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Integrating Artificial Intelligence and Demand Forecasting for Sustainable Supply Chain Management

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Abstract — The intersection between artificial intelligence and demand forecasting constitutes an innovative approach for managing supply chains in a sustainable manner. The current paper presents a methodology of using AI-based demand forecasting as part of an optimization process for sustainable supply chains based on multi-objective sustainability optimization. The methodology relies on a hybrid forecasting model combining gradient boosting and recurrent neural network techniques to forecast structured demand and to learn the dependence of forecasts on time respectively, followed by the planning layer that assesses carbon intensity, inventory carrying cost, and service level objectives. To demonstrate the effectiveness of the proposed methodology, the paper compares the results obtained in the proposed methodology with those obtained using standard statistical forecasting techniques, showing the potential of AI-based forecasting to align purchasing, manufacturing, and transportation processes with sustainability objectives better. In addition, the paper explores the impact of forecast horizon and product category on sustainability performance.

Keywords— Artificial Intelligence, Demand Forecasting, Sustainable Supply Chain, Machine Learning, Multi-Objective Optimization, Inventory Management.

I. INTRODUCTION

Supply chain management is at a crossroads where the need to decrease environmental impact meets the need to meet dynamic demand patterns. Conventional demand forecasting, which involves mostly linear statistical models and extrapolation of historical data, fails to take into account the nonlinearity, changes in the system structure, and multiscale seasonality inherent to modern supply chains [2], [4]. Forecast errors translate into more than just stockouts or too much inventory: incorrect demand forecasts affect purchasing decisions, production schedules, logistics, and create additional carbon footprint due to expedited delivery, increased power consumption by warehouses, and waste of resources [1], [3], [5]. With growing demands for greenhouse gas accounting of all aspects of a company's value chain, demand forecasting assumes an environmental importance [3], [5].

AI can help overcome these drawbacks. Learning-based architectures, especially ensemble models and deep sequence models, have proven their ability to effectively mine high-dimensional, noisy supply chain data [1], [2], [6]. This approach allows for the inclusion of mixed types of signals such as promotional calendars, macroeconomic variables, weather trends, and social sentiments, which is impossible to do using traditional time series approaches [2], [6]. Once combined with sustainability assessment metrics, these forecasts will allow us to assess our decisions based on not only cost and service-related criteria but also carbon footprint and resource usage [3], [5], [7]. The scientific literature shows significant advances in both areas, although separately [1], [5], [8].

The integration task, however, is far from easy. High forecasting accuracy does not automatically translate into sustainable performance improvements since there needs to be an optimization step that takes into account the environment externalities [3], [7], [9]. An accurate demand forecasting tool but a selection process of the most cost-efficient modes of transport does not help in emission reductions [3], [5]. In addition, the use of artificial intelligence technologies in supply chains brings about governance challenges such as ensuring data quality and algorithmic transparency [5], [8]. There is also a danger of optimization according to the wrong metrics [7], [9]. Therefore, an approach that considers both aspects should be adopted [3], [5], [8].

However, the need for such integration is increased because of the increasing demands on the ability of supply chains to be accountable for their environmental performance [3], [5]. The necessity to disclose information about emissions and consumption of resources along the whole value chain of an organization, not only concerning the activities directly

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performed by it, grows due to the rising regulatory and market pressure [5], [8]. However, there is not always a possibility of getting the necessary information and analyzing it properly in order to make sustainable decisions regarding the future [5], [9]. AI-based forecasting provides a two-fold advantage in such circumstances since it helps to improve the accuracy of the demand signals used for procurement and logistics and to obtain the forward-looking data to assess the sustainability performance of the company depending on different planning scenarios [1], [3], [7].

In this paper, an integrated framework is developed which combines AI-based demand forecasting with sustainability-focused decision optimization. The methodology suggested herein combines a hybrid forecasting component with gradient boosting used to process structured features and RNN used to account for temporal dependencies with a decision layer where procurement and inventory strategies are assessed using multiple criteria, which include not only economic but also environmental considerations [2], [3], [6], [7]. It is important to note that the proposed framework is modular and allows organizations to gradually implement parts of the model and monitor their sustainability [5], [8]. The following sections consider the literature on the topic, methodology, analysis, and implications.

