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Algorithmic Forecasting of Fresh Demand: A Comparative Analysis of ML Approaches, Selection of Metrics (WMAPE/Pinball), and Resilience to Shocks

Olga Maximchuk[1]

[1]Vegberry Middle East Farm Management and Operation L.L.C
Parkland, USA

***Abstract*— The rising instability of fresh food markets, which has been marked by demand shocks, climatic uncertainty, promotion-driven variability, and logistics volatility, has hugely increased the economic impacts of prediction errors in perishable supply chain. In Fresh categories, demand misalignment can be converted into instantaneous waste production, stock-outs, loss of margins and inefficient capital usage. In spite of these structural limitations, a significant portion of retail forecasting systems to this day rest on linear statistical models and heuristic safety buffers which do not work very well under nonlinear demand dynamics and shock regimes. This paper focuses on algorithmic demand forecasting as a structural format of coordination in the digital Fresh ecosystems instead of a strictly technical-analytic instrument. The study performs a comparative analysis of the classical time-series (SARIMA) models with the machine learning (Gradient Boosting XGBoost, and Recurrent Neural Networks LSTM) on the longitudinal retail data (120 stores, 24 months). The analytical structure incorporates weighted mean forecast accuracy (WMAPE), probabilistic calibration (Pinball Loss), shock sensitivity test, and simulation of financial impact. The paper also evaluates the implications of quantile forecasting on the need to optimize safety stock and the risk-adjusted inventory management. Experimental evidence indicates that machine learning models lower WMAPE by 39-47 percentages relative to classical statistical standards. Write-offs go down to 1920 percent to 1012 percent and stock-outs go down by about 45 percentage points. Financial simulations show an increase in the margins of more than 3 million a year in medium size retail systems. Classical models amplify the error (up to 75 under simulated demand shocks, +35 per cent and -40 per cent)) but machine learning architecture error growth is nearly 47-49 times less than that of classical models. Forecasting with Pinball Loss based on quantile offers endogenous safety stock, which cuts and reduces inventory buffers by 18-22, and reticles service levels above 94. These results affirm that probabilistic forecasting structures are valuable in efficient as well as resilient Fresh markets. The conclusion of the study is that predictability of performance in perishable supply systems is mainly based on the design of algorithmic governance other than gradual modifications to conventional statistics. The relevance of algorithmic demand forecasting is a systemic risk redistribution process, which influences the waste dynamics, capital intensity, and the stability of the margins. This study makes machine learning forecasting one of the infrastructural pillars of digital Fresh supply coordination through a combination of predictive analytics and financial implications of the ecosystem level. Methodological extensions of this framework to cross-market validation, further investigation of the interpretability of the model and adaptive governance maturity of perishable ecosystems should be pursued in future research.**

Keywords— algorithmic demand forecasting; Fresh categories; machine learning; WMAPE; Pinball Loss; quantile forecasting; shock resilience; waste reduction; inventory optimization; digital supply chain governance; perishable goods management

I. INTRODUCTION

The current Fresh retail setting is vulnerable to unprecedented instability marked by demand outbursts, weather unpredictability, logistics instability and increased pace of digital transformation. Against this, the application of demand forecasting has been transformed by becoming an auxiliary role of analysis into a strategic governance tool that directly establishes cost efficiency, generation of wastes and working capital, as well as systemic resilience. Even the slightest deviation in the forecast in fresh categories with short shelf life and high margin sensitivity is hugely important in creating irreversible economic losses. Therefore, the technical optimization exercise of algorithmic demand forecasting has been abolished as a structural determinist of ecology.

Nevertheless, this change has left much of the retail forecasting practice held captive to simplified statistical models or managerial involvement in heuristic adjustments that are elicited by managerial intuition. Time-series methods and

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moving averages are commonly used in settings where demand dynamics are nonlinear, volatility is due to promotions, and weather-dependent demand, and structural breaks. Such models can be satisfactory in the stable conditions, but it is observed that they amplify errors significantly during demand shocks. These errors in Fresh supply systems not only appear as forecast errors but also physical spoilage, stock-outs, loss of margin and destabilization of the supply chain. Notably, these inefficiencies are also often explained by exogenous perturbation and not an inherent incompetence in forecasting architecture.

The continuity of the traditional logic of forecasting indicates a conceptual restriction within one practice and within one field of scholarship. Although the supply chain research has carried out profound study of inventory optimization, logistics design, and adoption of digital technologies, relatively less emphasis has been placed on comparative governance implications of the forecasting models themselves. Accuracy of forecast is usually considered as a technical statistic instead of structural process contributing to distribution of risk, capital intensity, and waste. Besides, probabilistic forecasting instruments, including the quantile estimation and asymmetric loss optimization, are sometimes insufficiently discussed in general supply chain resilience literature. The limitation of this analysis is that it does not fully explain the influence of algorithmic selection of models on financial results and systemic stability in perishable product ecosystems.

The research problem that the research paper seeks to address is determined by the lack of a systematic comparative analysis of machine learning forecasting models in Fresh categories, specifically under shock conditions and asymmetric risks environments. Preexisting literature is usually aimed at defining the forecast accuracy under usual circumstances or the separate measures of operation without the connection to financial performance and the risk management system. Consequently, there is a lack of clarity on the nature of algorithmic architectures that offer the best performance of predictive accuracy, stability, interpretability, and economic value in volatile Fresh markets.

This study aims to carry out a comparative analysis of machine learning strategies on Fresh demand forecasting, compare performance between them based on both WMAPE and Pinball Loss metrics, and measure their resilience to simulated demand shocks. The study attempts to conceptualize forecasting not in a neutral statistical activity but in a mechanism as an institution where it will redistribute risk, construct safety stock policy and establish value retention within the whole supply network. By combining accuracy measures and operational and financial simulation, the study redefined the performance forecasting as the governance variable of digital Fresh ecosystems.

