Journal DOI: 10.36713/epra1013 | SJIF Impact Factor (2025): 8.619 ISSN: 2347-4378
EPRA International Journal of Economics, Business and Management Studies (EBMS)
Volume: 12 | Issue: 8 | August 2025 -Peer-Reviewed Journal

APPLICATION OF PREDICTIVE ANALYTICS FOR ASSESSING SHORT-TERM AND SEASONAL DEMAND FLUCTUATIONS IN RETAIL TRADE

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ABSTRACT

This article explores modern methods of predictive analytics used to assess short-term and seasonal demand fluctuations in retail trade. It analyzes the effectiveness of time series models, machine learning algorithms, and neural network approaches in a dynamic market environment. Particular attention is given to data preparation, the selection of accuracy metrics, and the integration of forecasting models into logistics and inventory management. Hybrid solutions are emphasized as crucial, and tuning models to outside drivers such as weather conditions and promotional activity are emphasized. The study concludes that predictive analytics is highly practically relevant to enhance the resilience and effectiveness of retail supply chains.

KEYWORDS: *Predictive Analytics, Machine Learning, Time Series, Logistics, Retail Trade, Forecasting.*

1.0. INTRODUCTION

Modern retail operates in the environment of high volatility of consumer demand, with a need for flexible and accurate tuning of logistics processes. The issue of forecasting becomes particularly acute in the short-term and seasonal horizon, where consumer activity changes under the impact of calendar effects, promotional campaigns, macroeconomic indicators, and social trends. In these environments, the application of predictive analytics tools turns into a strategically important element of supply chain management and inventory management.

Inventory and logistics planning is the most susceptible department to forecasting inaccuracies in retail. The over- or underestimation of demand leads either to redundant inventory or stockouts in stores, with a direct effect on operational performance and customer loyalty. The use of analytical models, including time series, regression algorithms, and machine learning techniques, allows for creating adaptive forecasts based on underlying trends and seasonality.

Analytical work is particularly relevant in the context of external economic transformations. For example, on the background of recent tariff changes and an increase in customs duties on imported goods, many USA companies have been faced with the need for partial rejection of raw materials of foreign origin and the transition to domestic supply chains. In such situations, a logistics data specialist operates not only as a prophet but also as a strategic planner who develops business adaptation scenarios in the face of new sourcing realities.

The aim of this stady is to provide an organized review of predictive analytics methods used to identify and quantitatively assess short-term and seasonal volatility in retail demand.

2.0. MAIN PART. PREDICTIVE ANALYTICS METHODS IN DEMAND ASSESSMENT

Modern approaches to demand forecasting in retail trade are based on a wide range of predictive analytics methods, among which time series models and machine learning algorithms occupy a prominent place [1]. Their application makes it possible to account for both regular seasonal fluctuations and unstable short-term changes caused by external and internal factors. The diversity of algorithmic solutions is due to the varying nature of demand across product categories, which requires a flexible selection of analytical tools depending on logistics tasks, assortment structure, and the level of data granularity.

Time series models are traditionally used for analyzing sequences of observations ordered over time. The classical **ARIMA model** (Autoregressive Integrated Moving Average) is effectively applied in cases where the time series is stationary or can be transformed into a stationary form through differencing (fig. 1).

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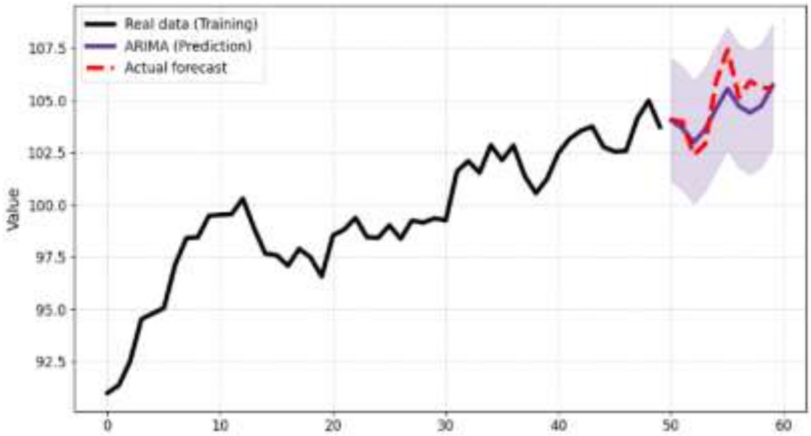