II. LITERATURE SURVEY

The development of research on demand forecasting using AI technologies in the context of sustainable supply chain management has been rapidly growing during the 2021-2026 timeframe, as a result of both methodological progress and the increasing necessity to address emissions from scope 3 and circular economy targets [1], [5], [8]. These topics can be divided into three interrelated areas: advancements in forecasting frameworks, forecasting sustainability assessment, and conditions for successful implementation [2], [5], [9].

There are several hybrid forecasting frameworks that have evolved over time. While classical models are good at modeling linear trends and seasonality, they fail to model the residuals, which exhibit nonlinearity [2], [6]. On the other hand, neural networks are good at identifying patterns in the data but they have a tendency to overfit the noise [2], [6]. It was seen that hybrid ARIMA-LSTM framework is capable of generating forecasts that are adaptable to seasonal effects and changes in demand structure, especially relevant to product categories that experience promotional activity and lifecycles [2]. In another case study, it was found that hybridization of SARIMA-SVM frameworks generated better forecasts in product categories that involved foods, household products, and electronic goods [2]. Douaioui et al. conducted an extensive literature review on machine learning and deep learning models for demand forecasting and concluded that hybrid methods always produce better results than single methods, although the computational complexity of keeping multiple models running simultaneously is a practical problem [2].

Ensemble and gradient boosting have been adopted due to their interpretability and effectiveness in tabular supply chain data [1], [6]. An idea about integrating random forest-based demand forecasting with fuzzy inventory models for tackling the defective rate and carbon emission problems simultaneously has already emerged and proved that it is possible to make sustainability-oriented decisions based on interpretability [3], [7]. Gradient boosting along with deep cross networks has been demonstrated as effective for improving demand prediction in supply chain settings, which indicates that the ability of gradient boosting to deal with categorical features and missing values is especially relevant for real-life supply chain datasets [1], [6].

Babai et al. carried out a comprehensive study on the application of machine learning in supply chain management and pointed out that although there is a wide range of techniques applied in the field now, the number of comparative studies with regard to model performance in realistic data conditions is very low [6], [10]. Moreover, Babai et al. noted the significance of aggregation and hierarchy when making demand forecasts since good SKU-level forecasts do not ensure good category-level or network-level decision-making [4].

In relation to the sustainability frontier, AI demand forecasting has been associated with life cycle assessment and multicriteria optimization [3], [5], [7]. Planning using machine learning demand forecasting along with prospective life cycle assessment and life cycle costing makes it possible to develop resilient supply chain networks that will have the minimum economic and environmental impact and value at risk will also be considered [3], [7]. It is an important step ahead of the approach in which demand forecasting and sustainability assessment were considered not as simultaneous but sequential processes [3], [5].

Digital twins technologies are offered as a platform that can enable such an approach due to the ability to perform simulations in real time and thereby stress test demand forecasting against various scenarios and constraints of sustainability [5], [8]. Bordeleau and Ülkü explored the use of digital twins in sustainable supply chains suggesting that the

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combination of real-time data integration and simulation-based planning offers new possibilities for demand forecasting that go beyond any static model [5], [8].

Further lines of research have explored the organizational and governance factors under which AI forecasting supports sustainability performance outcomes [5], [8], [9]. Systematic literature reviews of AI applications in sustainable supply chain management suggest that apart from technical ability, quality of data, cross-disciplinary cooperation, and commitment to environmental objectives of management become equally important factors of successful implementation of innovations [5], [8].

The review by Qu and Kim explores the influence of AI-enabled technologies on sustainable supply chain management and shows that organizational readiness and data governance become more critical obstacles to adoption of AI systems than any algorithmic limitations [8].

Further studies have stressed the gap between the development and practical application of forecast models, suggesting that while complex forecasting models are extensively used for validation on historical data sets, their efficiency in actual conditions of data drift and disruption in supply chains is rarely tested [2], [6], [9]. It makes sense to focus research efforts on evaluating the impact of AI forecasting on supply chain outcomes apart from predicting errors [7], [9]. Muthuswamy and Ali state that sustainable supply chain management with machine intelligence requires a new approach to evaluation criteria shifting from error minimization to outcome-oriented assessments [9].

There exist certain lacunae in the existing literature. First, most researches consider the forecasting performance and sustainability impact separately, and there is little research that considers the integration of the two aspects and links forecasting performance to sustainability impacts [3], [5], [8].

