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Time Series Forecasting in Inventory Management Using R and Python

Peeyush Patel
Oklahoma State University, Stillwater, OK, USA

Abstract: Inventory management plays a vital role in ensuring the efficiency of supply chains, where accurate demand forecasting is central to minimizing stockouts, reducing holding costs, and improving overall operational performance. Time series forecasting has emerged as a powerful approach for predicting future inventory requirements by capturing trends, seasonality, and irregular demand patterns. This review paper provides a comprehensive overview of traditional statistical methods such as ARIMA, SARIMA, and exponential smoothing, alongside advanced machine learning and deep learning models, including LSTM, Prophet, and XGBoost, with a focus on their applications in inventory management. Special attention is given to the use of R and Python, two widely adopted programming environments, which offer rich ecosystems of libraries and packages that facilitate model building, evaluation, and visualization. Through a critical analysis of existing literature and comparative implementations, this paper highlights the strengths, limitations, and applicability of various forecasting methods in real-world inventory contexts.

Keywords: Time Series Forecasting, Inventory Management, R Programming, Python, Machine Learning, Demand Prediction.

INTRODUCTION

Inventory control forms a significant aspect of the supply chain operations because it directly influences the degree of services, cost of operations, and profitability of the organization. Businesses always strive to maximize their stocks to avoid excessive holding costs or stock-out costs. Balancing such a trade-off is therefore significant through proper forecasting. However, these strategies are often based on simplified assumptions that consist of constant demand or lead times, which would barely reflect the dynamic market of the present (Silver, E. A. *et al.*, 2016; Chopra, S., & Meindl, P. 2019). The need to be more competitive, digitization, and globalization have made demand variability even more powerful, as forecasting is today more of a challenging but needed activity in the operations of a modern enterprise. The later introduction of advanced time series forecasting algorithms has been in the limelight of appropriate inventory management (Hyndman, R. J., & Athanasopoulos, G. 2018).

There have been time series forecasting approaches to mitigate the demand uncertainty. Classical statistics that have worked well in changing demand were Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Holt-Winters Exponential Smoothing. Holt-Winters and other models of exponential trend forecast and demand have been predicted through trends, seasonality, and autocorrelation (Hyndman, R. J., & Athanasopoulos, G. 2018; Giannopoulos, P. G. *et al.*, 2025). Even though these models are correct in most of their applications, they have been discovered to be restricted in irregular, intermittent, or highly nonlinear demand patterns as observed in retail, aerospace, and manufacturing sectors, among others. In a bid to solve them, the research community has resorted to machine and deep learning algorithms such as Random Forests, Gradient Boosting, Prophet, and Long Short-Term Memory (LSTM) networks (Bandara, K. *et al.*, 2020). The techniques can pick up on complex nonlinear patterns that interact with extraneous variables and provide greater flexibility to the evolving market situation. Thus, a paradigm shift in time series forecasting is underway, whereby more hybrid and AI-based models will be used to supplement or replace statistical-based models.

The diverse nature of ecosystems, versatility, and support of communities have seen R and Python to be the preferred programming environments. It has become somewhat popular in statistical analysis in R and academic literature with its dedicated packages forecast, series, and fable (Hyndman, R. J., & Athanasopoulos, G. 2018). Instead, Python has seen wider popularity as a platform with scalability, integration with machine learning frameworks, and application to enterprise applications, including libraries such as statsmodels, scikit-learn, pmdarima, and deep learning frameworks such as TensorFlow and Keras (Bandara, K. *et al.*, 2020). The two languages are also rich in visualization elements, and so, the decision-makers are able to understand forecasting results (Pinto, J. M. B. B. D. 2022). The present review article is a box-to-box analysis of time series forecasting tools in inventory

*Corresponding Author: Peeyush Patel
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management in both Python and R, their trends, challenges, and research opportunities.

