Point-of-Sale Event Streaming and Automated Replenishment Triggers: Real-Time Machine Learning Frameworks for Demand Forecasting and Inventory Optimisation

Dr. Yang Wang, Associate Professor of Electrical Engineering, Zhejiang University, China

1. Introduction

Demand forecasting and inventory replenishment are two important components of supply chain management that must evolve with the market. Accurate forecasting enables better planning decisions that help to minimize excess inventory levels as well as to meet customer demands in a timely and efficient manner. To date, traditional forecasting methods have contributed to the compiled forecasts for inventory replenishment. However, adapting to an inherent attribute of today's dynamic market – real-time data – requires evolving the demand forecast and using real-time information to adapt the replenishment. In addition to this practical aim, demand forecasting is also a major component in a plethora of industrial infrastructures and AI techniques such as industrial big data analytics, predictive maintenance, and transportation management systems.

Accurate demand forecasts have always been a challenge due to the risk associated with consumer behavior. Yet, in the current reality of an increasingly fast-paced environment combined with a rising volatility index, the need for daily demand forecasts that can adapt to market changes is growing. Revising demand forecasts in real-time is central to understanding consumer behavior and preferences, and how they are influenced by minor environmental changes. Artificial Intelligence has begun to revolutionize demand forecasting and is also being used to improve inventory practices. This study uses AI to predict real-time daily demand and align the inventory strategy with these demand forecasts. Ensuring that the forecast is adapted for triggers represents half the equation, while adapting the inventory operations is the other. This study extends the application boundaries with a new purpose – to serve these two needs: trigger-based demand forecasting and inventory replenishment decision-support systems. The accurate prediction of customer demand is a key factor impacting management.

1.1. Overview of Supply Chain Management

Supply Chain Management (SCM) encompasses all the activities required to produce a product and bring it to the end consumer. The supply chain consists of suppliers, manufacturers, warehouse service providers, and retailers. Suppliers are responsible for the delivery of the purchased components, manufacturers create the product using these components, and warehouse service providers store the product before selling it to other partners. The ultimate goal of SCM is to enhance customer benefits and to deliver necessary products promptly by improving system efficiency. The members of supply chains perform a wide range of functions, including ordering, buying, material handling, physical storage, transportation management, demand forecasting, and inventory control, to work effectively. Many of these functions have a direct connection with demand forecasting. The demand forecast influences the orders placed on the suppliers, the production volumes and schedules, the services offered to the customers, and more. In the integrated network of suppliers, manufacturers, and warehouses, the forecast made at any point influences the entire chain. The regular flow of financial, informational, and physical outputs throughout the supply chain guarantees that consumers have a sufficient supply of food for their needs. Physical products have data on their locations and distributions, and money and funds are transferred from suppliers at any point in the supply chain. To guarantee the smooth operation of the supply chain, real-time feedback and comprehensive information flow are critical. The integrated strategy for certain events can benefit all members of the supply chain. Although each of the supply chain partners can function separately from other partners, this procedure can have a negative impact on the overall supply chain efficiency. The accurate forecast of end-consumer demand in any supply chain agency can minimize inventory costs, backlogging costs, and consumer loss, thereby minimizing supply chain expenses, reducing excess products, and decreasing the impact of variability in demand and supply disturbances.

1.2. Significance of Demand Forecasting and Inventory Replenishment

Increased globalization has made the entire world a village where products and services of one part are available to the other part of the world. As a result, modern supply chain and operational management are becoming more complex. Demand forecasting and inventory replenishment are two of the most important operations involved in managing modern supply chains. Accurate demand forecasting and inventory management can help optimize operational performance at all levels. By forecasting future demand, a company can adapt its inventory levels to customer needs, which will optimize customer satisfaction while reducing inventory costs as well as the risk of stockouts. In turn, inventory optimization has a doubling effect on cost savings since it leads to higher cash flow. In recent years, there has been an increasing interest in the academic community in inventory strategy versus demand variability issues. It has been shown that better supply chain performance can be achieved by using an inventory strategy that considers the variability of the item's demand. Moreover, the variability in demand may influence the level of service provided to the final market as well as the overall supply chain costs and levels of investment. Other researchers have made significant contributions to the demand forecasting problem when deteriorating items are present in the inventory.

