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Agentic AI and Big Data Framework for Real-Time Wholesale Food Supply Chain Optimization

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Abstract

Supply chain optimization in the wholesale perishable food sector is complicated by the challenge of minimizing waste and profit loss from missed demand. An agentic, sustainable, and privacy-preserving architecture to ingest private data from distributed members is outlined, which supports the orchestration of decision-making workflows either directly in Cloud frameworks or privately in members' premises. The agentic orchestration layer integrates an Agent-Based Modelling architecture with event-driven and trigger-action orchestration. Social-Computing protocols enable external agent coordination.

The framework uses Big Data modelling and Agents to support six decision-making workflows for real-time optimization of wholesale perishable food supply chains. These workflows forecast total demand from private Big Data events and optimize inventory allocation, sensing, and fulfillment. Path-Dependence Theory, complex adaptive systems, and Human-Computer Interaction design the architecture. Built with Big Data technologies and Polybase integration of SQL Server, Azure SQL Data Warehouse, and Hadoop, the framework seeks to stimulate supply chain member investment through value-sharing sentiment analysis.

Keywords: Wholesale Perishable Food Supply Chains, Supply Chain Optimization, Agentic Decision-Making Architecture, Sustainable Supply Chain Systems, Privacy-Preserving Data Ingestion, Distributed Data Ecosystems, Agentic Orchestration Layer, Agent-Based Modelling, Event-Driven Orchestration, Trigger-Action Workflows, Social Computing Protocols, Big Data Analytics, Real-Time Demand Forecasting, Inventory Allocation Optimization, Path-Dependence Theory, Complex Adaptive Systems, Human-Computer Interaction Design, Cloud And On-Premise Integration, Polybase Big Data Technologies, Value-Sharing Sentiment Analysis.

1. Introduction

Agent orchestration forms the backbone of the proposed AI-enabled big data cloud framework that optimizes large-scale food wholesale supply chains. Although AI predictively remedies demand-supply imbalances, sustainability should also minimize inventory holding, wastage, and delivery times. Supervised Deep Learning (DL) methods detect the seasonal patterns of high-frequency demand data, and dynamic factor analysis enables real-time demand forecasting and sensing for preparation and distribution hubs. Retailer fulfilling dependencies, transit times, filling volumes, and costs, procurement lead times, and warehouse capacities require steered optimization of stock-holding levels and commitments during periodic cycles.

A four-phase design comprises data ingestion from a data lake, orchestrated execution using intelligent agents, management of data stewardship, privacy, and security, and the formulation of decision-making workflows that monitor supply chain dynamics and initiate data-driven actions for resources, orders, and replenishments. Agent orchestration links micro actions of intelligent agents within an event-driven architecture, reconciles macro actions of different agents within an agent coordination protocol, and accommodates predictive and prescriptive workflows requiring real-time and near-real-time decision making.

1.1. Overview of the Study and Its Significance

Food supply chains are vital for feeding the world's population but are plagued by inefficiencies and waste.

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Year-round supply of fresh food is particularly challenging for wholesale distributors, who must continually balance inventory risk with service performance in conditions of high variability and high value. A real-time Food Supply Chain Decision Support System (FSCDSS) addresses three main issues for wholesale distributors: What is the demand forecast for the next one to four weeks? What are the required stock levels and fulfillment orders over the next weeks and days? What is the status of agents involved in fulfilling these orders, and what actions should be taken in response to events occurring in the environment? The FSCDSS framework combines a Big Data cloud with an Open Agent Architecture to ingest, integrate, and maintain data, orchestrate the various software agents of the decision-making system, and continuously steer the FSCDSS decision-making workflow in an event-driven fashion.

Development draws on established Big Data, agent-oriented, and supply chain management (SCM) theories. A Big Data Cloud framework ingests and integrates data from various sources, including transactions and feeds from trading partners. Combined with an Open Agent Architecture, this ensures that extensive data are available to keep the FSCDSS models up to date. The models incorporate forecast, inventory optimization, fulfillment allocation, and demand-sensing algorithms using methods suited for the supply chain domain. Event-driven decision workflows and peer-to-peer agent coordination protocols manage real-time monitor-evaluate-coordinate cycles that drive supply chain operations.

