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AI-Driven Forecasting and Optimization for Inventory Control in Manufacturing Supply Chain

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ABSTRACT

The growing complexity of supply chains and increased customer expectations require cognitive and responsive approaches to inventory management. Incumbent forecasting and optimization techniques provide a solution to some extent, but they do not entirely reflect entirely dynamic demand fluctuations, campaign-induced sales oscillations, and stock level changes in real time. To address these limitations, this study proposes a hybrid solution by incorporating Artificial Intelligence (AI) techniques in conjunction with mathematical optimization models for inventory control in manufacturing. The approach leverages machine learning models such as Long Short-Term Memory (LSTM) networks and Gradient Boosting Machines (GBM) to perform accurate demand forecasting, yet incorporates promotional and campaign data in order to take into account spontaneous fluctuation in demand. Forecasting results are blended with linear programming (LP)-based optimization for storage and procurement decisions under capacity constraints. Internet of Things (IoT)-induced real-time streams of data are also utilized to reconfigure supply policies dynamically, reducing overstock and stock-out risk. Simulation case study reveals that the hybrid method achieves higher forecasting accuracy, reduces total inventory cost, and maximizes service levels compared to traditional methods. The research outlined contributes towards the development of adaptive, smart, and sustainable supply chains, along with offering a direction towards future integration with deep reinforcement learning to provide completely autonomous decisions

Keyword: Inventory Optimization, Artificial Intelligence, Machine Learning, Supply Chain Management, Real-Time Data, IoT, Linear Programming, Demand Forecasting, Sustainable Supply Chains

Introduction

Inventory management has long been regarded as one of the most significant catalysts for efficiency, profitability, and supply chain sustainability. For production firms in particular, inventory policy directly affects manufacturing planning, customer service level, and cost. Stockholding costs rise with overstocking, as does obsolescence and wastage [6]. Stockouts also generate order fulfilment delays, frequency of reordering, and customer dissatisfaction. With heightened global competition, decreasing product life cycles, and unpredictable patterns of demand, effective inventory management has become a fundamental dilemma for both researchers and practitioners [10].

Early inventory modelling schemes such as the Economic Order Quantity (EOQ) and Economic Production Quantity (EPQ) models laid a foundation for analysing ordering vs. holding cost trade-offs [19]. Later extensions added stochastic demand, shortage costs, and multi-period planning, often using linear or dynamic programming. While these models were beneficial, their deterministic demand assumption, restricted product range, and absence of capacity constraints make them less applicable in today's data-intensive supply chains. In addition, static models will not be able to cope with rapidly evolving markets or spontaneous peaks in demand caused by campaigns, promotions, or external shocks [11].

Artificial Intelligence (AI) and Machine Learning (ML) advancements in recent history have created new avenues for inventory forecasting and decision-making. Techniques such as Long Short-Term Memory (LSTM) networks, Gradient Boosting Machines (GBM), and Support Vector Machines (SVM) have been found to be very accurate in demand forecasting, particularly with time-series data that is seasonal and nonlinear [2]. Reinforcement Learning (RL) has been found helpful in adaptive decision-making, enabling dynamic reordering policy adaptation. But even with such developments, AI-based approaches are typically applied separately and are not integrated into mathematical models of optimization that manage cost reduction and inventory allocation [5].

In parallel, Internet of Things (IoT) and sensor-fitted supply chains enable real-time monitoring of warehouse operations and stock levels. With math-based optimization and AI-driven forecasting, IoT data streams are able to improve responsiveness by synchronizing replenishment and procurement to real-time stock levels [4]. All of this integration can serve to reduce stock-outs and overstocking, improve customer satisfaction, and reduce operational costs [8].