The importance of demand forecasting and inventory control in different industrial fields has been studied. For example, in the manufacturing field and distribution systems, inventory control is an essential process, and poor inventory control may lead to serious problems in materials and production management. In other areas such as the service industry, inventory control is also used to ensure the quality of services. The banking services industry may use the interest rate as an inventory product for fund management. A poor demand forecast may lead to disinvestments, which will increase the investment risk for the asset. Replenishment may not meet the demand, and the result is that the excess inventory is also waste. In some other service sectors, adding orders to suppliers in case of potential stockouts helps to avoid delays in business operations and maintain satisfactory customer service. In the supply chain area, effective feedback for controlling inventory replenishment between agents has a significant impact. Feedback is a kind of external control that provides a feedback mechanism in adaptive systems. It enables entities in a system to monitor and improve their decision-making in the face of uncertainties and instability in the system. Inventory inaccuracy is a significant problem faced by companies globally, with varying reliability estimates indicating that most companies do not achieve inventory record keeping greater than 95%.

2. Fundamentals of Demand Forecasting

Demand forecasting refers to the estimation of probable demand for a product or service during a future time period from the customers or consumers. Organizations achieve the same with the help of different methods and techniques under two categories: qualitative methods and quantitative methods. While a plethora of methods is already resulting in holistic demand forecasting processes, these age-old methods may not fare well when transformed into real-time demand sensing. Hence, the integration of traditional forecasting methods with artificial intelligence approaches becomes imperative. Different forecasting models have been developed and designed to depict the scenario and solve a particular decision-making problem. Both qualitative and quantitative forecasting models exist. Exponential smoothing and Box-Jenkins approaches have been in use for a long time. Exploratory techniques like judgment and Delphi models have also been developed besides time series and causal models.

The Box-Jenkins or the exponential smoothing forecasting models are used where the large scale available is predominantly short term in nature. Time series models, along with machine learning in the recent past, are gaining increased attention due to their better performance. The demand for time series forecasting models has been overgrowing across industries to gain predictive insight from historical data. The advent and upsurge in associative models are witnessed in the machine learning and artificial intelligence fields to predict future values using causative factors and manipulating functions. Dynamic regression can be seen as a common framework to integrate AI knowledge into time series modeling. Marketing research has sensitized managers with the spurt in sales data compensating for the early warning signals needed to anticipate and survive demand downturns. Seasonal index adequately depicts that a seasonal or cyclical factor contributes to demand for a product in question. The time series analysis classifications discuss the lasting behavior between forecast periods with the decomposition of demand patterns. Many hurdles occur in the execution and design stage of forecasting. Visibility of forecast data to improve quality and demand aggregation are a few of the many pitfalls. Data quality management is often taken for granted by market-based firms as the size of the data at the input process is perceived to be in abundance. Data is usually not in the shape and form it is desired to be, nor at the level of granularity. Proper methods associated with data cleansing are to be implemented. Equitable selection of demand forecasting models can result in enhanced accuracy of forecasts, which is often not the case faced in practice by forecasters across industries. Organizations are overcrowded with a variety of methods for demand forecasting, resulting in ambiguity. Increasingly, more data-driven demand forecasting solutions are resolving the issue, resulting in the development of cutting-edge ML techniques. In the sections below, there is a detailed discussion of traditional forecasting models and complementary subjects of predictive solutions for accurate forecasting.