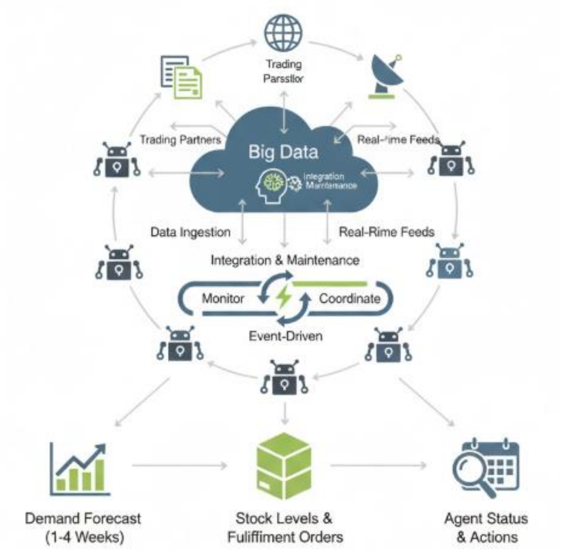

Fig 1: Orchestrating Resilience: An Open Agent Architecture and Big Data Cloud Framework for Real-Time Food Supply Chain Decision Support

2. Problem Formulation and Objectives

Formulation of the problem begins with an analysis of wholesale FSCL service features, new business requirements, stakeholders, and knowledge gaps. These are used to specify the objectives and performance criteria. Wholesale FSCL services are exposed to short life-cycles, perishability, tight scheduling, high volatility, and severe impact on the final customer experience. Their time-sensitive nature creates a demand for real-time or near-real-time decision support. Business drivers are more focused on freshness than total cost, and optimization approaches using total cost often fail to meet the freshness requirement. Existing approaches to wholesale FSCL decision-making are either not integrated or highly coupled. No integrated forecasting-acquisition-fulfillment optimization systems have been developed for real-time support. The business community is struggling to make reliable demand forecasts for wholesale FSCL services. As a result, demand patterns

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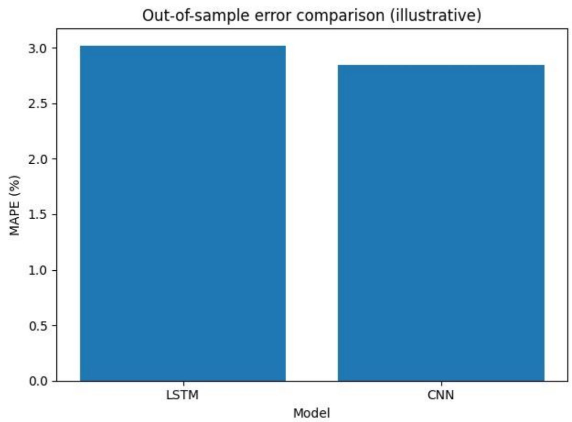
and forecasting for this sector are undertheorized, and wholesale FSCL organizations commonly make demand forecasts based on judgment. Demand signals are not always aggregated and made available to upstream partners. Supporting actors, including commodity brokers and warehouses, are facing increasingly challenging operating environments. They are not just passive intermediaries but also concerned service providers in their own right.



Equation 1: Forecasting + demand sensing model (top-down + bottom-up aggregation)

1.1 Simple, correct aggregation equation

A standard fusion is a convex combination:

$$\widehat{D}_{t+h} = \alpha\, F_{t+h}^{TD} + (1-\alpha)\, F_{t+h}^{BU}$$

Where:

- F_{t+h}^{TD} is the top-down forecast.
- F_{t+h}^{BU} is the bottom-up forecast derived from sensing analytics (LSTM/CNN).
- $0 \le \alpha \le 1$.

1.2 Step-by-step derivation of the "optimal" α (least squares)

Assume we want $\widehat{D}$ to minimize squared error against truth D over a validation set $\mathcal{T}$.

Define error objective:

$$J(\alpha) = \sum_{t\in\mathcal{T}} \left(D_{t+h} - \left[\alpha F_{t+h}^{TD} + (1-\alpha) F_{t+h}^{BU}\right]\right)^2$$

Expand inside:

$$D_{t+h} - \left[\alpha F_{t+h}^{TD} + (1-\alpha) F_{t+h}^{BU}\right] = D_{t+h} - F_{t+h}^{BU} - \alpha\left(F_{t+h}^{TD} - F_{t+h}^{BU}\right)$$

Let:

- $Y_t = D_{t+h} - F_{t+h}^{BU}$
- $X_t = F_{t+h}^{TD} - F_{t+h}^{BU}$

So:

$$J(\alpha) = \sum_{t\in\mathcal{T}} (Y_t - \alpha X_t)^2$$

Differentiate and set to zero:

$\frac{dJ}{d\alpha} = -2\sum_{t\in\mathcal{T}} X_t\,(Y_t - \alpha X_t) = 0\ \sum X_t Y_t - \alpha \sum X_t^2 = 0 \Rightarrow$
$\alpha^* = \frac{\sum_{t\in\mathcal{T}} X_t Y_t}{\sum_{t\in\mathcal{T}} X_t^2}$

