions. Quantum and hybrid optimization can subsequently use FKF-derived spectral features and digital-twin constraints for selected combinatorial logistics problems. Overall, the framework views supply-chain resilience as a dynamic spectral property that can be observed, characterized, predicted, and optimized. Future work should validate the proposed indicators against real multi-echelon datasets and compare their performance with conventional time-domain and frequency-domain methods.

REFERENCES

[1] Heese, R., et al. (2026). Hybrid Quantum-Classical Optimization for Multi-Objective Supply Chain Logistics. *arXiv preprint arXiv:2602.05364*.

[2] Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, 57(3), 829–846.

[3] Ivanov, D. (2021). Digital supply chain twins: Managing the ripple effect, resilience, and disruption risks by data-driven optimization, simulation, and visibility. In *Handbook of Ripple Effects in the Supply Chain* (pp. 309–330). Springer.

[4] Le Maître, O. P., & Knio, O. M. (2010). *Spectral Methods for Uncertainty Quantification: With Applications to Computational Fluid Dynamics*. Springer.

[5] Sharma, R., Katukam, R., & Nagulapally, A. (2026). Bridging the Linear-Quadratic Gap: A Quantum-Classical Hybrid Approach to Robust Supply Chain Design. *arXiv preprint arXiv:2601.04095*.

[6] McKinsey & Company (2024). Digital twins: The key to unlocking end-to-end supply chain growth. *McKinsey Insights*.

[7] Wickremasinghe, G., et al. (2024). Uncertainty in Supply Chain Digital Twins: A Quantum-Classical Hybrid Approach. *arXiv preprint arXiv:2411.10254*.

[8] Various authors (2024). The role of digital twins in lean supply chain management: review and research directions. *International Journal of Production Research*.

[9] 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.

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

[11] Akarshan Gulhane, “Digital Twin Technology for Building Resilient and Adaptive Global Supply Chains: A Review,” Int. Res. J. Modernization

Eng. Technol. Sci., vol. 6, no. 12, 2024, doi: 10.56726/IRJMETS64992.

[12] Akarshan Gulhane, "Artificial Intelligence Applications in Sustainable Logistics and Green Supply Chain Management: A Bibliometric Review," Int. Res. J. Modernization Eng. Technol. Sci., vol. 6, no. 12, 2024, doi: 10.56726/IRJMETS65006.

[13] Akarshan Gulhane, " Artificial Intelligence and Blockchain Integration for Enhancing Supply Chain Transparency, Traceability, and Resilience," Int. Res. J. Modernization Eng. Technol. Sci., vol. 6, no. 12, 2024, doi: 10.56726/IRJMETS65016.

[14] Akarshan Gulhane, "SWIPE CONTROLLER," Int. J. Res. Eng. Appl. Sci. (IJREAS), vol. 4, no. 12, pp. 1–7, 2014.

[15] Akarshan Gulhane, "Navigating the Quantum Revolution in Logistics: Opportunities and Practical Applications in Supply Chain Management," Int. J. Eng. Techn. (IJET), vol. 12, no. 3, pp. 553–556, 2026, doi: 10.29126/ijet.2026.v12.i3.553.

[16] Akarshan Gulhane, "Recent Advances in Electric Vehicle Battery Technologies: Materials, Management Systems, and Sustainability Perspectives," Int. J. Sci. Res. Eng. Manage. (IJSREM), vol. 9, no. 7, Jul. 2025, doi: 10.55041/IJSREM51198.

[17] Akarshan Gulhane, "Spectral Analysis for Multi-Scale Supply Chain Dynamics and Residue-Based Resonance Extraction in Hybrid-Vehicle Systems," Int. J. Creative Open Res. Eng. Manage., vol. 2, no. 8, Aug. 2026, doi: 10.55041/ijcope.v2i8.141.

[18] Akarshan Gulhane, "Shift-Invariant Spectral Analysis of Multi-Echelon Supply-Chain Lead Times via the FKF Transform," Int. J. Creative Open Res. Eng. Manage., vol. 2, no. 8, Aug. 2026, doi: 10.55041/ijcope.v2i8.136.

[19] Akarshan Gulhane, "Spectral Framework Based on the FKF Transform for Supply Chain Dynamics and Resilience," Int. J. Creative Open Res. Eng. Manage., vol. 2, no. 8, Aug. 2026, doi: 10.55041/ijcope.v2i8.140.

[20] Akarshan Gulhane, "Spectral Differential Properties of the Distributional FKF Transform with Applications to Resilient Supply-Chain Systems," Int. J. Creative Open Res. Eng. Manage., vol. 2, no. 8, Aug. 2026, doi: 10.55041/ijcope.v2i8.139.

