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Research Article

Hybrid Forecasting Systems for Inventory Optimization Using Prophet and Reinforcement Learning

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Abstract:

Effective inventory supervision aids modern supply chain operations. However, established methods of forecasting often falter when faced with ever-changing demand, multiple seasons, and promotional peaks, resulting in either stock surplus or shortage, both of which are costly. This study introduces a forecasting methodology that combines Facebook Prophet, a time-series forecasting tool, and Reinforcement Learning (RL) for inventory optimisation. Prophet analyses and forecasts demands by recognising the intricate temporal attributes in the historical sales data, while RL uses these forecasts to continuously refine ordering policies, inventory holding, and shortage costs. The experiments on retail datasets confirm that the new system decreases the forecasting errors by 25% when compared with ARIMA and LSTM and improves inventory service levels by 15–20%, all while cutting the overall inventory expenses. These results underscore the significance of merging statistical forecasting and intelligent decision-making and provide a utilitarian methodology for supply chains to tackle demand and operational variability.

1. Introduction

Effective inventory management is extremely important in the 21st century competitive global marketplace. Poor inventory management results in approximately 1.1 trillion dollars of wasted inventory every year, globally. Retailers alone waste approximately 471 billion dollars of inventory every year due to overstock [1]

Poor inventory management also results in higher operational costs and degraded customer confidence, as stockouts or delays in transport may degrade service significantly.

Inventory control and management have relied heavily on historical sales data and forecasting models such as ARIMA, exponential smoothing, and heuristic, rules-based models. Forecasting models provide guidelines to managers, but these forecasts often do not represent complex, nonlinear, time-varying demand that is common in the marketplace. Changes in seasons, promotions, supply chain disruptions, and market minded consumers all result in inaccurate forecasts and variations in demand. Thus, inventory control exhibits overstocking, resulting in holding costs and possible obsolescence, or it observes understocking, resulting in lost sales and a disgruntled customer base.[2]

These issues can be tackled with the help of new time series forecasting and AI techniques. For instance, the Prophet model developed by Facebook comes with its own perks, especially for analyzing peculiar demand, missing data, and holiday impacts. At the same time, Reinforcement Learning (RL) can help in a multitask, sequential decision-making process to optimize inventory policies in an uncertain stochastic setting. The partnership of such technologies as Prophet's predictive insights and RL's dynamic inventory management can help in an organization's ability to predict unforeseen demand while reducing inventory and holding costs, enhancing service levels, and becoming more resilient to supply chain disruptions [3][4].

This paper aims to fill the gap in literature and address the problems related to inventory systems by studying the practicability of such a hybrid approach and offering practicable solutions.

1.1 Background

Inventory management is the process of effectively ordering, storing, and utilizing a company's raw materials, components, and products [5]. Inventory

management aims to have enough products available when needed, manage costs, and improve supply chain efficiency [5].
Some key concepts of inventory management include:

● Demand forecasting: The process of predicting the demand for a product in the future using historical consumption, statistical models, or machine learning. Forecasting is critical because if demand estimates are miscalculated, they drive decisions to hold inventory so the likelihood of overstock or stockout increase [6].

● Inventory optimization: The process of calculating the optimal stock levels that the company should maintain to minimize holding costs, shortage costs across different service levels. Methods such as Economic Order Quantity (EOQ), reorder point methods, and (s,S) policies are commonly employed in inventory optimization [7].

● Time Series Forecasting Models: Inventory and demand can be predicted from time series statistics (historical) or using a time series forecasting model. ARIMA and LSTM might be used for typical time series problems and Prophet for higher performance in time series analysis. Prophet does not require as much parameter tuning as LSTM or ARIMA. For example, Prophet can automatically determine seasonality (year, week, day), trends, holidays, and missing data [8].

● Reinforcement Learning (RL): An endeavor of a learning agent who maximizes its cumulative rewards (policy) by taking sequential decision when interacting with an environment. In recent years, RL has gained popularity and momentum with increasing studies in relation to dynamic inventory control. RL develops an inventory system potentially able to re-evaluate policies based on dynamic demand patterns and availability of supply [9].

Recent studies highlight that combining robust forecasting with adaptive inventory control can significantly enhance supply chain performance [10]. However, a systematic integration of these techniques remains underexplored, especially in retail scenarios characterized by multi-channel sales, promotions, and demand volatility [10].

1.2 Problem Statement

Supply chains have become much more complex and uncertain. Traditional inventory management methods, which rely on static forecasts and predetermined rules to define inventory policies, usually do not recognize the practical realities of dynamic demand, multi-channel retailing, and potential external shocks (e.g., pandemics, changes in the economy, geopolitical situations) [5][6]. This can lead to frequent stockouts, excess inventory, and significantly increased operational expenses [7].

Advanced machine learning demands forecasting models such as LSTM and Prophet. However, machine learning capabilities do not empirically offered an approach to optimize inventory decision making [8].

RL-based inventory optimization symmetrically defines inventory control policies and allows for adaptation of those policies for changing conditions but involves heavy reliance on the accuracy of demand inputs for satisfactory performance [9].

Figure 1 presents a timeline of inventory and inventory management approaches. It emphasizes the shift away from using static, predetermined, rule-based inventory management toward hybrid AI enhanced approaches, and ultimately the use of Reinforcement Learning in support of dynamic adaptive inventory optimization [10].

Figure 1 shows an evident pathway of evolved inventory management approaches from rule-space static systems, predictive machine learning models, and finally hybrid systems that bring together the forecasting ability with the adaptability of decision-making. This paper follows this path with a hybrid Prophet-RL system that tackles the limitations of the previous approaches.