RELATED WORK

To learn about the development of the forecasting methods in managing inventories, a thorough analysis of the existing literature is necessary to evaluate the suitability of the methods under different demand factors. The initial models used classical statistical models like ARIMA, Holt-Winters, that gave good baselines to capture trends and seasonality (Box, G. E. *et al.*, 2015). But due to their poor performance in handling nonlinear, complex, or intermittent demand, machine learning and deep learning algorithms and models, such as Random Forests, Gradient Boosting, Prophet, and Long Short-Term Memory (LSTM) networks, and others, were explored (Syntetos, A. A., & Boylan, J. E. 2005). Such methods are not only effective in enhancing the predictability of a behavior, but also allow inclusion of external factors like promotions, economic factors, and weather patterns (Taylor, S. J., & Letham, B. 2018). Furthermore, the last 10 years have witnessed the rapid adoption of high-end forecasting tools in both research and practice due to the presence of powerful open-source programming environments such as R and Python. The table below outlines major forecasting methods in inventory management together with their characteristics, benefits, and shortcomings.

Table 1: Summary of Time Series Forecasting Techniques in Inventory Management

Method	**Type**	**Key Features**	**Advantages**	**Limitations**	**Reference**
ARIMA/SARIMA	Classical Statistical	Captures autocorrelation, trends, and seasonality	Well-established, interpretable	Struggles with nonlinear & intermittent demand	(Box, G. E. *et al.*, 2015)
Holt-Winters (ETS)	Statistical Smoothing	Trend and seasonality decomposition	Easy implementation, fast computation	Poor with irregular demand	(Box, G. E. *et al.*, 2015)
Croston’s Method	Specialized Statistical	Designed for intermittent demand	Effective for spare parts & aerospace	Biased in certain demand profiles	(Syntetos, A. A., & Boylan, J. E. 2005)
Prophet (Facebook)	Hybrid (Statistical + ML)	Handles seasonality, holidays, and external regressors	User-friendly, scalable	Less accurate for highly irregular data	(Taylor, S. J., & Letham, B. 2018)
Random Forest / XGBoost	Machine Learning	Captures nonlinear relationships, feature integration	Robust, works with large datasets	Needs careful tuning, less interpretable	(Makridakis, S. *et al.*, 2018)
LSTM/GRU	Deep Learning	Sequential learning, memory retention	Captures long-term dependencies	Computationally expensive, data-hungry	(Makridakis, S. *et al.*, 2018)
Hybrid Models	Statistical + AI	Combines the strengths of multiple models	Improved accuracy, flexibility	Complex to implement, interpretability issues	(Smyl, S. 2020)

TIME SERIES FORECASTING TECHNIQUES

Time series forecasting is one of the key components of inventory management as it offers the opportunity to predict changes in demand, detect seasonal patterns, and optimize stocks. Traditional statistical models have been developed in the past into modern machine learning and deep learning algorithms, with each having its own set of benefits. ARIMA, SARIMA, and Holt-Winters are still popular methods used because of their interpretability and statistical rigor (Box, G. E. *et al.*, 2015). More or less recently, machine learning

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methods such as Random Forests, Gradient Boosting, and hybrid methods have shown their ability to model nonlinear effects, as well as integrate external predictors (Makridakis, S. *et al.*, 2018) Deep learning models, especially Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), are found to become effective tools for processing complex and sequential data on inventory management (Makridakis, S. *et al.*, 2018). The combination of these approaches, together with their R and Python implementation, offers a practitioner a variety of options that can be applied depending on a particular forecasting need.

