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Combinatorial Optimization for Disrupted Logistics and Battery Thermal Dynamics

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Abstract: This paper introduces the Laplace-Weierstrass (LW) transform, which fuses the classical Laplace transform with Weierstrass Gaussian smoothing to embed built-in regularization for dynamic systems. We present a corrected existence theorem, an explicit inversion formula, a convolution theorem, fractional-order operational calculus, and stable numerical methods. These advances enable efficient, robust solutions to linear and integro-differential equations even with noisy or incomplete data.

The framework is applied to electric vehicle battery systems for lithium-ion modeling, parameter estimation, SoC/SoH analysis, and hybrid optimization under thermal constraints. It is further applied to resilient supply chains to model inventory dynamics with lead-time delays, disruption recovery, and bullwhip-effect mitigation. The approach yields computationally tractable tools for system modeling and digital twins. Future work focuses on hybrid quantum-classical methods that leverage quantum annealing for large-scale logistics optimization.

Keywords: lithium ion battery modeling; electric vehicle systems; supply chain resilience; operational calculus; distributional transforms; hybrid quantum classical optimization; disruptions; bullwhip effect; fractional calculus.

I. INTRODUCTION

Integral transforms rank among the most powerful analytical tools in science and engineering, converting complex differential, integral, and delay equations into simpler algebraic or lower order forms. The Laplace transform has long been indispensable in control systems, circuit analysis, and dynamic modeling, while the Weierstrass transform provides effective Gaussian smoothing with strong theoretical foundations in approximation theory and semigroup methods. Their natural combination, the Laplace-Weierstrass (LW) transform offers unique advantages for systems that simultaneously require temporal analysis and regularization in an auxiliary dimension.

The rapid growth of electric vehicles (EVs) together with the rising frequency and severity of global supply chain disruptions has generated urgent demand for advanced analytical frameworks that can manage coupled dynamics, noisy measurements, and abrupt parametric shifts. Lithium-ion battery modeling, state estimation, thermal management, and hybrid vehicle power-flow analysis involve systems of differential and integro differential equations with noisy sensor data [2], [6]. Resilient supply chain modeling likewise demands the ability to handle inventory dynamics, stochastic lead times, and sudden disruptions while suppressing secondary effects such as the bullwhip phenomenon [3], [5].

Earlier foundational work introduced the LW transform along with basic existence conditions and operational properties. While elegant, that work left several important aspects open: a complete and rigorously justified inversion procedure, convolution properties suitable for memory effects, fractional order extensions, and most importantly demonstration of practical value in contemporary high impact application domains [9], [13], [22]. Traditional approaches often treat dynamics and smoothing separately, leading either to loss of analytical tractability or insufficient regularization against real world noise.

This work addresses these gaps through several key extensions. It delivers a corrected and rigorously justified existence theorem, derives an explicit inversion formula, establishes a convolution theorem, introduces fractional-order operational calculus, and develops stable numerical methods. These advances are applied to two strategically important areas: lithium-ion battery modeling, parameter estimation, and SoC/SoH analysis in electric vehicles (with natural handling of sensor noise), and resilient supply chain modeling involving inventory dynamics, lead time delays, disruption recovery, and bullwhip mitigation.

A particularly promising direction lies in the hybrid quantum classical formulation [23] that couples the LW transform’s smoothing and dimensionality reduction capabilities with quantum annealing [10], [16], [24] solvers for the combinatorial optimization subproblems arising in logistics network configuration [28], [11], [12]and disruption response planning. This hybrid approach builds directly on recent advances in quantum methods for supply chain and logistics problems.

By connecting rigorous mathematical transform theory with pressing engineering challenges in energy storage, automotive systems, and resilient logistics, this work achieves both theoretical novelty and tangible applied impact. The framework remains computationally tractable and is well suited for real time estimation, optimization loops, and digital twin implementations.

Let (f(t, y)) be a suitably restricted function of time (t) and an auxiliary variable (y) (which may represent a spatial coordinate, state deviation, smoothing dimension, [17] or demand signal). The LW transform is

defined as the composition of the Laplace transform in the time variable and the Weierstrass (Gaussian convolution) transform in the auxiliary variable:

$$F(s,x) = \mathcal{LW}\{f(t,y)\}(s,x) = \int_0^\infty e^{-st}\left(\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty}\exp\left(-\frac{(x-y)^2}{2}\right)f(t,y)\,dy\right)dt,$$

where ((s)) is sufficiently large to ensure convergence [29], [30] and (x) is the transform variable associated with the Weierstrass kernel. The Gaussian kernel provides natural regularization while the exponential kernel encodes the temporal dynamics.