Figure 1. ARIMA model scheme

Overall, ARIMA makes it possible to model trends and autocorrelated dependencies, offering an interpretable and relatively simple approach to implement. However, the weakness of the model lies in that it does not make seasonal adjustment explicit, which is typical to most retail product categories.

To avoid this deficiency, **SARIMA** (Seasonal ARIMA) is employed – an extension of the basic ARIMA model incorporating season factors. SARIMA projects both short-term and seasonal patterns of the time series and hence performs best in predicting demand for items with high cyclicality, such as beverages, gift packages, and outdoor seasonal products (fig. 2).

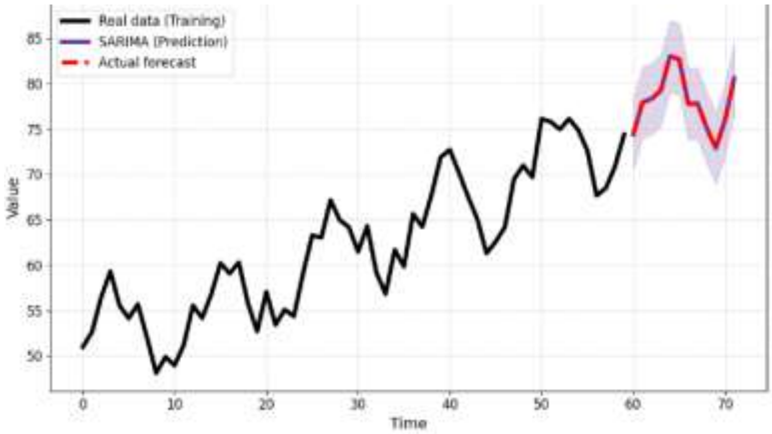

Figure 2. SARIMA model scheme

For instance, on the other hand, ARIMA and SARIMA models, though as effective as they are, possess no great ability in handling a number of external variables such as weather, marketing campaigns, or macroeconomic variables. Yet another approach is **STL decomposition** (Seasonal-Trend decomposition using Loess) which splits the time series into trend, seasonal, and residual components using local polynomial smoothing (fig. 3).

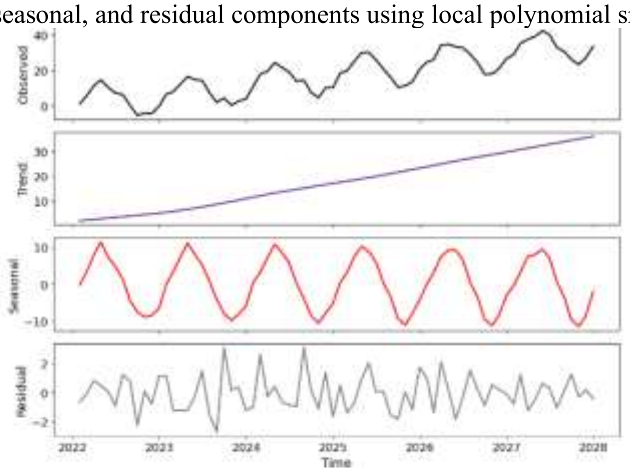

Figure 3. STL decomposition scheme

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The method offers high flexibility and robustness to outliers, allowing for detailed analysis of demand structure. STL decomposition can be used as a standalone analytical tool or in combination with regression and machine learning models to improve forecast accuracy.