2.1. Traditional Methods vs. AI-based Approaches

The traditional demand forecasting approaches are widely divided into two sections: qualitative and quantitative. Among quantitative forecasting methods, moving averages and exponential smoothing are the simplest approaches. In fact, most of the advanced forecasting methods were developed on top of these two methods, thereby showing their importance. Although these techniques form the building blocks of the forecasting literature and are easy to understand, their inability to account for nonlinear variation patterns, seasonality, and make reasonable results is well documented. Conversely, in order to manage increased competition, globalization, and complexity in the business environment, the approaches should be able to quantify and use all types of data with high accuracy that traditional methods are not capable of doing. Therefore, in the highly volatile and unpredictable market, rigid planning strategies prevent companies or suppliers from obtaining some advantages, such as lower stock networks and costs to be able to answer consumer needs in real time. In this context, AI-based approaches are considered promising solutions for forecasting-related problems.

Artificial Intelligence (AI) involves several techniques and methodologies such as fuzzy logic, Artificial Neural Networks, expert systems, and genetic algorithms, simulation-based models, etc., in dealing with a variety of business issues in recent years. In general, AI is a method, an approach, and a way of thinking that engages the philosophy and techniques of these two main paradigms: symbolic reasoning and connectionist computation based on neural networks. Symbolic reasoning is logic-based, rule-based, high-level, and explicit form programming of AI where symbolic forms and their formal manipulations are used in problem-solving, finding solutions, imitating behavior, and developing new knowledge. On the other hand, connectionist computation is model-based, containing learning as a crucial part, behaves in some way like a brain in perceiving, recognizing, interpreting, and manipulating the environment and adapting to it. An Artificial Neural Network is a widely utilized model that has the potential to learn from real big datasets, recognize hidden patterns, and therefore be used for analyzing and estimating demand realistically. They are self-adaptive and used in learning, recalling, and generalizing complex pattern functions. With their superior feature of being able to uncover hidden relationships among large amounts of imprecise, uncertain, and noisy data, AI-based approaches have been of interest to both researchers and professionals. Therefore, they use different forms of learning and the ability to adjust themselves according to new observations, and they have lately attracted increased attention from both scholars and business professionals.

The main benefits of employing such techniques are the capability to process and perceive vast and diverse information about different problems, model and forecast the dynamics and interactions between real-world systems. An AI-based forecasting technique is able to explore a colossal amount of historical transaction data on the system, look for seasonal issues or plausible valid predispositions, extracting them from data that different traditional one-dimensional methods may overlook, and structure the complex relationships between input and output variables. Not only decomposing extremely complicated wholesale and retail environments into models but also providing real-time decision-making forces the AI-based solution developers to include these types of procedures in their systems. Through this system-based thinking, large and medium-scale corporations, disjoint supply chain units, and retailers can be connected into the supplier's network in a real-time and demand-driven manner.

2.2. Key Concepts in Demand Forecasting

Accurately forecasting product demand is an essential component of modern supply chain management. Technological advancements have enabled managers to analyze increasingly large datasets for more reliable demand forecasts. In practice, a sales and operations planning process aligns sales, marketing, and promotional plans with financial and supply chain objectives. Inventory and capacity planning is then based on the output of the collaborative demand forecasting process. In the context of this study, accuracy is defined as the lack of error in point forecasts. While some studies have also used qualitative measures for accurate forecasting, this study relies on the quantitative measure to separate accurate from biased predictions. Measurement of accuracy is typically done for one-period-ahead forecasts at the most disaggregated level and is expressed in a specific forecasting error.

A biased forecasting model typically employs historical data, such as sales or lifting rates, and often includes more forward-looking signals in a demand forecasting model than a simple univariate time series model. Refinement of the full model, assembly model, and holding model forecasts includes trend changes and forecast seasonality factors. In this context, assembly refers to expected deliveries by the company equal to receipt, whereas holding refers to expected deliveries greater than receipts. This briefing does not focus on the effect of stockouts. The combination of the order lead time and the forecast is often referred to as timing inventory management. When the plan is changed, it is important to consider the time lag of monthly and quarterly supply chain processes. Together, forecast accuracy and forecast bias help to account for future economic conditions, actual consumer demand, technology, and shopping behavior that were not captured in the model forecasts. Informally, it has consistently been observed that a continuous flow of information during a given monthly plan delay is crucial to getting a forecast right and establishing a critical lead time framework in sales forecasting.