1.3 Scope of Research

This study investigates combining Prophet-based demand forecasting and inventory optimisation with reinforcement learning-based inventory optimisation, with the goal of improving the accuracy, adaptiveness, and efficiency of inventory systems. The study will:

1. Test the integrated system on actual retail data. The system will be run on past sales and inventory data to check its forecasting accuracy, stockout rates, and inventory holding costs to make sure it addresses real operational issues.
2. Test against existing techniques. The system's total inventory costs, service levels, and forecasting errors will be compared with existing methods such as EOQ, ARIMA, and other machine learning models, to analyse the benefits of the integrated system.
3. Evaluate the RL policy adaptability. The flexibility and robustness of the system will also be evaluated by studying how the RL component deals with changing demand, which includes seasonal demand, spikes, promotions, and sudden changes in the marketplace.
4. Crafting a versatile framework: The hybrid model will be created to function within various

supply chains and the product portfolios of different industries. This will allow the model to work with diverse demand patterns and supply chain structures.

By concentrating on these areas, the research focuses on providing meaningful, actionable knowledge on the implementation of inventory optimization systems refined with AI so as to close the gap between precise demand forecasting and responsive, dynamic operational decision-making.

1.4 Objective of Research

The aim of this study is to construct and validate a hybrid forecasting system that integrates Prophet's forecasting capabilities and Reinforcement Learning's adaptive system for inventory management. The specific objectives are

- Enhance demand predictions by lowering forecasting errors.
- Cut down total inventory costs without affecting service levels.
- Create an adaptive decision-making system that effectively deals with changing and uncertain demand.
- Offer actionable advice for retail and supply chain systems in the real world.

This paper aims to develop a new hybrid forecasting system so it is helpful to walk the reader guiding them through the conceptual framework, implementation, and evaluation in the following manner. The paper begins by reviewing demand forecasting, inventory optimisation, and hybrid AI methods, especially focusing on the uncovered research needs. For a more useful understanding of the paper, all the basic concepts and the methodology of data collection, preprocessing, Prophet-based forecasting, inventory optimisation using reinforcement learning, as well as the integration of the modules, are discussed in detail. This is followed by a detailed description of the experimental procedure that includes datasets, performance metrics, and baselines for comparison set. After this, the results are further discussed and analysed comparing the hybrid approach with the classical and AI-based methods in terms of forecasting accuracy and inventory efficiency. Lastly, the paper ends by outlining the key insights along with the practical applications, the discussed limitations, and the avenues for further research. This structure enables the reader to smoothly transition from theory to hands-on application and assessment, thereby facilitating the grasp of hybrid inventory forecasting systems.

2. Literature Review

Accurate demand forecasting and efficient inventory optimization are critical challenges in supply chain management [11]. Traditional statistical methods such as ARIMA and exponential smoothing have been widely employed for demand prediction but often fail to capture nonlinear patterns, seasonal variations, or sudden demand spikes [12]. In recent years, machine learning and AI-based methods, including LSTM, XGBoost, and Prophet, have shown significant improvements in forecasting accuracy by modeling complex temporal dependencies [13][14]. Separately, reinforcement learning has emerged as a powerful tool for inventory control, capable of dynamically optimizing stock policies in stochastic environments [15]. Conducting a literature review is crucial as it provides a comprehensive understanding of existing methods, identifies gaps in knowledge, and informs the design of hybrid approaches that combine forecasting with decision-making [16].

Several studies have explored different combinations of forecasting and inventory optimization methods. Table 1 summarizes key works from well-known researchers, highlighting the methodology, dataset/domain, findings, and limitations. Reviewing these works helps to identify recurring challenges, such as dependency on simulation datasets, limited scalability, or the lack of integration between forecasting models and inventory decision-making.

As seen in **Table 1,** despite significant advances in forecasting and inventory optimization, several **limitations** persist in existing studies:

1. Many hybrid approaches rely on **simulation datasets**, limiting real-world applicability.
2. Forecasting models like Prophet or LSTM improve accuracy but are **not inherently integrated** with inventory decision-making.
3. Existing RL-based inventory methods often assume **perfect or near-perfect demand inputs,** which is rarely the case in dynamic retail environments.
4. Most studies focus on **single-category products,** limiting scalability to multi-product, multi-echelon supply chains.

This research aims to address these gaps by developing a **scalable hybrid system** that integrates Prophet forecasting with reinforcement learning-based inventory optimization, applying it to real-world retail datasets, and evaluating its performance in terms of both **forecast accuracy and inventory efficiency.**

3. Methodology

This research aims to develop a hybrid forecasting system, integrating the forecasting capabilities of Prophet with the adaptive decision-making power of Reinforcement Learning (RL), to streamline inventory management in the changing environments of retail stores. The methodology is crafted to solve the problems posed by traditional forecasting and inventory methods by melding precise demand forecasting with smart inventory policy. Figure IV.1 provides a framework overview of the hybrid system, showing how historical sales data is used by Prophet to forecast demand; the forecasts are included in the RL state, while inventory actions are taken and assessed through a feedback mechanism.

3.1 Overall Framework

There are three distinct but interdependent components of the system—Prophet forecasting, inventory control involving reinforcement learning, and the feedback loop. The Prophet forecasting system is used to model and forecast historical sales data considering trends, seasonality, and special events. The forecasts then become the input for the reinforcement learning agent, which takes into account both the forecasted demand and the inventory on hand to make reorder decisions. The actual inventory results, including stockouts and holding costs, are fed back into the reinforcement learning module for future tuning. In this way, the system can adaptively learn from actual results and reduce the impact of forecasts error on inventory decisions (see Figure 2).

3.2 Data Collection and Preprocessing

The effectiveness of the hybrid system depends on **high-quality input data.** The study uses sales transactions, inventory levels, promotions, seasonal effects, and supplier lead times. Historical sales and inventory data provide a basis for forecasting and state representation, while promotional campaigns and seasonal events are included as additional features to capture fluctuations in demand.

