RADemics

AI-Based Supply Chain Forecasting and Inventory Management

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Abstract

Rapid digitalization, increasing demand volatility, and growing supply chain complexity have exposed significant limitations in traditional forecasting and inventory management approaches. In response to these challenges, Artificial Intelligence (AI) has emerged as a powerful enabler of data-driven, adaptive, and intelligent supply chain decision-making. This book chapter presents a comprehensive and systematic examination of AI-based supply chain forecasting and inventory management models, focusing on the integration of machine learning, deep learning, and reinforcement learning techniques within modern supply chain environments. The chapter synthesizes recent advances in demand forecasting, inventory optimization, multi-echelon coordination, and real-time decision support, emphasizing the role of external data, sensor-driven visibility, and network-level intelligence. Key methodological developments, practical applications, and implementation challenges related to data quality, model interpretability, and system integration are critically analyzed. The chapter also highlights emerging research directions in explainable AI, resilient inventory systems, and sustainable supply chain operations. By bridging predictive analytics with prescriptive inventory decision-making, this chapter provides valuable theoretical insights and practical guidance for researchers and practitioners seeking to enhance supply chain performance in increasingly dynamic and uncertain markets.

Keywords: Artificial Intelligence; Supply Chain Forecasting; Inventory Management; Machine Learning; Deep Learning; Multi-Echelon Supply Chains.

Introduction

Supply chain forecasting and inventory management represent foundational pillars of effective supply chain planning, directly influencing cost efficiency, service reliability, and organizational competitiveness [1]. Accurate demand forecasting enables alignment between production, procurement, and distribution decisions, while efficient inventory management ensures product availability without excessive capital investment [2]. In contemporary business environments, these functions face unprecedented pressure due to increasing market volatility, shortened product life cycles, customization requirements, and intensified global competition [3]. Demand uncertainty has grown substantially as customer preferences evolve rapidly and supply networks expand across geographically dispersed regions [4]. Under such conditions, even minor forecasting inaccuracies can propagate across supply chain tiers, resulting in stock imbalances, service disruptions, and elevated operational costs. Traditional approaches to forecasting and inventory control, although analytically robust in stable environments, struggle to cope with such complexity. These challenges have elevated forecasting and inventory management from routine operational tasks to strategic decision-making functions requiring advanced analytical capabilities and adaptive control mechanisms [5].

Supply chain forecasting and inventory decisions have relied heavily on statistical and optimization-based models grounded in assumptions of linearity, stationarity, and well-defined probability distributions [6]. Time-series techniques, causal regression models, and classical inventory policies have provided structured methodologies for managing uncertainty and balancing trade-offs between holding and shortage costs [7]. These methods remain valuable for their interpretability and mathematical tractability. Yet, modern supply chains increasingly operate within environments characterized by non-linear demand behavior, intermittent sales, demand shocks, and complex interactions among multiple influencing factors [8]. The growing influence of pricing strategies, promotional campaigns, competitive actions, and external disruptions has weakened the predictive power of models that depend primarily on historical averages and fixed parameters [9]. As a result, reliance on traditional approaches alone often leads to delayed responses, rigid inventory policies, and limited ability to exploit the growing volume of available supply chain data [10].

The digital transformation of supply chains has fundamentally altered the nature and scale of data available for forecasting and inventory decision-making [11]. Enterprise systems, point-of-sale technologies, e-commerce platforms, and automated logistics operations continuously generate detailed transactional and operational data [12]. In parallel, sensor technologies, connected devices, and cyber-physical systems provide real-time visibility into inventory levels, material flows, and environmental conditions [13]. External data sources such as economic indicators, weather information, and digital consumer behavior signals further enrich the data landscape. This proliferation of structured and unstructured data offers significant opportunities for improving demand visibility and inventory responsiveness [14]. Yet, it also introduces analytical challenges related to data volume, heterogeneity, and velocity. Conventional analytical tools often lack the capacity to process and learn from such complex datasets, creating a gap between data availability and effective decision utilization within supply chain systems [15].