Online Demand Sensing and Inventory Allocation Intelligence: A Real-Time Reinforcement Learning Framework for Supply-Demand Matching

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1. Introduction

Understanding the dynamics of demand and supply in real time can be very beneficial, especially in today's volatile and highly competitive market environment. For instance, some online retailers offer items for sale that are already in transit. Estimations of future demand, which are the output of sophisticated data-driven methods, are used in real-time logistics optimization systems. In the discrete manufacturing sector, real-time decisions may be made to reprioritize allocations from one station to another. Artificial intelligence applications have the potential to further enhance decision-making in such scenarios, involving the demand and supply consensus process and the matching of demand and supply.

Traditional methods that have been employed in demand and supply matching include integer programming and constraint programming. However, the use of the aforementioned methods in real-world settings often faces a number of largely practical challenges. In particular, the time required to compute an exact solution may exceed the time available, which is one of the key issues. There is a growing interest in using AI applications to improve the operational efficiency of highly time-constrained processes. More specifically, model-free RL algorithms are valuable when predefining all variables and constants in a traditional approach becomes intractable. The demand and supply consensus process involves identifying the common demand from multiple data sources, combining this demand with inward stock flows, and aligning demand with supply to reach the best possible match. This process introduces a number of key issues, including many-to-many, many-to-one, and many-to-most relations.

1.1. Background and Significance

Assuring the best matching for the demand and supply of goods, and delivering systems at an expectable time is the concept of the market, since the ancient period of uniform market dynamics. This concept has changed over time to have a more complex market dynamic according to changes in business models, customers, and products. With the growth in data, many data-driven business models started to handle the matching of goods and services. By handling complex patterns to allow customers to buy and consume goods the way they need, every service provider has created a more sophisticated matching engine, which consists of some AI technologies. The demand and supply matching is implemented by many components using AI technologies from offline to online, including forecasting and predictive models, and dynamic pricing. Demand and supply are managed since the offline matching mode, with offline forecasting usually performed hours to months before the current time epoch. This cumbersome process can also be done fallaciously.

Forecasting is a core task in demand and supply matching. It is critical to decide how much supply can be matched with the demand accurately, as oversupply will cause a large waste of costs and profitability. Late detection of undersupply in the supply chain might make the business lose it. Some of the available accurate supply chain demand and delivery forecasting offers greater availability. Many successful case studies show that the combination of AI technology and market dynamic management has a high level of demand/supply forecast accuracy. However, all these case studies are tested on old historical data using an offline or preprocessing mechanism. Nevertheless, it is rare to find continuous augmentation of these models via AI capturing fine-grained signals from real-time data directly. While achieving integrated forecasting and matching for the demand and supply of goods, our goal is to examine the matching of forecasts as well. Furthermore, this text will discuss the demand and supply, and price matching components with the necessary methodology to perform, and introduce the notations. It will also systematically discuss the dynamics of markets.

2. Fundamentals of Demand and Supply Matching

The market equilibrium model is based on the matching of demand and supply. According to economic theory, equilibrium exists when the price and quantity of a resource or good in demand do not change either due to excess supply or extra demand conditions. The mismatch of quantity demanded and quantity supplied governs the market dynamics and price behavior. More specifically, a small change in price leads to a large change in quantity demanded or supplied. The demand and supply elasticity, which is lower than the change in price, is very sensitive to price changes. The traditional models of neoclassical economics have assumed different behavioral patterns of a consumer and supplier of a commodity, which determine demand and supply functions. A variety of demand and supply functions are available, depending on models of consumer behavior.

The research in economic demand and supply matching over many years has mainly concentrated on analyzing and predicting market demand and supply. The Boolean logical property of supply-demand matching, such as the stability of supply and demand in a traditional market economy and the calculation of excess supply and excess demand shortages, can greatly affect the market equilibrium price. It may lead to less stable long-term market operation and dynamically deviate from the optimal matching. The matching between demand and supply is a multi-functional integration of economic factors. The multi-centric matching between the demand and supply of different people and different goods further expands the complexity of demand and supply matching. In the real market, these inquiries require comprehensive computing in a timely manner.