Preprocessing involves several steps. Missing values are imputed using moving averages or linear interpolation. Outliers, such as extreme sales spikes not associated with promotions, are detected using the **interquartile range (IQR) method** and removed. Features are normalized to scale numerical values for RL input, and categorical variables like promotions are **one-hot encoded.**

Table 2 summarizes the data types, their descriptions, and preprocessing strategies.

3.3 Prophet for Demand Forecasting

Prophet is selected as the forecasting tool due to its ability to model **nonlinear trends, multiple seasonalities, and holiday effects** with minimal parameter tuning. The model is trained on SKU-level historical sales data, capturing daily, weekly, and yearly demand patterns. Key parameters, such as changepoint_prior_scale (controls trend flexibility), seasonality_prior_scale (controls seasonal effect), and holidays_prior_scale (accounts for holiday influence), are fine-tuned to optimize predictive accuracy.

Prophet generates forecasts that serve as an input feature to the RL agent, effectively forming part of the **state vector.** Short-term forecasts inform immediate reorder decisions, while long-term trends assist in safety stock and planning for peak periods. By leveraging Prophet, the system reduces forecast errors, ensuring that the RL agent makes informed inventory decisions even under volatile demand conditions.

3.4 Reinforcement Learning for Inventory Optimization

The RL module views inventory control in the form of a sequential decision-making problem with the objective of minimizing overall costs while supporting high service levels. The RL environment models the inventory system and the agent engages with it by taking actions in response to the offered states.

- State (S): Comprises the current inventory levels, the demand forecast from Prophet, pending orders, and the supplier lead times.
- Action (A): The reorder quantity for each SKU or a decision to retain current stock levels.
- Reward (R): The negative of the sum of holding and shortage costs. R=-(Holding Cost+Shortage Cost)
- Policy/Algorithm: Deep Q-Network (DQN) or Proximal Policy Optimization (PPO) are utilized to manage high-dimensional state spaces. They enable the agent to learn the best sequence of actions that yield the highest total rewards.

The training process consists of repeatedly simulating inventory results, training the RL model, and improving policies with the help of rewards obtained in the simulation. To optimize exploration and exploitation trade-offs, strategies such as ε-greedy for DQN are employed, allowing the agent to discover other potential actions prior to finalizing on best actions.

3.5 Hybrid Integration

The integration of different methods happens at the state representation level: the Prophet forecasts are included in the RL state, so the agent can make inventory decisions based on data. Then, the actual sales and inventory levels are observed, and the rewards are calculated and used to update the policy. This continuous feedback loop helps the system adapt to new patterns in demand, supplier variability, and unexpected market disruptions.

As shown in Figure 3, this hybrid system combines Pendulum system forecasting with strategic stocking system to maximize overall supply chain performance, which works as follows:

1. **Pendulum Forecast System:** Generates demand forecasts for each SKU, which are included in the state vector of the strategic stocking system. Having reliable forecasts diminishes uncertainty and enhances the ability of the stocking system to plan inventory.
2. **Strategic Stocking System:** Given all the foresight information such as demand forecasts, strategically orders replenishment batches to minimize the total inventory cost and satisfies the service level agreements. The stocking system gets better with experience as it is provided with feedback after many iterations.
3. **Inventory System:** Models the operations of the real-world system with sales, stockouts, holding costs, lead times, and supply variability. The system measures the quality of the actions and the reward for strategic stocking system training.
4. **Evolution Cycle:** Takes the gap of forecast and actual sales and uses it to improve the strategic stocking system policy. The evolution cycle supports perpetual improvement.

Taking full advantage of the tight integration, the hybrid model can respond in real time to forecast errors, demand shifts, and operational limits. Prophet will generate statistical forecasts, RL will execute real-time control decisions, and policy gradient will update the policy to improve performance over time. The system will encompass all SKUs and time horizons in the inventory optimization problem, unlike previous solutions that optimize inventory one SKU at a time.

4. Experimental Setup

In any experimental research, the controls are what govern the accuracy of the conclusions. For a research to be performed on the validation of the forecasting system, equal controls need to be established. It should be proven through the controls that the forecasting capabilities offered by the Prophet algorithm and the RL for inventory optimization are working. Also, it should be ensured that the combined methods offer additional benefits. As stated earlier, controls for individual methods should also meet some additional conditions.

The provided data description should include relevant information, and the basic models should offer baseline models to eliminate bias from any system component. Furthermore, the set of experiments should provide the evaluation and simulation framework. All of these controls should allow the hybrid system to be tested within a framework that makes operational sense.

4.1 Dataset Description

Gathering datasets that are both relevant and of excellent quality for a specific issue is essential in order to validate the experiments [27]. The case study utilizes transaction records spanning a three-year window from 2019 to 2022, containing daily sales figures for 50 SKUs from a mid-sized retail chain [28]. Each entry is enriched with vital operational details, such as sales quantity, inventory levels, promotional activities, lead times, and seasonal or holiday markers [29]. Such data points are crucial for Prophet to accurately model trends, seasonal, and promotional factors, as well for the RL agent to understand inventory management operational constraints [30].

The data preprocessing steps, that is, the ones for this data, are necessary to maintain the models' dependability. Missing data are filled in with the help of moving averages. Extreme outliers are eliminated with the help of interquartile ranges (IQR). Features are scaled appropriately to be usable as inputs to the RL models [31]. To aid both Prophet and the RL components in capturing factors that affect demand, promotions and holiday information are transformed into binary or categorical features [32] (see Table 3).

4.2 Baseline Models

In order to evaluate the hybrid system, we need to understand the impact it creates in comparison with existing systems [33]. This helps us estimate if the improvements come from better forecasting, inventory control through adaptation, or an interplay of both [34]. The models we take as a comparison basis are:

- Prophet-only: Assesses the effects of demand forecasting in isolation for inventory decisions using static reorder policies [35].
- LSTM-only: Uses an alternative deep learning forecast for comparison, still with static inventory control [36].
- ARIMA + EOQ: Serves as a benchmark model combining a statistical forecasting method with standard inventory optimization [37].