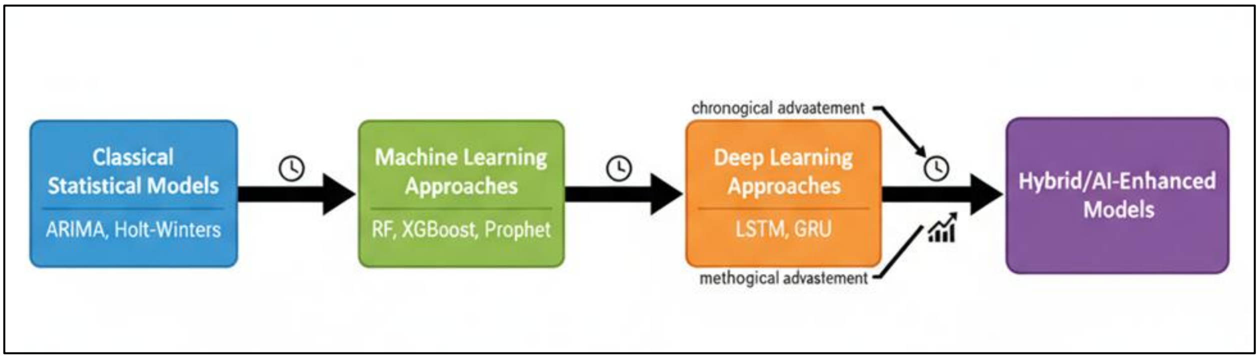

Figure 1: Evolution of Time Series Forecasting Methods in Inventory Management

Over the past few years, the increased complexity of supply chains and access to large-scale datasets have required more complex forecasting methods. Traditional models are effective in short-term forecasting with unchanging demand, but tend to fail when there is intermittent or extremely volatile demand. XGBoost and Random Forests are machine learning models that are effective in detecting non-linear interactions between features and the ability to include exogenous variables such as promotions, weather, or economic variables (Taylor, S. J., & Letham, B. 2018; Makridakis, S. *et al.*, 2018). Deep learning algorithms, and LSTMs specifically, achieve this by learning long-term dependencies in sequential data, and therefore are highly useful in retailing, automotive, and aerospace industries, where demand cycles are not regular (Makridakis, S. *et al.*, 2018). Nevertheless, there are still issues with the computational complexity, interpretability, and integration in enterprise decision systems. Hybrid solutions are becoming more popular, involving the interpretability of statistical solutions with the predictive capability of AI to provide powerful forecasting solutions (Smyl, S. 2020)

Table 2: Comparative Framework of Time Series Forecasting Models

Criteria	Classical Models	Machine Learning	Deep Learning (LSTM/GRU)	Hybrid Approaches
Accuracy	Moderate- effective for stable/seasonal demand	High-better for nonlinear relationships	Very High- captures long-term dependencies	Very High- combines strengths of classical & AI
Interpretability	High results are easy to explain	Moderate- some black-box concerns	Low-requires XAI for explanations	Moderate-depends on design and XAI tools
Computational Complexity	Low-fast training & prediction	Medium- moderate resources	High-requires GPUs and longer training	Highly complex integration, but optimized pipelines are possible
Data Requirements	Small medium datasets	Medium-large datasets	Very large datasets	Medium–large datasets with preprocessing/hybrid tuning
Handling Seasonality	Good-built-in seasonal models	Good-needs feature engineering	Strong can learn seasonality automatically	Strong combines statistical seasonality with AI learning
Intermittent Demand	Poor struggles with irregular	Moderate- some predictive	Moderate customization	Strong e.g., Croston + LSTM for intermittent

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	sales	power	needed	demand
Real-world Adoption	Highly used in traditional industries	Growing increasingly adopted in enterprises	Emerging is used in research and tech-forward firms	Growing pilot projects show strong results
Quantitative Performance (RMSE / MAPE)	RMSE moderate, MAPE ~15–25%	RMSE lower, MAPE ~10–18%	RMSE lowest, MAPE ~7–12%	RMSE lowest, MAPE ~5–10%, best balance of accuracy & interpretability

Data cleaning and preprocessing play an important role in inventory management time series forecasting since they have a direct effect on the model performance. Inventory records are frequently missing some days or products, or duplicate these records, or with different stock levels, which can bias the demand patterns. An example is that the sales information about a product may be missing on a particular day, which will cause a decrease in the demand and increase the stock requirements through repeated entries. The preprocessing techniques of filling in missing values with forward/backward fill or statistical techniques, elimination of duplicates, and fixing anomalies are necessary to address these problems. Moreover, the standardization of data representations and the intermittent or seasonal demand dynamics will ensure that the forecasting tools, be it classical, machine learning, or deep learning, will reflect the actual inventory dynamics and will result in better stock predictions and efficient inventory management.

