Економічні науки

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# APPLICATION OF DEMAND FORECASTING MODELS IN INVENTORY MANAGEMENT

Summary. *The study focuses on improving inventory management efficiency through accurate demand forecasting. It provides an overview of key statistical methods (ARIMA, exponential smoothing) and modern machine learning techniques (decision trees, neural networks), along with their hybrid versions. The impact of forecast accuracy on critical logistics aspects—inventory levels, safety stock, turnover rates, and shortage risks—is examined. Successful implementation practices in leading companies are analyzed, highlighting the economic benefits achieved. The author's contribution includes recommendations on selecting and adapting models to the specifics of logistics processes, as well as proposals for integrating demand forecasting with other elements of supply chain management.*

Key words: *demand forecasting, inventory management, ARIMA, machine learning, neural networks, logistics, supply chain, forecast accuracy.*

Introduction. Demand forecasting plays a crucial role in logistics and supply chain management, directly affecting the efficiency of inventory control. In a global economy with fragile supply chains and resource shortages, accurate forecasts are essential for minimizing losses and ensuring business resilience [1]. Studies indicate that inaccurate demand planning leads to either excess inventory or stock shortages, both of which can result in significant financial losses. For example, McKinsey analysts estimate that miscalculations in planning contribute

to annual food waste worth $600 billion, or approximately 33–40% of global food production [1]. Thus, improving forecast accuracy has become a strategic priority: even a 10–20% increase in accuracy can reduce inventory costs by approximately 5% and boost revenue by 2–3% [2]. These metrics are particularly relevant to the logistics sector, where inventory must align with fluctuating consumer demand along the entire supply chain, from warehouses to retail stores. Demand forecasting is recognized as the "foundation" of successful planning, underpinning both profitability and the ability to respond swiftly to market fluctuations [3]. However, achieving high forecast accuracy is challenging due to multiple factors influencing demand, such as seasonality, trends, promotions, and consumer behavior.

Modern organizations utilize a broad range of demand forecasting models, from traditional statistical approaches (e.g., ARIMA, exponential smoothing) to advanced machine learning techniques (decision trees, neural networks, etc.), to predict customer needs effectively. This study examines the application of demand forecasting models in inventory management, with a focus on logistics. An overview of key forecasting methods is provided, along with an assessment of their impact on inventory management. Practical examples of successful implementation in well-known companies, including retail chains and manufacturing enterprises, demonstrate measurable improvements. The structure of the study includes an introduction, several main sections covering forecasting methods, their impact on inventory, real-world case studies, and a conclusion with the author's findings [4].
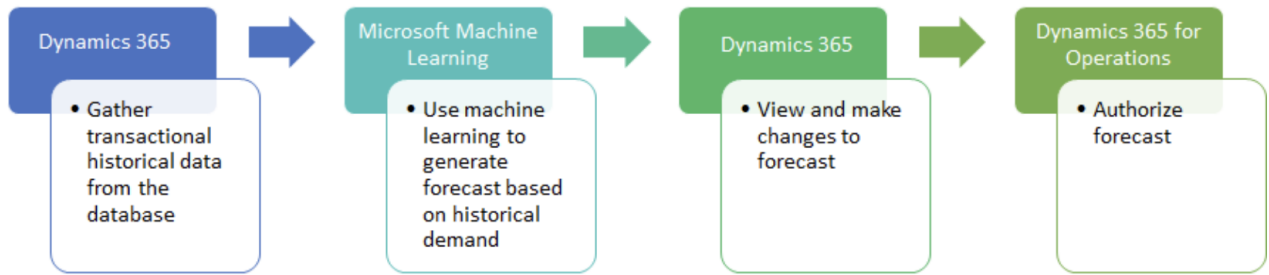
Figure 1. Demand Forecasting Process in Supply Chain Management. Historical sales data is collected from an operational system (e.g., ERP) and processed by a machine learning algorithm to generate a statistical forecast. Specialists then apply necessary adjustments and approve the forecast for use in planning [4]. Such technological integration simplifies and accelerates the forecasting process, enhancing its accuracy and efficiency in logistics