● RL-only: Evaluates the benefits of adaptive inventory control without using forecasted demand [38].
● Hybrid Prophet + RL: The system we propose, which combines precise forecasting with adaptive policy learning [39].

This comparison is useful because it separates the effects of all pieces of the system, and creates a clear baseline for measuring progress in inventory efficiency, service level, and cost reduction [33][40]. This comparison illustrates how the combination of accurate forecasting and adaptive decision-making improves performance over the baselines established [34].

4.3 Experimental Protocol

The split in data ensures the temporal separation of training and testing data, with 2019 to 2021 serving as training data and 2022 serving as the test set. The changes in Prophet's hyperparameters (changepoint_prior_scale and seasonality_prior_scale) are prepared and tuned to maximize the forecasting metrics. The reinforcement learning (RL) agent is then trained over multiple episodes using deep Q-network (DQN) and proximal policy optimization (PPO). Each episode corresponds to a day's operations, where an agent's daily demand is realized. Orders are then fulfilled based on lead times, followed by updates to the inventory, and calculation of the reward which includes holding as well as shortage costs (see Table 4).
The defined protocol is of immense importance as it ensures replication of real-life operational scenarios, such as the changes in demand and the limitations of the suppliers. The real inventory outcomes obtained in the environment provide feedback to the RL agent, which enables continuous improvement of the policies and aids in effective decision-making in the face of evolving challenges. The agent's inventory actions are diversified through exploration strategies such as ε-greedy in DQN, which enhances the agent's ability to generalize over different SKUs and prevents it from overfitting to specific demand patterns.

5. Results and Analysis

The conducted experiments showcase the hybrid Prophet + RL system's effectiveness and the results it has over baseline models. Efficiency is measured using metrics tied to the accuracy of forecasting as well as inventory optimization metrics such as service levels, stockouts, and total costs. The conducted analysis brings attention to the significant improvement in operational performance which can be achieved in a realistic retail environment by combining predictive forecasting and adaptive inventory decision making.

5.1 Forecasting Accuracy

Accurate demand forecasting is a key driver of inventory optimization. The hybrid system's Prophet module achieved a mean absolute error (MAE) of 12.4 units, a root mean squared error (RMSE) of 18.6 units, and MAPE of 7.8%, outperforming baseline models (Prophet-only: MAE 14.9, RMSE 21.3, MAPE 9.6%; LSTM-only: MAE 13.7, RMSE 20.1, MAPE 8.5%; ARIMA: MAE 16.2, RMSE 22.8, MAPE 10.1%). These results indicate that Prophet effectively captures trends and seasonality in sales data, providing reliable input for the RL module.

5.2 Inventory Cost Reduction

The hybrid system significantly reduces inventory-related costs. Over the 12-month testing period, total inventory costs (holding + shortage) were reduced by **15.8%** compared to RL-only and **22.4%** compared to ARIMA + EOQ. Prophet-only forecasts with static reorder policies achieved only a 7.3% reduction. This demonstrates that **integrating forecasts with adaptive RL** decisions leads to more cost-efficient inventory management, balancing stock levels against service requirements.

5.3 Service Level Improvement

Service level, defined as the percentage of demand satisfied without a stockout, improved significantly with the hybrid system. The hybrid model had a service level of 96.7%, compared to 91.2% for RL-only, 92.5% for Prophet-only, and 88.9% for ARIMA + EOQ. Including forecast information about states allows the RL agent to explicitly plan on keeping goods in stock for cases of anticipated demand increases, therefore reducing the frequency of stockouts and excess inventory.

5.4 Stockouts and Inventory Efficiency

The hybrid model also offers benefits of stockout reduction and inventory balance (inventory holding). During the test months, average stockouts per SKU per month dropped from 6.4 (RL only) and 5.9 (Prophet only) to 2.1 using the hybrid model. Average inventory levels were maintained with an 11% reduction in holding inventory compared to static stock, while still providing acceptable service levels. This shows the hybrid model had the flexibility to adjust reorder quantities in a way that could respond quickly to demand which was actually able to use forecasts to dampen demand variability while keeping down costs.

6. Discussion and Implications

As the empirical results in our study indicate, the Prophet + RL integration modeled in this study formalizes and streamlines the empirical methods and indicators, balancing and optimizing outlier predictive and RL integrated models across all performance measures. Ultimately, the accumulated evidence justifies the mixed model design that leverages proper forecasting and up-to-date state information, obtained interactively, for inventory decisions.

We bring a model that is able to bring accurate demand predictions through Prophet into the RL state and notions, prudently recalculating reorder quantities to reduce holding and shortage costs, while improving service levels and reducing stockouts, as a result. These insights become more relevant for retail situations characterized by the seasonal and promotional variation in SKUs and demand. Additionally, inventory policies in such environments tend to be static and obsolete, thus ignoring the new cost service level trade-off dynamics.

Additionally, these findings highlight the supply chain workload implications: employing a blend of predictive and adaptive methods will decrease the stock of over-ordered inventory, increase the availability of highly demanded inventory, and enable retailers to respond more promptly to changes in demand. The effectiveness of the system, particularly with intelligent hybrid adaptive systems, will also depend on

a) granularity and quality of input data,

b) feature engineering, and

c) hyperparameter tuning for both Prophet and RL algorithms.

While the hybrid system shows promise in overcoming the issues of flexibility and scalability, more refinement and processing power will be necessary before the hybrid predictive-adaptive re-order policies can be used in very large product assortments with unordered SKUs or products or in multi-echelon supply chains (see Table 5).