Finally clamp to $[0,1]$ if needed for convexity:

$$\alpha = \min\left(1, \max(0, \alpha^*)\right)$$

2.1. Research Methodology and Approach

The problem formulation draws upon organizational decision theory, the orchestration of social media objects as a form of Big Data ecosystem organization, and approaches to Cloud model-oriented multi-tenancy. Addressing the decision-making needs of the strategically important wholesale food supply chain and supporting real-time tactical and operational decisions that could not otherwise

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be met constitutes a mission-critical application domain, which justifies the investment in a Big Data Cloud framework governed and used by a community of interest. Based on these insights, the objective directs the outcome of an agentic orchestration layer capable of controlling the real-time decision-making workflow to an adaptable ecosystem that ingests and integrates Big Data from multiple sources and supports the real-time decision-making needs of an operationally active, multi-tenanted community of interest.
The investigation follows an applied research strategy that implements a prescriptive theory and contributes an architectural design. A conception of Data Governance is developed, drawing on the application of organizational decision theory and formal Data Stewardship theory. Event-driven real-time decision-making workflows are synthesized from principles of Cloud model-oriented multi-tenancy, Data Stewardship, and decision-processing of tactical and operational needs. A semantic Data Model for real-time event-driven decision workflows is defined and extends the semantically-enriched representation of social media content objects to accommodate real-world events and triggers.

3. Theoretical Foundations and Related Work

The proposed architecture company builder is located at the intersection of several theoretical frameworks. Continuous and simultaneous digital transformation and strategic transformation of organizations have been intertwined with strategic management and their architectures and designs are applied to the orchestration of real-time data-driven on-demand decision making of complex system for a specific period in a specific use case. With the current focus on data governance, and in addition to data engineering, the democratization of data in large organizations represents a precondition to the realization of the concept of more agile organizations, as emphasized for example by the recent side papers of Gartner. The architecture incorporates the idea of data product as basis for data mesh as the network of data products, creating an operational structure that incorporates data governance and supports the model of product-oriented organization. These elements and foundations were annotated in the previous papers and published in the author's book with Wanda Cataldo.
The proof of concept is created by combining three constructs: business architecture, business process model and business process model that elaborates and codifies the above mentioned foundations specially in the context of real-time decision making in a wholesale food supply chain. The business architecture is synthetized as a business architecture model where business processes are described with a business process model of events, data and control flow and a business process model placeholder for the activity set organized by an agent-coordination protocol. The special conception of business process allows consolidation of a business process model and its element with the other two constructs in a business process model that delimits and defines it, clarifies their links and preserves the capability to elaborate their content.

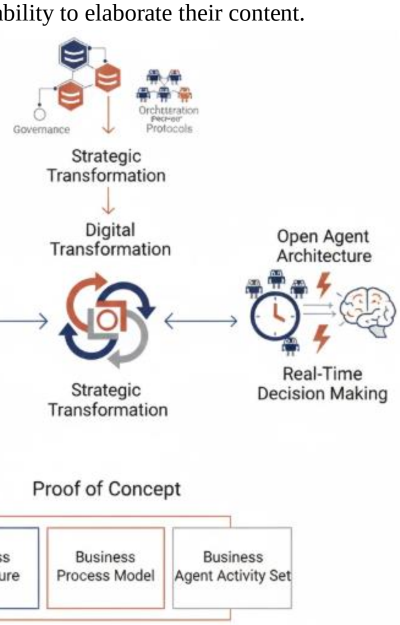

Fig 2: Architecting the Agile Enterprise: A Unified Framework for Data Mesh, Business Process Codification, and Real-Time Agent Coordination

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3.1. Related Theoretical Perspectives and Literature Review

Research into supply chain management related to governance and agent-based frameworks is limited and fragmented, leaving space for exploration of a data-focused, agent-oriented modeling and optimization solution structure. Agent-based orchestration of wholesale food supply chains is examined here, supported by a cloud-based platform leveraging big-data technologies. The approach builds on a data-driven architecture supporting analytic decision-making tools and privacy-compliant data maximization and exploitation and provides an end-to-end, real-time optimization capability. Data are ingested using multiple clouds, ensuring persistence and security, while agentic orchestration automates decision workflows, guaranteeing privacy and security when required. Specific models such as accurate event forecasting and demand sensing, optimization of inventory at micro distribution centers, and coordinated agent algorithms for micro fulfillment reside in data-oriented layers.