1. Demand forecasting methods in inventory management

Demand forecasting relies on two broad categories of approaches: traditional statistical methods and artificial intelligence and machine learning techniques. Traditional methods include time series models based on statistical techniques, such as moving averages, exponential smoothing methods (e.g., Holt-Winters model), and ARIMA (Autoregressive Integrated Moving Average). These approaches have been widely used for demand forecasting over the past decades and have demonstrated effectiveness when demand patterns remain relatively stable [5]. ARIMA models and their variations, including seasonal ARIMA, ARIMAX with regressors, and ETS models, perform well when demand exhibits clear trends or seasonality and follows linear dependencies [5]. Their main advantage lies in theoretically justified results and interpretability, allowing for a clear distinction between trend and seasonal components in the forecast. Studies indicate that properly calibrated statistical models can provide high forecasting accuracy, which is why they continue to be used in many supply chains [5]. For instance, ARIMA models remain effective for short-term consumer demand forecasting and often serve as a benchmark when comparing newer methods [5].

However, traditional methods have limitations. They often assume linearity and stationarity in time series, making it difficult to account for the complex interplay of factors influencing demand [6]. In modern markets, demand is shaped by numerous dynamic influences, such as fashion trends, promotional campaigns, social media effects, and weather conditions, leading to nonlinearities and sudden fluctuations. Simple statistical models are not always capable of capturing such rapid changes. As noted by Hyndman and Athanasopoulos, classical methods like moving averages and exponential smoothing frequently struggle with the complexity of contemporary demand data [6, 7]. As a result, companies have started supplementing or replacing these models with machine learning techniques that can incorporate a broader range of factors and process real-time data.

Another challenge with traditional models is the need for frequent manual adjustments. When a new trend emerges, analysts must recalibrate the model or manually introduce explanatory variables, making the process labor-intensive and less adaptive. Given the dynamic nature of logistics—such as demand surges before holidays or the impact of sales events—this approach is not always efficient.

Nevertheless, traditional models remain valuable. In many cases, a simple model can be more stable and interpretable than a complex algorithm. For example, exponential smoothing quickly adapts to changes in baseline demand, while ARIMA effectively captures seasonal fluctuations. In practice, hybrid approaches are often used, where a baseline statistical forecast is combined with machine learning-based adjustments. This ensemble method helps balance interpretability with flexibility, a topic discussed further in this study.

Machine learning (ML) methods, particularly deep learning, have introduced a new level of capability in demand forecasting. Their primary advantage is the ability to identify hidden nonlinear relationships within large datasets. Unlike ARIMA, ML models do not require an explicitly defined model

structure; instead, they learn from data, determining optimal dependencies between features and resulting demand. In inventory management, this allows for the consideration of multiple influencing factors such as prices, marketing promotions, weather conditions, customer behavior, and economic indicators, ultimately improving forecast accuracy.

Popular ML methods for demand forecasting include:

● Regression models (linear and nonlinear regression) are simple and interpretable and are often used as a baseline for comparison [6]. For example, linear regression can establish relationships between demand, pricing, or advertising budgets.

● Decision trees and ensemble methods (Random Forest, Gradient Boosting, XGBoost) effectively capture nonlinear interactions and work well with categorical features [5, 6]. In demand forecasting, these methods can help identify which product categories are most sensitive to seasonality or holidays. Studies indicate that ensemble methods often outperform standalone models. For instance, the XGBoost algorithm demonstrated the highest demand forecasting accuracy in multiple experiments, such as predicting blood donation needs, compared to other ML models [5].

● Support vector machines (SVM) are suitable for high-dimensional feature spaces and are resistant to overfitting [6]. In the FMCG retail sector, SVM has been used for forecasting large product matrices containing thousands of SKUs, delivering results comparable to ARIMA [5, 6].

Neural networks and deep learning have had a particularly revolutionary impact on demand forecasting. Neural networks are capable of modeling extremely complex dependencies. In particular:

● Multilayer perceptrons (MLPs) can approximate virtually any nonlinear function and have been used for demand forecasting with multiple factors, including social media and search data.

● Recurrent neural networks (RNNs) and their advanced versions, such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), are well suited for time series forecasting as they retain long-term dependencies [6]. LSTM models have been successfully applied for weekly and daily sales forecasting, effectively handling complex seasonal patterns and anomalies that traditional methods struggle with [6].