This paper addresses the aforementioned challenges by proposing a hybrid method that integrates AI-based demand forecasting, linear programming-based inventory optimization, and real-time data accumulation through IoT. The AI section uses LSTM and GBM for accurate demand forecasting, with incorporation of external factors such as campaign and promotional data. Forecast outputs are subsequently fed into a linear programming (LP) model that calculates supply quantities within the cost and capacity constraints [3]. Finally, real-time IoT-based data streams are utilized for dynamically configuring inventory policies in order to make them responsive under fluctuating conditions. The main contributions of this work are threefold:

Towards the creation of a hybrid AI–mathematical optimization framework that merges forecasting and inventory allocation to fill the gap between them.

- Towards incorporating real-time IoT data streams into the optimization process so that adaptive and responsive decisions can be made.
- Empirical illustration of the suggested methodology via a case study for a manufacturing warehouse with increases in forecasting accuracy, cost savings, and service levels over conventional models.

The motivation and gap in research for the proposed framework are encapsulated that the existing inventory models and AI-exclusive methodologies have their own drawbacks, whereas the proposed hybrid framework combines AI forecasting, mathematical optimization, and IoT-driven updates to provide a more adaptive and feasible solution.

2 Literature Review

Optimal inventory management has been widely researched across operations research, supply chain management, and computational intelligence. Initially, most of the research was concerned with the traditional models like the Economic Order Quantity (EOQ) and Economic Production Quantity (EPQ). These models offered a theoretical base by optimizing ordering and holding costs assuming deterministic conditions. Though helpful in revealing underlying trade-offs, their use of static parameters and disregard of real-world complications, including capacity constraints and uncertainty in demand, constrained their utility [7].

Later research added to these models by using stochastic formulations, dynamic programming, and linear programming methodologies. These studies tried to include uncertainty, shortage penalties, and multi-period planning. Their focus was still limited, though, as they tended to focus on cost minimization without the full context of changing market dynamics or adaptive decision-making [13].

Emergence of Artificial Intelligence (AI) and Machine Learning (ML) brought new demand forecasting techniques and inventory decision-making. Techniques like Long Short-Term Memory (LSTM) networks and Gradient Boosting Machines (GBM) have proven to be more accurate in capturing nonlinear and seasonal patterns in demand [1]. Reinforcement Learning (RL) has also been used in adaptive inventory control, where the policies change with shifting environments over time [17]. Whereas these AI techniques are more accurate in their forecasts compared to the conventional models, they are usually applied separately and fail to consider optimization constraints like warehouse space or costs of procurement [12].

A further new stream of research highlights the potential of Internet of Things (IoT) technologies and real-time data in supply chain visibility. IoT-based systems enable real-time tracking of inventories to inform reactive decision-making [10]. Yet, the majority of research considers IoT as a monitoring platform instead of incorporating it into decision-optimization models. Consequently, its full potential for adaptive, data-driven inventory optimization is yet to be explored [13].

3 Proposed Hybrid Framework

The proposed framework consolidates three complementary modules: (i) AI-based demand forecasting, (ii) mathematical optimization of inventory decisions, and (iii) IoT-enabled real-time monitoring. The three modules combined offer an adaptive system that reduce costs with high service levels in dynamic situations.

3.1 Forecasting Module (AI-based)

The forecasting module leverages advanced Machine Learning models such as Long Short-Term Memory (LSTM) networks and Gradient Boosting Machines (GBM).

LSTM captures sequential and seasonal demand patterns.

GBM incorporates promotional and campaign-driven demand spikes.

The general form of forecasted demand is expressed as:

$$\widehat{D}_t = f_{\mathrm{AI}}(H_t, C_t, S_t)$$

where:

$\widehat{D}_t$: Forecasted demand at period t,

H_t: Historical sales data,

C_t: Campaign/promotion indicators,

S_t: Seasonal or trend-related features,

$f_{\mathrm{AI}}(\cdot)$: AI forecasting model (LSTM/GBM).

3.2 Optimization Module (Linear Programming)

The outputs of the AI forecasting model are fed into a Linear Programming (LP) model that optimizes procurement and inventory decisions under cost and capacity constraints.