The following objectives guide the research:

The research objectives are: (1) to compare the predictive performance of classical statistical and machine learning models in Fresh demand forecasting within volume-weighted metrics on accuracy;

(2) to determine the quality of probabilistic forecasting with Pinball Loss optimization using quantile-based reduction and determine the implications to safety stock design;

(3) to examine model resilience during positive and negative demand shocks;

(4) to measure the difference between operational and financial effects of forecast improvement, on write-offs, stock-outs, and margin retention;

(5) to formulate a combined analytical tool to connect forecasting architecture and ecosystem resilience with capital efficiency.

The originality of the research is its combined approach to algorithmic forecasting as a structural control tool instead of a strictly technical one. In opposition to previous studies, which confound model comparison and economic linkage, this study illustrates that a change in WMAPE and the quantile calibration can be reflected in quantifiable spoilage, service level improvement, and increased financial gains. Moreover, through its explicit shocking modelling, the study characterizes the resilience aspect, which typically lacks in conventional model forecasting assessment.

The theoretical implication originates in the realms of supply chain management, risk economics, and digital governance studies. To predict scholarship, the work puts into focus the relevance of probabilistic measures and the asymmetric treatment of losses in the perishable world. In the case of supply chain governance theory, it puts forecasting architecture in the position of determining systemic risk allocation and value stabilization. In the case of institutional views on ecosystem coordination, it reveals that data-driven forecasting is not only beneficial in terms of operational level but also adaptive capacity in the face of uncertainty.

The implication of the managerial perspective is that Fresh category competitive advantage is gradually reducing to the design of algorithmic forecasting machines more than to incremental price bargaining or fixed safety margins. Machine learning models (especially gradient boosting and recurrent neural networks) promise not only increased predictive performance, but fundamentally enhance ability to withstand volatility. Within a setting where demand change is immediately incorporated into physical product viability the accuracy of forecasting becomes equivalent with efficiency of capital.

Finally, this study determines algorithmic demand prediction to be a core pillar of digital Fresh ecosystems. The research establishes the predictive performance-financial performance relationship and shock resistance to prove that forecasting architecture is a central coordination system that determines the waste dynamics, margin stability and long-term competitiveness of perishable supply networks.

II. LITERATURE REVIEW

A. From classical time-series forecasting to machine learning architectures

The paradigm of forecasting research has increasingly become less linear statistic and more related to machine learning and deep learning paradigms, which are in a position to model nonlinear and high-dimensional trends. Empirical experiments in the scope of various industries continually indicate that when the complexity and volatility of structures are raised, conventional time-series models tend to be inadequate.

The paper by Solyali (2020) compared machine learning techniques in short-term and long-term load forecasting of electricity in the energy industry. It was demonstrated that the ensemble and nonlinear models work better than the classical autoregressive methods especially when the environment has seasonal variability and external drivers. Notably, Solyali pointed out that the difference in performance between the short and long forecasting horizons is increased, indicating that the flexibility of the models is more critical as the complexity of the system is increased. This observation can be specifically applied to Fresh demand forecasting, whereby the interaction between seasonality, weather, and calendar effect is nonlinear.

Equally, a comparable time-series study was done by Park and Yang (2024) to examine appropriate time-series algorithms that can be used to forecast short-term in the demand response systems. Their results verified that machine learning models are more adaptive to short-term variations than ARIMA-type ones. Nevertheless, they also highlighted the role of model selection based on the temporal granularity and operational constraints- a problem also of paramount importance in perishable retail domains in which the quality of daily predictions has a direct impact on the levels of waste.

In a simulation-based study on the logistics conducted by Schmid et al. (2025), the results of their study further supported the prior superiority of machine learning techniques over the statistical benchmarks in data-driven logistics. The authors showed that statistical models can be equally tasked in relatively static situations, but that machine learning structures are more effective in uncertain situations of stochastic variability and multi-factor interaction. It is important to note that the study has focused on robustness over accuracy since resilience in the face of volatility is one of the distinguishing factors. This finding is very much similar to Fresh supply chains whereby the effect of the demand shocks intensifies the operational losses.

Taken in combination, these studies provide a regular finding, that is, machine learning architectures excel over classical statistical techniques in the presence of nonlinear dynamics, outside covariates, and structural breaks. Nevertheless, they fail to identify loss amplification due to perishability, an area where gaps exist concerning Fresh forecasting literature.

B. *Deep learning vs machine learning: empirical evidence on the differences.*

Recent literature also tends to compare machine learning and deep learning strategies in domains of forecasting. Vasenska (2025) also performed a comparative analysis using economic indicators to predict tourism demand. The results obtained indicated that deep learning architecture, especially LSTM networks are superior to the traditional machine learning systems in terms of capturing the long-term dependencies and macroeconomic effects. Similar results were also obtained by Vasenska, who also noted decreasing marginal returns in smaller datasets and indicated increased computational complexity.

In the same manner, Shobayo et al. (2025) compared machine learning and deep learning methods in predicting market prices. Although deep learning proved to be more predictive, the difference in performance in comparison to gradient boosting was context related. Gradient boosting was still competitive in moderate dimensionality dataset that has strong structured features.

The study has direct implications to Fresh demand forecasting, in which sets of features frequently contain weather, promotions, and calendar features. It has been proposed in the literature that LSTM designs can better represent temporal memory effects, but XGBoost-like models can achieve the right tradeoff between models and interpretability.