● Convolutional neural networks (CNNs), originally developed for image processing, have recently been adapted for time series analysis. For example, Amazon reported using CNNs in its demand forecasting system, achieving a twofold increase in model training speed and a 30% improvement in accuracy [11].

● Generative models and neural network ensembles represent the latest advancements, incorporating architectures such as Transformers for time series forecasting and combining different neural network models. While still in the research phase, these solutions are already demonstrating high accuracy in complex scenarios involving multiple interdependent time series, such as simultaneous demand forecasts across an entire retail network.

The primary advantage of AI-based models is their flexibility and adaptability. These models can continuously retrain on new data, incorporating real-time demand changes—a concept known as "demand sensing." Unlike traditional methods that require manual adjustments, modern ML systems can automatically detect new patterns. A practical example is Amazon's forecasting system, which analyzes millions of transactions and customer behavior data, updating demand predictions almost in real time. This enables the company to reposition inventory efficiently and prevent stock shortages [12].

However, ML models introduce new challenges. First, high-quality and diverse historical data are essential for training. Data has become the fuel for AI-driven forecasts, forcing companies to invest in data collection and cleansing [6]. If the data is biased or fails to account for future scenarios—such as sudden

demand spikes or declines due to unforeseen events—even the most sophisticated model can produce inaccurate forecasts.

Second, model complexity makes interpretation difficult. A logistics manager may struggle to explain why a neural network predicts a decline in demand for a specific product, whereas a simpler model might reveal a clear downward trend. This issue is being addressed through Explainable AI (XAI) techniques aimed at improving transparency in decision-making [6].

Third, training and maintaining ML models require expertise and computational resources. Companies face a shortage of qualified data science and AI specialists, as well as challenges in integrating ML systems into existing processes [6]. Despite these challenges, the trend is clear: logistics is increasingly adopting hybrid approaches that combine traditional models with AI to leverage the strengths of both methodologies.

Studies indicate a significant improvement in accuracy when combining different models. For example, a hybrid SARIMA–LSTM model (integrating seasonal ARIMA and an LSTM neural network) reduced demand forecasting errors for automobiles by approximately 18% compared to standalone ARIMA or LSTM models [5]. These results encourage further adoption of AI in demand forecasting.

For clarity, a summary comparison of forecasting methods is provided in Table 1.

Table 1

Comparison of demand forecasting methods and their characteristics

Method	Approach	Strengths	Limitations / requirements
Exponential Smoothing (ETS)	Statistical, time series smoothing	Simplicity, fast adaptation to baseline changes, effective for stable seasonal patterns [5].	Assumes regular patterns, does not account for complex external factors, requires parameter recalibration when structural shifts occur.

Method	Approach	Strengths	Limitations / requirements
ARIMA (and SARIMA)	Statistical, time series model	Captures autocorrelations, trends, and seasonality; theoretically sound; widely applicable with sufficient historical data [5].	Linear in nature, struggles with nonlinearities; requires stationarity (differencing may be needed); model identification is labor-intensive with manual tuning.
Machine Learning (decision trees, Random Forest, Gradient Boosting, etc.)	Data-driven learning, ensemble algorithms	Captures nonlinear dependencies and interactions between multiple features; can incorporate external factors (prices, weather, events); typically higher accuracy than simpler models [5].	Requires large datasets for training; risk of overfitting if too complex; less interpretable (difficult to isolate individual factor contributions).
Deep Learning (neural networks: RNN/LSTM, CNN, Transformers)	Data-driven learning, neural networks	High flexibility, ability to detect complex patterns and long-term dependencies [6]; adaptive to changes with continuous training; best results for highly complex demand relationships.	Requires large datasets and computational resources; "black-box" nature makes interpretation difficult; implementation and maintenance complexity, need for data science expertise.
Hybrid Models (e.g., ARIMA + ML combination)	Combination of statistical and ML models	Balances interpretability with the ability to account for external factors; often improves forecast accuracy over standalone models [5].	Increased implementation complexity; requires tuning of both statistical and ML components; potentially longer computation times.