Table 3: Data Preprocessing in Inventory Management

Challenge	**Description**	**Solution / Approach**
Missing Inventory Data	Sales or stock records are missing for certain days or items	Impute missing values using forward-fill, backward-fill, mean/median, or predictive methods
Duplicate Records	Same inventory entry recorded multiple times, inflating stock levels	Identify duplicates by date and item, then remove or aggregate
Outliers / Anomalies	Errors in stock counts, sudden spikes/drops in demand	Detect using statistical (Z-score, IQR) or model-based methods; correct or remove
Inconsistent Formats	Different date formats, inconsistent product IDs, or categories	Standardize formats, normalize IDs/categories, and validate data types
Intermittent / Seasonal Demand	Products with irregular or seasonal sales patterns	Use smoothing, seasonal decomposition, or specialized methods (e.g., Croston's method) to maintain trends
Large-Scale Inventory Datasets	Manual cleaning is impractical for hundreds/thousands of SKUs	Automate preprocessing with scripts, ETL pipelines, or data validation frameworks

R AND PYTHON ECOSYSTEMS FOR FORECASTING

The identification of the programming environment is an important aspect in the operationalization of the forecasting models in inventory management. R and Python have become the most popular ecosystems of the given choice, as both are open-source, have extensive libraries, and robust communities of users. The two environments can make very precise forecasts, though they are not suitable in all cases, given the application situation, the type of data, and the objectives of the organization.

R Ecosystem for Forecasting

Historically, R has been popular in the academic and research world because it has an in-depth statistical capability, built-in time series analysis packages, and is easy to visualize. R packages like forecast, tseries, fable, and prophet render it highly efficient when it comes to univariate, as well as multivariate time series forecasting, statistical diagnostics, and model interpretability (Petropoulos, F. *et al.*, 2022)

R would best fit when the main goal is statistical exploration, hypothesis testing, or methodological validation. It is commonly used in scholarly and research-based undertakings where there has to be transparency, reproducibility, and statistical rigour. R is generally better suited to small and medium-sized datasets that require fast model development and diagnostic visualization since R is an in-memory system. Furthermore, in controlled sectors like pharmaceuticals and finance, R can provide solid support for reproducible reporting and

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statistical documentation, which can be suitable for complying with the standards. In short, R is preferred in cases where interpretability, statistical accuracy, and exploratory projection are desired and not automation at a large scale.

Example: Forecasting in R using Prophet

```
# R Example: Inventory Forecasting using Prophet
library(prophet)
# Simulated daily demand dataset
df <- data.frame(
  ds = seq(as.Date('2023-01-01'), as.Date('2023-12-31'), by = 'day'),
  y = 100 + sin(1:365 / 20) * 10 + rnorm(365, 0, 5)
)
# Fit Prophet model
m <- prophet(df)

# Forecast next 30 days
future <- make_future_dataframe(m, periods = 30)
forecast <- predict(m, future)
# Plot forecast
plot(m, forecast)
prophet_plot_components(m, forecast)
```

This R-based example demonstrates how easily users can model trends and seasonality for demand forecasting using the Prophet package, making it a preferred choice for statistical and research-driven analyses.

Python Ecosystem for Forecasting

Conversely, Python has found its way to industry-level and production-grade forecasting systems through its scale, integration with enterprise applications, and compatibility with machine learning and deep learning systems. Libraries like statsmodels, pmdarima, scikit-learn, TensorFlow, and Keras can be used to create both classical statistical models and highly complex hybrid models to solve complex forecasting problems (Raschka, S. *et al.,* 2021; Chollet, F. 2021; Sun, G., & Deng, S. 2025; Alicke, K. *et al.,* 2019; Destino, M. *et al.,* 2022)

Python is best suited to the scenario when forecasting models have to be put to use in production pipelines or integrated with bigger data designs. It finds application especially in industrial and commercial settings where scalability, automation, and the capability to work with large or distributed data sets can be required. The ecosystem is also powerful in that it has the power to be interoperable; predictions may be directly integrated into dashboards, APIs, or real-time decision-making systems. Python is also flexible in the sense that it allows the integration of time series techniques with machine learning or deep learning models and is therefore very useful in data-intensive applications where accuracy and adaptability are important. As such, Python is recommended when it is to be deployed in operations, scalable forecasting, or to be integrated with AI-driven systems.