3. Machine Learning Models for Demand Forecasting

Machine learning is currently the preferred method for demand forecasting because it can be used to model large-scale sales and customer data for highly accurate demand forecasts. Compared with traditional time series forecasting techniques, the biggest advantage of machine learning algorithms is their ability to model flexible demand patterns. Trees are joined and pruned according to the needs of the data. Trees allow feature interactions with if-else constraints and do not require extensive feature analysis to identify the corresponding patterns.

Two tree-based models that achieve state-of-the-art performance in demand forecasting are decision trees and gradient boosting decision trees. Several of these models are aggregated in a boosting manner, so each tree captures the remaining structures of the previous tree. Gradient boosting decision trees also tend to be robust not only from the datasets but also from hyperparameter settings. For demand forecasting, temporal relationships and spatial dependencies can be captured by gradient boosting decision trees the same way a neural network captures complex customer insights. Unlike powerful models like neural networks, gradient boosting decision trees handle larger datasets at almost the same computational complexity as simpler models.

The machine learning models of neural networks and decision trees have thrived in demand forecasting because of their ability to capture patterns where access to sales and customer data is aligned. For retailer data, decision trees capture demand patterns of raw sales and customer data. The power of feature engineering captures various demand patterns whether it is changing ranges between periods, supply chain events, changing patterns between aggregations, and many other factors that change demand. Neural networks, on the other hand, capture relationships between customer and sales data. Deep learning's ability to process time-series data while capturing features in demand forecasting patterns makes structured sales data a good alternative for sparse unstructured time-series datasets. Neural networks can be used when data are processed for each timestamp as an input component, thus incorporated with feature engineering. For instance, recurrent neural networks and convolutional neural networks have been trained from customer and sales data in the various resale industry with end-to-end design. However, because of the potential plethora of data enrichment opportunities that have yet to be conducted, feature engineering is a pertinent necessity that can be done repeatedly. Exploratory analysis, hypothesis testing, and data analysis are essential to provide a model. Without these, the worth of a model would be dubious. Data must also be cleansed of inconsistencies, duplicates, and outliers. Resampling and rolling windows are useful data preparation techniques. Bootstrap techniques can be used for larger datasets. Model training requires substantial information to get accurate results. For a weekly sales prediction, it could accommodate at least two years' worth of data. Furthermore, the data used for training should not contain missing sales of 1-3 days. This common issue may require some helpful feature engineering to overcome. Model training results from machine learning can be seen in many various areas, such as digital marketing, sales, and e-commerce transactions.

3.1. Regression Models

Demand forecasting is a fundamental process in supply chain management. As a basic forecasting approach, different models have been developed. One of the very first models used in forecasting situations is regression analysis, which is included in quantitative models. Regression models are applied to establish the relationships between dependent and independent variables. The dependent variable, also called the response or the target, should be forecasted. The independent variables are used as predictors to forecast the dependent variable. Regression models can be simple, which includes one independent variable, or multiple, which includes more than one independent variable. In supply chain departments, using regression models is common for short-term and long-term demand forecasting. Due to the perception that future demand could be affected by different factors with particular time dependency, using different independent variables is common. Every independent variable might be related to some promotional activities, sales, economic environment, supply chain parameters, global events, weather conditions, or others. These independent variables should be used as timestamps when they have an impact on demand. Thus, every independent variable should be updated when its impact changes. Linear regression models can forecast the increase, decrease, or steady demand, where time series components such as a linear trend are captured by this model. Instead of a linear pattern, a polynomial regression model can be applied when the relationship between the dependent variable and independent variable has a polynomial shape. Capturing the real impact of the trend can still be challenging because when either little information or autocorrelation exists between the data, losing historical data can have an impact. Additionally, when the trend path differs between periods with no seasonality impacts, the polynomial regression model might lose the flexibility of selecting the best fitting parameters depending on actual demand information. Especially, the practicality of the regression model is constrained by this issue. Detecting polynomial coefficients, dependent variable forecast contribution, and autonomous variables are representatives of some regression challenges. To avoid overfitting of the prediction model and random fluctuations and noise correlations, preliminary data analysis diagnostics should be performed. For example, the existence of inter-correlation within independent and dependent variables can be detected by calculating a correlation matrix, as well as the correlation between the independent and dependent variables.