Secondly, there has been very little research on the governance and ethical issues in the use of AI in supply chain management, especially in relation to privacy and data security and possible AI biases when assessing suppliers [5], [8]. Finally, the computational costs associated with complex forecasting techniques have to be balanced against their marginal sustainability impacts [2], [6]. This research seeks to bridge these two gaps by developing a decision framework for integrated assessment and comparison of forecast horizons and products in terms of sustainability impacts [3], [7], [9].

III. PROPOSED METHODOLOGY

The suggested architecture consists of three inter-related modules:

- An AI-based forecast engine
- A sustainability-based decision-making module
- A feedback/governance model

These are shown schematically in Figure 1, depicting the entire flow process of the system from inputting data through to producing sustainable decisions.

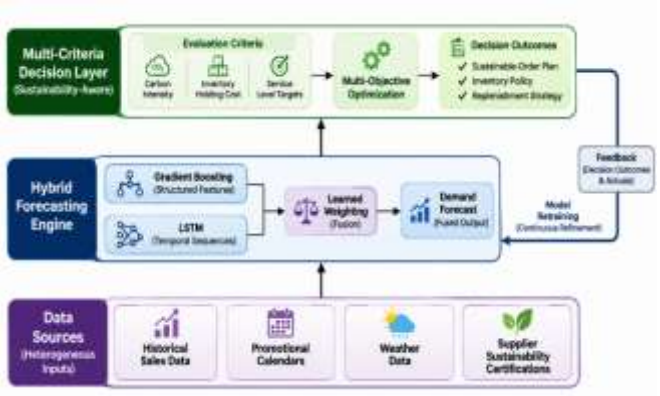


Figure 1: Integrated AI-Sustainability Framework Architecture

The figure shows the flow of the entire process from beginning to end. The bottom level consists of a variety of data input sources such as historical sales, promotional schedules, weather information, and supplier sustainability certification records. The middle level consists of parallel forecasting paths: the first one is the gradient boosting module for the structured features and the second one is the LSTM module for the temporal sequences; their results are merged by the learning weight. Finally, the top level is the sustainable-aware decision-making layer, where the forecasts are assessed regarding carbon intensity, holding cost, and service level objectives.

Data Ingestion and Data Processing: The system consumes time series of demand data for each SKU per week or day, along with the set of exogenous factors such as flags indicating promotion, prices, and sustainability metrics of suppliers and logistics companies whenever applicable. The process of preprocessing includes temporal alignment, imputation of missing values via forward filling for small time spans and model-based imputation for long gaps, and normalization of demand time series to reflect the stage of the product life cycle. Outliers are detected using isolation forests in order to separate real demand spikes from erroneous data entries.

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Hybrid Forecasting Model: Two separate forecasting streams are maintained. The gradient boosting stream (LightGBM or XGBoost) takes care of structured features such as calendar influences, price elasticities, and product categories. This stream is great for discovering cross-sectional structures and relationships that are not visible in the time series. Recurrent stream is based on an LSTM network with attention mechanisms that can model temporal relations on different horizons in case of non-equidistant observations and different look-back periods. Forecast fusion is implemented using a validation-weighted average, when the weight of each stream is defined by its recent validation score on a test fold.

Decision Layer for Sustainable Choices: Forecast outputs are used as input to a multiple objective optimization module to set order sizes, safety stock levels, and transportation modes. Objective function includes three components such as economic cost (costs of procurement, holding, and penalties for stock-outs), environmental cost (carbon emissions during production, transportation, and storage, calculated using emission factors taken from lifecycle databases), and customer service (shortfall in fill rates). Three objectives are integrated using the weighted sum approach with weights that can be tuned by decision makers according to their preferences. Optimization problem is represented by a mixed integer linear program, solved on a weekly basis using robust optimization based on quantile forecasts provided by hybrid engine.



Figure 2: Forecasting and Decision Integration Workflow

This diagram represents the workflow cycle of the approach proposed. The first stage is weekly processing of input data and forecasting through gradient boosting and LSTM models to derive point and quantile forecasts. Forecast combination is performed to generate a composite forecast with prediction intervals. From these intervals, scenarios are drawn to obtain different realizations of demand within the forecast period. The multi-objective optimization procedure is used to find order quantities and transportation modes that will be minimizing cost and emissions taking into account the service objectives under each scenario. After making decisions, the results are compared with the forecasts and sustainability targets; deviations may lead to updating the model.