Example: Forecasting in Python using ARIMA

```
# Python Example: Inventory Forecasting using ARIMA
import pandas as pd
import numpy as np
from statsmodels.tsa.arima.model import ARIMA
import matplotlib.pyplot as plt

# Simulated daily demand dataset
dates = pd.date_range(start='2023-01-01', end='2023-12-31', freq='D')
data = 100 + np.sin(np.arange(len(dates)) / 20) * 10 + np.random.normal(0, 5, len(dates))
df = pd.DataFrame({'Date': dates, 'Demand': data})
df.set_index('Date', inplace=True)

# Fit ARIMA model
model = ARIMA(df['Demand'], order=(5,1,0))
model_fit = model.fit()

# Forecast next 30 days
forecast = model_fit.forecast(steps=30)
# Plot results
plt.figure(figsize=(10,4))
plt.plot(df.index, df['Demand'], label='Observed')
plt.plot(pd.date_range(df.index[-1], periods=31, freq='D')[1:], forecast, label='Forecast', color='red')
plt.legend()
plt.title('Inventory Demand Forecast using ARIMA')
plt.show()
```

This Python example illustrates an ARIMA-based forecasting approach suited for operational environments, emphasizing automation and scalability in enterprise-level applications.

Table 4: Comparison of R and Python Ecosystems for Time Series Forecasting

Aspect	R	Python
Primary Strength	Statistical modeling, academic research	Machine learning, deep learning, integration
Key Time Series	*forecast, tseries, fable, prophet*	*statsmodels, scikit-learn, pmdarima,*

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Packages		*prophet*
Machine Learning Support	Limited (add-ons required)	Extensive (native + libraries)
Deep Learning Support	Moderate (*kerasR*, TensorFlow via wrappers)	Strong (*TensorFlow*, *Keras*, *PyTorch*)
Visualization	*ggplot2*, *lattice*	*matplotlib*, *seaborn*, *plotly*
Industry Adoption	High in academia, niche industries	Very high in enterprises & startups
Ease of Integration	Moderate (ERP/enterprise links limited)	Strong (APIs, cloud platforms, ERP systems)

APPLICATIONS IN INVENTORY MANAGEMENT

The methods of forecasting are practically useful in the real-life inventory management scenario, where the predictability of demand and variability of supply a significant drawback. There are the right predictions and therefore, there are strategic and operational decisions such as calculating reorder points, calculating safety stocks, and the optimal replacement schedules. Predictions in retail and e-commerce help in the organization of stocks based on the regional preferences and seasonal demand, and marketing features. In production companies and more so in those that have implemented the just-in-time systems, the forecasts of the demand for raw materials and related parts will keep the production processes going without any unnecessary expenses incurred in keeping the storage area. To achieve the efficiency of inventory levels of spares, industries with intermittent demand profiles, such as the aerospace and defense industry, rely on specific forecasting models, either Croston's or hybrid statistical-AI models. By the idea of predicting into Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES), companies can decide on inventory without human intervention and be more resilient to the supply chain.