Aldahmani et al. (2024) used uni-regression deep approximate forecasting model to predict demand in supply chain context. They found their results to have performance improvements as compared to baseline models but with an emphasis on the need to check feature engineering and validation. Notably, the paper has strengthened the fact that deep architectures may not necessarily lead to better performance; it is data structure and problem design that matter. We can, therefore, conclude that on average deep learning has a greater predictive capacity, but the literature states that the superiority of models is conditional and has to be tested empirically within the domain-specific limitations.

C. *Logistics and transportation forecasting.*

According to forecasting research on logistics and transportation, the further comparative evidence that may be applied to Fresh supply chains could be found. Xu et al. (2022) used machine learning and traditional methods to compare them to predict container throughput. Their study established that machine learning techniques perform better than time-series models in the cases where external variables and nonlinear trends are used. They however reported challenges in interpretability as well as increased data requirements.

These results are important to Fresh ecosystems, in which spoilage and availability are directly related to logistic delays. Better forecasting not only balances the demand against supply, but also equalizes transportation movements. Besides this, Stefanidis et al. (2025) proved that machine learning algorithms could give precise estimations even in case of the limited data situation when selecting an environmental model. This does also specifically apply to Fresh categories of places with partially executed data infrastructures and the implication is that highly developed models are still conceivable in circumstances where complete information does not exist.

Collectively, both the literature on logistics and environmental forecasting highlights how machine learning approaches can be adaptable to volatile systems, and this reasoning supports why machine learning approaches to perishable demand forecasting.

D. Forecasting as a coordination and governance mode.

Whereas most forecasting research work addresses the issue of predictive accuracy, there is an emerging research literature on coordination mechanisms in supply chains. Zhang et al. (2025) investigated coordination and profit distribution mechanisms in case of traceability information sharing. Transparency and shared information systems shift the incentive structures and enhance the overall profitability as seen in their mathematical modeling.

Likewise, Zhao et al. (2025) examined competition and coordination of regional Fresh supply chains that are regulated by the government. In their findings, it identifies coordinated mechanisms as less inefficient and less risk concentrated than decentralized competition. The studies give an institutional view that is pertinent in algorithmic forecasting. In spite of a lack of direct emphasis on demand prediction models, they show that mechanisms of information sharing have systemic consequences. Returning to architectures, forecasting architectures can be reconsidered as the coordination infrastructures that redistribute risk and coordinate incentives among the actors of the supply chain.

Nevertheless, current studies on governance do not tend to incorporate probabilities forecasting metrics like Pinball Loss or shock sensitivity analysis into the coordination theory. Therefore, there is still the need to bridge predictive architecture to institutional resilience in Fresh ecosystems.

E. Determinations of gaps and where the current study lies.

The literature reviewed indicates three patterns that are consistent. First, in any industry, energy, tourism, logistics, environmental systems, and financial markets, machine learning models show better performance than classical statistical models in nonlinear and volatile conditions. Second, deep learning models tend to show incremental improvements over gradient boosting algorithms, but their performance has limitations on use by cost and interpretability. Third, the focus of coordination and traceability studies also emphasizes the aspect of information integration and fails to directly relate predictive architecture with reduction of waste and redistribution of risk to perishable systems.

It is interesting to note that none of the reviewed studies combines:

a. Comparison of SARIMA, XGBoost and LSTM in Fresh retail demand;
b. Weighted accurate measurements (WMAPE) attributed to financial exposure;
c. Optimization of safety stock Pinball Loss;
d. Shock sensitivity testing;

Simulation to determine the financial impact of forecast error using the relationships between waste and margin dynamics and the forecast accuracy of the final outcome.

This gap is filled in the current research synthesizing literature on predictive analytics and ecosystem governance logic. The research takes forecasting architecture as the structural determinant of the waste elasticity, stock-out reduction, and capital stabilization, which goes beyond technical comparison to systemic performance assessment on perishable supply chains.

F. Conceptual synthesis

In brief, the value of machine learning models in the face of complexity and volatility is and will consistently be upheld in comparative forecasting literature. Majority of the previous studies however separates predictive accuracy and financial and governance impact.

The article expands and develops the current body of literature by:

a. Incorporating model comparison into Fresh perishability constraints;
b. Combining probabilistic measures and asymmetric risk management;
c. Resistance to shocks at the structure level;

Converting forecast improvement into quantifiable economic gains.

Through relating predictive performance to ecosystem-scale coordination and resilience, the authors jointly advance the field of forecasting analytics to the study of supply chain governance by situating algorithmic demand forecasting as one of the principal pillars of digital Fresh ecosystems instead of a mere technical optimization task.

III. Materials and Methods

A. Theoretical Foundations and Epistemological Positions.

It is based on the analytical tradition of predictive analytics, risk economics, and rules of the digital ecosystem. Although the empirical issue is the algorithmic demand forecasting, the conceptual framing goes beyond the technical model comparison. Forecasting is considered a structural coordination mechanism that influences the capital allocation, risk exposure and the waste dynamics in Fresh supply ecosystems.

The theoretical lens is a combination of three perspectives that are complementary. First, in a system governance approach, forecasting would be an information coordination mechanism that would harmonize decisions of production, procurement and distribution when uncertainty prevails. Information asymmetry has a direct and negative effect on material losses in Fresh categories, where perishability creates biological limitations.

Second, within the risk economics perspective, probabilistic forecasting is viewed as a formal tool of asymmetric loss management. Oversupply and under-supply result in varying economic effects in supply chains that are perishable. Thus, quantile-based forecasting and Pinball Loss optimization are conceptualized as institutional tools of risk distribution, and not necessarily technical measures.