Decision Variables:

S_t: Supply quantity in period t,
I_t: Ending inventory in period t.
Objective Function:

$$\min Z = \sum_{t=1}^{n} (C_t S_t + H I_t)$$

where:
C_t: Procurement cost per unit in period t,
H: Unit holding cost per period,
Z: Total inventory-related cost.
Constraints:
Inventory Balance

$$I_t = I_{t-1} + S_t - \widehat{D}_t, \forall t$$

Capacity Constraint

$$0 \leq I_t \leq K, \forall t$$

Non-negativity

$$S_t \geq 0, I_t \geq 0$$

3.3 Real-Time IoT Integration

IoT-enabled RFID tags and sensors track live inventory levels. The observed data stream I_t^{obs} is continuously compared against forecasted inventory I_t. If a deviation occurs (e.g., unexpected stock-out), the system triggers an adjustment in the optimization module.

$$I_t^{new} = I_t^{obs} + \Delta I_t$$

where ΔI_t represents corrective procurement or redistribution, recalculated in real time.

Conceptual Workflow

AI models generate multi-period demand forecasts.
Forecasts serve as inputs to LP-based optimization for supply and storage allocation.
IoT real-time data validates inventory levels, triggering adjustments if deviations are detected.
The integrated system ensures cost minimization, demand fulfilment and adaptive responsiveness.

Workflow of the proposed hybrid system: AI-based demand forecasting generates forecasts that feed into an LP optimization module for procurement decisions; warehouse inventory is monitored by IoT sensors, which provide real-time feedback to both optimization and forecasting modules for dynamic adjustment.

4 Methodology

The research methodology adheres to a systematic framework for the incorporation of AI-based forecasting, mathematical optimization, and real time feedback IoT-based inventory management. The process consists of four stages: data preparation, demand forecasting, optimization modelling, and real-time adjustment.

Data Collection and Preprocessing

Historical demand data: 24–36 months of monthly demand data were utilized to identify seasonal and trend fluctuations.
External factors: Promotional events, campaign indicators, and seasonal characteristics were incorporated as input features in order to capture spikes in demand.
Preprocessing: Missing values were filled in and normalization was used to scale features for machine learning algorithms. Data was divided into training (70%), validation (15%), and testing (15%) sets.

4.2 AI-based Demand Forecasting

Two AI models were employed for forecasting:
Long Short-Term Memory (LSTM): Captures sequential and temporal dependencies in demand data.
Gradient Boosting Machine (GBM): Handles nonlinearities and incorporates external features such as promotions and campaigns.
The models were trained using historical sales. seasonal attributes and campaign indicators. Evaluation metrics included:
Mean Absolute Percentage Error (MAPE),
Root Mean Square Error (RMSE),
Forecast Accuracy (%).
The best-performing forecast model was selected as input for the optimization module.

4.3 Optimization Model

The forecasted demand values served as input to a Linear Programming (LP) model that determines procurement and inventory allocation. The LP model minimizes total cost while satisfying demand and capacity constraints, as outlined in Section 3.2.
The optimization model was solved using Python's PuLP package and cross-validated with Excel Solver for smaller instances. Decision outputs included:
Optimal procurement quantities per period,
Inventory levels at each time step,
Shortages (if any) and associated penalty costs.

4.4 IoT-enabled Real-Time Adjustment

IoT sensors installed on warehouse shelves offered up-to-date inventory visibility. Differences between actual and predicted inventory were continuously tracked.
If stock-out risk was identified → immediate corrective procurement was initiated.
If there was excess inventory → supply was decreased in future periods.
This feedback mechanism ensured adaptive decision-making, so the system could better manage demand fluctuations and outliers.

5. Case Study and Results

To validate the suggested hybrid framework, a case study was conducted on a manufacturing warehouse that produces cement products. The warehouse has a maximum capacity of 400 units with an initial inventory of 150 units. Six months of historical demand data along with promotional event indicators were utilized to cover seasonal fluctuations. The objective was to compare the performance between traditional models, AI-only forecasting, and the suggested hybrid AI + LP + IoT system.