3.2. Time Series Forecasting Techniques

Capturing demand patterns over time is important in inventory replenishment. Time series forecasting performs forecasts of a series of data points ordered by time, making it attractive to model demand forecasting due to its natural chronological order. It consists of three components: the basic principle of time series analysis, the stationarity of time series data, and important components for demand forecasting.

Time series data might have four components: trend (general direction in time series data), seasonality (repeating short-term cycle in time series data, such as orders completed weekly), cyclic patterns (repeating long-term patterns in time series data, such as library usage examined per year), and random noise (residual fluctuations in time series data that cannot be modeled in the previous three components). Many forecasting methods are employed based on various time series forecasting techniques to capture these components in time series data. Most time series forecasting techniques assume stationary time series data for developing forecasting models, which could be achieved by differencing the data, and it makes use of the unimodal or test for stationarity.

Time series forecasting creates models based on the history of time series data for forecasting series data in the testing period. Data exploration through visualization facilitates understanding the nature of time series data, including the temporal pattern, seasonality, direction of data, and presence of outliers. Classical approaches such as Mean Absolute Error, Mean Absolute Percentage Error, and Root Median Square Error are often utilized for evaluating the performance of forecasting models. The wide use of time series forecasting is due to the classical forecasting methods and new features of machine learning methods, owing to the robustness of time series forecasting, data exploration, and modeling in the presence of missing data.

4. Inventory Replenishment Strategies

With real-time demand forecasting, different inventory replenishment strategies can also be applied seamlessly to satisfy the business constraints and dynamics. Today, businesses are constantly pursuing more efficient supply chain performance, such as reduced operational costs, reduced lead time, faster order response, and the highest customer service with minimal investment. Most successful or growing organizations adopt various inventory control strategies or supplementary options in line with the organization-specific constraints, culture, and requirements in a given industry. Just-in-Time (JIT) is a Japanese inventory management concept. The main idea behind JIT is to have the right material at the right time, in the right amount, and of the right quality, exactly at the time of demand, minimizing the excess stock before or after the production process. The order cycle or pipeline stock is also minimized, and the total lead time can be reduced under JIT. In contrast, JIT involves coordination among production, marketing, transportation, engineers, and suppliers to achieve the desired goals. JIT advocates minimal inventory control but with synchronized functions to ensure timely fulfillment of customer demand.

Compared to JIT, the Economic Order Quantity (EOQ) model also targets reduced total inventory costs, while JIT focuses on just-in-time delivery or production, which is close to demand. Unlike JIT, the EOQ is the expected order size that minimizes total inventory costs, which include holding costs and ordering costs, with the inclusion of reorder decision-making points in the planning horizon. The EOQ model can be used effectively with the demand pattern, with an annual demand or setup cost that is not exactly incremental in the extension of the quantity. Implementing JIT or EOQ consists of evaluating forecasted demands to adjust inventory control variables such as the amount of safety stock, order quantity, reorder level, and order cycle when needed for synchronization. The lead time, as well as the demand pattern for every product, is another aspect to consider when applying JIT or EOQ with demand forecasting. Experience shows that the JIT concept has been widely applied in manufacturing, engineering, and construction industries. The EOQ or reorder point - order quantity model has been applied effectively in several sectors such as automotive, electronic items, and mining companies.