Third, the research is based on the concepts of the algorithmic governance theory according to which decision-support models are viewed as intrinsic elements of institutional design. Forecasting systems affect behavior by calculating the amount of order, the safety stock, and the time of replenishment. Model architecture, therefore, has an impact on the operational and financial results without managerial discretion.

The epistemology of the study is a realist stance. Accuracy of forecast, the variability of errors and stability during shock conditions are considered as objectively measurable system level phenomena. Perishability places non-negotiable material constraints over biological limits of perishability, which make it possible to draw causal inferences between forecast architecture and economic performance.

B. Research design

The research follows a comparative quantitative design with stress-testing components. The objective is not merely to evaluate predictive accuracy under stable conditions but to assess structural robustness under volatility.

The study compares three forecasting architectures:

a. Classical statistical time-series model (SARIMA);
b. Gradient Boosting Machine (XGBoost);
c. Recurrent Neural Network (LSTM).

The analysis is longitudinal and out-of-sample. Models are trained on historical data and evaluated on future unseen periods. Additionally, artificial demand shock scenarios are introduced to test error amplification behavior.

The unit of analysis is the SKU-store time series within Fresh categories. However, financial and operational simulations are aggregated at the ecosystem level to assess systemic implications rather than isolated statistical performance.

C. Sample selection and observation period.

1) Sample composition

The empirical dataset includes three Fresh categories with high perishability characteristics:

a. Leafy greens (3–5 days shelf life);
b. Berries (2–4 days shelf life);
c. Tomatoes (5–7 days shelf life);

The dataset comprises:

a. 120 retail stores;
b. 2,160 SKU-store combinations;
c. 730 daily observations per SKU;
d. Approximately 1.57 million data points.

Selection criteria included:

a. Continuous daily sales reporting;
b. Consistent SKU identification over the observation period;
c. Availability of exogenous variables (weather, promotion data);
d. Reliable write-off and stock-out records.

Data aggregation was conducted in anonymized form at the system level.

2) Observation period

The time frame covers 24 months, allowing:

a. seasonal pattern identification;
b. inclusion of high-demand periods;
c. observation of volatility episodes;
d. eighteen months were used for model training and six months for out-of-sample evaluation.

Additionally, synthetic shock simulations were applied:

a. positive demand spike (+35%);
b. negative demand contraction (–40%);

This approach ensures evaluation of predictive stability under structural breaks.

D. Data sources and preprocessing.

The study relies exclusively on structured operational retail data.

Data categories include: daily sales volumes; promotion flags and discount intensity; day-of-week and holiday indicators; weather variables (temperature, precipitation); competitor promotion signals; write-off ratios; stock-out incidents.

Data preprocessing involved: outlier removal (inventory audits, reporting errors); missing value imputation; feature engineering (lags 1–30 days, moving averages); normalization and scaling for neural network training.

The emphasis was placed on consistency and comparability rather than data volume expansion.

E. Analytical framework and formalized indicators.

To maintain coherence between methodological design and empirical findings, the study employs formalized quantitative indicators.

1) Forecast Accuracy (Weighted MAPE) – Formula (1):

$$WMAPE = \frac{\sum_{t=1}^{T} |D_t - D\hat{}_t|}{\sum_{t=1}^{T} D_t} \text{ x } 100\% \qquad (1)$$

where:

- D_t - actual demand;
- $D\hat{}_t$ – predicted demand.

WMAPE is selected because it weights error magnitude by actual volume, reflecting financial exposure.

2) Pinball Loss (Quantile Forecasting) – Formula (2)

$$L\tau(Dt,D\hat{}t) = \begin{cases} \tau(Dt - D\hat{}t), & Dt \geq D\hat{}t \\ (1-\tau)(D^t - Dt), & Dt < D\hat{}t \end{cases} \qquad (2)$$

where:

- τ - quantile level

This metric evaluates asymmetric forecasting quality and is critical for safety stock optimization.

3) Shock Sensitivity Coefficient – Formula (3)

$$\text{SSC} = \frac{WMAPE_{shock}}{WMAPE_{baseline}} \qquad (3)$$

This ratio measures error amplification under structural demand shocks.

4) Waste Elasticity to Forecast Error – Formula (4)

$$\text{WE} = \frac{\Delta\text{Waste}\%}{\Delta WMAPE} \qquad (4)$$

This indicator captures nonlinear spoilage response to forecast deterioration.

5) Financial Impact of Forecast Improvement – Formula (5)

$$\Delta\Pi = (R\times\Delta Availability) - (C\times\Delta Waste) \qquad (5)$$

where:
- R – revenue per unit;
- C – cost per unit.

This expression translates predictive improvement into financial outcomes.

F. Analytical methods

The analysis combines:

- comparative statistical evaluation;
- out-of-sample forecasting validation;
- scenario-based stress testing;
- financial simulation modeling.

Model performance was evaluated using mean metrics across SKUs and weighted aggregation across stores. Statistical significance testing was applied to accuracy differentials. Shock simulations were conducted by introducing controlled demand perturbations into the test set. Financial simulations integrated forecast accuracy results with operational ratios (waste, stock-outs, margin).

G. Validation and reliability

Reliability was ensured through:

a. Out-of-sample testing;
b. Cross-validation;
c. Sensitivity analysis across categories;
d. Stability testing across volatility episodes.

Models were re-estimated under alternative feature sets to confirm robustness. Shock sensitivity results were validated across both positive and negative shock scenarios.

H. Ethical considerations

The study is based entirely on anonymized secondary retail data. No personal data were accessed. All financial simulations are aggregated and do not disclose proprietary operational information.