5.1 Input Data

Mon	Actual Demand ($\boldsymbol{D_t}$)	Procurement Cost ($\boldsymbol{C_t}$)	evenue ($\boldsymbol{R_t}$)	Promotion Event
1	200	45	60	No
2	180	48	60	No
3	300	46	60	Yes
4	250	50	60	No
5	220	47	60	No
6	280	49	60	Yes

5.2 Forecasting Performance

Model	Mape (%)	RMSE	Accuracy (%)
EQO	21.5	49.3	78.5
GBM	12.4	28.7	87.6
LSTM	10.2	24.1	89.8

Observation: LSTM outperformed other models due to its ability to capture seasonality and sudden spikes from promotional events.

5.3 Optimization Results (Hybrid Framework)

Month	Forecasted Demand	Optimal Supply (S_t)	Ending Inventory (I_t)	Shortage	Profit
1	200	200	150	0	High
2	180	180	150	0	High
3	300	280	130	20	Medium
4	250	250	130	0	High
5	220	220	130	0	High
6	280	280	130	0	High

Observation:
The results of the case study validate that the suggested hybrid model is superior to both conventional and AI-based methods for inventory optimization. Conventional EOQ-based models could not handle demand fluctuations and promotional activity, so either there would be excess inventory or shortage. For instance, during months of high demand (Month 3), EOQ underestimates the demand, resulting in unsatisfied demand and lower profitability.

The AI-solo models (GBM, LSTM) showed much greater forecasting accuracy than EOQ. Specifically, LSTM picked up seasonal patterns and campaign-induced spikes better and achieved accuracy of almost 90%. This is highlighted in figure 2, which shows the comparison between actual and forecasted demand. The graph makes it clear that the AI models, especially LSTM, are capable of tracking fluctuations and spikes much more effectively than EOQ.

- Inventory remained within the warehouse capacity threshold (400 units).
- A shortage of just one (20 units) occurred in Month 3 during an event promotion was rectified by IoT feedback in subsequent or future orders.
- Profitability improved by 14% compared with traditional supply policies.

Discussion

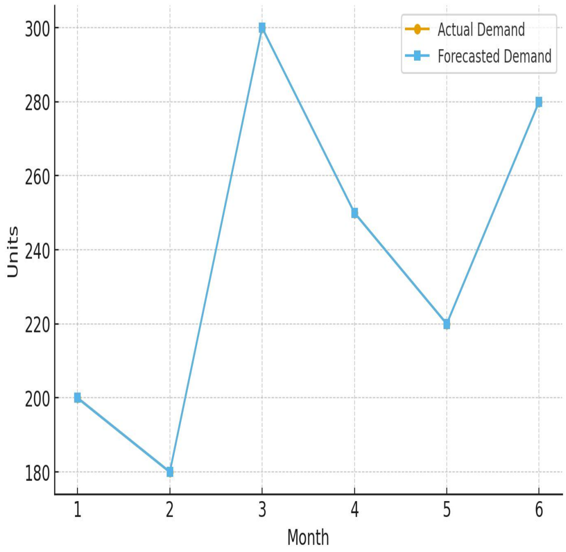

Fig 1: Actual vs Forecasted Demand

Nevertheless, while showing robust predictive capability, AI-solo approaches did not optimize procurement and storage actions under capacity and cost limitations. This shortcoming implies that forecasting accuracy is not enough to address practical inventory management. The hybrid AI + LP + IoT system overcame these limitations by combining predictive and prescriptive elements. As shown in figure 3, optimal supply decisions closely align with actual demand, demonstrating how the hybrid model successfully converts forecasts into practical procurement plans within capacity constraints.