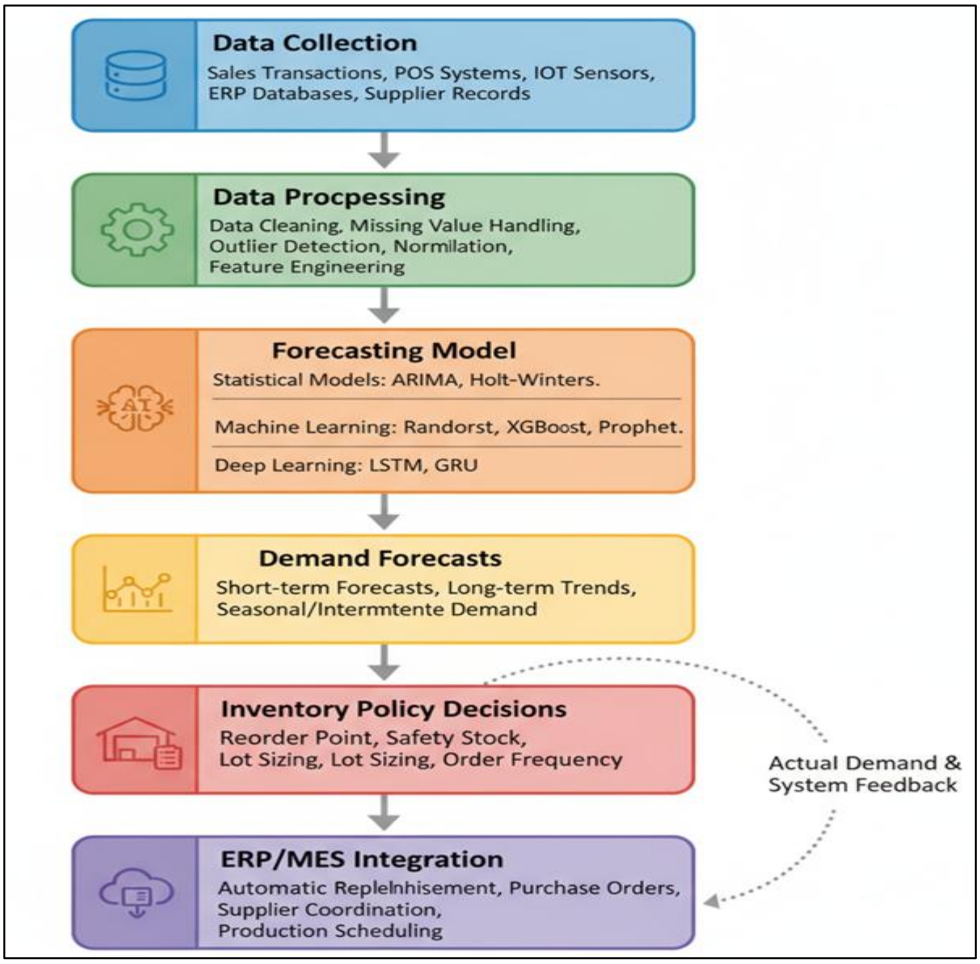

Figure 2: Generic Workflow of Time Series Forecasting in Inventory Management

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CRITICAL ANALYSIS AND PERSPECTIVES

Although the success of forecasting techniques is very effective in improving inventory management, some serious problems remain, which are not only problematic in the methodology but also in the implementation process. Even though classical statistical models are simple to interpret and are computationally efficient, they usually do not work well when demand trends are non-standard, extremely seasonal, or intermittent. Instead, machine learning algorithms are more commonly used to model nonlinear relationships, introduce external variables, but need larger databases, feature engineering, and adjusting hyperparameters. More recent deep learning neural networks, such as LSTM and GRU, can also be trained to capture long-term dependencies, but are computationally expensive, less interpretable, and do not always apply to smaller businesses. In addition to this, the barriers to the adoption of these models have also limited their application to barriers like integration with ERP/MES systems, explainability, and real-time adjustability, despite their technical complexity.