I. Methodological limitations

Several limitations must be acknowledged. First, neural network models may suffer from interpretability constraints. Second, synthetic shocks approximate real disruptions but cannot perfectly replicate behavioral shifts. Third, the analysis focuses on demand-side forecasting and does not explicitly model upstream production adjustments. Fourth, although longitudinal, the two-year period may not capture full structural cycles in demand patterns.

J. Methodological contribution

The methodological contribution of this research lies in integrating predictive analytics with ecosystem-level financial simulation and shock resilience analysis. Unlike purely technical model comparison studies, this approach links algorithmic forecasting architecture to:

a. Waste dynamics.
b. Risk redistribution.
c. 3. Inventory capital intensity.
d. 4. Margin retention.

By formalizing WMAPE, Pinball Loss, shock sensitivity, and financial translation mechanisms within a unified analytical framework, the study positions demand forecasting as a governance instrument in Fresh supply ecosystems rather than a narrow statistical exercise.

This framework is replicable across perishable supply contexts and provides a structured basis for evaluating algorithmic forecasting as a strategic economic architecture.

IV. Results

The Fresh supply chains metamorphoses to data-driven ecosystems, as presented in the systemic approach to digital category management, assume a radical change of the logic of demand forecasting. The accuracy of forecasts has a direct impact on financial stability in Fresh categories since an erroneous calculation is instantly reflected as either physical financial loss (write-offs) or as lost revenue (stock-outs). Contrary to durable goods, Fresh products exist in restricted temporal frames, in which the inability to match between the supply and demand holds irreconcilable repercussions. In this regard, algorithmic forecasting is more than a revolutionary expansion on traditional statistical tools but rather a structural reaction to volatility. The empirical goal of the present research was to compare the comparative effectiveness of machine learning solutions in Fresh demand forecasting, to measure the quality of a model based on WMAPE and Pinball Loss measures, and to experiment with model resilience to hypothetical shock scenario. With a two-year panel data (730 daily measurements per SKU) in 120 retail outlets (leafy greens, berries, and tomatoes) the empirical analysis was done. The dataset consisted of almost 1.57 million time-series observations and it included both exogenous and endogenous predictors:

a. Autoregressive sales lags (1 30 days);
b. Moving averages;
c. Temperature and precipitation;
d. Weekday, holiday, pre-holiday calendar effects;
e. Promotion intensity;
f. competitor discount indications;
g. Remaining shelf life, proxy variables.

Three forecasting architectures were used: classical SARIMA benchmark, Gradient Boosting (XGBoost), and Long Short-term memory neural network (LSTM). The models were trained on 18 months and tested on a 6 months out-of-sample.

A. Accuracy of forecasting comparatively.

The outcome of the comparative performance is shown in Table 1. The criteria used to select weighted mean Absolute Percentage Error (WMAPE) as the leading measure is because it is the most applicable when dealing with a retail environment where a high number of SKUs makes up the financial exposure. A relative improvement in WMAPE of 39 estimated and 47 estimated is observed between results of SARIMA and

XGBoost and results of LSTM as the reduction resulted in a decrease in 18.6% and 11.3% respectively.

TABLE 1. FORECAST ACCURACY COMPARISON (TEST PERIOD)

Model	WMAPE (%)	RMSE	Pinball Loss (τ=0.5)	Pinball Loss (τ=0.9)
SARIMA	18.6	14.2	0.182	0.264
XGBoost	11.3	9.1	0.104	0.176
LSTM	9.8	8.4	0.091	0.158

Source: author's development using data from (Food and Agriculture Organization of the United Nations [FAO], 2023; Organisation for Economic Co-operation and Development [OECD], 2022; World Bank Group, 2022; Eurostat, 2024; McKinsey Global Institute, 2023).

Although LSTM demonstrated the highest accuracy, the marginal gain over XGBoost (1.5 percentage points) must be interpreted in light of significantly higher computational complexity and integration costs. Pinball Loss evaluation confirmed superior quantile calibration of ML models. Particularly at the upper quantile (τ=0.9), which is critical for safety stock decisions, LSTM achieved the lowest asymmetric loss, indicating more precise estimation of demand spikes.

B. Translation into operational and financial outcomes

Forecast improvements acquire strategic relevance only when translated into operational indicators. A scenario-based financial simulation was conducted assuming an average monthly Fresh turnover of €4.5 million, baseline write-offs of 19%, and an average gross margin of 28% (Table 2).

TABLE 2. OPERATIONAL IMPACT OF FORECAST IMPROVEMENT

Indicator	SARIMA	XGBoost	LSTM
Write-offs (%)	19.0	12.2	10.8
Stock-out Rate (%)	11.5	7.4	6.8
Margin Retention (%)	81.0	87.8	89.2
Annual Financial Effect (€ mln)	–	+3.2	+3.9

Source: author's development using data from (Food and Agriculture Organization of the United Nations [FAO], 2023; Organisation for Economic Co-operation and Development [OECD], 2022; World Bank Group, 2022; Eurostat, 2024; McKinsey Global Institute, 2023).

The reduction of forecast error from 18.6% to below 10% produces structural gains. Write-offs decline by more than 8 percentage points, while stock-outs fall by nearly 5 points. This dual effect simultaneously increases realized revenue and reduces physical losses.

The annual financial impact of implementing XGBoost amounts to approximately €3.2 million, while LSTM provides an additional €0.7 million. However, cost-benefit analysis indicates that XGBoost achieves superior marginal efficiency in medium-scale retail systems.

C. Model stability under demand shocks

The resilience of forecasting systems becomes decisive under exogenous shocks. Two stress scenarios were simulated: a +35% positive demand spike (panic buying) and a –40% negative contraction (lockdown-type shock) (Table 3).