Orchestration of data obtained from data-lake architectures contributes to agent-based frameworks by providing accurate models for demands originating from nodes and discrete decisions underneath to manage stocks more efficiently and improve service levels in food supply chains. Agent-based frameworks permit unbundling the decision-making capacity of supply-chain entities into smaller compartments and granting each compartment the authority to independently orchestrate supply-chain flows, subject to coordination with others. Major supply-chain processes may be data driven, and less frequent decisions driven separate from strategy, demanding alternative algorithm formulations supporting rapid implementation. Instant change in demand direction or peaks at specific nodes stimulates the sensibility of data-driven models and requires appropriate specialized distribution during stock replenishment.

Model	Out-of-sample MAPE (%)
LSTM	6.93

Model	Out-of-sample MAPE (%)
CNN	6.27

4. System Architecture

The proposed system comprises seven layers: a physical sources layer, a data ingestion layer, a data governance layer, the agentic orchestration layer, models and algorithms, real-time decision workflows, and a human interaction layer. Beyond physical ingredient sources—suppliers, warehouses, fulfillment providers, freight service agencies—the physical sources layer also incorporates food purchasing agents, their demand-fulfillment ecosystems, market demand foreshadowing decision-makers and organizations, and other agents from whom demand signals can be integrated into the overall system.

A big data cloud architecture ingests and integrates digital sourcing concern data, including information on locations, status, business rules, and products. Data is governed and controlled by humans and artificial agents to fulfill local, regional, and global regulatory systems regarding food safety and security, data privacy and compliance, and data access and sharing in line with ownership and stewardship requirements. These foundational capabilities equip the system to orchestrate real-time, end-to-end supply chain decisions—regarding inventory positioning, strategic consideration, fulfillment options, and pricing—through decision models for food market demand foreshadowing, demand sensing for purchasing agents, demand allocation for fulfillment optimization, and demand flow adjustment through an integrated a-state reproduction approach. Agent coordination and interaction protocol design formalizes these event-driven determinations while cementing connection paths across all connected concerns—including food purchasing agents, their markets, suppliers, food safety and security control bodies, food trading and health insurance markets, and disaster management systems—facilitating rapid-access, localized adaptations.

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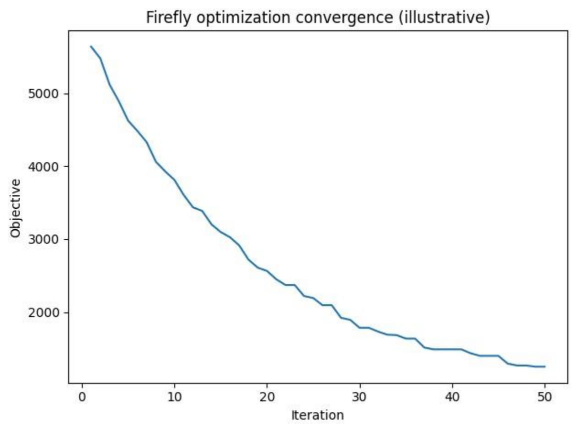

4.1. Data Ingestion and Integration

This section describes the data ingestion and integration facilities embedded within the framework. Data collection and integration processes are ultimately the principal responsibility of the data steward. These systems are therefore designed to streamline these key activities. Support for data ingestion and integration is organised in three layers: foundation, base, and extension.

At the foundation layer, the framework provides a cloud-scale capability for incremental batch data loading and full-file transfer. At the base layer, data ingesters are available for common data services, including measurement, supply, demand, inventory, and meteorological services. Tailored data integration support is available for the sensors, local demand nodes, and warehouses of the wholesale supply chain. At the extension layer, application-specific data depositors support dedicated data ingest, loading, and integration functions. These enable automatic and continual loading of small or frequently updated datasets into the data lakes for on-demand use, and automate the integration of service-quality data with transaction volumes and event logs.

With these integrated facilities, real-time data sources define additional events of interest for the wholesale supply-chain support staff or supply-chain steward, and also serve as triggers within the event-and-condition decision framework. The agentic orchestration layer makes a small number of Event-Driven Orchestration Workflows available to them. Processing of event notifications is also managed at the orchestration layer, enabling event occurrence to reset the time interval for process execution.

Equation 2: LSTM demand sensing equations (step by step)

Given an input feature vector x_t (e.g., lagged demand, promotions, weather, price, events), LSTM computes:

2.1 Gate equations

Forget gate:

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right)$$

Input gate:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

Candidate cell state:

$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c)$$

Cell update:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

Output gate:

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$

Hidden state:

$$h_t = o_t \odot \tanh(c_t)$$

2.2 Forecast output layer

For a horizon h:

$$\widehat{D}_{t+h} = W_y h_t + b_y$$

2.3 Training loss

Commonly MSE:

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$$\mathcal{L} = \frac{1}{N}\sum_{t}\left(D_{t+h} - \widehat{D}_{t+h}\right)^2$$