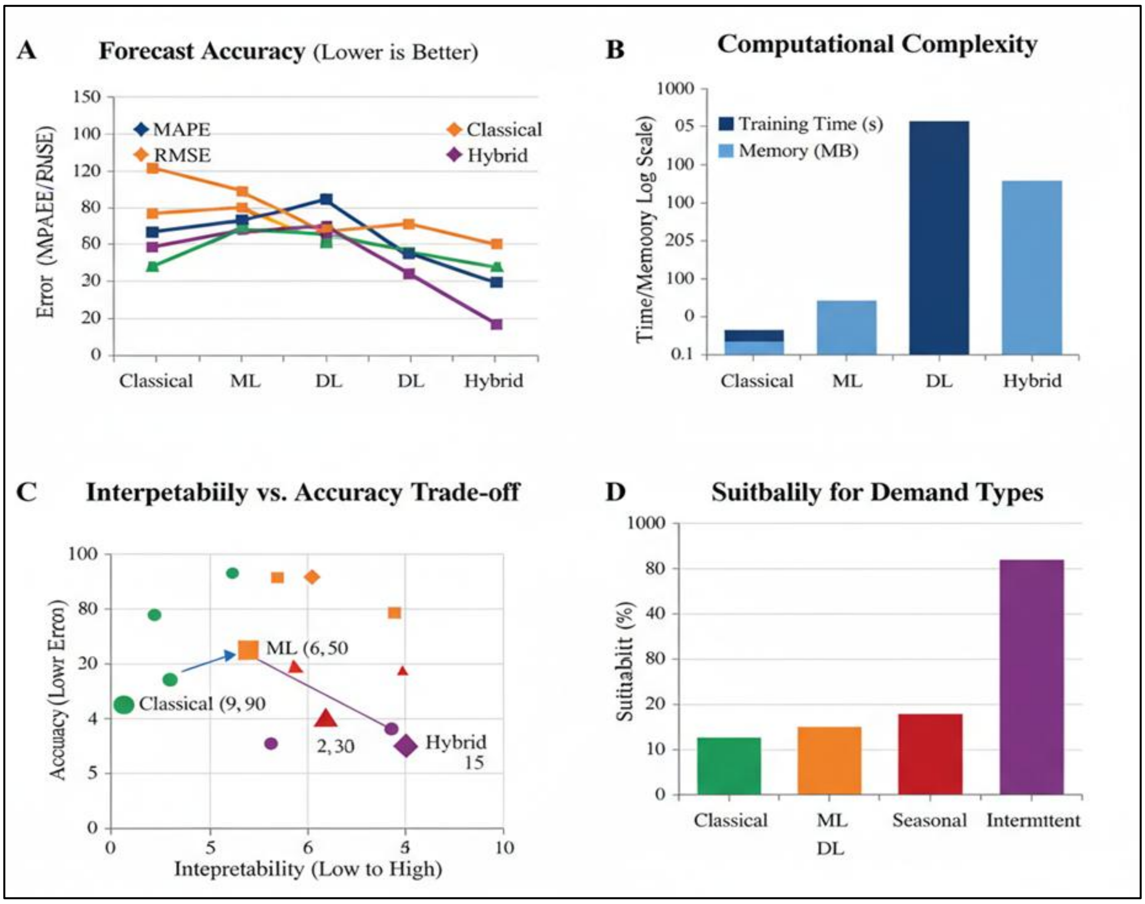

Figure 3: Comparative Performance of Forecasting Approaches

Notwithstanding all these deficiencies, there is emerging research that may hold the promise of a chain of successful visions that would go a long way in enhancing the contribution that time series forecasting has in the management of inventory. Mixed methods built upon a combination of statistical models and machine learning or deep learning methods are now thought to be in a position to achieve the accuracy, robustness, and interpretability trade-off, as well. These solutions enable organizations to enjoy the advantage of conventional approaches to address seasonality and trends, but also use the forecasting ability of the AI to predict nonlinear and high-dimensional trends. Simultaneously, the increasing interest in explainable AI (XAI) is addressing the demand for the black-box-like characteristics of advanced models by displaying graphicization tools and interpretable models that can help simplify complex predictions and, consequently, are more acceptable to the decision-makers in regulated fields. Another new trend is forecasting in real-time, where organizations can dynamically react to a shock in the supply chains (production bottleneck, logistical delay, or demand surge) by predicting them with the help of streaming data

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pipelines, cloud-native design, and IoT sensors. The studies of the future, however, should challenge the standards of accuracy in investigating other important factors like scalability, cost of the implementation, energy saving, and easy integration with the ERP/MES system. By having the capacity to close these gaps not only as a study discipline, but as a practical and strategic tool of supporting the resiliency, agility, and sustainability of the global supply chain, forecasting methods will become better.

In terms of cost and time frame, implementing the use of advanced forecasting systems usually depends on the magnitude, the data infrastructure, as well as the level of automation needed. As an example, a small to medium enterprise with an R-based statistical forecasting model can pay USD 10,000-25,000 in development, and the model-building process will require 4-8 weeks, including model building, testing, and integration of a dashboard (Alicke, K. *et al.*, 2019; Destino, M. *et al.*, 2022). By comparison, a large-scale industrial deployment of a Python-based hybrid AI forecasting system, combined with ERP, IoT, and cloud services, can cost USD 50,000-150,000 or even more, and take 3-6 months depending on the quality of data and the complexity of the system itself. Incremental costs, Real-time streaming architecture, and explainable AI modules provide important benefits in the long term in flexibility and visibility of decisions. Intelligent forecasting may become more affordable in various industries and levels of operation as research and tooling advances, and these costs are likely to decrease.