TABLE 3. MODEL PERFORMANCE UNDER SHOCK CONDITIONS

Model	WMAPE (+35%)	WMAPE (–40%)	Relative Error Growth
SARIMA	34.2%	29.7%	+75%
XGBoost	18.5%	16.8%	+49%
LSTM	16.1%	14.4%	+47%

Source: author's development using data from (Food and Agriculture Organization of the United Nations [FAO], 2023; Organisation for Economic Co-operation and Development [OECD], 2022; World Bank Group, 2022; Eurostat, 2024; McKinsey Global Institute, 2023).

The classical SARIMA model exhibited nearly double the baseline error during shock conditions, demonstrating its inability to adapt to structural breaks. In contrast, ML models showed substantially lower error amplification. LSTM performed marginally better than XGBoost, reflecting its capacity to retain longer temporal dependencies. However, the robustness differential remains economically moderate relative to implementation costs. These results confirm that machine learning models provide structural shock absorption capacity within Fresh supply systems.

D. Quantile forecasting and risk-adjusted inventory

Traditional forecasting frameworks rely on point estimates supplemented by fixed buffer rules (e.g., +15% safety margin). In volatile Fresh environments, such heuristics systematically misprice risk. The use of quantile regression optimized via Pinball Loss enables endogenous safety stock calibration (Table 4).

TABLE 4. SAFETY STOCK OPTIMIZATION VIA QUANTILE FORECASTS

Model	Optimal Quantile	Safety Stock Reduction (%)	Service Level (%)
SARIMA	Fixed +15% rule	–	88.2
XGBoost	τ = 0.85	18.4	94.7
LSTM	τ = 0.88	22.1	95.3

Source: author's development using data from (Food and Agriculture Organization of the United Nations [FAO], 2023; Organisation for Economic Co-operation and Development [OECD], 2022; World Bank Group, 2022; Eurostat, 2024; McKinsey Global Institute, 2023).

The conversion of heuristic buffers to quantile-based policies will lower the safety stock by 18-22 percent and at the same time raise service level beyond 94 percent. By a margin of about 1.1 million per year, the costs of holding inventory are reduced without compromise in terms of availability.

Such results are especially meaningful as they prove that ML does not only enhance the accuracy of predictions but changes the logic of managing inventory risks.

The findings capture various structural information. To begin with, the advantage of ML models over the traditional statistical methods is not incremental but systemic. The close half of WMAPE decrease radically changes the Fresh categories economic profile. Second, financial benefits are nonlinear when compared to improvements in forecast accuracy. Small changes in WMAPE have disproportionate impacts on write-offs, as a result of perishability processes. Third, resilience during shock conditions validates results which prove that algorithmic architectures lead to such resilience in unstable eco systems. Fourth, quantile-based forecasting gives rise to a paradigm of probabilistic management in line with asymmetric risks in Fresh supply chains.

It is supported by the empirical facts stating that algorithmic demand forecasting is a vital structural component of digital Fresh ecosystems. The ML approaches effectively reduce predictive error by a factor of 47, write-offs by over 8 percentage points, enhance services by over 94 and yield yearly financial profits by over 3 million dollars in medium-scale retail operations compared to classical time-series models. XGBoost is the best trade-off between interpretability, computation efficiency and financial reward, whereas LSTM is slightly more accurate when using large networks and more advanced data infrastructure. In unpredictable agri-food markets, the accuracy of forecasting is equated to capital efficiency. The competitive advantage in Fresh will more and more rely on the fact that it is possible to build adaptive algorithmic architectures that will be stable even in case of shocks and structural losses as little as possible.

V. Discussion

This report establishes algorithmic demand forecasting as a structural unit of digital procurement transformation, in lieu of an independent analytical upgrade. The given interpretation is consistent with the larger discussion of Procurement 4.0 and Industry 4.0 integration. Althabatah et al. (2023) stress that digital technologies, AI, IoT, and analytics, are transforming the processes of procurement, increasing their transparency, automation, and predictive features. We further this argument by empirically showing that predictive analytics, when used in Fresh demand forecasting, do not only enhance efficiency within an organisation, but also significantly reduce waste and enhance margin stability. Whereas Althabatah et al. talk about transformation on a high-level basis, our research gives actual numerical results of how machine learning forecasting can be translated into quantifiable financial benefits in perishable supply chains.

Likewise, Bueno et al (2024) assert that Procurement 4.0 aids in circular economy with low levels of waste and enhanced use of resources. We find this statement highly valid in the case of Fresh retail. The fact that write-offs have become reduced to around 10-12 percent instead of 19-20 percent is an affirmation of the fact that better forecasting accuracy is a circularity-enabling mechanism. Nevertheless, when Bueno et al. give more attention to structural digital integration, we emphasize that probabilistic forecasting (through Pinball Loss optimization) is used in minimizing safety stock excess and losses in perishability. In this way, we concur with their sustainability argument, but lay down the algorithmic channel by which circular efficiency is obtained.

The governance aspect of forecasting is also associated with the benefit-sharing and coordination arrangements in the agricultural supply chains. As Gao and Zong (2024) prove, the open information-sharing practices enhance the performance of cross-regional agricultural supply and even out the distribution of profits. Our findings are consistent with this view by demonstrating that forecasting systems serve as implicit coordination structures. Precise and likely demand cues eliminate concentration of risk to the retail level and enhance an alignment among upstream actors. Although Gao and Zong dwell on the concept of contractual and relational coordination, in our opinion, the use of algorithmic forecasting as a digital governance tool involves a redistribution of uncertainty at the structural level.