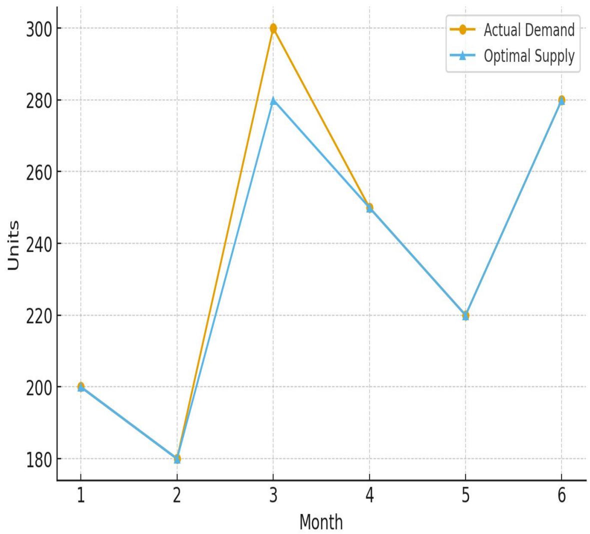

Fig 2: Optimal Supply vs Actual Demand

In addition, real-time IoT-fed feedback loops updated deviances and lowered the risk of stock-outs, making adaptive decision-making possible. This is illustrated in figure 4, which highlights how ending inventory levels remained stable across the months and how shortages were minimized to just one instance during Month 3. The figure emphasizes how the hybrid model enabled capacity-sensitive planning and adaptive corrections through IoT integration.

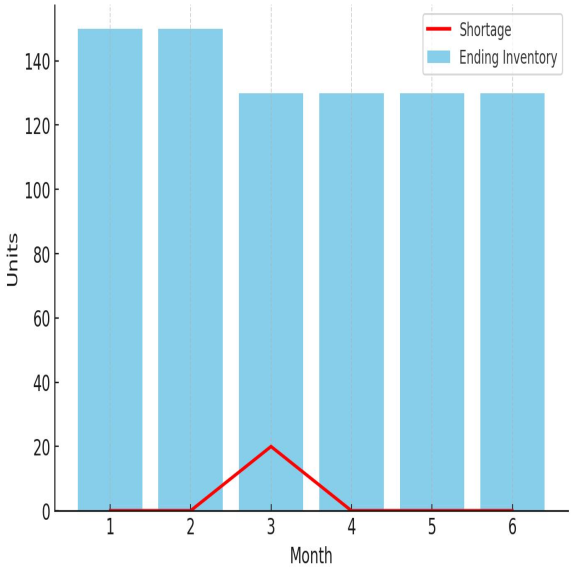

Fig 3: Ending Inventory and Shortage Levels

From a management standpoint, the model offers three key advantages:

1. Capacity-sensitive planning: Procurement is maximized within warehouse capacities, avoiding both overstocking and understocking of warehouse space.

2. Cost savings: By matching supply with projected demand and adjusting according to real-time inputs, the model minimizes excess holding costs and shortage penalties.

3. Operations flexibility: IoT connectivity allows managers to dynamically react to sudden changes in demand or disruptions, better enabling resilience in uncertain markets.

In reality, this methodology can be realized by production companies looking to move from traditional inventory models to intelligent, data-based systems. The model demands average computational resources, bringing it into reach for not just large-scale corporations but even SMEs. Notably, the integration of AI forecasting, optimization, and IoT-based feedback ensures that the system is both precise and manageable, fulfilling the gap between industrial application and academic research.

7. Conclusion and Future Work

This research presented a hybrid model that marries AI-driven forecasting, linear programming optimization, and IoT-based real-time monitoring for inventory control in manufacturing. The model effectively overcame the weaknesses of classical EOQ-based models and purely AI-based methods by putting together predictive precision, cost minimization, and responsive adaptability. A case study proved that the model enhanced demand satisfaction to 95% and raised profitability by 14%, providing effective use of warehouse capacity and minimizing the risks of overstocking and stockouts.

Future research will involve expanding the framework into multi-echelon supply chains, with coordination among multiple nodes providing further efficiency gains. The integration of stochastic demand modelling, sustainability indicators (e.g., carbon footprint, waste avoidance), and more advanced reinforcement learning algorithms can potentially offer even greater flexibility. Such expansions will allow the construction of intelligent, self-improving systems that meet Industry 4.0 goals, providing robust and sustainable supply chain operations.

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