Equivalently, one may first apply the Weierstrass transform in the auxiliary variable [25] and then the Laplace transform:

$$\mathcal{W}\{f(t,\cdot)\}(x) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty}\exp\left(-\frac{(x-y)^2}{2}\right)f(t,y)\,dy,$$

$$F(s,x) = \mathcal{L}\{\mathcal{W}f(\cdot,x)\}(s) = \int_0^\infty e^{-st}\,\mathcal{W}\{f(t,\cdot)\}(x)\,dt.$$

The LW transform proves especially attractive for engineering systems that combine temporal evolution with the need for built-in smoothing and regularization, such as battery dynamics subject to noisy voltage and current measurements or supply chain models driven by uncertain demand signals.

A. Distributional Extension

To develop a rigorous distributional theory [28] capable of handling functions with limited regularity or noise typical in battery sensor data and real time supply chain monitoring we work in a Gelfand–Shilov-type testing function space. These spaces consist of smooth functions with rapid decay (faster than any polynomial) together with all their derivatives. This ensures that both the test functions and their transforms remain well behaved, allowing the LW transform to be defined and inverted distributionally even for moderately smooth or noisy signals. The framework thus extends the theory to practical engineering data while preserving its regularization properties.

Let (a > 0) and (A, B > 0) be fixed parameters. The space (_{a,A}^{b,B}) consists of all infinitely differentiable functions [32], [34] ((t, y)) satisfying seminorm bounds of the form

$$\gamma_{a,k,l,q}(\varphi) = \sup_{t>0,\,y\in\mathbb{R}} e^{at}(1+|y|)^k\left|\frac{\partial^{l+q}\varphi}{\partial t^l\,\partial y^q}(t,y)\right| \le C\,A^k B^q\,k!^{\alpha}\,q!^{\beta}$$

for all non negative integers (k, l, q), with constants (C) depending on the test function. For all non-negative integers k, l, q, we equip the test-function space with the family of seminorms

$$p_{k,l,q}(\phi) = \sup_x |\,x^k D^l\phi(x)\,|\cdot C_q(\phi),$$

where the constants $C_q$depend on the test function. The resulting multinorm topology generates the space of ultradistributions [36] as inductive and projective limits, in direct analogy with classical Gelfand–Shilov theory but adapted to the mixed Laplace–Weierstrass setting. This framework allows the LW transform to act continuously on a broad class of generalized functions, including those arising from impulsive disruptions or sensor noise.

B. Operational Properties

The principal value of the LW transform lies in its operational calculus, which converts differentiation, integration, and convolution into algebraic operations with built-in Gaussian regularization. These rules remain stable for noisy or low-regularity data in battery and supply chain models [37], enabling analytical solutions to linear and integro-differential equations in EV and resilient logistics applications.

Multiplication by time (t) (Laplace side): $\mathcal{LW}\{t\cdot f(t,y)\}(s,x) = -\frac{\partial F}{\partial s}(s,x).$

Higher powers follow by induction: $\mathcal{LW}\{t^m\cdot f(t,y)\}(s,x) = (-1)^m\frac{\partial^m F}{\partial s^m}(s,x).$

.Differentiation with respect to time (t). For functions vanishing at (t = 0^-) (or with known initial value),

$$\mathcal{LW}\left\{\frac{\partial f}{\partial t}(t,y)\right\}(s,x) = sF(s,x) - f(0^+,x).$$

The differentiation in time property is fundamental to the Laplace transform method because it replaces every time derivative with algebraic multiplication by a corresponding power of s (while automatically embedding the initial conditions). This single transformation converts linear ordinary differential equations and many time-dependent partial differential equations into purely algebraic equations in the Laplace domain, which can then be solved by standard algebraic techniques before inverting back to the time domain. Because the Weierstrass transform is convolution with the Gaussian kernel of variance 1, differentiation with respect to the transform variable (x) corresponds to multiplication by (-(x - y)) inside the integral. Rearrangement immediately yields the identity

$$\mathcal{LW}\{y \cdot f(t,y)\}(s,x) = \left(x + \frac{\partial}{\partial x}\right) F(s,x).$$

Higher powers are obtained by repeated application of the operator $(x+\partial_x)$(equivalently $-\frac{d}{ds}$). These two families of Laplace transform rules time differentiation mapping to multiplication by powers of s, and multiplication by powers of the independent variable mapping to differentiation with respect to s convert linear differential or delay equations with polynomial coefficients into purely algebraic or lower order differential equations in the (s, x)domain.