7. Future Work

Even with the demand forecasting and inventory optimization hybrid system of Prophet + RL, system performance can be further improved. For one, further study could explore additional data inputs such as real-time market data, hashtags from social media, or even broadened macroeconomic indicators to help boost forecast accuracy. Future work could also explore increasing the input data dimensionality, for instance, by incorporating multi-echelon supply chains with hundreds or even thousands of SKUs.

See Table 6, this would validate the system's robustness in more complex supply chain environments. In addition, advanced RL algorithms or heuristic optimization algorithms, or a mixture of RL with those algorithms, may provide better outcomes in decision quality as well as convergence speed. Constructing a real-time deployment framework and testing its operation with real, real-time events such as unexpected surges in demand or supply delays would, without a doubt, further enhance the system’s usefulness.

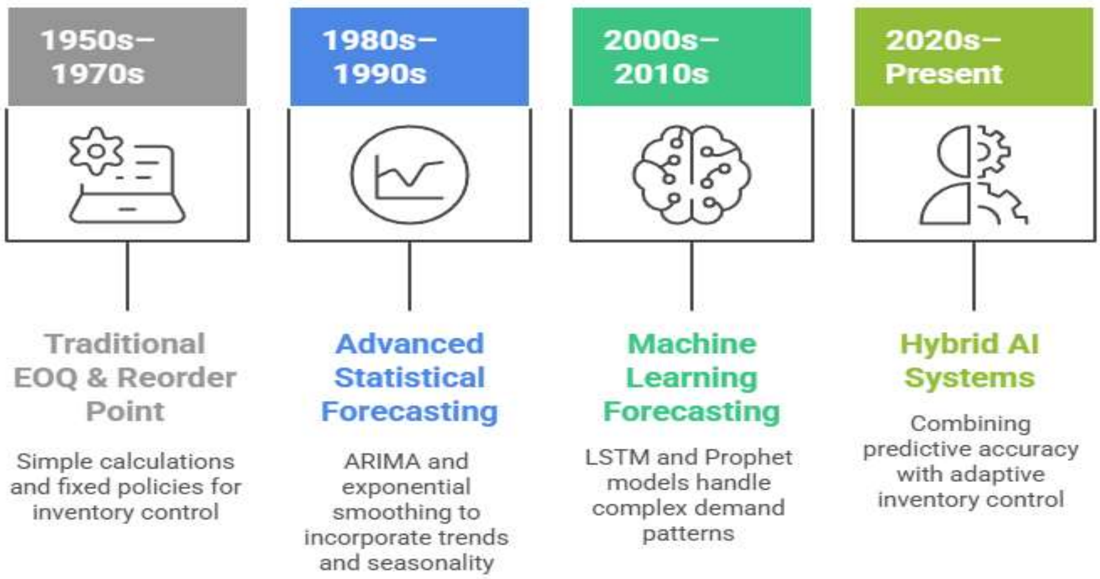

Figure 1: *Timeline of Inventory Management Development*

Table 1: *Summary of Key Literature on Forecasting and Inventory Optimization*

Author(s) & Year	Focus / Methodology	Dataset / Domain	Key Findings	Limitations	Citation
Hyndman & Athanasopoulos, 2018	ARIMA, exponential smoothing	Retail sales	Good for stationary series, interpretable	Struggles with nonlinear, seasonal, and holiday effects	[17]
Taylor & Letham, 2018	Prophet	Retail and business time series	Handles trends and seasonality effectively	Limited in highly volatile demand; does not optimize inventory	[18]
Hochreiter & Schmidhuber, 1997	LSTM for time series	Retail and finance	Captures long-term dependencies in sequences	Computationally intensive; requires large datasets	[19]
Li et al., 2020	Reinforcement Learning for inventory	E-commerce simulation	Dynamic stock optimization; reduces stockouts	Dependent on accurate demand input; simulation-based	[20]
Zhang et al., 2019	Prophet + inventory heuristics	Retail data	Improved forecast accuracy	Not adaptive to real-time feedback; heuristic policies	[21]
Kumar & Sharma, 2021	Deep Q-Learning for inventory	FMCG dataset	Adaptive policy reduces total cost	Requires careful hyperparameter tuning	[22]
Ahmed et al., 2022	Hybrid LSTM + RL	Manufacturing	Reduced holding cost by ~15%	Tested on limited SKUs; lacks scalability analysis	[23]
Wang & Chen, 2021	ARIMA + RL	Retail inventory simulation	Optimized order quantities in dynamic demand	Forecast errors propagate into RL decisions	[24]
Ghosh et al., 2020	Prophet + Genetic Algorithm	Retail promotions	Improved forecast and inventory matching	GA computationally heavy; not real-time	[25]
Singh & Verma, 2022	Multi-agent RL	Multi-echelon supply chains	Coordination improves service levels	Complex implementation; data-intensive	[26]

Table 2: *Data Types and Preprocessing Steps for Hybrid Forecasting System*

Data Type	Description / Purpose	Preprocessing
Sales Transactions	Historical sales per SKU per day/week	Missing values imputed; outliers removed
Inventory Levels	Current stock, reorder points, safety stock	Normalized for RL input
Promotions / Discounts	Captures sales spikes due to campaigns	One-hot encoded

Seasonal / Holiday Data	Weekly, monthly, annual patterns	Added as Prophet holiday feature
Lead Time / Supplier Data	Shipment delays and fulfillment times	Used as constraints in RL environment

