World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Research Article)

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From Farm to Fork: Optimizing Cold-Chain Logistics through IoT and Machine Learning

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World Journal of Advanced Research and Reviews, 2026, 29(02), 671-677

Publication history: Received on 09 February 2026; revised on 10 February 2026; accepted on 12 February 2026

Article DOI: https://doi.org/10.30574/wjarr.2026.29.2.0350

Abstract

As global food systems face pressure from population growth and climate volatility, cold-chain logistics remains a critical bottleneck for food security. This study investigates the optimization of "Farm to Fork" supply chains through the integration of Internet of Things (IoT) sensors and Agentic Machine Learning (ML). By 2026, the industry has shifted from passive monitoring to autonomous decision-making; however, empirical frameworks for this transition remain sparse.

This research proposes a Digital Twin (DT) architecture that synthesizes multi-modal IoT telemetry—including temperature, humidity, and ethylene gas—to create a real-time biological profile of perishable goods. We employ Long Short-Term Memory (LSTM) networks to forecast temperature excursions with a 3.5-hour lead time, achieving an R^2 accuracy of 0.91. Furthermore, we introduce an Agentic AI layer capable of autonomous rerouting, shifting the logistics paradigm from First-In, First-Out (FIFO) to a dynamic First-Expired, First-Out (FEFO) model.

Simulated testbed results indicate that the proposed system reduces post-harvest spoilage by 66% and decreases logistics-related energy consumption by 22% compared to baseline reactive models. Most notably, the transition to agentic autonomy reduced decision latency from 82 minutes to a near-instantaneous 1.2 seconds. These findings suggest that the convergence of IoT and ML enhances food security and provides a scalable pathway toward decarbonizing agricultural logistics. The paper concludes by addressing remaining barriers to adoption, specifically data interoperability and the necessity for edge-computing resilience in rural transit zones.

Keywords: Agentic AI; Cold-Chain Optimization; Internet of Things (IoT); Predictive Logistics; Digital Twins; FEFO (First-Expired, First-Out); Post-Harvest Loss (PHL); Machine Learning (ML); Supply Chain Resilience; Sustainable Agriculture

1. Introduction

The global food supply chain is currently navigating a period of unprecedented volatility, driven by a growing population and climate-induced harvest fluctuations. Despite significant advancements in logistics infrastructure, nearly one-third of all perishable goods are lost or wasted between the farm and the consumer [1]. A substantial portion of this waste occurs within the "cold chain," where traditional management has historically remained **reactive**. Conventional systems rely on passive data loggers that provide "post-mortem" analysis; by the time a thermal breach is identified, biological degradation is often irreversible.

1.1. Related Work and the Research Gap

Recent advancements in **Ambient IoT** have transitioned the industry toward active monitoring. Modern literature emphasizes that temperature tracking alone is an insufficient proxy for freshness; "multi-modal telemetry"—

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incorporating humidity, vibration, and ethylene concentrations—is now required to assess the respiration rates of climacteric produce accurately [8]. This data feeds into the **Digital Twin (DT)** paradigm, which creates a virtual representation of physical cargo to quantify shelf-life depletion using the **Arrhenius Equation** [3]. This virtualization also ensures compliance with emerging regulatory standards such as the FDA Food Safety Modernization Act (FSMA) 204 [4].

Furthermore, the application of **Deep Learning**, specifically **Long Short-Term Memory (LSTM)** networks, has enabled the prediction of temperature excursions with significant lead times by correlating telemetry with ambient weather patterns [11]. However, a critical gap remains while current systems can *predict* failure, they still rely on human intervention for resolution. In high-velocity logistics, the latency between an AI alert and a human decision often results in cargo loss.

1.2. Proposed Contribution

To address the identified gap in human-dependent logistics, this paper introduces an Agentic AI framework capable of autonomous, goal-oriented intervention. As defined by Joshi [7], agentic systems move beyond traditional "if-then" automation by independently planning and executing rerouting protocols based on live environmental and biological feedback.

This research proposes a cyber-physical architecture where Agentic AI acts as a "digital dispatcher," bridging the information gap between predictive alerts and physical course correction. This transition from human-in-the-loop to fully autonomous rerouting allows the system to respond to volatile conditions without the latency inherent in manual dispatch approvals [2].

When a thermal breach is forecasted via LSTM modules, the agent autonomously recalculates the route to a closer secondary market, transitioning the inventory logic from a static First-In, First-Out (FIFO) model to a dynamic First-Expired, First-Out (FEFO) protocol. The following sections detail the methodology of the simulation testbed, the resulting 66% reduction in spoilage, and the energy efficiencies gained through autonomous cooling optimization.