Another approach used for demand forecasting involves machine learning methods. These demonstrate high effectiveness in predicting complex and nonlinear relationships in data [2]. In contrast to time series models, these algorithms do not assume a prior stationarity and can process a great deal of features, including even exogenous variables.

One of the most widely used is **Random Forest**, which is a collection of decision trees. It is resistant to overfitting, capable of learning nonlinear interactions between variables, and contains built-in methods for determining variable importance (fig. 4).

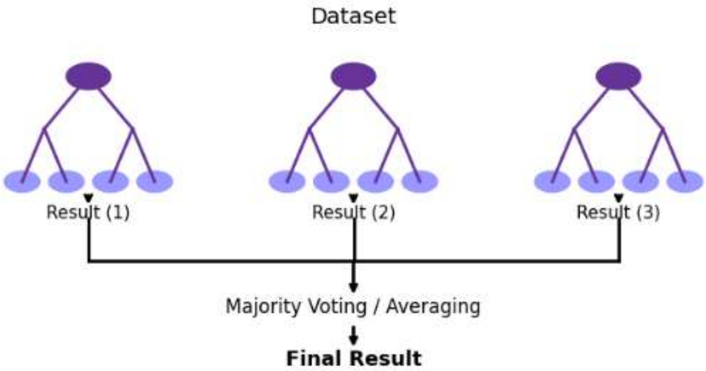

Figure 4. Random Forest scheme

Random Forest is used at individual product, store, or time-period level of demand in demand forecasting and logistics. The technique can be scaled up with ease and cleans missing values and noise effectively, making it a preferred technique for studying retail operation data.

Faster is the ensemble method variant **XGBoost** (Extreme Gradient Boosting), a gradient boosting library based on decision trees (fig. 5).

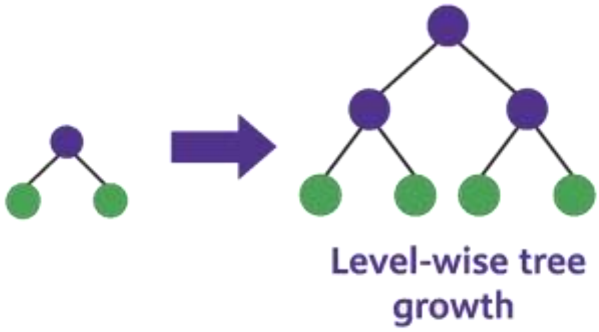

Figure 5. XGBoost scheme

XGBoost delivers high forecasting accuracy even in cases with complex data structures and small training datasets. It supports dynamic parameter tuning of model parameters, tuning of regularization, and removal of overfitting. On seasonal demand forecasting tasks, XGBoost can involve not only time features but also category features such as product, region, and channel of sales, which facilitates the creation of highly accurate and adaptive models.

Of newer methods, a leading place is held by artificial neural networks, among them the **LSTM (Long Short-Term Memory)** as an extension of recurrent neural networks specifically designed for sequence analysis (fig. 6).

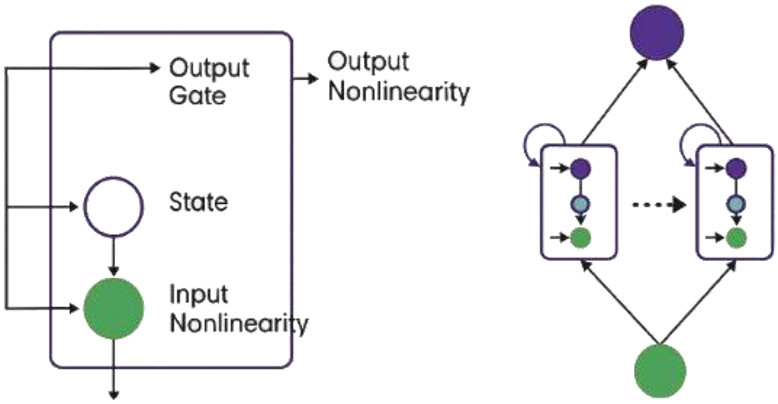

Figure 6. LSTM scheme

Generally, LSTM networks can learn long-term dependencies and can be used to analyze trends, broken time series, and volatile patterns. Their applications are particularly justified where data cannot be defined mathematically in terms of linear or seasonal models, such as predicting demand amid crises, sudden spikes, or declines in consumption.