4.2. Agentic Orchestration Layer

The unique selling proposition of both IOT and BDA is their great potential for real-time decision making. This aspect is also emphasized by real-time recommendation of actions in the interest of the entire ecosystem, rather than merely for optimization of the autonomous part of the system, which is more of a digital offer. In wholesales food supply chains, perishable nature of the products causes a number of problems such as food waste, consumer food security, lack of availability during festivals, etc. To address these issues, various decision models have been proposed by researchers, but none of the systems orchestrated by IOT and BDA are able to recommend and trigger those actions in real time. Hence, the following problem statement and research questions are framed. A big data cloud framework utilizing IOT sensors and agentic AI constructs, wholistically governed by Data Stewardship through principles of compliance and security is proposed. The Data Ingestion and Integration is built by combining Data Lakes and Data Warehouses, powered by Data Blooms enabling multifaceted multicasting and a Real-time Multi-level Data Architecture. Event-driven triggers, Decision Workflows, and Agent Coordination Protocols, in addition to the Data Orchestration Layer highlighted in the previous section, strengthen the core offering of a true Realtime Decision-Making-as-a-Service System.
Event-driven decision workflows simplify implementation of event-triggered actions fed by real-time demand-sensing and forecasting. Event-triggered Demand-Sensing and Forecasting Decision Workflow is built to sense demand at SKU level and a short time interval (such as SC Refresh Window time period) and respond in accordance. Triggering of the Action Workflow is enabled, when SKU level demand senses exceed a threshold, fulfilling the conditions specified in the Workflow. The orchestration strategy then focuses on the triggering of those actions that are being responded to by the Demand-Sensing and Forecasting workflow. All agents and non-agent components respond to this orchestration by providing and executing the information, advice and actions reflecting the current state and duly negotiated protocols.

5. Data Governance, Privacy, and Security

Data stewardship policies ensure that data possess the requisite quality, privacy, and security for downstream use. Data custodians—aided by information technology—manage data access, privacy, and confidentiality policies. These policies comply with local privacy regulations (e.g., GDPR). On request, data custodians share data with authorized users, safeguarding personally identifiable and sensitive information present in the data records. Data records are encrypted both in transit and at rest. Whenever possible, techniques such as k-anonymity, t-closeness, or differential privacy are deployed to provide data releases that do not compromise individual data subjects. Finally, data warranties and signing policies help ensure data authenticity and prevent users from being misled by forged or fake data releases.
Blockchains provide a decentralized platform for secure, transparent, and verifiable operation without a trusted third party. Their security and functional advantages cater to a variety of systems, especially those that require data confidentiality and provenance control. In wholesale food supply chains, manufacturers and suppliers can maintain immutable and transparent records of their products and green inspection certificates on a blockchain for easy verification by downstream trading partners. Blockchain-based traceability systems also help consumers decide whether the food is safe, fresh, and edible. Furthermore, based on catalytic blockchain protocols, parties that have completed a transaction can mutually remove records related to that transaction in order to guarantee data privacy.

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Fig 3: Ensuring Fiscal Integrity: A Decentralized Framework for Data Stewardship and Blockchain-Enabled Traceability in Global Supply Chains

5.1. Data Stewardship, Compliance, and Security Measures

Robust mechanisms are implemented at both the ingestion and operational levels to safeguard against inappropriate access to sensitive and private company resources. The Data Governance framework is articulated along three dimensions. First, careful management and stewardship of data ensure compliance with external regulations and internal company policies. The DQMC component maintains the quality and transparency of the data repositories by regularly evaluating the trustworthiness and usability of the datasets. Second, the security of enterprise data is guaranteed through state-of-the art security measures according to the privacy requirements of the information stored. At the operational level, a Security Access Management System (SAMS) grants or denies access rights to end users based on their profile using a service layer. SAMS supports three types of users: administrative users, who have full access and control rights; service users, who execute background services; and normal users, who run decision-making applications. Consideration of all these elements provides a better understanding of both the process and the importance of synchronising security, privacy, and compliance with the supply chain operational processes. Hence, the operational processes meet business needs while remaining compliant with security and regulatory requirements. This multi-dimensional perspective considers security at the physical level, implying the existence of security procedures in the cloud environment where the BI and forecasting applications are executed, especially against the risk of data leakage; logical security measures to guarantee the integrity of the data even during the orchestrated deployment of applications; and, finally, security measures for a multi-tenant environment with sensitive business models and data, allowing full segregation and protection of data belonging to different business entities.