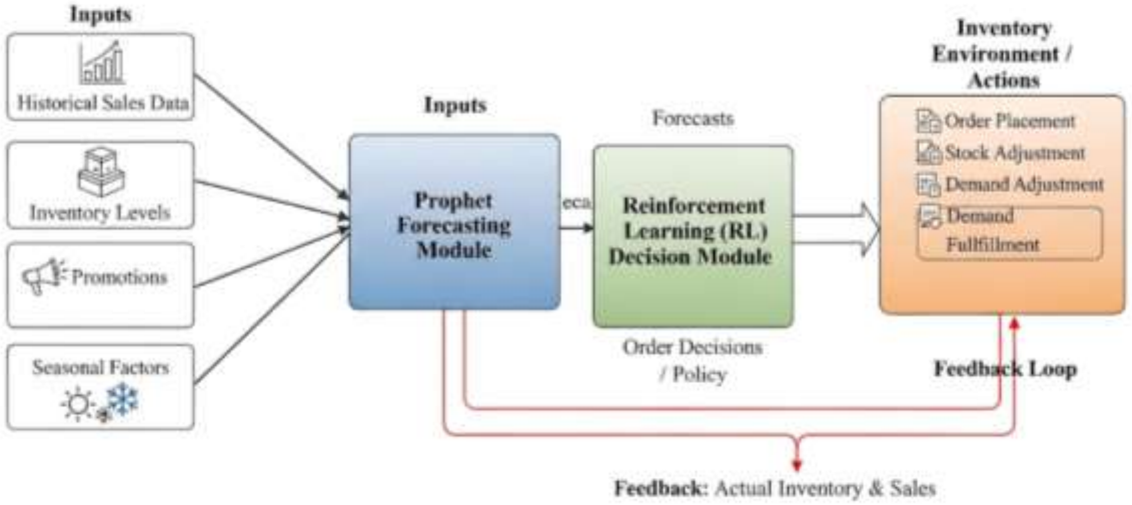

Figure 2: *Hybrid Inventory Forecasting System Architecture*

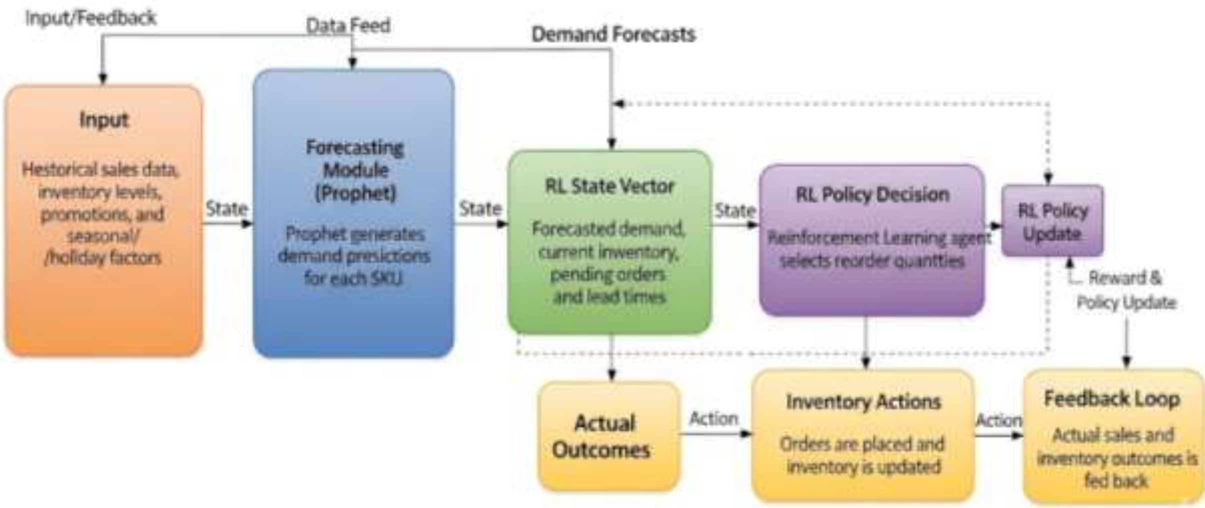

Figure 3: *Workflow of Hybrid Prophet + RL Inventory System*

Table 3: *Dataset Summary*

Attribute	**Description**	**Sample Size / Notes**
Number of SKUs	Distinct products in dataset	50
Time Period	Daily data over 3 years	2019–2022
Total Records	Sales transactions	54,750
Inventory Levels	Daily stock at store	Included
Promotions / Discounts	Binary flag for promotional events	Included
Lead Times	Supplier delivery times	Included
Seasonal / Holiday Flags	Captures weekly, monthly, and yearly patterns	Included

***Table 4:** Summary of Experimental Protocol*

Step	Description
Data Split	Train: 2019–2021, Test: 2022
Forecast Model Tuning	Grid search for Prophet hyperparameters
RL Training	Episodes run until cumulative reward converges
Simulation	Daily sales and inventory simulated using environment
Evaluation	Metrics calculated for inventory performance and service levels