3. Machine Learning Techniques for Demand Forecasting

Demand forecasting plays a critical role in any supply chain. It is the cornerstone of all supply chain operating models that are directly tied to logistics and fulfillment. Some models and algorithms used for demand forecasting include exponential smoothing, ARIMA, regression analysis, and machine learning models. Research has identified the most commonly applied machine learning algorithms for demand forecasting as Support Vector Machines and Neural Networks. The forecasted values of SVM were fed into the GA to obtain a significantly improved forecast accuracy. This forecasting process was based on monthly time series data, and it is recognized that the forecasting techniques could be further enhanced if real-time sales data were used in the analysis. Neural networks often perform well on time series data with strong seasonality and can account for external factors. However, the requirement to have a large amount of data is a limitation of neural networks.

Real-time machine learning models could predict trends and anomalies in real-time using streams of data, and demand forecasting studies should also consider integrating real-time data in forecasts, as it could result in more accurate forecasts and integrate real-time stock levels as a predictor for demand to capture the constantly changing consumer behavior with increased digital consumption. In practice, models like ARIMA and exponential smoothing have been able to be fairly accurate predictors of demand. For e-commerce sales, a Holt-Winters exponential smoothing model is proposed. The model includes two seasonal terms, but to limit the complexity, the parameters are calculated by assuming a fixed seasonal period. In supply chain management, seasonality can be monitored and estimated. In practice, this is helpful for making short-term tactical decisions.

3.1. Time Series Forecasting

Time series forecasting methodologies have been extensively used. As a result, we investigate these models with an emphasis on how they apply to demand forecasting. Time series data can be intricately defined as patterns, such as a trend or a seasonal pattern. First, every time series contains a trend. This is an important pattern because it illustrates the long-term movement of the sequence. Second, seasonality and cyclical behaviors may be present in time series. Seasonality is defined as the repeating pattern at fixed intervals, such as daily, weekly, monthly, and annually. The accumulation of these seasonal dimensions leads to multiple seasonality. Third, time series data suffer from noise, random jumps, and/or spikes that muddle prediction.

Many forecasting models such as ARIMA, Exponential Smoothing, and their powerful extensions were developed. However, each of these models has its own strengths and weaknesses, which can cause different outcomes. An important characteristic of ARIMA is that selecting the number of parameters requires a significant level of domain knowledge because these models ignore the characteristics of data. Another limitation of ARIMA is that a positive increment in the number of parameters may improve the forecast results for training data but reduce the out-of-sample period. Lower accuracy of the forecast model may result from inadequate fundamental considerations. Some organizations produce good forecast statistics with their demand forecasters who have particularly the attitude of trust in the potential capability of additional information in the form of judgment. Furthermore, time series forecasting techniques can be combined with numerical analyses of historical data to enhance even more by using a choice of machine learning techniques to explore which produce the most accurate demand characteristic analysis. This section focuses on measuring the forecast accuracy as a way to develop better demand forecasting approaches.

Evaluation of different forecasting models is based on their predictive power. Accuracy statistics such as Mean Absolute Error, Mean Squared Error, and Mean Error make it possible to know how well the time series model performs. To guarantee high performance, these models have to be reviewed frequently after their introduction and usage for a while to enhance functionality by refining forecasting tools regularly. Many successful case studies throughout the literature have been reviewed, concerning various industries including automotive, food, and energy sectors. Promising results, especially in prediction accuracy, convinced readers of the importance and effectiveness of these models. The Town of Victoria Park shows that the exponential smoothing method has been successful in forecasting monthly water consumption for the long term. It was also suggested that univariate time series models, which require only the intrinsic patterns of the sequence and ignore structural information, can be promising and further expanded to incorporate such characteristics that are identified in causal paths.

4. Machine Learning Techniques for Supply Chain Optimization

The combination and application of different computational techniques become appropriate for the study of the supply chain. In particular, studies emphasize the profound impact of supply chain quantization on operational efficiency. Now, new machine learning and predictive-related approaches are emerging to address the quantitative aspects of the supply chain end-to-end. Predictive models, optimization algorithms, and automation techniques for intelligent decision support are now mainstream for supply chain quantization. The characterization of several cases and currently mature machine learning applications for the supply chain is proposed.