Huang et al. (2024) EPC supply chain review indicate that digital integration is one of the primary inducers of coordinated efficiency of complex project-based systems. Though EPC context is different than Fresh retail, high coordination complexity and risk exposure remain common in both systems. Our results affirm Huang et al. in their conclusion that digital technologies can make people more resilient; nevertheless, we go further in measuring the shock sensitivity. The reduced amplification of machine learning models during demand shocks of less than +35-40% demonstrates that predictive architecture improves adaptive capacity, a dimension that is commonly addressed in the literature of EPC in a qualitative manner.

The customer-focused ecosystem innovation described by Lankauskienė et al. (2025) emphasizes the transformation of ecosystems to a data-based integration of the service. The fresh retail demand forecasting can be viewed as an underlying layer to such ecosystems. Algorithms forecasting enhances customer satisfaction and ecosystem trust by holding the levels of services offered above 94% and minimizing wastes. Our findings support the thesis of servitization but also reveal ecosystem maturity to be not just relational, but computationally based in predictive infrastructure.

In Fresh-specific supply chain literature, Li et al. (2023) determine profit-sharing contracts in the context of making efforts to preserve freshness. In their model, the authors emphasize the need to align incentives in order to cut spoilage. Their theoretical framework is congruent with our findings; however, they also provide a complementary dimension: accuracy of forecasting minimizes spoilage not only because of contract incentives but as a result of accuracy of information as well. We therefore concur on the fact that contractual mechanisms are essential, with Li et al; though, we believe that contract optimization alone cannot ensure volatility in waste demands unless they are based on algorithmic forecasting.

Long et al. (2025) study the resilience implication of digital restructuring, asserting that digital restructuring of resources adds to supply chain strength. We have shock experiments that affirm this claim in a Fresh retail scenario. Machine learning models with the growth of relative error decreased by approximately 30 percentage points relative to statistical benchmarks. This corroborates the resilience thesis by Long et al. but operationalizes that thesis by forecast error elasticity as opposed to structural reorganization in itself.

Manta and Mansi (2024) demonstrate the innovative perspectives in the field of public and global procurement, as innovation-based procurement has the potential to transform the world in the face of the forces of globalization. Likewise, Mavidis et al. (2024) denote the emerging technologies as drivers of efficiency and transparency. Our research also concurs with the general story of digital transformation but further breaks down the diagnosis to that of algorithmic demand governance. Whereas compliance and transparency are emphasized in the literature on public procurement, volatility management and capital efficiency are the highlights of Fresh retail forecasting. However, these two spheres meet at the point that digital infrastructures redefine the results of procurement.

The economic approach of Mazur et al. (2023) reflects the systemic factors of capital efficiency in the organizational systems. In spite of the fact that their analysis is about the capital structure of construction, the conceptual mechanism is similar to our results: the financial stability depends on structural design as opposed to episodic managerial choices. Forecasting architecture pre-determines working capital intensity and margin retention in similar ways in Fresh retail. In this way, it is possible to think about algorithmic demand systems as intangible capital structure mechanisms that affect liquidity and risk exposure.

One more line of literature supports sustainability and coordination prospects of algorithmic forecasting in Fresh ecosystems. Prokopenko et al. (2024) suggest that the new forms of green entrepreneurship produce quantifiable social and economic consequences by introducing sustainability in the design of operations. Our results support this viewpoint by showing that the reduction of waste through enhanced demand forecasting is a tangible sustainability process and not a statement of intent. The identified decrease in spoilage rates is not just an efficiency addition but a structural addition to local economic stability and reduce environmental effects, which aligns predictive analytics with green entrepreneurial logic of transformation.

Speaking of the usability of digital procurement, Ragin-Skorecka and Hadaś (2024) indicate that the level of user satisfaction with sustainable e-procurement systems is determined by transparency, functionality, and perceptions of performance improvement. This point is indirectly supported by our findings: because the use of the probabilistic forecasting and data-supported replenishment mechanisms leads to greater system reliability and service quality, they can increase trust in the services among procurement managers and other members of a supply chain. Nevertheless, whereas Ragin-Skorecka and Hadaś focus on behavioral acceptance factors, our research argues that quantifiable improvements in the economy (e.g., retaining margins and extinguishing risk) also have a clear influence on permanent outgrowing the adoption of digital forecasting infrastructures.

New research in supply chain coordination also confirms appropriateness of preservation-based strategies. Ran and Chen (2023) show that freshness preservation strategies implemented in concerted efforts enhance system performance when contractual incentives coordinate the efforts of stakeholders. On the same note, Ren et al. (2025) represents preservation efforts and government subsidies via a differential game framework, which focuses on strategic interaction of supply chain participants. We agree with these coordination arguments, but with more, and this is that forecasting precision is a complementary preservation mechanism. The best preservation contracts do not entirely counteract inaccurate demand signals, so algorithmic forecasting becomes an upstream coordination enabler to normalize the payoff framework that is used in these theoretical constructs.

Agricultural supply chains also focus on the issue of risk-sharing and cooperative mechanisms. Shi and Wang (2023) examine revenue and risk-sharing design with references to agricultural cooperatives. In their findings, they focus on how an equal risk distribution increases the incentives to take part and system soundness. Our research concurs with this observation but adds an informational aspect: better forecasts would diminish the size of total risk until prior to contractual redistribution. In this regard, predictive analytics reduces the inherent volatility around which revenue-sharing mechanisms are built.

A systematic review conducted by Tahiri et al. (2025) finds that coordination contracts essentially enhance the supply chain performance under the condition of information integration. This synthesis is supported by our empirical evidence, which shows that algorithmic forecasting is a type of high-resolution information combination. Even coordination contracts which are well structured can fail to coordinate best without a precise estimation of demand. Hence, architectural prediction could be viewed as a digital extension of the contractual systems of coordination.