4.1. Just-in-Time (JIT) Inventory Management

4.1. Just-in-Time (JIT) Inventory Management Just-in-Time (JIT) inventory management seeks to streamline the production process by having the right parts in the right quantities at the exact time they are required. JIT is used to integrate the system of production and distribution in such a way as to maximize efficiency. The central principles are therefore the demand-pull system or simply put: we do not produce until there is a demand. This system relies on close cooperation with suppliers who deliver the required parts at the exact time they are needed. In more advanced forms of JIT, companies collaborate with suppliers to realize common continuous improvement projects. JIT reduces the holding costs associated with inventory, the problems of obsolescence, and the costs of holding all such inventory. It also enhances cash flow, reduces the problems of stockouts by its very nature, reduces handling costs, can reduce ordering and chasing up costs, and in principle means the warehouse can be almost eliminated. Overall, the lack of inventory means a simpler streamlined process occurs from the customer through goods inwards to invoices out.

However, it is not without risk, for if one part of the supply chain should collapse, the entire chain becomes paralyzed. Therefore, supplier relationships need to be checked and rechecked, and a long-term supplier approach is necessary, maintaining contractual relationships through thick and thin. Although demand forecasts are minimal in terms of purchasing and can be adjusted for an upturn or a downturn, an important part of JIT is the forecasting relationship in terms of being supplied with the day-by-day, hour-by-hour changes in customer needs. Companies can have new model changes without shutting the production line briefly and began building the new models with parts delivered just in time. Agility and customer responsiveness in terms of producing what the customer wants are also seen as part of the demands that we place on the 21st-century supply chain. For some companies, although 99% of their output is the same as the last customer, they still have to provide customized products and provide that service if they are to remain competitive in an ever-changing marketplace. The total inventory system was designed to carry enough stock on-site to ensure they could cope with disruptions in the early stages, but over time, the reduction in inventory levels meant that more emphasis was placed on the entire supply chain.

4.2. Economic Order Quantity (EOQ) Models

In the two-bin policy, a reorder occurs at the level of the safety stock. For this purpose, a formalism has been provided by Economic Order Quantity models, which complement an act of restocking with a mathematical structure that determines how much the inventory should be, given restocking costs and holding costs. The classical and very simple version of the model consists of considering costs related to making an order and costs related to holding the inventory. These are the key factors driving the model, given the constant demand and lead time. EOQ is the quantity that minimizes the cost made by the sum of the ordering and holding costs.

EOQ models are aimed at analyzing the trade-offs between ordering little quantity often and the alternative. They highlight that, if demand is steady, a constant flow related to time minimizes the cost because it is cheaper in terms of holding. Like any model, EOQ simplifies reality. It is primarily based on the assumption of constant demand. The model cannot forecast well dynamic demand with decreasing or increasing periods, when it should be better to build up inventory. This can be, however, integrated with the forecasting method application to enhance inventory management accuracy. That is the most promising field of further investments considering the different cases. There are hundreds of successful cases of application of EOQ in the most different sectors. The biggest issue with the classic EOQ model is the hypothesis: the constant demand. There are theories that develop this schedule in an environment of changes. In fact, it is heavy to manage a reorder-point policy. Typically, the production costs only have a reorder-point because it is an eternity to empty the inventory and the safety stock is not a material to produce more than the quantity in the inventory. Even using two-bin with other ordering rules is something that a company does rarely. The reality is a fixed batch, and the industries have made a huge improvement to cut the batch size in order to be lean. Therefore, the EOQ still applies.

5. Real-World Applications and Case Studies

Researchers have developed various ways of forecasting customer demand and using these forecasts for managing inventory. Different industries such as retail, fashion, electronics, agriculture, and manufacturing have integrated the demand forecasting and inventory replenishment process using various forecasting methods. One study forecasted quarterly demand by using different models saved on the model of the unprocessed data. Another developed a hierarchical forecasting model with the grouping information according to the seasonality and interrelation of the time series and proved that combining simple models provides better accuracy than univariate models. Time series classification has been used to forecast automobile sales and make stock decisions. A new supply chain system for fashion products that is based on the synchronization of mobile sales and production by using a forecasting method has been discussed. The study shows how the application of appropriate forecasting techniques in a food processing firm can shorten lead time and reduce stock holding costs.