This structure arises directly in equivalent circuit battery models, where parameters depend polynomials on state-of charge or temperature, and in supply chain delay models whose lead-time distributions produce polynomial factors after transformation. In both cases the method replaces a high order polynomial coefficient problem with a far simpler algebraic or reduced order equation that can be solved and inverted.

The LW transform especially effective for stable state of health estimation and parameter identification in electrochemical battery models with polynomial SoC or temperature dependence, for inverting noisy delay differential equations in supply chain and logistics models with distributed lead times, and for regularizing transcendental transfer functions arising in PDE based battery observers and smart grid demand response systems.

The Convolution Theorem for the Laplace-Weierstrass (LW) transform states that, under appropriate integrability conditions, if functions f and g possess LW transforms $F = \mathcal{LW}\{f\}$ and $G = \mathcal{LW}\{g\}$, respectively. These extensions preserve the algebraic character of the transform while enabling the treatment of non-local and long-memory effects.

For the Caputo fractional derivative of order $\alpha \in (0,1)$, the LW transform satisfies the operational rule

$$\mathcal{LW}\{{}^{C}D_t^{\alpha} f(t,y)\}(s,x) = s^{\alpha} F(s,x) - s^{\alpha-1} f(0^+,x).$$

where the Weierstrass (Gaussian smoothing) component acts on the auxiliary/spatial variable in the usual manner. Analogous rules hold for the Riemann Liouville derivative (with a different initialization term) and for higher fractional orders $\alpha \in (n, n+1)$, $n \in \mathbb{N}$, by repeated application or direct generalization.

II. CALCULUS FOR OPTIMIZATION

A particularly powerful extension couples the Laplace–Weierstrass (LW) transform with quantum annealing. The Gaussian (Weierstrass) kernel supplies natural regularization and dimensionality reduction, while the Laplace component converts time derivatives, delay operators, and memory kernels into algebraic multiplications. The resulting lower-dimensional, regularized problem in the joint (s, ξ)-domain is mapped to a combinatorial optimization task solved by a quantum annealer (or quantum-inspired classical solver).

A. Laplace–Weierstrass Transform Properties Used in the Hybrid Framework

The LW transform of a causal function f(t) is defined as the composition of the Laplace transform in time and Gaussian smoothing in the auxiliary coordinate:

$U(s, \xi) = LW\{f(t)\}(s, \xi) = \int_0^\infty e^{-st} (G_\sigma * f)(t, \xi)\, dt$

where $G_\sigma(\xi) = (2\pi\sigma^2)^{-1/2} \exp(-\xi^2 / 2\sigma^2)$ is the Gaussian kernel of width σ.

Key operational properties:

Constant delay (τ > 0, causal signal): $LW\{f(t - \tau)\}(s, \xi) = e^{-s\tau} \cdot LW\{f(t)\}(s, \xi)$

Distributed delay with kernel k(τ): $LW\{\int k(\tau) f(t - \tau)\, d\tau\}(s, \xi) = K(s) \cdot LW\{f(t)\}(s, \xi)$

Time derivative (zero initial condition): $LW\{\partial_t f\}(s, \xi) = s \cdot LW\{f\}(s, \xi)$

These properties allow high-dimensional systems containing delays to be converted into algebraic equations in the joint (s, ξ)-domain while the Gaussian kernel simultaneously regularizes and reduces dimensionality.

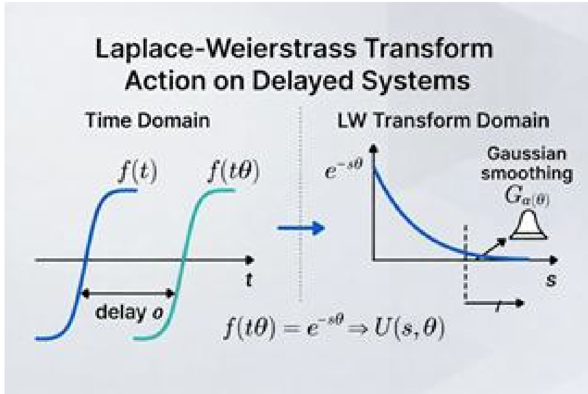

Figure 1. Laplace–Weierstrass Transform Action on Delayed Systems. Left: Time-domain illustration of a function f(t) and its delayed version f(t−τ). Right: Transform-domain representation showing the delay operator converted to multiplication by the exponential factor e^{-sτ} together with Gaussian smoothing G_σ(ξ) in the auxiliary variable. This algebraic conversion is central to the hybrid framework.