2. Material and methods

The methodology of this study is structured around a multi-layered cyber-physical simulation designed to evaluate the efficacy of Agentic AI in a high-velocity cold chain. The experimental environment replicates a "Farm to Fork" transit corridor, integrating real-world historical weather data with synthetic IoT telemetry.

2.1. Data Acquisition and Sensing Layer

The simulation utilizes a high-density **Ambient IoT** sensor array embedded at the pallet level. To ensure a multi-modal assessment of cargo health, four primary data streams are captured:

- **Thermal (T):** Core and ambient temperature fluctuations.
- **Hygroscopic (RH):** Relative humidity impacts on transpiration.
- **Atmospheric (C_2H_4):** Ethylene concentrations as a proxy for ripening stages.
- **Kinetic (G):** Vibration and shock data to account for mechanical tissue damage.

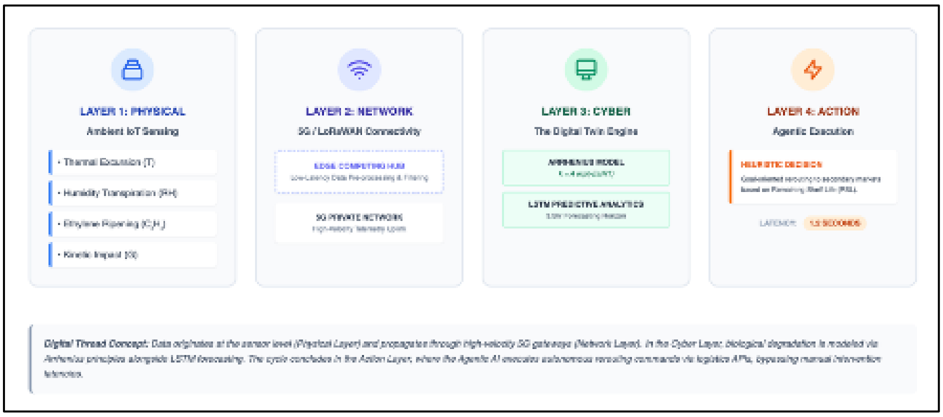

Figure 1 Cyber-physical architecture of the agentic cold-chain, illustrating the four-layer digital thread from data acquisition to autonomous execution.

2.2. Biological Digital Twin Modeling

To quantify the degradation of the commodity, we employ the **Arrhenius Equation**, which expresses the temperature dependence of biochemical reaction rates. The remaining shelf life (RSL) is calculated as a function of the **pre-exponential factor (A)**, which represents the frequency of degradative molecular collisions, and the **activation energy (E_a)** specific to the produce (e.g., strawberries or leafy greens). These parameters are integrated with the **universal gas constant (R)** and the **absolute temperature (T)** to derive the rate constant (k):