Unlike traditional models, machine learning methods require significant computational resources and a more complex validation process. However, given a sufficient volume of historical and contextual data, they demonstrate high accuracy and adaptability. Combining time series models with learning algorithms (hybrid approaches) allows for the compensation of individual method limitations and the creation of demand forecasting systems that are resilient to fluctuations and noise.

2.1. COMPARISON OF THE EFFECTIVENESS OF TRADITIONAL AND INTELLIGENT DEMAND FORECASTING METHODS

Within the framework of predictive analytics, traditional time series models such as ARIMA and SARIMA compete with modern machine learning algorithms, including Random Forest, XGBoost, and LSTM networks. Each group of methods has its own advantages and limitations, depending on the data structure, the degree of seasonality, the availability of exogenous variables, and the computational resources required (table 1).

Table 1. Comparative overview of demand forecasting methods in retail [3, 4]

Method	Application conditions and advantages	Limitations	Typical use cases
ARIMA / SARIMA	Suitable for time series with clear trend and seasonality. High interpretability, low data and computational requirements.	Poor handling of external variables, unstable fluctuations, and nonlinear relationships.	Forecasting stable product categories (e.g., staples), weekly or monthly replenishment planning.
STL Decomposition	Flexible decomposition into trend, seasonality, and residuals. Effectively reveals hidden cycles. Useful as preprocessing for other models.	Not a standalone forecasting model. Does not incorporate external variables.	Seasonality structure analysis, smoothing before applying machine learning algorithms.
Random Forest	Robust to noise, handles large numbers of features including external ones. No assumptions about data distribution.	Limited interpretability, sensitive to feature correlation and class imbalance.	Store-level or item-level demand forecasting with marketing, pricing, and weather as input features.
XGBoost	High accuracy in complex patterns, supports both categorical and numerical data. Offers flexible tuning and regularization.	Requires feature engineering, prone to overfitting without tuning, more computationally intensive than RF.	Short-term forecasts in omnichannel retail, adjusting logistics based on marketing campaigns.
LSTM	Capable of modeling long-term and nonlinear dependencies. Handles temporal context without manual lag specification.	High complexity, low interpretability, demands large data volumes and computational power.	Demand forecasting under volatility: promotions, external shocks, or new products with atypical sales patterns.

The comparative analysis of demand forecasting methods stresses the richness of analytical methods used in the retail industry with variation depending on attributes of data, business objectives, and market dynamics. Traditional statistical methods such as ARIMA and SARIMA still work adequately for the management of stable time series with periodic seasonality. STL decomposition is easy to handle trend and cycle, especially as a preprocessing. Machine learning methods like Random Forest and XGBoost are more adaptable to external variables and non-linear relationships, hence performing better in high-frequency demand variation and heterogeneous input data settings [5]. Neural network architectures like LSTM are weakest against complex temporal patterns and best suited for prediction under unstable consumer behavior. In practice, hybrid approaches that combine the strengths of several approaches are often employed to achieve high predictive accuracy and robustness based on data availability and maturity of the analytical infrastructure.

2.2. DEVELOPMENT AND VALIDATION OF FORECASTING MODELS BASED ON RETAIL SALES DATA

Building effective retail forecasting models requires thorough data preparation, normalization, and contextual structuring, using inputs from POS and ERP systems, along with variables like holidays and promotions. The modeling process involves transforming time series data for stationarity, engineering relevant features, and validating performance through rolling tests or holdout sets [6]. Model accuracy is assessed using metrics tailored to data characteristics and business goals, ensuring both temporal dynamics and category-level variability are captured (table 2).