As shown, there is no single ideal method—selection depends on the nature of demand, available data, and company resources. In inventory management, logistics companies increasingly adopt a hierarchical approach to forecasting, where different methods are applied at various levels and time horizons. For example, long-term forecasting of overall trends may rely on regression models incorporating macroeconomic indicators, medium-term forecasts at the product category level may use ARIMA, while short-term predictions for specific SKUs may employ machine learning models that factor in weather and current trends. This combination helps mitigate the weaknesses of individual methods. Research

by Nikolopoulos et al. demonstrated that combining various algorithms, including nearest neighbor methods, yields stable results when forecasting intermittent ("sporadic") demand for spare parts, where standalone models often perform inconsistently [5; 10].

In recent years, joint forecasting and supply chain alignment methods have been advancing. The CPFR (Collaborative Planning, Forecasting, and Replenishment) framework facilitates demand forecast sharing between suppliers and retailers, helping to smooth forecasting errors and prevent situations where each supply chain level overestimates demand. These practices, supported by advanced models, are designed to reduce the "bullwhip effect" in supply chains. The following section will explore how forecast accuracy influences inventory management and the bullwhip effect in greater detail.

2. Impact of forecast accuracy on inventory management

Inventory management is closely linked to the quality of demand forecasting. The primary goal of inventory management is to balance stockouts and overstocking. Accurate forecasting helps determine optimal inventory levels—high enough to meet demand and prevent lost sales but not excessive to avoid increased storage costs and the risk of unsold product write-offs. The key effects of forecast accuracy on inventory logistics are outlined below.

1.   Safety stock levels and inventory turnover. Forecasts always involve uncertainty, which is why companies maintain safety stock—extra inventory beyond the expected demand to cover forecasting errors or sudden demand spikes. The higher the forecasting error, the larger the required safety stock, leading to increased storage costs. Improving forecast accuracy directly reduces the need for safety stock, allowing companies to operate with leaner inventories and increasing inventory turnover. Practical assessments suggest that every ~10% improvement in forecasting accuracy can reduce inventory levels by 5% without negatively impacting customer service levels [2]. This represents significant cost savings for large distributors. Additionally, reducing excess inventory lowers the

risk of product obsolescence, which is particularly critical for perishable goods and fashion items with short life cycles. A McKinsey study found that AI-driven forecasting allowed some companies to reduce average inventory levels by 20–50%, leading to a 5–10% reduction in storage costs [13]. Thus, accurate forecasting serves as the foundation for a lean inventory approach.

2. Service levels and lost sales. Forecast inaccuracies can lead to stock shortages when demand exceeds expectations, resulting in lost sales and lower customer service levels. Improving forecast accuracy, particularly in short-term planning, enables logistics teams to replenish inventory on time and avoid stockout situations. AI models capable of tracking demand fluctuations almost in real time have delivered impressive results, reducing forecast errors by 20–50% and cutting stockout-related sales losses by up to 65% [13]. This has a dual effect—on one hand, meeting demand generates additional revenue, while on the other, it strengthens customer trust and improves service quality. For example, Walmart leveraged AI-driven demand forecasting to accurately predict holiday season demand for key products, allowing the company to increase stock levels in stores and warehouses in advance, successfully avoiding major out-of-stock incidents [6]. High-accuracy forecasting is also crucial for just-in-time operations: in manufacturing logistics, raw materials and components must arrive precisely when needed. A forecasting error in component demand at a factory can halt production, whereas a reliable forecast ensures a steady material flow while minimizing inventory.

3. Resource planning and operational efficiency. Accurate demand forecasts enable better planning not only for inventory levels but also for related resources such as warehouse capacity, delivery schedules, and vehicle utilization. If forecasts indicate an expected rise in demand for the following month, managers can proactively increase procurement and reserve additional transportation. Conversely, when demand is projected to decline, orders can be adjusted accordingly to prevent overstocking. This enhances overall supply chain

flexibility. Studies indicate that AI-driven forecasting improves supply chain efficiency and cost management. For instance, telecom and energy companies reported that automated forecasting reduced manual planning efforts by 50% and improved real-time decision-making, such as staff scheduling optimization [13]. In warehouse logistics, accurate forecasting streamlines operations by allowing managers to pre-plan labor allocation, optimize inbound shipments, and prevent peak-time bottlenecks. Ultimately, these improvements enhance capital turnover and reduce overhead costs.