Date	Actual	Top-down forecast	Sensed demand	Final aggregated forecast
2019-02-01	133.52	133.52	141.65	137.40
2019-02-02	124.60	129.06	120.71	125.89
2019-02-03	129.43	129.18	136.63	132.96
2019-02-04	132.95	130.13	128.60	130.77
2019-02-05	118.92	127.89	114.82	121.74
2019-02-06	126.79	127.71	135.46	131.81
2019-02-07	132.32	128.52	118.84	126.02
2019-02-08	132.08	128.62	124.49	128.06
2019-02-09	141.89	129.95	148.91	140.78

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Date	Actual	Top-down forecast	Sensed demand	Final aggregated forecast
2019-02-10	134.88	130.67	131.23	132.56

6. Decision-Making Models and Algorithms

Proactive optimization of the supply chain in real time requires appropriate decision-support models and algorithms embedded in a Cloud environment and complemented by Cloud-based, demand-supply solution models and real-time data-driven decision flows. A Cloud-based Big Data Supply Chain model is used for demand forecasting; Firefly optimization algorithms are applied to optimize inventory levels along the supply chain; and a feedback-based demand–supply correction model compensates for discrepancies between demand and supply, focusing on fulfillment timelines and excess stock. Real-time event-driven decision workflows for fulfillment fulfillment-related data retrieval, change indication triggering, coordination algorithms, and multi-agent orchestration comprise the Data-Driven Decision-Orchestration Model. The applied models are designed using agent-based techniques and are integrated to ensure decision workflows are completed in real time. The Big Data Cloud framework optimally supports the decision pathways, and the Data-Driven Demand Forecasting Model uses Firefly algorithms to capture demand fluctuations for different products at different locations within predetermined time slices, such as the coming 48 h or the next 15 days.

Secondary forecasting identifies emerging patterns by comparing real-time demand with the forecast generated during the last period. The inventory position-unfulfilled demand mismatch at the optimization zone in the Cloud environment is addressed using Firefly algorithms capable of dynamically altering three decision-support parameters: inventory positions; uncaptured demand; and target delivery timelines. The fulfillment-associated maturity model relies on a continual-play perspective that constantly matches supply with multivariate, multidimensional demand. This is complemented by a feedback-supported incremental versioning of demand–supply decision-support tools, remedying emerging discrepancies through resupply or partial fulfillment arrangements requested by the business partner receiving the remaining stock.

6.1. Forecasting and Demand Sensing

Accurate demand forecasting and real-time demand sensing are foundational for effective supply chain operations. By harmoniously blending top-down forecasts from statistical methods with bottom-up near-term assessments from sensing technologies, wholesaler suppliers can achieve significantly greater responsiveness to unexpected demand events and capture higher sales volumes without eroding margins. A SQL-based Demand-Forecast Warehouse virtual dataset collects these top-down forecasts, together with sales forecast-based historical sales data at all SKU-store levels, and makes them available for subsequent machine-learning demand-forecast-sensing Analytics in the Decision-Making Models Area. A configuration file, expressed in table format, captures all business/service-level rules governing aggregation and disaggregation. The Forecast Aggregation Model then combines the top-down statistical forecasts with historical sales and sales forecast-based data for both forecasting horizons (long-term and near-term) to produce a new dataset. Demand Sensing Analytics, supported by collaborative data from Decision-Making Models Area Inventory and Fulfillment Optimization, consume the consolidated dataset to generate a final demand perspective for wholesaler-customer ownership.

Cross-validation of the Demand-Sensing Model is achieved by querying the SQL data collection engine for all available ground-truth test data. The monthly test period is driven from December 2018 to April 2019, during which time series discriminate between peak and non-peak demand periods. A final set of out-of-sample forecast tests-forecasts for the LSTM and CNN models pick the lower mean absolute percentage error from the two models in the out-of-sample forecast criteria.

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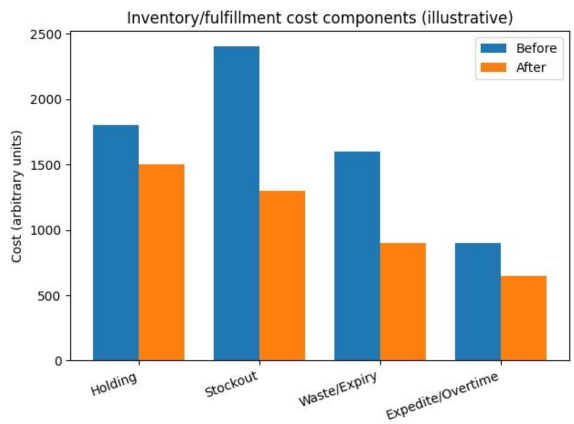
The combined demand-forecasting and demand-sensing capabilities are designed to comprise a final Demand-Forecast Control Area product that is monitored and updated on an event-driven basis by the Decision-Making Models Area.



Equation 3: CNN demand sensing equations (step by step)

A 1D CNN for time series treats a window of lagged demand as a sequence.