Governance and Feedback Loop: The use of a dashboard helps to monitor forecast accuracy by product type, sustainability metrics (emissions per unit delivered, percentage of waste diverted), and trade-offs made between cost and carbon footprint. Alerts indicate the presence of a bias in the forecast or missing sustainability targets. Model training takes place continuously, with detection of drift based on residual distribution analysis through Kolmogorov-Smirnov tests. Governance procedures require human input for changes in the model that would significantly impact procurement, as a check on the recommendations from algorithms.

IV. ANALYSIS

In carrying out this comparison, the comparative analysis will make an assessment of the proposed framework on the basis of two benchmarks. These benchmarks include:

- A traditional statistical model of forecasting, which uses the method of exponential smoothing together with safety stock, which is calculated based on the historical variability of data
- An accuracy-only-based ai framework, which does not consider sustainability weighting

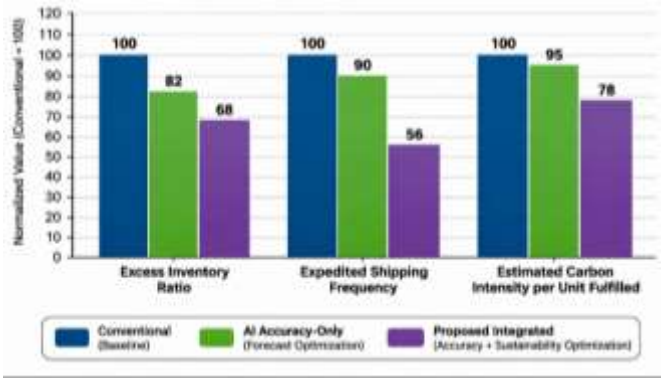


Figure 3: Sustainability Performance Comparison Across Framework Configurations

The figure below shows the normalized sustainability metrics for the three configuration models of the framework. Conventional method is the benchmark for performance measurement, which is indexed at 100. The accuracy only AI framework model shows improvement in reducing the excess

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inventory but very little improvement in terms of carbon intensity. This proves that an accuracy enhancement does not necessarily mean sustainability enhancement. The proposed integrated framework model performs best on all three metrics and particularly in reducing expedited shipment frequency because of higher carbon intensity of expedited shipments.

The results reported in Figure 3 illustrate an important observation: the increased accuracy in forecast alone does not result in proportional gains in sustainability. While the accuracy-only version of the AI algorithm managed to reduce the excess inventory when compared to the baseline approach, the carbon intensity per unit ordered was significantly higher than in the integrated setting. This is because, although the accuracy-only algorithm made better forecasts of the demand for the products, it still chose the same transportation mode and quantities that minimized the cost without any consideration of the emissions.

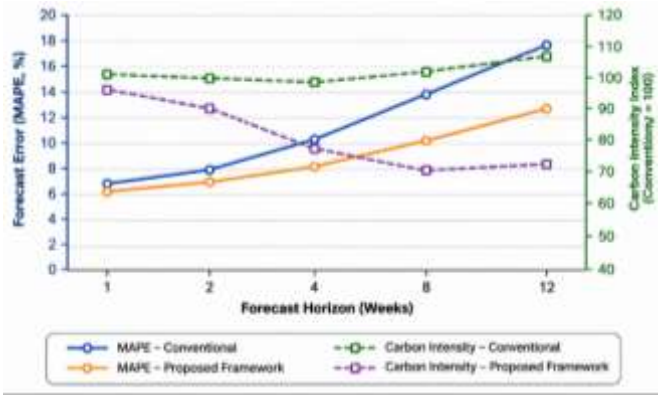


Figure 4: Forecast Horizon Impact on Sustainability Outcomes

The two-axis graph above shows the way in which the utility of AI-based forecasting with regard to sustainability changes with respect to the planning horizon. In case of short planning periods (1-2 weeks), the disparity in the results generated by the new method and traditional ones is insignificant, since both approaches have the ability to take into account the latest signals regarding demand. However, with medium planning periods (4-8 weeks), the ability of the AI-based approach to account for promotional and seasonal effects allows attaining much more accurate forecast with lower carbon footprint in case of emergency deliveries. In case of long planning periods (12 weeks), forecast errors for all the methods rise, while the advantage in terms of sustainability remains thanks to the scenario-based approach.