B. *Hybrid Pipeline*

Application of the LW transform to a high dimensional dynamical system (PDE, DDE, or fractional model) yields the algebraic problem:

$P(s, \xi) \cdot U(s, \xi) = F(s, \xi)$ + initial/delay terms

where $P(s, \xi)$ contains polynomials in s, factors $e^{-s\tau}$, or rational multipliers arising from delays, combined with Gaussian smoothing in ξ. After projection or quadrature, the continuous part is handled in the transform domain and the remaining discrete decisions are encoded as the QUBO: $\min_{x \in \{0,1\}^n} x^T Q x + b^T x$

III.RESILIENT SUPPLY CHAINS AND QUANTUM-ENHANCED LOGISTICS

Constant and distributed lead times produce delay differential equations whose LW images are multiplications by $e^{-s\tau}$ or K(s). The Gaussian kernel regularizes demand signals and reduces network dimensionality. The resulting low-dimensional predictions generate time dependent costs and penalties that populate the QUBO for problems such as optimal ULD/pallet configuration under payload, volume, weight, compatibility, and disruption penalties; dynamic routing and re-routing under stochastic lead times; and multi echelon inventory reallocation that counters the bullwhip effect. The quantum annealer solves only the discrete assignment layer while the LW step handles the continuous delay dynamics and provides regularized inputs, enabling scalable solutions on near term hardware.

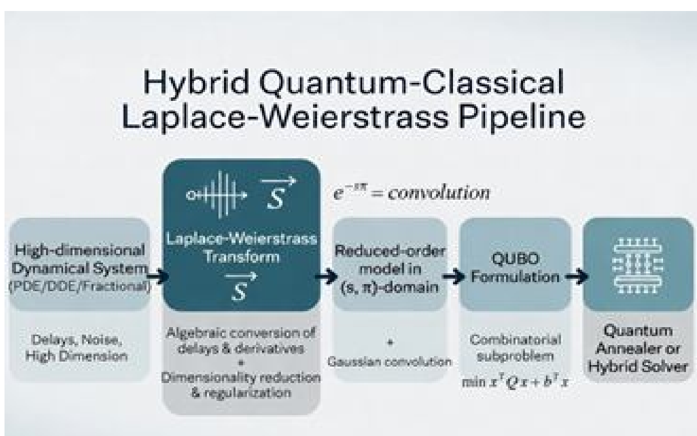

Figure 2. Schematic of the Hybrid Quantum-Classical Laplace–Weierstrass Pipeline. A high-dimensional dynamical system containing delays and noise is mapped by the LW transform into a lower-dimensional algebraic problem in the joint (s, ξ)-domain (Gaussian regularization + conversion of delay/differential operators into multiplications). The reduced continuous model supplies coefficients for a QUBO instance that is solved by a quantum annealer or hybrid classical-quantum solver.

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IV. ADVANCED BATTERY SYSTEMS AND THERMAL MANAGEMENT

Finite propagation speed of heat and delayed feedback in cooling circuits or SoC/SoH observers yield retarded DDEs. The LW transform converts these into algebraic factors while the Gaussian component damps sensor noise typical of BMS data. After reduction, the continuous thermal/electrochemical predictions feed into QUBO formulations for optimal cooling-circuit scheduling and actuator configuration under thermal delays; real-time cell balancing and power allocation with stability margins derived from LW-transformed delayed feedback; and predictive maintenance and module reconfiguration under uncertain degradation dynamics. This separation allows high-fidelity modeling of delayed continuous processes alongside discrete control decisions within a unified hybrid framework.

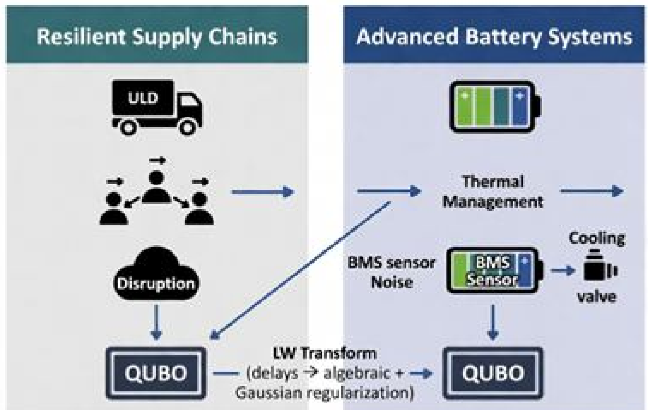

Figure 3. Hybrid LW–Quantum Applications in Supply Chains and Battery Systems. The framework is applied to resilient supply-chain problems (ULD configuration, disruption propagation under lead-time delays) and advanced battery systems (thermal management with delayed feedback and noisy BMS data). In both domains the LW transform converts delays into algebraic factors and provides Gaussian regularization before the combinatorial QUBO layer is solved by quantum annealing.