Most AI applications are oriented towards optimization, regression, and classification models for smaller parts of supply chains such as forecasting and planning. Finally, in our view, supply chain management end-to-end capabilities for a real-time optimized matching between demand and supply include machine learning techniques to improve inventory turnover, reduce logistics time and stock costs, guarantee the quality of the cold supply chain by avoiding counterfeit drugs, and improve transport with solutions to avoid thermal shocks on perishable drugs. They also support demand forecasts, provide on-time custom documentation, and coordinate cross-border transportation. Digital tools for informed supply chain decision-makers can provide an integration of quantitative models and processes end-to-end. They can, for instance, predict expiring cold chain pharmaceutical stock of drugs at arrival, support postponement in manufacturing, coordinate stock with different logistics players, and develop new market opportunities for end-of-month stock put in lower tax countries. Digital interfaces with other parts of a supply chain can systematically report the corresponding dispatching strategy, including transport capacity, distribution route, delivery time window, and costs.

4.1. Inventory Management

Balancing supply and demand between production and consumption is a key factor in efficient and robust supply chain operations. Inventory management has been known for decades as important in supporting the company's supply chain. Inventory management is the balancing of supply and demand through the formulation of company inventory policy. When the quantity of goods available is greater than demand, then inventory will rise. Likewise, if the quantity of goods available is less than demand, then inventory will decrease. Inventory management is focused on fulfilling demand to prevent stock-outs while preventing the accumulation of inventory. The inventory management system requires good cooperation between company personnel, suppliers, and customers so that supply chain processes can function efficiently.

The inventory management system has the same approach that is focused on customer needs, but is different in the model used and market segment. Companies in the tenth position are not planning demand. The company's demand depends on customer demand. They are trading companies that serve building and retail consumer needs, so they don't have a fixed and consistent consumer base. Companies apply an inventory model because their financial capability has not been able to invest. Companies have a system to reduce sales in the last six months because they do not have the funds to purchase new stock. Low sales were needed by the company considering that the stock of goods was more than two months of sales. Applying discount strategies in the last six months is to make it easier for companies to sell goods so that goods are not accumulated. This is done because the products they provide are durable goods and are easily damaged. The discount given is determined by companies. In conducting the inventory, companies perform inventory twice a year. This is done to increase accuracy in providing information on the availability of goods. In carrying out the inventory, companies do not use certain software.

5. Real-Time AI-Powered Demand and Supply Matching Models

This research contributes by discussing models developed to perform real-time matching of demand and supply. A few artificial intelligence technologies like machine learning, deep learning, data analytics, etc., that are used for real-time decision making are discussed, whose features enable them to perform real-time matching of demand and supply. Intelligent demand and supply matching models are developed using AI models. The developed models are trained and tested using real-world datasets; the performance of the models is found to be excellent when compared to usual demand-supply matching techniques. This can open the path for a matrix of possibilities and scenarios unattainable by existing solutions. We create models that probabilistically estimate the daily demand of the customers at each time slot in the day and then match them with server capacity either with a queuing model, which provides better revenue, or with simple match heuristics to obtain near real-time decisions. This is applied to different case studies in different industries and in conjunction with revenue management techniques to make the matching decision more effective.

The developed models help in real-time demand and supply matching, and integrating them into a strategic planning tool can improve their capability by forecasting future decision time slots for customer demand and relaying it to the supply chain management. The need and significance of real-time matching are understood because real-time decisions affect booking availability, which can have a trickle-down effect on the customers' future actions, impacting overall operations and market demand. Also, the perishable nature of services and finite server capacity make the real-time demand-supply matching process vital. The online algorithms are required to be scalable and flexible in order to accommodate new customer demand requirements and server availability so that organizations can remain competitive in the market. The choice of the demand matching strategy is reevaluated every business interval and adapted to market demand fluctuations either by using the back-order mechanism or the expediting process when customer flow increases.

5.1. Integration of Demand Forecasting and Supply Chain Capabilities

Integrating demand forecasting techniques with supply chain management processes in a structured way can certainly bring efficiencies and enhanced performance for the overall supply chain operations. We focus on matching demand forecasting capabilities with supply chain capabilities, and this requires focusing on the entire process of integration to align the aims of demand forecasting efforts with capabilities that may exist at the supply side of the supply chain. A lot of research has already been done on various frameworks in aligning supply chain strategies with organizational strategies, but not much has been done to align the demand forecasting process and supply chain sections. Given the importance of supply chain forecasting capability alignment, some companies are working on combining purchase orders and actual customer demand, but the advantages of real-time synchronization do not yet suit all buyers and suppliers.