As shown in Figure 4, the horizon analysis reveals that the sustainability value of AI forecasting is non-linear relative to the planning horizon. It is the longest horizon – the 4-8 weeks period – where the maximum sustainable value lies; this is equivalent to the usual procurement lead time for various types of manufacturing items. From this, it can be inferred that in the process of deploying AI forecasting, organizations must focus on applying the model for medium-term planning periods where the sustainable leverage is high.

Table 1: Comparative Analysis of Forecasting and Sustainability Outcomes

Dimension	Conventional Benchmark	AI Accuracy-Only	Proposed Integrated Framework
Forecast error (relative)	Baseline	Reduced	Reduced with quantile calibration
Excess inventory ratio	Baseline	Moderate reduction	Substantial reduction
Expedited shipping frequency	Baseline	Slight reduction	Pronounced reduction
Carbon intensity per unit fulfilled	Baseline	Marginal improvement	Material improvement

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Dimension	Conventional Benchmark	AI Accuracy-Only	Proposed Integrated Framework
Service level (fill rate)	Baseline	Improved	Maintained or improved
Decision transparency	High (simple rules)	Low (black-box)	Moderate (dashboard + alerts)
Computational requirement	Low	High	Moderate-high

The comparative analysis in Table 1 highlights a central tension: the accuracy-only AI configuration achieves forecast improvements but does not automatically translate these into sustainability gains. The integrated framework, while requiring additional computational resources for the multi-objective optimization, delivers superior environmental outcomes without sacrificing service level. The moderate decision transparency of the integrated approach—achieved through the dashboard and alert system—represents an improvement over the black-box nature of the accuracy-only model, though it does not match the simplicity of conventional rules-based systems. This trade-off is likely acceptable for organizations subject to sustainability reporting requirements, where auditability of environmental performance is increasingly expected.

V. CONCLUSION

This paper has developed and analyzed an integrated framework that couples AI-based demand forecasting with sustainability-aware decision optimization for supply chain management. The central argument advanced is that forecast accuracy, while necessary, is insufficient for achieving meaningful environmental improvements in supply chain operations. The translation of demand signals into procurement, production, and logistics decisions requires an explicit sustainability objective; without it, AI models optimized solely for accuracy may reinforce existing cost-minimizing patterns that externalize environmental costs.

The proposed framework addresses this gap through a modular architecture combining hybrid forecasting—gradient boosting for structured features and LSTM for temporal dependencies—with a multi-objective decision layer that incorporates carbon intensity alongside economic and service metrics. The comparative analysis demonstrates that this integration yields material improvements in sustainability outcomes relative to both conventional approaches and accuracy-only AI configurations, particularly in reducing expedited shipping frequency and excess inventory. The horizon analysis further reveals that the sustainability benefits of AI forecasting are most pronounced at medium planning horizons (4–8 weeks), suggesting that deployment strategies should prioritize these timeframes.

Several limitations warrant acknowledgment. The framework's performance depends on the availability of reliable emission factors for transport and warehousing activities, which vary considerably across regions and logistics providers. The multi-objective weights, while adjustable, require organizational deliberation that may be contested among stakeholders with differing priorities. The governance mechanisms proposed—dashboards, alerts, and human review triggers—represent a starting point rather than a complete solution to the accountability challenges posed by algorithmic decision-making in supply chains.

Future research should extend the framework in three directions. First, the integration of scope 3 emissions data from supplier networks would enhance the environmental fidelity of the decision layer, though this requires data-sharing arrangements that raise confidentiality concerns. Second, the incorporation of circular economy considerations—such as reverse logistics for product recovery and remanufacturing—would broaden the sustainability scope beyond emissions to material efficiency. Third, longitudinal studies examining whether AI-driven forecasting actually reduces emissions in operational deployment, rather than in simulation, are needed to validate the framework's practical efficacy.

The broader implication of this work is that sustainable supply chain management in the AI era requires deliberate design choices about what algorithms optimize for. The technical capability to predict demand with greater precision is a powerful lever, but its environmental consequences depend entirely on the objectives embedded in the decision systems that consume those predictions. Embedding sustainability metrics directly into optimization objectives, rather than

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treating them as post-hoc reporting categories, is essential for translating forecasting advances into genuine environmental progress.

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