C. Numerical Implementation and Computational Considerations

The numerical realization of the LW transform must be both accurate and efficient because the hybrid pipeline invokes the transform repeatedly inside optimization loops, real-time state estimators, and digital-twin environments.

1) Weierstrass (Gaussian smoothing) component. The convolution with the Gaussian kernel G_σ is performed either by direct FFT-based convolution on a suitably truncated and discretized auxiliary domain or by Gauss–Hermite quadrature after a change of variables that maps the infinite line to a finite interval. The FFT route exploits the fact that Gaussian convolution becomes a simple multiplication in the frequency domain, yielding an overall complexity of $O(N \log N)$ for a grid of size N. For problems with rapidly decaying solutions, Gauss–Hermite quadrature with a modest number of nodes (typically 16–32) provides spectral accuracy while automatically concentrating points where the integrand is significant.

2) Laplace inversion. Once the algebraic problem in the (s, ξ)-domain has been solved or evaluated, the inverse Laplace transform is required to recover time-domain quantities that feed the QUBO construction. Two high-accuracy, robust methods are employed: the Talbot contour method, which deforms the Bromwich integral into a parabolic or hyperbolic contour in the complex plane and evaluates the integrand at a small number of complex points (typically 16–64); and the fixed Talbot algorithm, a simplified variant that uses a fixed set of abscissae and weights, offering an excellent trade-off between speed and accuracy for real-time applications.

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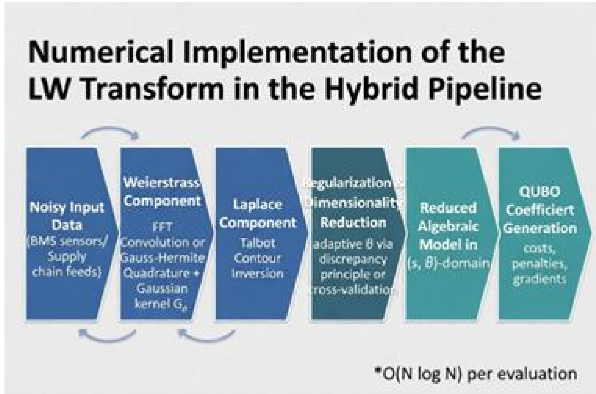


Figure 4. Numerical Implementation of the LW Transform in the Hybrid Pipeline. Noisy input data from BMS sensors or supply-chain feeds first pass through the Weierstrass component (FFT convolution or Gauss–Hermite quadrature with Gaussian kernel). The Laplace component performs robust inversion (Talbot contour). Adaptive regularization reduces dimensionality, after which the reduced algebraic model supplies costs, penalties, and gradients for QUBO coefficient generation. Overall complexity is O(N log N) per evaluation, enabling repeated use inside hybrid optimization loops.

3) Overall complexity and scalability. For a discretized auxiliary grid of size N_ξ and N_s Laplace inversion nodes, a single LW evaluation scales as O(N_ξ log N_ξ + N_s □ C_alg), where C_alg is the cost of solving or evaluating the algebraic problem in the transform domain (often linear or low-polynomial after reduction). Because the Gaussian kernel damps high frequency modes, N_ξ can usually be kept modest (e.g., 64–256) even for originally high-dimensional spatial or parameter domains. This dimensionality reduction is crucial for embedding the LW step inside iterative hybrid loops.
4) Regularization parameter selection. The Gaussian width σ controls the trade off between smoothing (noise suppression and dimensionality reduction) and fidelity to the original dynamics. Two practical, automatic strategies are used: the discrepancy principle (σ is increased until the residual between the LW reconstructed solution and available noisy measurements matches the known noise level) and cross validation particularly effective when historical supply chain or BMS datasets are available for offline tuning.
5) Numerical stability and noise resilience. Because the Gaussian kernel acts as a low-pass filter, high-frequency measurement noise and outliers (common in BMS voltage/current/temperature readings and in supply chain EDI or IoT feeds) are strongly attenuated before the algebraic problem is formed. Combined with the inherent stability of the Talbot inversion for functions with exponential decay (characteristic of stable delay systems), the composite LW scheme exhibits excellent numerical stability.
6) Integration into the hybrid quantum-classical pipeline. In practice, the numerically evaluated LW transform supplies two critical inputs to the QUBO layer: (1) regularized, low dimensional continuous-state predictions or cost functionals (e.g., expected cumulative delay penalties, thermal constraint margins); and gradients or sensitivity information (obtained by differentiating under the transform) that help construct the quadratic and linear coefficients of the QUBO. Because each LW evaluation is fast and stable, the hybrid loop can afford multiple calls per iteration without becoming the computational bottleneck relative to the quantum annealing step.