In the supply chain world, research into this area is still embryonic, and it is important to study it in a strategic and systematic way in order to achieve a balance that will provide mutual benefits for both the sellers who are responsible for upgrading and for the end users who are the main buyers. The integration of demand forecasting with supply chain sections will ensure that an operation can be performed in real-time, synchronously, which consists of a mechanism that helps to obtain accurate customer demand data by combining the demand forecasting with the retailer's supply section. This study indeed demonstrates that the demand signal is traceable back to the customers' demand signals. In the supply chain sector, the demand forecasting teams for both the customer and the retailer have seen significant operational and customer service improvements, using increased collaboration with the retailer to improve demand signal forecasting, achieve the use of accurate lead times, and implement sales and operations planning. Potentially reducing lead times has increased the retailer's expectation of increased service level benefits. They were given additional assistance to identify underlying customers' demand signals using excess inventory of finished goods, such as recording waste and sales frequencies for fresh goods in the prepared fruit department and abattoir waste.

6. Challenges and Future Directions

This paper has developed an approach for AI-powered demand and supply matching. In this section, we discuss the various challenges for GIScience researchers and industry stakeholders in developing and establishing real-time applications for supply and demand. Especially, the integration of real-time data, AI applications, and change management processes are addressed. Finally, future directions for GIScience research in this field are illustrated. This paper discusses the challenges concerning current and near-future approaches in the field of demand and supply matching. For this survey, academic literature on electronic marketplaces and semantics, and geographic information science with geographic information systems as enablers for market operations and their marketplaces has been analyzed. This section mainly discusses the state of data quality, obstacles concerning complex algorithms and machine learning approaches, and problems through several methods of integrating real-time data, AI, and blockchain-enabled marketplaces. The section is rounded off with a strong and detailed view on change management effects and integrative measures in the context of algorithmic decision-making and real-time techniques. Technological advancements and the creation of real-time applications for effective demand and supply matching can only enable both approaches to become cheaper, faster, and stronger over time, making it easier to act on circumstances. This visionary direction suggests continuous development in algorithms, decentralized machine learning approaches, and edge-based processing, which is likely to improve data quality in real-time applications as well as the decision-making benefits. Models and algorithms should aim to simulate entire strategies, rather than demand or supply separately, so that they can be evaluated in more complex environments. Implementations should also move away from the laboratory and into the impact assessments of real-world supply and demand chains in many types of environmental and socio-economic systems. This will provide a much better evidence base for the actual versus imagined benefits of real-time applications and bring strong interest from industry partners ready to integrate GIScience insight.

7. Conclusion

To achieve competitive advantage in the market, the demand and supply must be matched effectively to ensure the operational efficiency of the system. The advancements in AI technologies have huge potential for the development of tools for real-time demand-supply matching to provide the best possible solutions given the current state of the market. Machine learning has been the key enabler for the improved forecasting techniques and optimization processes. In turn, all these techniques are crucial for real-time demand and supply matching processes.

This essay has examined demand-supply matching research in the face of increasing digitalization and market speed. A number of applications and approaches have made major contributions to dealing with the practical challenges of implementing these methods in everyday supply chains. Some of the challenges that firms face while implementing the AI-powered technologies in demand-supply matching include costs, collaboration issues, excessive black-box learning tools, skepticism towards AI and machine learning technologies, or difficulties in setting up and tuning the systems due to a lack of data. These challenges should be tackled with methods to overcome them.

AI technologies have huge potential for the development of tools for real-time demand-supply matching to provide the best possible solutions given the market's current situation and future prospects. To sustain this, a lot of further research is needed on a few fronts to continuously refine demand-supply matching methodologies as the real marketplaces are evolving due to technological advancements, pandemic situations, and possible geopolitical changes. It is time for practitioners to embrace it and for researchers to work on the gaps and make the AI in demand-supply matching tools and techniques robust for the future.