4.   Bullwhip effect in supply chains. One of the fundamental challenges in logistics is the bullwhip effect, where minor fluctuations in end-user demand amplify as they move upstream in the supply chain, leading to increasingly erratic order volumes for suppliers [14]. When demand forecasts at each level are inaccurate or based on limited local data, each supply chain participant—distributor, manufacturer—tends to overcompensate by either ordering slightly more "just in case" during demand surges or drastically cutting orders in response to small dips in sales. These distortions accumulate, causing suppliers to experience far greater order variability than actual consumer demand. Research shows that a mere 5% fluctuation in retail demand can be perceived as a 40% change for suppliers higher up the chain [15]. This effect leads to chronic inefficiencies, such as overproduction, excessive raw material stockpiling, or, conversely, recurring shortages. Accurate and coordinated demand forecasting across the supply chain is a critical tool for mitigating the bullwhip effect. When all supply chain participants rely on a unified and reliable end-consumer demand forecast, order fluctuations are smoothed out. Collaborative planning (CPFR) and data sharing allow manufacturers to track actual consumer demand and adjust production accordingly without overreaction. Modern digital platforms enable retailers to share real-time sales data with distributors and manufacturers, who, using advanced forecasting models, can accurately determine production needs based on actual market trends. Case studies have shown that companies

implementing AI-driven collaborative forecasting systems significantly reduced order variability, leading to lower average inventory levels across the supply chain and faster response times to demand shifts (Praveen Kumar et al., 2024).

In summary, demand forecast accuracy directly impacts inventory management efficiency. High-accuracy forecasting enables companies to reduce inventory levels without losing sales, optimize storage costs, enhance customer service, and prevent destabilizing effects in the supply chain. However, even the most advanced models provide only a forecast, while actual demand always contains an element of uncertainty. Therefore, success depends on a comprehensive approach that combines modern forecasting models with flexible operational planning, rapid response mechanisms, and close collaboration among all supply chain participants. The following sections will examine real-world examples of companies that have successfully implemented forecasting models and the results they have achieved.

3. Practical examples of forecasting model applications

Many leading companies in logistics, retail, and manufacturing already use demand forecasting models to optimize inventory and gain a competitive advantage. Several well-known cases illustrate the impact of forecasting models on supply chain efficiency.

Walmart. As one of the largest retail chains, Walmart was among the first to integrate AI into its demand forecasting operations. Walmart processes massive volumes of sales data (hundreds of millions of transactions per week) and applies ML algorithms to forecast demand for each product at each store. The implementation of these technologies has significantly improved forecasting accuracy, thereby enhancing supply chain performance. According to publicly available reports, Walmart has leveraged AI-based forecasting to improve supply chain efficiency, reduce inventory levels, and increase product availability in stores [6]. Automated monitoring and forecasting of high-turnover items have helped reduce stockouts and minimize losses from expired perishable goods.

Marr highlights that Walmart has achieved substantial cost savings on inventory and increased customer satisfaction after transitioning to AI-driven demand planning [6, 9]. Machine learning-based forecasting now influences all aspects of Walmart's logistics, from shelf replenishment in individual supermarkets to strategic planning of new distribution centers. Notably, Walmart developed its own platform, "Element," to scale ML models, enabling teams to rapidly deploy new forecasting algorithms across different divisions [16]. This demonstrates the strategic importance Walmart places on forecasting, viewing it as an essential part of its digital logistics ecosystem.

Amazon. The e-commerce giant Amazon is renowned for its advanced supply chain management technologies. Amazon's demand forecasting relies on a multi-layered system that incorporates both traditional models and deep neural networks. The company collects not only sales data but also user activity data, including product views, wish lists, and search queries, all of which contribute to highly accurate order predictions [6]. According to Reuters (Dastin, 2018), Amazon's AI forecasting system is so precise that it optimizes inventory levels and minimizes delivery times to the lowest possible thresholds [6]. Amazon employs a predictive logistics strategy, using forecasts to pre-position goods closer to potential buyers (e.g., at regional warehouses) even before an order is placed. This is made possible by the high reliability of the predictions, ensuring that products will be in demand. Amazon also integrates hybrid models, combining statistical approaches for baseline forecasts with neural networks to account for anomalies, such as viral demand spikes for specific items. During the COVID-19 pandemic, Amazon quickly adjusted its forecasting models to the new demand landscape—managing surges in certain product categories and declines in others—avoiding supply chain chaos that disrupted many traditional retailers relying on historical data-based forecasts. The combination of highly accurate forecasting and a flexible distribution network is one of the key reasons Amazon

maintains exceptionally high service levels (fast delivery and near-universal product availability) while keeping logistics costs relatively low.