Although more accurate forecasting models, like deep learning or hybrid models, exist, they are more expensive to implement in terms of computational and data storage resources, time to train a model, and specialized staffing is required. It does not turn out, though, that increased cost necessarily leads to increased returns proportionately. In most instances, simpler or classical machine learning models are accurate enough to be used in real-world inventory management, especially when the company has no or static demand, or the dataset is small. The ROI begins to decline when incremental returns on forecast accuracy require incommensurately increased computational resources, challenging integration with ERP /MES systems, or maintenance costs. That is why organizations are advised to make a trade-off in terms of forecasting accuracy, implementation complexity, and costs of operations, and to adopt a model that provides the best performance at the scale and variability of their inventories without over-investing in overly complex solutions.

Table 5: Cost vs. Accuracy and ROI in Inventory Forecasting

Model Type	Implementation Cost	Accuracy	When ROI Diminishes	Best Use Case
Classical Models	Low	Moderate	ROI remains high; additional spending is rarely needed	Stable demand, seasonal products, small to medium datasets
Machine Learning	Medium	High	ROI starts falling if the dataset is small or the feature engineering is complex	Nonlinear trends, medium–large datasets, external variables
Deep Learning (LSTM/GRU)	High	Very High	ROI diminishes for small businesses or datasets <1 year	Large-scale operations with complex, sequential demand patterns
Hybrid Approaches	Very High	Very High	ROI falls if integration, maintenance, and XAI setup costs outweigh accuracy gains	Large enterprises seeking high accuracy + interpretability; seasonal + nonlinear demand

FUTURE RESEARCH DIRECTIONS

In today’s inventory management landscape, time series forecasting is advancing quickly, driven by technological innovation and the growing complexity of global supply chains. The line of research that will follow is the hybrid modeling, where there would be a focus on the integration of statistical models, machine learning, and deep learning to utilize their synergy. The possibility of reinforcement learning can be indicated using an example, according to which the adaptive decision-making based on direct use of forecasts to inform the policies of ordering and replenishment can have potential. The following trend is real-

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time forecasting with the assistance of cloud-native architecture and streaming data platforms that may give real-time information about the disruption, such as the supply chain shock, the pandemic, or the unpredictable geopolitical issues. Also, explainable artificial intelligence (XAI) will play a major role in ensuring that high-level forecasting models are implemented since practitioners mandate the transparency of prediction generation. It is not only that they will understand how to increase trust by integrating XAI techniques with deep learning, but also that the managers will be able to justify the decision within the regulated industries. It can also use graph neural networks (GNNs) to approximate complex interdependency in global supply chains, where the demand pattern is influenced by the upstream and downstream variability. The conjunction of forecasting systems with blockchain-built systems of traceability and networks of IoT sensors also opens prospects to more resilient and data-driven systems of inventory.

CONCLUSION

Time series forecasting is important in facilitating modern inventory management, which enables the organization to cope with uncertainty, optimize stock, and create resiliency in the supply chain. The review has drawn the chronological history of classical models of statistics, including ARIMA and Holt-Winters, to present-day machine learning and deep learning models, and concluded that classical models are easier to interpret and work in non-complex and volatile demand environments, whereas AI-based models are more accurate. Its importance in retail, manufacturing, and aerospace applications has attracted attention to its utility in inventory policy alignment to both flexible demands, although there are problems in data requirements, computational intensity, interpretation, and integration with ERP/MES systems. The appearance of hybrid systems, reinforcement learning, explainable AI, and sustainable prediction is only a new step, and it is possible to say that the future will be more interdisciplinary because the precision will be covered with transparency, flexibility, and environmental responsibility. Finally, the forecasting process is also becoming not only a strategy, but also a strategic emergence of competitiveness and competency of global supply chains.

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