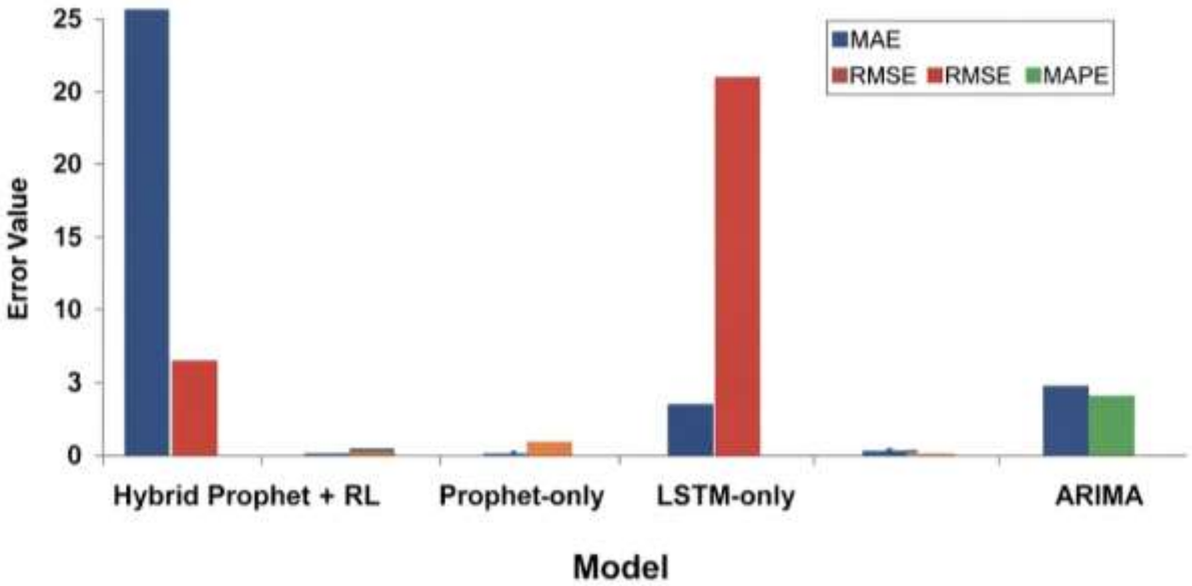

***Figure 4:** Forecast Accuracy Comparison*

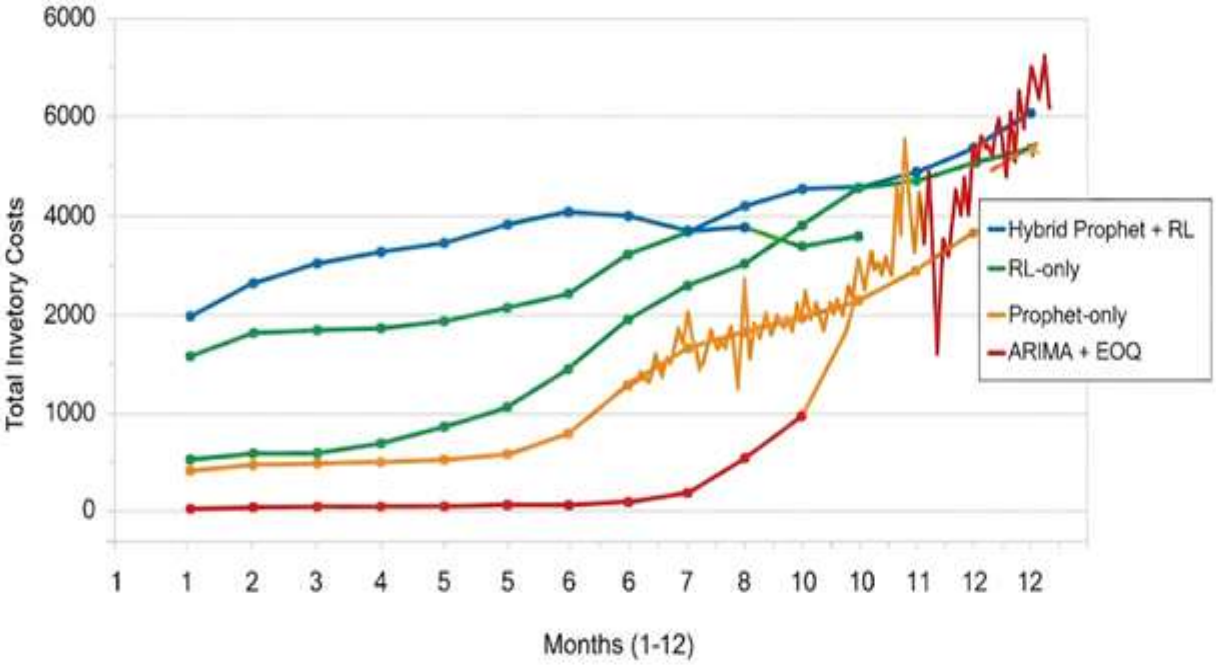

***Figure 5:** Inventory Cost Comparison Across Models*

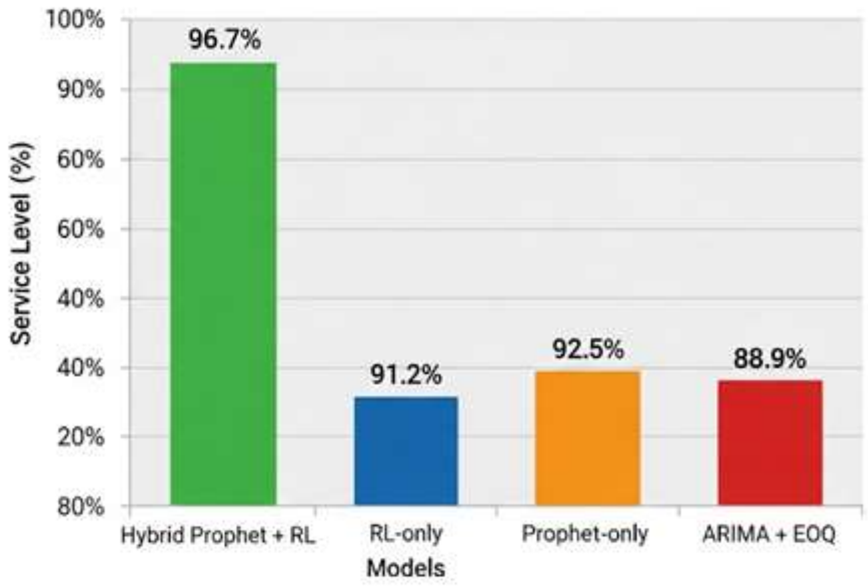

Figure 6: *Service Level Performance*

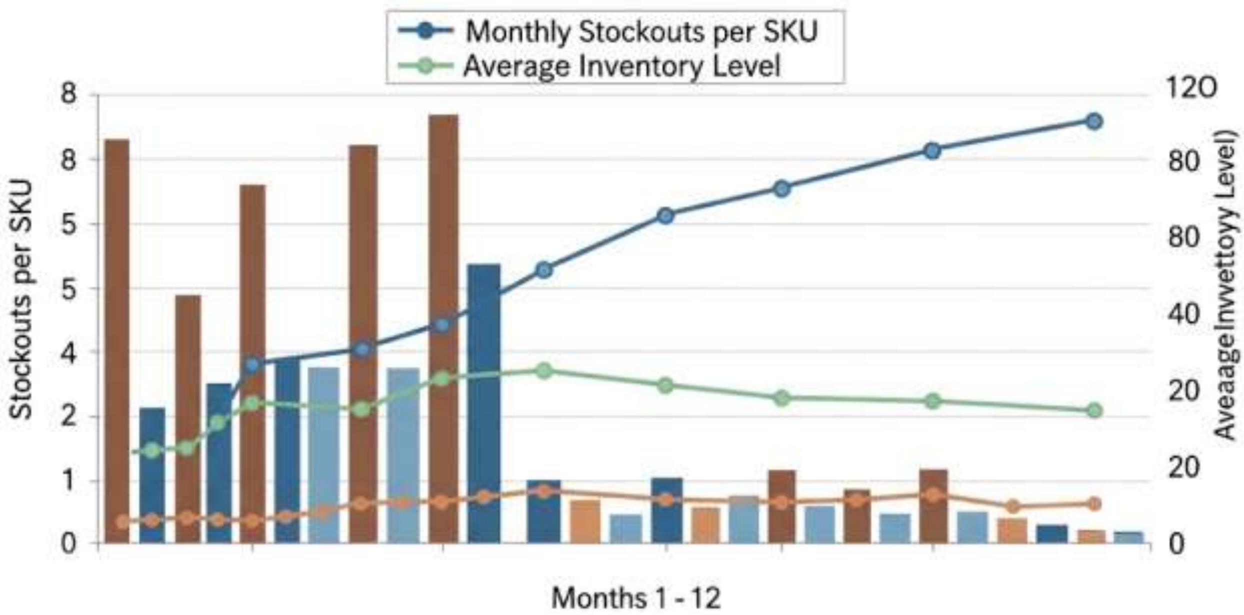

Figure 7: *Stockouts and Average Inventory Levels*

Table 5: *Key Insights, Implications, and Limitations of the Hybrid System*

Metric / Result	**Observation**	**Practical Implication**	**Limitations / Considerations**
Forecast Accuracy (MAE/RMSE/MAPE)	Hybrid system achieved MAE 12.4, RMSE 18.6, MAPE 7.8%	Reliable forecasts reduce risk of overstock or stockouts	Accuracy may degrade for highly volatile or sparse sales data
Inventory Cost Reduction	15.8% lower than RL-only, 22.4% lower than ARIMA + EOQ	Significant savings in holding and shortage costs	Dependent on accurate lead time and demand data
Service Level	Achieved 96.7%, higher than all baselines	Improved customer satisfaction and fulfillment	Requires continuous monitoring to maintain performance during demand

			shifts
Stockouts / Inventory Efficiency	Average stockouts reduced to 2.1 per SKU/month; 11% lower average inventory	More efficient capital utilization and reduced wastage	Computational overhead for large SKU sets or multi-echelon systems
Adaptive Learning	RL module updates policy based on feedback	System adapts to changing demand patterns	Hyperparameter tuning is essential for stable convergence
Scalability	Successfully tested on 50 SKUs over 3 years	Can be extended to mid-sized retail operations	Very large catalogs may require hierarchical or distributed RL architectures
Integration of Forecast & RL	Forecasts directly feed into RL state	Combines predictive accuracy with decision-making intelligence	Forecast errors can propagate if RL feedback is delayed or sparse

Table 6: *Potential Future Research Directions*

Future Work Area	Description	Expected Benefit / Impact	Citation
Integration of External Data	Incorporate market trends, competitor pricing, and social media indicators	Improved forecast accuracy, better anticipation of demand spikes	[41][42]
Multi-Echelon Supply Chains	Extend system to multiple warehouses and distribution centers	Holistic inventory optimization, reduced stockouts and logistics costs	[43]