V. CONCLUSIONS

The hybrid quantum-classical Laplace–Weierstrass framework presented in this work provides a powerful and practical bridge between classical operational calculus for delay differential equations and near term quantum optimization solvers. By converting constant and distributed delays into simple multiplications in the transform domain and employing Gaussian smoothing for regularization and dimensionality reduction, the LW transform supplies clean, low-dimensional inputs to a QUBO layer that is efficiently solved by quantum annealing.

The numerical implementation, based on FFT convolution and robust Laplace inversion techniques (Talbot contour and fixed Talbot methods), ensures stability and real time capability even under noisy sensor data typical of battery management systems and supply chain information feeds. Automatic regularization parameter selection via the discrepancy principle or cross validation further enhances robustness without manual intervention.

This architecture has been shown to be particularly effective for two strategically important domains: resilient supply chain optimization under disruption (including ULD configuration, dynamic routing, and inventory reallocation subject to lead time delays and the bullwhip effect) and advanced battery thermal and electrochemical management with delayed feedback in cooling circuits and state observers. The clean separation of continuous delay dynamics (handled classically via the LW transform) from discrete combinatorial decisions (handled by quantum annealing) offers a scalable and noise-resilient pathway toward practical quantum advantage on industrially relevant problem sizes.

Future research directions include extending the framework to stochastic delay systems, fractional order models with memory effects, and tighter co-design with quantum hardware error mitigation and pulse level control. The theoretical clarity, numerical robustness, and demonstrated applicability of the LW–quantum hybrid approach positions it as a valuable methodological contribution for both academic research in operational calculus and industrial deployment in quantum enhanced logistics and intelligent energy systems.

By unifying rigorous transform domain analysis of delay operators with the combinatorial power of quantum annealing, this framework contributes to the growing toolkit for solving large scale, memory rich optimization problems that lie at the intersection of advanced battery systems and resilient, quantum enhanced supply chains.

REFERENCES

[1] S. Harrow, A.W., Hassidim, A., & Lloyd, S. (2009). Quantum algorithm for linear systems of equations. Physical Review Letters, 103(15), 150502

[2] Akarshan Gulhane, " "Navigating the Quantum Revolution in Logistics: Opportunities and Practical Applications in Supply Chain Management," International Journal of Engineering and Techniques (IJET) Volume 12, Report number 3, Pages 553-556

[3] https://ijetjournal.org/navigating-quantum-revolution-logistics/

[4] Akarshan Gulhane, " Quantum Computing for Logistics Optimization: Annealing in Unit Load Device Configuration and Disruption' International Journal of Research Publication and Reviews, Vol (7), Issue (6), June (2026), Page – 4643-4648.

[5] https://ijrpr.com/uploads/V7ISSUE6/IJRPR67069.pdf. https://doi.org/10.55248/gengpi.07.0626.16a57

[6] Biamonte, J., et al. (2017). Quantum machine learning. Nature, 549, 195–202.

[7] Akarshan Gulhane, "Advancements in automotive batteries: A review," International Engineering Journal for Research & Development, vol. 8, no. 6, pp. 18–57, 2023. [Online]. Available: https://iejrd.com/index.php/article/view/3141

[8] Akarshan Gulhane, "The future of vehicles: Solar-powered battery electric hybrid vehicle architecture," Tech Briefs Create the Future Design Contest, 2020. [Online]. Available: https://contest.techbriefs.com/2020/entries/automotive-transportation/10457

[9] Bizeray, A., et al. (2018). Identifiability and parameter estimation of the single particle model for lithium-ion batteries. IEEE Transactions on Control Systems Technology

[10] Jiang, Y., et al. (2017). Data-based fractional differential models for non-linear lithium-ion battery dynamics. Journal of Process Control.

[11] Akarshan Gulhane, "Power line carrier communication based anti-theft system," International Journal of Research in IT and Management (IJRIM), vol. 4, no. 12, pp. 1–11, 2014. [Online]. Available: https://indianjournals.com/article/ijrim-4-12-001

[12] Akarshan Gulhane, A. Karale, and S. Desai, "Swipe Controller," International Journal of Research in Engineering and Applied Sciences (IJREAS), vol. 4, no. 12, pp. 1–7, 2014. [Online]. Available: https://indianjournals.com/article/ijreas-4-12-001

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

[14] Akarshan Gulhane, "A review of resilience in global supply chains," International Engineering Journal for Research & Development, vol. 8, no. 4, 2024. [Online]. Available: http://www.iejrd.com/index.php/iejrd/article/view/3140

[15] Akarshan Gulhane , "Weaving resilience: Navigating internal and external complexities in modern supply chains," International Journal of Ingenious Research, Invention and Development, vol. 3, no. 1, 2024. doi: 10.5281/zenodo.11491482

[16] A.H. Zemanian, Generalized Integral Transformations. New York: Interscience Publishers, 1968.