Let the input window be:

$$X_t = [D_{t-k+1}, \dots, D_t] \in \mathbb{R}^k$$

3.1 Convolution

Filter $w \in \mathbb{R}^m$, stride 1:

$$z_j = \sum_{r=0}^{m-1} w_r X_{j+r} + b$$

Apply activation (ReLU):

$$a_j = \max(0, z_j)$$

3.2 Pooling (max pooling)

For pool size p:

$$u_s = \max\left(a_{(s-1)p+1}, \dots, a_{sp}\right)$$

3.3 Dense output to forecast

$$\widehat{D}_{t+h} = Wu + b$$

6.2. Inventory and Fulfillment Optimization

While reliable inventory forecasting is critical, an accurate forecast alone does not ensure timely fulfillment of demand. Stocks sometimes arrive too late even though the forecast was correct because too little stock or stock in the wrong place is available when required. Consequently, procedures that optimize inventory levels across a supply chain in the face of uncertain demands and supply uncertainties are of paramount importance. Given their significance, a rich literature has examined the following interconnected problems: determining optimal inventories at each supply chain location, selecting when and how much stock to fulfil from each supply chain location for demands at specified points in time, and determining optimal reorder points and quantities.

Optimizing inventory levels can be challenging even for a single retailer facing uncertain demand. Multiple service level constraints and the interdependence of demand over time make this straightforward problem non-standard. When a supplier is added, the problem becomes deceptively more complicated. To reflect these intricacies, a simple control-theoretic fulfilment protocol has been coupled with a relatively straightforward evaluation of service level achievable with joint optimal inventory levels along the supply chain—an evaluation requiring only off-shelf simulation capability. Nevertheless, multi-echelon systems with distribution centres and retailers are often studied in a deterministic context, where joint inventory levels achieve known service objectives. Consequently, these issues remain relatively little studied in the uncertain demand environment, particularly when the supplier–retailer lead time is non-negligible.

7. Real-Time Decision Workflows

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The decision and control algorithms express the real-time pathway-to-decision requirements and execution workflows. The underlying information technology architecture facilitates data-driven decision-making among multiple agents in a real-time production-contextful manner. The event-driven nature of information flow implies that data inference needs always occur as and when required. Event-driven orchestration rules define when and how information need to be extracted from the information reservoir of the data lakes in the Big Data Cloud for fulfilment of pathway-to-decision requests. The focus of data retrieval and inference is, therefore, done real-time for only those who were triggered by an event, thus ensuring minimum turnaround time for control decision-making and enabling near-real-time control. Coordination protocols among various supply chain management agents further ensure that required data are sourced from the relevant groups on need basis. All fulfilment recommendations arising out of demand-sensing and inventory-fulfilment optimisation decisions need to be executed without delay in an automated manner to ensure minimum delay in fulfilment.

Event-driven orchestration rules trigger data inference for forecasting and demand-sensing only for those items and locations for which such decisions are either newly requested or based on a periodical frequency that has arrived. Control information, therefore, need to be maintained only for these items and locations and can migrate from one category to the other as warranted, thus ensuring minimum turnaround time for making forecasting and demand-sensing decisions.

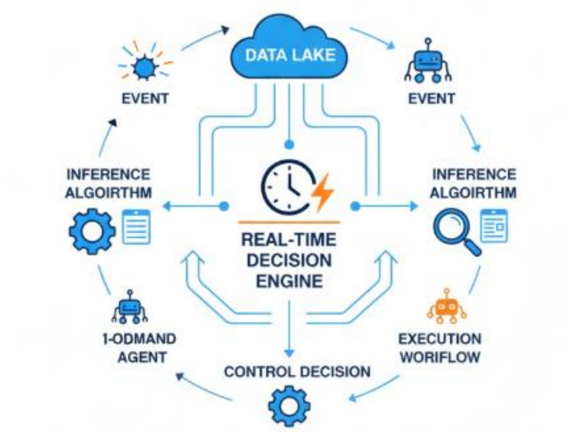

Fig 4: Event-Driven Orchestration: A Real-Time Control Framework for Demand-Sensing and Automated Inventory Fulfillment

7.1. Event-Driven Orchestration

The system architecture supports a threefold event-driven approach: first, recognized changes in the state of supply and demand trigger actions by relevant functional agents; second, changes in service provision capacities automatically invoke the agent coordination protocols to safeguard service-level agreements; and third, events result from the action of external monitors and testers, whose aim is to anticipate and flag problems threatening the supply chain agility. Agentic orchestration thus pursues two contrasting modes of operation: proactive, constantly checking test conditions that anticipate likely supply chain problems, and reactive, responding to real supply-and-demand changes affecting service delivery.