Companies are trying to improve the accuracy of collaborative planning, forecasting, and replenishment by using various advanced forecasting and replenishment methods, such as the differencing method and wavelet method. One study used models to forecast sales for five or seven years ahead and achieved a certain level of accuracy. Another used ad-hoc methods and found that a specific model achieved the highest accuracy compared with that using various moving average methods in an experiment. Demand forecasting and inventory replenishment techniques have been implemented and operated to control the level of inventory under uncertainty in the selection of the most effective method to suit the context of each organization. Different methods based on AI and machine learning models have been used to forecast demand for activities at a specific corporation. The problem faced by a product manager is how to manage inventory to handle the uncertainty in demand. The product manager manages stock control in the face of this uncertain demand, diverting temporary warehouses to reduce the number of deliveries for items with high demand.

6. Future Direction

The development of technology and changing global dynamics will continue to push the frontiers of demand forecasting and inventory management in the future. There are numerous possible directions in which demand forecasting and inventory management practices could evolve. Trends point to a future where the use of AI and forecasting with big data is the crucial aspect. Capable systems learning will lead to accurate demand forecasting, predictive analytics, and it will be possible to assess and remediate threats as they emerge. Aggressive commercial organizations are currently leading the way in achieving these benefits. 1) AI and demand forecasting are becoming one. The AI market has been growing rapidly and will continue over the next few years. 2) Looking to real-time data. Being able to adjust stock levels based on recent demand and stock level trends can only improve demand forecasting accuracy. 3) Big data and IoT. Big data is set to revolutionize inventory management in the supply chain and the way demand forecasting is conducted. The IoT is all about managing data because it is the connection that everything has in common. Specialists believe that by utilizing IoT data, demand forecasting and inventory management will be more efficient. 4) Adaptive strategic policies. The most commonly identified need was for well-thought-out adaptive policies and strategies with links between different business areas. 5) Skills and people. The barrier to competition is not about fighting with the best data; it is about having the best fighting with the same data. Leading practice organizations believe in the value of analytics and in having access to a new breed of supply chain professionals who are comfortable in the big data world. Ongoing innovation is more important than ever. The piloting of new forecasting methodologies could be immeasurably great as it may uncover mispriced options.

7. Conclusion

In this paper, we discussed the main actors and practices in the field of operations and supply chain management. Our focus was on demand forecasting practice and its two critical aspects: inventory replenishment and demand satisfaction. We provided an overview of real-time demand forecasting, emphasizing its importance in managing safety stock and cost reduction. Our stance was that businesses need to adopt advanced techniques to improve the forecasting process further, gain additional benefits, and retain their competitiveness. Artificial intelligence and machine learning are contextualized in the current state of the art, and important challenges that have to be addressed before the adoption of these innovations were raised. The main limitations of the research suggested some operational concentration on real-time forecasting while underlining the necessity to better investigate the interaction between forecasting, inventory replenishment, and operational management within logistics, supply chain, and production.

In conclusion, forecasting and inventory replenishment remain critical to maintaining operational efficiency. Organizations need to take advantage of the most advanced methods to optimize these two areas. While AI and machine learning can increase forecasting accuracy, we have to keep in mind that the complexity of these new innovations is linked to the large computational power they require. The additional costs that derive from using huge amounts of data to make predictions can be justified only in specific sectors. Demand uncertainty is still mainly tackled by standardized technical solutions, relegating the more advanced methods to the status of 'innovation' at the service of a few pioneering sectors. Furthermore, the complexity of the new methods makes it necessary to plan for long- and short-term adaptation. Anticipating internal adjustments to be implemented in parallel with the possible adoption of the new techniques is essential to support overall business adaptation right from the early experimentation stages.