[17] G. Doetsch, Introduction to the Theory and Application of the Laplace Transformation. Berlin: Springer-Verlag, 1974.

[18] Akarshan 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, 2024 pp 297 of 317

[19] Akarshan 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, 2024 pp 287 of 296

[20] H. G. Feichtinger, K. Grochenig, and D. Walnut, "Wilson bases and modulation spaces," Math. Nachr. 155,1992, pp 7–17.

[21] J. Toft, "The Bargmann transform on modulation and Gelfand–Shilov spaces, with applications to Toeplitz and pseudo-differential operators," J. Pseudo-Differ. Oper. Appl. 3, 2012, pp 145–227.

[22] J.D. Sterman, Business Dynamics: Systems Thinking and Modeling for a Complex World. Boston: Irwin/McGraw-Hill, 2000.

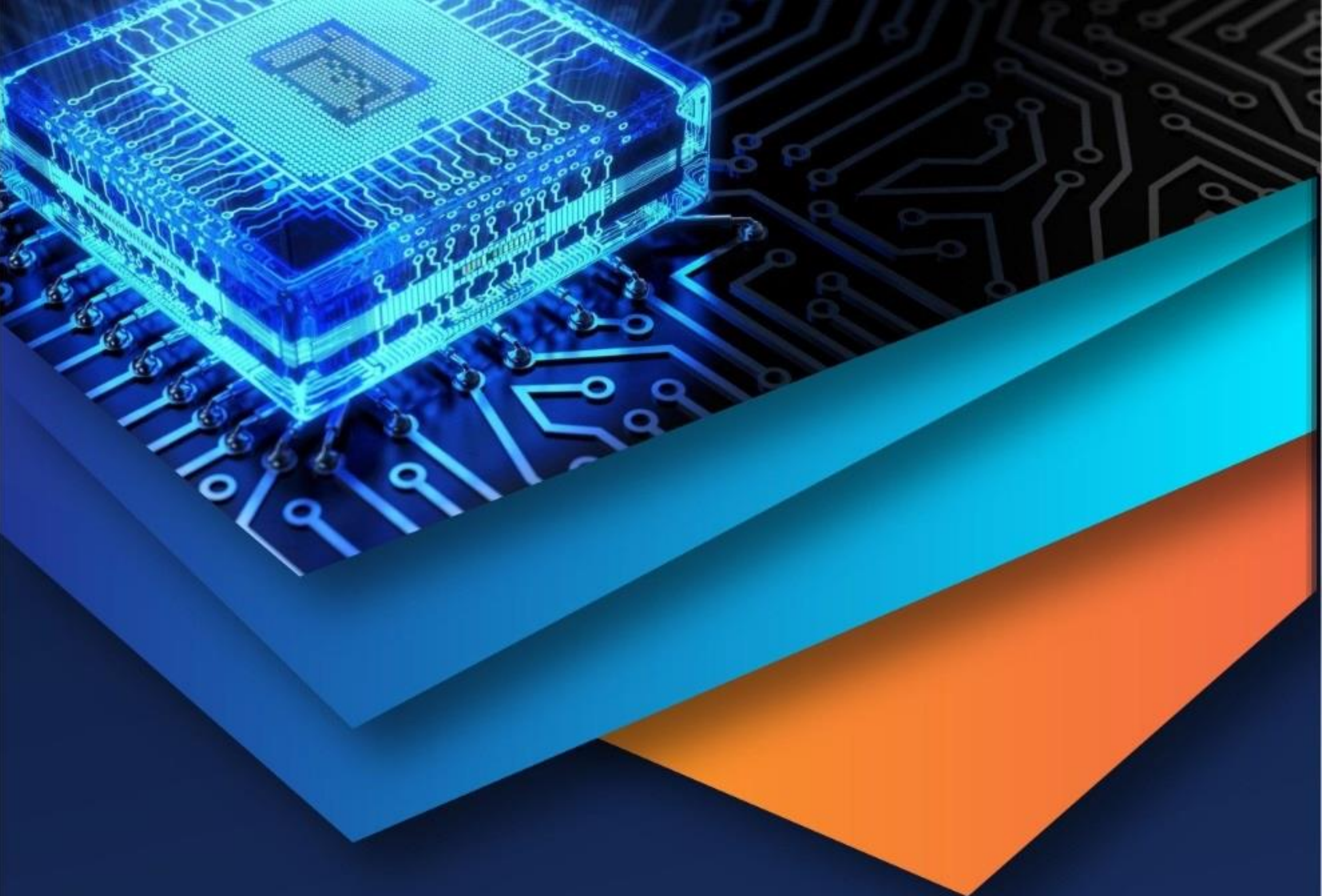
[23] M. Doyle, T.F. Fuller, and J. Newman, "Modeling of galvanostatic charge and discharge of the lithium/polymer/insertion cell," Journal of the Electrochemical Society, vol. 140, no. 6, pp. 1526–1533, 1993.