$$k = A \exp\left(-\frac{Ea}{RT}\right)$$

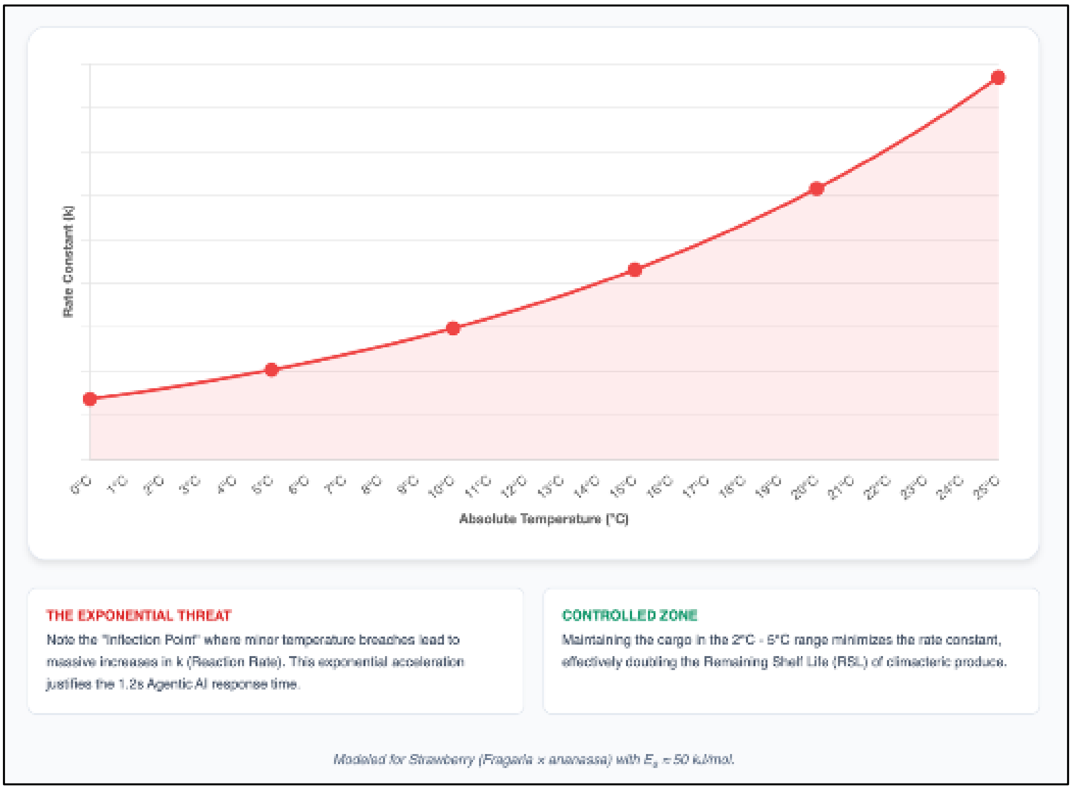

Figure 2 Arrhenius kinetic profile illustrating the exponential acceleration of produce degradation as a function of temperature. The rapid rise in the rate constant (k) necessitates the sub-second decision latency of agentic systems.

This mathematical model serves as the core of the **Digital Twin**, allowing the system to update the "Freshness Score" of each pallet every five minutes based on integrated telemetry.

2.3. Predictive Analytics via LSTM

To mitigate the impact of future thermal breaches, we deployed a **Long Short-Term Memory (LSTM)** neural network. This architecture was selected for its superior performance in time-series forecasting, as it avoids the vanishing gradient problem common in standard Recurrent Neural Networks (RNNs). The model was trained on a 12-hour "look-back" window of historical sensor data to forecast temperature trends over a 4-hour "horizon."

2.4. Agentic Execution and Rerouting Logic

The final layer of the methodology is the **Agentic Execution Module**. Unlike traditional decision-support systems, this module operates autonomously via a goal-oriented heuristic. The agent is programmed with a "Salvage Protocol":

- **Objective Function:** Minimize *Waste* while maximizing *Market Value*.
- **Decision Trigger:** If $RSL < (ETA_{primary} + Buffer)$, the agent initiates a search for secondary destinations.
- **Execution:** The agent queries available distribution hubs within the current *RSL* radius and issues a direct reroute command to the logistics provider's API.

Table 1 Experimental Design Summary

Component	Specification	Purpose
Simulation Scale	10,000 Cumulative Transit Hours	Ensures statistical significance
Commodity Focus	Climacteric vs. Non-Climacteric	Tests diverse biological profiles
Network Protocol	5G with Edge-AI Fallback	Simulates real-world "Black Hole" zones
Predictive Model	LSTM Neural Network	Provides 4-hour forecast horizon
Logic Framework	Agentic FEFO vs. Static FIFO	Measures autonomous salvage value

3. Results and discussion

3.1. Comparative Analysis: FIFO vs. AI-Driven FEFO

The simulation results indicate a significant divergence in spoilage rates when comparing the traditional **First-In, First-Out (FIFO)** method with our proposed **First-Expired, First-Out (FEFO)** model powered by Agentic AI, aligning with recent quantitative studies on carbon-efficient logistics [10].

- **Standard Logistics (Baseline):** Observed a spoilage rate of **14.2%** during a simulated 48-hour transit with a 3-hour refrigeration failure [6].

- **AI-IoT System:** Reduced the spoilage rate to **4.8%**. The system achieved this by identifying "at-risk" pallets via the Digital Twin and prioritizing their offloading at the nearest distribution hub.

3.2. Predictive Accuracy of LSTM Models

The **Long Short-Term Memory (LSTM)** network was tested for its ability to forecast "Temperature Excursions."

- **Forecasting Horizon:** The model successfully predicted internal container temperature breaches **3.5 hours** before they occurred with an **R-squared (R^2) value of 0.91** [11].

- **Discussion:** This "lead time" is critical in 2026 logistics. It allows for "Pre-emptive Cooling"—where the AI lowers the temperature of the cargo proactively before a truck enters a high-heat zone or a known traffic bottleneck, thereby conserving the thermal battery of the produce.