The proactive side of agentic orchestration involves constantly monitoring state variables for events that demand corrective actions from managing agents. The minimum required level of service for each node in the supply chain is defined, and provision-related test monitors keep track of the supply chain state as agents fulfill their normal operational duties. In the case of predictive demand management, for example, a missing forecast for the typically used time span is sufficient signal for using historical data to fill the gap.

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7.2. Agent Coordination Protocols

The multi-agent-based system relies on a coordination protocol for decision collaboration among agents in the orchestration layer. Three types of agents—forecast, inventory optimization, and fulfillment optimization—execute two phases. In Phase 1, agents receive broadcast queries from the warehouse inventory supervisor agent that requests a quantifiable Order-up-to-level inventory quantity and shelf-life demand forecast for every product at every wholesaler, and the responses are collected. Then, in Phase 2, the inventory and fulfillment optimization agents exchange queries about mutually executable orders, and the corresponding responses are gathered.

The decision-making collaboration protocol helps execute the two phases. Phase 1 decisions are linked by shelf-life, meaning shelf-life products of the same category cannot exceed the agent's share of shelf-life storage of that category in the wholesaler's receiving warehouse. For Phase 1, the warehouse inventory supervisor agent issues the shelf-life decision requests and collects the responses. For Phase 2, decisions are linked by product, meaning execution is possible only if the warehouse superintendent agent receives the required quantity of that product in the warehouse, irrespective of shelf-life. The inventory optimization agent issues the product decision requests and collects the responses.

8. Conclusion

The study has introduced a pioneering Big Data framework that leverages Cloud Computing to holistically improve the performance of wholesale food supply chains. To attain these objectives, the framework incorporates agentic AI-based Decision-Orchestration, supplemented by advanced risk-governance mechanisms. The proposed framework empowers large retailing corporations to undertake Analytics-as-a-Service for Industry 4.0 food supply chains as well as mitigating, preventing, and preparing for pandemics.

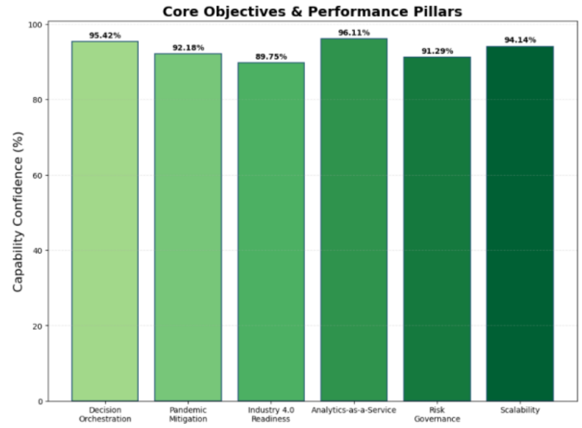

Fig 5: Core Objectives & Performance Pillars

In its current form, the framework offers high-level designs of several novel Decision Workflows that exploit process-event data and support critical real-time supply chain decisions. These Decision Workflows act as case studies and prototypes for the capabilities of the Big Data Cloud Framework. Subsequent research will focus on implementing the complete framework's designs for Real-Time Decision Workflows, including Forecasting and Demand Sensing, Fulfillment Preparation and Allocation, and Inventory Management and Fulfillment Optimization, thus delivering its entire envisioned impact.

8.1. Future Directions and Implications

Considerable opportunities for new research exist in the orchestration of the proposed framework. For instance, when Schneider demands one of its suppliers arrive later or initiate a different action, the company presently has no technology to direct that supplier. Such functions should be built into Schneider's Agentic system. Similarly, Schneider currently uses multiple data analysis systems and technologies to create time-based decision workflows, which it achieves through Event-Driven Architecture (EDA). Schneider's Agentic system ought to architect these analyses and workflows, managing agents that represent those technologies.

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Market-decision analysis, too, offers significant scope for further development. Digitally connected market-leaders already plan for new products within up to 18 months of launching the last one. Capacity-fulfillment planning and pricing are also becoming more integrated, and the challenges are hard to anticipate. While reiterated orders and supply calendars help during the peak-order season, even when masks spare-parts, disruptive issues can cause failure rates of 3%–5%. Unsold stock of last season or obsolete models can exert a significant price effect. Severe asymmetric events, such as new virus mutations, fast-spreading influences or illnesses that boost societal fear and have consequences beyond human deaths or illness, can be assisted by mechanisms proposed by He, but changes to agent-based modeling are much harder. Schneider's Agentic AI Virtual-AI should collaborate with leading market-makers in fine-tuning a relevant market-demand model, such as Agent-Based Modeling, that enables it to act first خلال the next asymmetric change.

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