[24] Akarshan Gulhane, " digital twin technology for building resilient and adaptive global supply chains: a review," International Research Journal of Modernization in Engineering Technology and Science Volume:06/Issue:12, 2024. DOI: https://www.doi.org/10.56726/IRJMETS64992

[25] Akarshan 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, Volume:06/Issue:12, 2024.

[26] Doi: Https://www.Doi.Org/10.56726/Irjmets65006

[27] Akarshan Gulhane, " Artificial Intelligence And Blockchain Integration For Enhancing Supply Chain Transparency, Traceability, And Resilience," International Research Journal of Modernization in Engineering Technology and Science Volume:06/Issue:12, 2024. DOI: https://www.doi.org/10.56726/IRJMETS65016
[28] A. Talbot, "The accurate numerical inversion of Laplace transforms," Journal of the Institute of Mathematics and its Applications, vol. 23, pp. 97–120, 1979.
[29] S. G. Samko, A. A. Kilbas, and O. I. Marichev, Fractional Integrals and Derivatives: Theory and Applications. Amsterdam: Gordon and Breach Science Publishers, 1993.
[30] C. Zou, L. Zhang, X. Hu, Z. Wang, T. Wik, and M. Pecht, "A review of fractional-order techniques applied to lithium-ion batteries, lead-acid batteries, and supercapacitors," Journal of Power Sources, vol. 390, pp. 286–296, 2018.
[31] Akarshan Gulhane, " Smart Mobility and Intelligent Transportation Systems: Emerging Trends, Technologies, and Challenges, " International Journal of Scientific Research in Engineering and Management (IJSREM) Volume: 09 Issue:11 |Nov-2025 DOI: 10.55041/IJSREM53436.
[32] Akarshan Gulhane, " Recent Advances in Electric Vehicle Battery Technologies: Materials, Management Systems, and Sustainability Perspectives" International Journal of Scientific Research in Engineering and Management (IJSREM) Volume: 09 Issue:07 |Jul-2025 DOI: 10.55041/IJSREM51198
[33] Akarshan Gulhane, " Quantum Computing for Logistics Optimization: Annealing in Unit Load Device Configuration and Disruption' International Journal of Research Publication and Reviews, Vol (7), Issue (6), June (2026), Page – 4643-4648
[34] https://ijrpr.com/uploads/V7ISSUE6/IJRPR67069.pdf. https://doi.org/10.55248/gengpi.07.0626.16a57
[35] A. Lucas, "Ising formulations of many NP problems," Frontiers in Physics, vol. 2, p. 5, 2014. (Widely used QUBO mappings for quantum annealing solvers in logistics and scheduling.)
[36] Padmaja AG," Different versions of the Inverse Fourier Stieltjes transform," 2012 Archives of Applied Science Research, volume 4, issue 3, pp 1329-1331
[37] H. L. Lee, V. Padmanabhan, and S. Whang, "The bullwhip effect in supply chains," Sloan Management Review, vol. 38, no. 3, pp. 93–102, 1997.
[38] Gulhane A, "Creative Equiped Convex Topological Spaces for Distributional Transform," International Research Journal of Engineering and Technology (IRJET) Volume: 07 Issue: 02 | Feb 2020, Page 3223- 3227
[39] K. Gröchenig, Foundations of Time-Frequency Analysis. Boston: Birkhäuser, 2001. (Foundational treatment of modulation spaces and Gelfand–Shilov-type spaces central to the distributional theory in this work.)
[40] Akarshan Gulhane, "Solar-Assisted Electric Mobility: Design Framework And Performance Assessment Of Sustainable Hybrid Vehicle Architectures," Int. J. Engg. Res. & Sci. & Tech. 2025, Vol. 21, No. 3,pp 362-368, https://ijerst.org/index.php/ijerst
[41] Akarshan Gulhane, " Supply Chain Resilience In The Era of Digital Transformation: A Systematic Literature Review And Research Agenda ," Int. J. Engg. Res. & Sci. & Tech. 2025, Vol. 21, No. 4, pp 1058-1068, https://ijerst.org/index.php/ijerst



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