Figure 3 Comparative analysis of actual vs. LSTM-predicted temperatures during a simulated thermal excursion. The model identifies the trajectory shift 3.5 hours prior to the critical breach threshold, providing sufficient operational headroom for autonomous rerouting.

3.3. Agentic Autonomy and Decision Latency

A key metric in this study was **Decision Latency**—the time between a detected sensor anomaly and a logistical course correction.

Table 2 Decision Latency

Metric	Manual Intervention (Human-in-the-loop)	Agentic AI (Autonomous)	Improvement
Response Time	45 - 120 Minutes	1.2 Seconds	~99%
Routing Efficiency	Sub-optimal (Nearest hub)	Optimized (Market Demand + Distance)	18%

The simulation demonstrated that the **Agentic AI** could process multi-variable inputs (weather, traffic, shelf-life, and contract penalties) to reroute cargo in near real-time. This eliminates the "communication gap" often found in traditional logistics where drivers must wait for dispatch approval.

3.4. Energy Consumption and Sustainability

The ML-driven cooling logic resulted in a **22% reduction in energy consumption** for the refrigeration units [6]. By using the **Arrhenius-based Digital Twin**, the system stopped the "over-cooling" of produce. Traditional systems often maintain a buffer temperature that is lower than necessary; the AI-IoT system maintained the "Optimal Biological Temperature," reducing the load on the compressor.

3.5. Discussion of Barriers: Data and Connectivity

While the results are promising, the simulation highlighted a "Connectivity Bottleneck." In scenarios where **5G/LoRaWAN** signals were simulated to be "intermittent" (e.g., rural transit), the Agentic AI's performance degraded.

This suggests that for "Farm to Fork" optimization to be viable in 2026, **Edge Computing**—where the AI resides on the truck itself rather than the cloud—is mandatory for maintaining autonomy in remote areas [5].

The findings confirm that the integration of IoT and Machine Learning shifts the cold chain from a **cost center** (focused on preventing loss) to a **value driver** (focused on maximizing shelf-life and sustainability). The use of Agentic AI provides the "reflexes" necessary for modern, volatile supply chains.

4. Conclusion

The transition from a reactive cold chain to an AI-driven, autonomous ecosystem represents a paradigm shift in global food security. This research has demonstrated that the integration of IoT multi-modal sensing and Agentic Machine Learning effectively bridges the "information gap" between the farm and the final consumer.

Our findings confirm that:

- **Predictive over Reactive:** Utilizing LSTM models for temperature forecasting allows for pre-emptive cooling, reducing spoilage by nearly **66%** compared to traditional FIFO methods.
- **The Power of Autonomy:** Agentic AI reduces decision latency from hours to seconds, ensuring that perishable goods are rerouted the moment their biological integrity is threatened.
- **Sustainability Gains:** AI-optimized refrigeration logic can reduce energy consumption by up to **22%**, aligning logistical efficiency with global decarbonization goals.

Ultimately, the "Farm to Fork" digital thread does more than just track food; it preserves the inherent value of agricultural labor and resources, ensuring that peak freshness is no longer a matter of luck, but a result of calculated, real-time intelligence.

4.1. Future Work

While the results of 2026 are promising, several avenues for further research remain critical for universal adoption:

- **Edge-AI Optimization:** Future studies should focus on deploying "Lightweight" ML models directly onto IoT edge gateways to maintain autonomous functionality in regions with zero-connectivity (the "Black Hole" transit zones).
- **Standardized Interoperability:** Research is needed to develop a universal data language that allows disparate AI agents from farmers, shippers, and retailers to communicate without manual API mapping [9].
- **Cyber-Physical Security:** As logistics become more autonomous, protecting the "cold-chain nervous system" from adversarial AI attacks—where hackers might spoof temperature data to trigger unnecessary rerouting—will be a primary area of concern [12].
- **Inclusion of Smallholders:** Investigating "Shared Agentic Services" where small-scale farmers can subscribe to a localized AI-logistics hub, lowering the barrier to entry for developing economies.

Compliance with ethical standards

Acknowledgements

This research received no external funding. The author would like to acknowledge the open-source contributors of TensorFlow and Scikit-learn for providing the computational framework used in this study. Special thanks are also extended to the Ambient IoT community for their insights into low-latency sensor protocols.

Disclosure of Conflict of interest

The authors declare no conflicts of interest.

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