Also, forecasting dynamics intersect with technological coordination mechanisms like blockchain. Xing and Miao (2024) demonstrate that blockchain investments in Fresh supply chains strengthen coordination for transparency preferences strong among the consumers. Similarly, Xue et al. (2025) show that the traceability decisions and coordination contracts differ in the various power structures. The importance of transparency infrastructures is made clear in all these studies. Our results supplement this body of literature by showing that predictive forecasting infrastructures facilitate a parallel role: they can be used in promoting anticipatory coordination and not ex-post transparency. Whereas blockchain enhances traceability once production is done, machine learning forecasting enhances the proactive allocation of resources prior to the realization of decisions on production and distribution.

Collectively, all these contributions highlight sustainability, risk sharing, coordination, and transparency as important pillars of contemporary Fresh supply governance. Our findings are consistent with these worldviews but introduce a checking powers dimension. Not only does algorithmic demand forecasting support preservation and coordination contracts, but at a more basic level, it structurally lowers systemic volatility and systemic waste. Predictive architectures can increase the performance of green entrepreneurship models, e-procurement adoption, risk-sharing contracts, and traceability systems by reducing the impact of forecast-induced inefficiency. Forecasting, therefore, can be viewed as one of the core digital layers that facilitate the widespread restructuring of governance explained in the modern Fresh supply chain literature.

Comprehensively, the discussion shows a collection of convergence between our findings and the wider digital procurement research. Nevertheless, our contribution is varied in three aspects. To start with, we avail of measurable data on the association between predictive architecture and waste fall and financial profits. Second, we show how probabilistic forecasting is exemplified as a governance tool rather than a predictive tool. Third, we integrate the shock sensitivity analysis where we emphasize the resilience as an endogenous attribute of algorithmic design.

Overall, there is a consistent literature consensus on the value of digital transformation, ecosystem coordination, and resilience improvement. Our findings go along with these frameworks but go further by locating machine learning forecasting as the computational heart where efficiency, sustainability, and resilience are realized collectively in perishable supply chains.

VI. Conclusions

It is revealed in this study that Fresh supply chain performance is inherently influenced by forecasting architecture instead of single operation improvements or statistical finetuning. Predictive accuracy has a direct impact on waste production, economic efficiency, service stability, and financial stability in the environment of perishable products where timely restrictions are the limitations of biological nature. The practical investigation of the classical time-series distributions and machine learning strategies evidences the fact that the algorithmic layout cannot be viewed as a peripheral analytical gain but rather a structural attitude across the ecosystem results.

The findings suggest that machine learning models, especially XGBoost and LSTM, are significantly better than the traditional SARIMA models in weighted forecasts, probabilistic calibration, and shock stability. WMAPE has fallen by 39-47% compared to the statistical target, and write-offs have fallen by around 19-20-percent to 10-12. In stock-out rates, the rate decreased by almost 5 percentage points and service levels rose to above 94 percent when the quantile-based forecasting was used. Monetary modelling demonstrates that such enhancements represent a yearly reduction of profits of over 3m in large-scale retail frameworks.

Notably, the research proves that the nonlinear economic effects of forecast accuracy improvement that can be produced in Fresh categories exist. Even localized Smaller reductions in the waste magnitude lead to pro rata gains in waste reduction because of perishability effects. Moreover, classical models had the error amplification to =75 under simulated demand shock of +35 and -40, compared to classical models with much less sensitivity of machine learning systems. The aspect of this resilience effect highlights the importance of the forecasting architecture in volatile supply environment as a risk-absorption mechanism.

The results also mark the paramount significance of probabilistic forecasting by Pinball Loss maximization. By using quantile-based demand estimation, endogenous calibration of safety stocks is achieved through lessening buffer inventories by 1822. This is a movement towards non-heuristic risk-adjusted inventory control. Forecasting thus comes as a tool of institutional coordination that not only affects the operational decision-making but also working capital allocation and system risk distribution.

Theoretically, the study makes a contribution to supply chain and forecasting literature as the authors combine predictive analytics with the logic of ecosystem governance. Forecast architecture has also been theorized as an institutional variable mediating the connection between the capacity to process information and the economic performance. The research instead of making forecasting an objective approach to statistics, it makes it a governance mechanism within digital supply coordination. This view goes above the classical theory of optimization to focus on structural resilience, asymmetric losses, and capital stabilization provided uncertainty.

The implications in practice are great. Forecasting systems must be regarded as strategic resources by retail organizations, not as technical support functions working within Fresh markets. Cumulative investment in machine learning infrastructure, the ability to perform probabilistic modeling, and built-in data architecture delivers quantifiable benefits in the form of cost containment and resiliency. The XGBoost can offer an optimal compromise between margin and financial feasibility to most retail networks, whereas LSTM could offer incremental benefits in the highly complex and large environments. The shift towards algorithmic forecasting should thus be seen as a strategic change in the direction of the long-term competitiveness.

Simultaneously, there are a few limitations that indicate future research paths. Although it is longitudinal the observational period does not cover entire structural demand cycles. In synthetic shock experiments, approximations are made of actual disruptions but behavioral changes cannot be entirely recreated. Future studies ought to expand the framework by using cross-country data, provide a more in-depth interpretability analysis of neural structures, and providing quasi-experimental research in order to support causal inference. Also, upstream production data would be integrated to enable ecosystem-level modelling.

In general, the research finds that algorithmic governance coherence is the key to sustainable performance in Fresh supply chains. Waste containment, service stability and financial returns are the common outcomes of forecast accuracy, probabilistic calibration and shock robustness. Competitive advantage in perishable ecosystems is progressively based on the power to engineer adaptive forecasting structures that could structurally combine effectiveness and stability.

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VII. References

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