Zara (Inditex). The global fashion retailer Zara follows a different inventory management strategy, prioritizing rapid response, but demand forecasting has also become a critical tool. The company analyzes sales data for each clothing model and accessory in stores worldwide in near real-time. Machine learning algorithms process this data along with customer preference insights, such as survey results and social media trends [6]. This enables Zara to predict demand at the design and size level more accurately and plan inventory replenishment accordingly. Unlike traditional long-term forecasting, Zara relies on short-term forecasts to restock stores twice a week. AI models help determine which products should be sent to specific stores based on local demand predictions. This approach minimizes unsold inventory. Baigorri & Gomez note that by implementing such technologies, Zara significantly reduced the percentage of unsold clothing at the end of each season and decreased the need for heavy markdowns to clear excess stock [6, 8]. Accurate trend forecasting has effectively allowed Zara to shift toward an almost on-demand production model, where small batches of clothing are rapidly produced and shipped only to the markets where demand has been identified through data analytics. This has dramatically improved inventory turnover and reduced storage costs. Additionally, Inditex (Zara's parent company) has reported that integrating AI into logistics, including forecasting, has enhanced customer satisfaction by ensuring that the right products and sizes are available in stores more frequently, reducing the likelihood of stockouts.

Other examples. Beyond retail, manufacturers and distributors have also achieved significant success with forecasting models. FMCG companies such as Procter & Gamble and Unilever utilize global demand forecasting systems that collect sales data from retail partners and generate forecasts for each country and product category. This helps optimize inventory at distribution centers and

improve production planning, reducing excess stock. The automotive industry is also actively adopting forecasting models. Automakers use ML to predict demand for spare parts and services, optimizing inventory management at dealerships and forecasting demand for new vehicles to aid production planning [5]. In e-commerce, companies use predictive models to manage micro-fulfillment warehouses in urban areas, forecasting which products customers are likely to order online in the coming days and pre-positioning them at local pickup points. This reduces delivery times and optimizes central warehouse operations. Even in the public sector, major postal and logistics operators use forecasting models to plan parcel volumes and optimize delivery routes—essentially an inventory management task applied to network capacity planning. These examples highlight how demand forecasting has become an integral part of modern logistics, with successful case studies demonstrating significant economic benefits.

At the same time, publications also point out challenges. Implementing AI-driven forecasting models in large companies requires process adjustments and workforce training [6]. Walmart and Amazon invested substantial resources in IT infrastructure and personnel (data scientists, analysts) before realizing significant returns. Additionally, organizational trust in the models is essential—initially, managers may be skeptical of algorithmic recommendations. Overcoming these barriers is part of the transformation process that market leaders undergo. Successful cases show that the effort is worthwhile, as companies gain a more transparent and controllable supply chain.

Conclusion. The application of demand forecasting models in inventory management has proven its effectiveness and has become a fundamental best practice in logistics. The conducted review demonstrates that the modern logistics sector operates at the intersection of statistical methods and artificial intelligence algorithms. Traditional models such as ARIMA and exponential smoothing provide a foundational framework and interpretability, while machine learning

and deep data analysis methods introduce flexibility and high accuracy, particularly in rapidly changing demand environments. The combination of these approaches forms the basis for building reliable forecasting systems.

Both scientific research and practical business experience indicate that accurate demand forecasting leads to inventory optimization and reduced logistics costs. Improved forecast accuracy allows companies to maintain lower excess stock levels (reducing storage costs and freeing up working capital) while simultaneously preventing shortages of critical items (enhancing service levels and revenue). Additionally, high accuracy enables more precise planning, facilitating automated supplier orders and dynamic stock replenishment in retail stores. Ultimately, demand forecasting becomes the central component of decision-making throughout the supply chain, with its data being utilized for production planning, distribution, procurement, and even marketing activities.

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