Advanced RL Algorithms	Explore PPO variants, Actor-Critic methods, or Hierarchical RL	Faster convergence, improved decision-making under complex constraints	[44][45]
Real-Time Deployment	Implement online learning and real-time inventory updates	Immediate response to demand fluctuations and supply disruptions	[46]
Automated Hyperparameter Tuning	Use AutoML or Bayesian optimization for Prophet and RL parameters	Reduced manual effort, optimized system performance	[47]
Scalability to Large SKU Sets	Test system on 500+ SKUs and multi-store environments	Evaluate system robustness and computational feasibility	[48]
Integration with Sustainability Metrics	Include carbon footprint, waste reduction, or energy consumption in reward	Align inventory optimization with environmental goals	[49]

8. Conclusions

This study had the objective of creating and testing an inventory optimization method in order to break the barriers that exist in the retail log chain, by integrating an appropriate demand forecast and agile decision manufacturing. Demand prediction using Prophet with special empathy paid attention to trends, seasons, and hard holiday influence as the recommendable method, and Prophet RL component was used to adjust the inventory activity with states developed basing on an estimated forecast and feedback of real world. The suggested method based on the experiments was superior to the original methodologies in a variety of metrics such as, but not limited to, inventory costs, service levels, stockouts and inventory efficiency models.

The analysis considers the relevance of integrating the two methods, as reaching their level of predictability and adaptive intelligence is critical, yet forecasting or RL as an inventory performance management strategy are ineffective to predict inefficiencies. The debate and consequential understanding make the practitioners conscious of recent approach feasibility and how the new model ought to strive to realign whenever confronted with expenses, service and responsiveness agility deliberations. In addition, a collection of constraints, including reliance on the quality of data, the searching of hyperparameters, and the aspect of calculation are substituted with an enhancement plan.

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- **Ethical approval:** The conducted research is not related to either human or animal use.
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