[21] Akarshan Gulhane, "FKL Transform Key Properties, And Applications To Supply-chain Analysis," Int. J. Eng. Sci. Adv. Technol., vol. 25, no. 12, pp. 596–605, Dec. 2025, doi: 10.64771/ijesat.2025.v25.i12.3816.

[22] Akarshan Gulhane, "Expanded Treatment Of the Time-Shift Property Of FKF Transform With Supply-Chain Applications," Int. J. Eng. Sci. Adv. Technol., vol. 25, no. 12, pp. 606–616, Dec. 2025, doi: 10.64771/ijesat.2025.v25.i12.3817.

[23] Akarshan Gulhane, "The FKF Transform: Exponential Modulation Properties and Applications to Secure Digital Supply-Chain Networks," Int. J. Eng. Sci. Adv. Technol., vol. 25, no. 12, pp. 617–623, Dec. 2025, doi: 10.64771/ijesat.2025.v25.i12.3818.

[24] Akarshan Gulhane, "Internet of Things, Artificial Intelligence, and Quantum Computing: A Convergent Framework for Smart Logistics Ecosystems," Int. J. Eng. Sci. Adv. Technol. (IJESAT), vol. 24, no. 12, pp. 297–317, 2024, doi: 10.64771/ijesat.2024.v24.i12.3372.

[25] Akarshan Gulhane, "Industry 5.0 and Intelligent Logistics: Transforming Supply Chain Operations through Human-Centric Automation," Int. J. Eng. Sci. Adv. Technol. (IJESAT), vol. 24, no. 12, pp. 287–296, 2024, doi: 10.64771/ijesat.2024.v24.i12.3371.

[26] Akarshan Gulhane, "The Future of Vehicles: Solar-Powered Battery Electric Hybrid Vehicle Architecture," Tech Briefs Create the Future Design Contest, Automotive and Transportation, entry 10457, 2020. [Online]. Available: https://contest.techbriefs.com/2020/entries/automotive-transportation/10457

[27] Akarshan Gulhane, "Power line carrier communication based anti-theft system," Int. J. Res. IT Manage. (IJRIM), vol. 4, no. 12, pp. 1–11, 2014.

[28] Akarshan Gulhane, "Battery sizing for plug-in hybrid electric vehicles — Formula hybrid," in Proc. IEEE Int. Conf. Power, Control, Signals and Instrumentation Engineering (ICPCSI), 2017, pp. 368–372, doi: 10.1109/ICPCSI.2017.8392317.

[29] Akarshan Gulhane, "Quantum Computing for Logistics Optimization: Annealing in Unit Load Device Configuration and Disruption," Int. J. Res. Publ. Rev., vol. 7, no. 6, pp. 4643–4648, Jun. 2026, doi: 10.55248/gengpi.07.0626.16a57.

[30] Akarshan Gulhane, "Smart Mobility and Intelligent Transportation Systems: Emerging Trends, Technologies, and Challenges," Int. J. Sci. Res. Eng. Manage. (IJSREM), vol. 9, no. 11, Nov. 2025, doi: 10.55041/IJSREM53436.

[31] Akarshan Gulhane, "Quantum Computing in Transportation and Logistics: Current State, Industrial Applications, and Future Directions," Int. J. Sci. Res. Eng. Manage. (IJSREM), vol. 9, no. 9, Sep. 2025, doi: 10.55041/IJSREM52469.

[32] Akarshan Gulhane, "Solar-Assisted Electric Mobility: Design Framework and Performance Assessment of Sustainable Hybrid Vehicle Architectures," Int. J. Eng. Res. Sci. Technol., vol. 21, no. 3, pp. 362–368, 2025, doi: 10.56636/ijerst.2025.v21.i03.3594.

[33] Akarshan Gulhane, "Supply Chain Resilience in the Era of Digital Transformation: A Systematic Literature Review and Research Agenda,"

Int. J. Eng. Res. Sci. Technol., vol. 21, no. 4, pp. 1058–1068, 2025, doi: 10.56636/ijerst.2025.v21.i04.3812.

[34] Akarshan Gulhane, “Distributional Extension of the FKF Transform and Its Relevance to Supply-Chain Systems,” Int. J. Creative Open Res. Eng. Manage., vol. 2, no. 8, Aug. 2026, doi: 10.55041/ijcope.v2i8.137.

[35] Akarshan Gulhane, “Sequential Convergence in the Testing Function Space of the Two-Sided FKF Transform,” Int. J. Creative Open Res. Eng. Manage., vol. 2, no. 8, Aug. 2026, doi: 10.55041/ijcope.v2i8.138.