Table 2. Key forecast accuracy metrics in retail demand prediction

Metric (name and abbreviation)	Description and application features
MAE – Mean Absolute Error	Reflects the average absolute deviation between forecasted and actual values, expressed in units. Easy to interpret. Suitable for comparing models within uniform scales.
RMSE – Root Mean Squared Error	More sensitive to large deviations and outliers than MAE. Useful in cases where penalizing major forecast errors is critical.
MAPE – Mean Absolute Percentage Error	Measures average forecast deviation in percentage terms. Effective for comparing accuracy across categories with different sales volumes. Can be unstable at low values.

A comprehensive validation approach includes comparing models across multiple metrics, which makes it possible to select the most balanced solution depending on business objectives – whether it is minimizing forecast deviations, ensuring robustness to demand spikes, or achieving high accuracy during promotional activity periods [7]. An effectively developed and validated model not only improves forecasting precision but also establishes a foundation for automated supply chain management, cost reduction, and enhanced service levels.

2.3. PRACTICE OF USING PREDICTIVE ANALYTICS FOR SEASONAL DEMAND FORECASTING

Managing seasonal assortments is one of the most sensitive logistics tasks in retail. These product categories are subject to sharp demand fluctuations driven by calendar events, weather conditions, and promotional activity. Under such conditions, traditional approaches based on averaged historical data often fail to deliver the necessary accuracy. The use of predictive analytics enables the generation of adaptive forecasts that take into account external variables and increase logistics resilience during peak periods. Among the most clearly defined seasonal categories are soft drinks, chilled products, and holiday goods. According to statistics from the National Retail Federation (NRF), the months of November and December account for an average of about 19% of annual retail sales volume [8].

A prominent example of large-scale implementation of predictive analytics is **Amazon**, which employs machine learning for demand forecasting through its services Amazon Forecast and Amazon Demand Planning [9]. These tools account for climate factors, holiday calendars, price dynamics, and promotional activities. Amazon uses models based on XGBoost and Prophet, integrating them with ERP and WMS data to optimize inventory levels in distribution centers and reduce returns. According to AWS, the implementation of Amazon Forecast enabled one major retail client to increase forecast accuracy from 27% to 76% and reduce fresh product waste by 20%. Furthermore, as estimated by McKinsey and AWS, the application of AI-based forecasting in retail can improve forecast accuracy by 10-20% and increase revenue by 2-3%. In preparation for the holiday season, Amazon forecasts peak delivery volumes with weekly accuracy, enabling route adjustments and warehouse buffering.

Another example is **The Home Depot**, which actively uses predictive analytics based on Random Forest and Gradient Boosting (including XGBoost) to forecast demand and manage inventory in construction and seasonal product lines. The models are trained on historical sales data, seasonal fluctuations, weather, and economic indicators. As stated in industry practice materials, this system allows for more accurate assessment of needs for specific product categories such as gardening tools or home improvement items, especially during peak demand periods [10]. As a result of implementing such solutions, Home Depot achieved improved forecast accuracy, optimized warehouse stock, and reduced costs by avoiding both shortages and surpluses – as confirmed by industry reports on the use of machine learning in retail.

3.0. CONCLUSION

Predictive analytics is an effective technique for establishing and numerically assessing short-term and seasonal variation in retail demand, providing companies with improved forecasting accuracy, supply chain elasticity, and adaptive inventory management. Use of time series modeling, machine learning algorithms, and neural network approaches allows for the integration of a wide range of influencers on customer activity like calendar events, weather, and promotions. Empirical data from the practice of USA retail chains show that the use of analytical solutions in logistics leads to the realization of cost savings, reduced shortage and surplus levels, improved speed and quality of managerial decisions in market instability conditions.

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