Demand Planning: Riding Disruptive Wave of AI and Accelerated Computing

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Abstract— Traditional demand planning methods often struggle to keep pace with the complexity, volatility, and vast datasets inherent in modern supply chains. Artificial intelligence (AI) offers a transformative solution, revolutionizing demand planning with its ability to analyze vast amount of data, identify complex patterns, and generate highly accurate forecasts. This paper explores the latest advancements in AI for demand planning, encompassing machine learning, deep learning, and natural language processing (NLP). The focus is on how these techniques enhance demand sensing capabilities, incorporating real-time market signals, external data sources, and unstructured text information. Furthermore, the potential of AI to optimize inventory management, enable scenario planning, and increase supply chain resilience in response to unexpected disruptions are examined. The paper also addresses practical challenges in implementing AI-powered demand planning solutions, and outlines areas for future research. Most importantly, the paper provides the robust methodologies to integrate the emerging AI developments in demand planning process.

Keywords— *Demand Planning, LSTM, Forecasting, TCNN, E-commerce, Deep Learning, ARIMA*

1. Introduction

1.1 Demand Planning

Demand planning is a strategic process used by companies to forecast the demand for their products or services to optimize their supply chain operations. It involves using historical sales data, market analysis, and statistical algorithms to predict future customer demand[1]. This process is crucial for businesses as it helps them align their inventory with anticipated demand, ensuring they can meet customer needs without overstocking or running into stock shortages, and increasing the efficiency in their overall operations.

The importance of demand planning in business operations can be highlighted in several key areas:

1.1.1 Inventory Management

Effective demand planning enables businesses to maintain optimal inventory levels. By accurately forecasting demand, companies can avoid excess stock, which ties up capital and incurs storage costs, and prevent stockouts, which can lead to lost sales and customer dissatisfaction[2], [3].

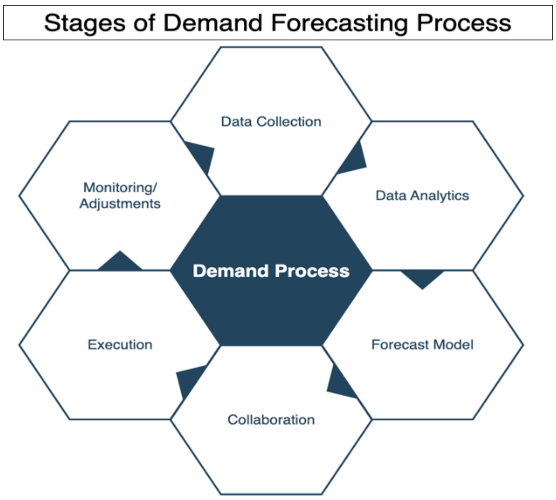

Figure 1. Testing data- load current (amperes)

1.1.2 Cost Reduction

By aligning supply with demand, businesses can reduce wastage and inefficiencies in the supply chain. This leads to lower operational costs, as it minimizes the expenses associated with holding and managing inventory, such as warehousing, obsolescence, and logistics costs.

1.1.3 Increased Profitability

Accurate demand planning helps businesses to better match their supply with customer demand, which can lead to increased sales and higher profitability. It allows for more effective allocation of resources, ensuring that investment in production and inventory is closely aligned with market demand.

1.1.4 Improved Customer Satisfaction

Being able to meet customer demand reliably and promptly improves customer service and satisfaction. It ensures that products are available when and where they are needed, which enhances the overall customer experience.

1.1.5 Strategic Planning and Decision Making

Demand planning provides critical insights into market trends and customer preferences, which can inform strategic business decisions. Companies can use this information to guide product development, marketing strategies, and expansion plans[3], [4].

1.1.6 Risk Management

By forecasting future demand and preparing for various demand scenarios, businesses can mitigate risks associated with market volatility and economic fluctuations. Demand planning helps in building a resilient supply chain that can adapt to changes in market conditions.

1.2 Role of AI in Demand Planning

Artificial Intelligence (AI) plays a pivotal role in transforming demand planning processes by injecting precision, speed, and adaptability. AI algorithms analyze vast datasets, encompassing historical sales, market trends, and external factors, to produce more accurate demand forecasts. This precision allows businesses to fine-tune their inventory levels, reducing both overstock and stockouts[5][6]. With AI, demand planning becomes dynamic, leveraging real-time data processing to swiftly adjust to market changes, ensuring businesses stay aligned with actual demand. AI's predictive analytics capabilities enable proactive decision-making, anticipating market shifts before they occur. This forward-looking approach helps companies to strategize effectively, optimizing supply chain operations and enhancing customer satisfaction. Moreover, AI automates routine tasks within demand planning, freeing up resources for strategic analysis and decision-making. Overall, AI is revolutionizing demand planning, making it more data-driven, efficient, and strategically aligned with market dynamics.

Since the advent of the ERP systems, the big organizations started collecting the data related to customer demands and supply chains. But, with the proliferation of ecommerce, the business models become more complex resulting in the higher accuracy of demand planning. With lower cost of storage and big leaps in computing, AI has made strides in different areas from large ensemble tree-based models to large deep learning models[7], [8]. Due to this advancement, the overall approach for demand forecasting also revolved where sophisticated AI models are used to cater the increasing complex and connected marketplaces. There is no one-fit-all approach when it comes to demand forecasting and research needs to get a stock of various available methods to explore the best solution for their use case. This paper provides a comprehensive survey of established forecasting techniques covering the traditional methods and the advanced methods. It also covers the application of this methods in different scenarios. As the landscape is changing very fast, we will also discuss more research areas in demand forecasting.

1.3 Scope of the document

The scope of the document is to:

- Provide the evolution of the demand forecasting along with advancements in computation technology and machine learning
- Discuss various traditional demand forecasting models
- Survey the most advanced AI/ML techniques in demand forecasting
- Challenges and Limitation of current models
- Discuss industry applications
- Discuss future research and advancements

2. Historical Background

The evolution of demand planning practices can be traced through several stages, marked by technological and methodological advancements that have significantly improved the accuracy and efficiency of forecasting demand [1]. Here’s an overview of how demand planning practices have evolved:

2.1 Manual Processes and Historical Trends (Pre-1970s)

Initially, demand planning relied heavily on manual processes, with businesses using past sales data and simple statistical methods to project future demand. These practices were often time-consuming and prone to human error, with limited ability to handle complex data or predict sudden market changes.

2.2 Introduction of Computers and Basic Software (1970s-1980s)

During the 1970s and 1980s, the introduction of computers marked a significant shift in demand planning practices[2]. This era saw the integration of more advanced statistical models and data processing capabilities into demand planning processes. Companies embraced the use of spreadsheets and basic software tools to handle and analyze sales data, leading to enhanced efficiency and accuracy in demand forecasting.

2.3 Enterprise Resource Planning (ERP) Systems (1990s)

The development of ERP systems integrated various business functions, including demand planning, inventory management, and procurement. These systems allowed for better coordination and data sharing across departments, leading to more comprehensive and accurate demand planning[3], [5].

2.4 Advanced Planning and Scheduling (APS) Systems (Late 1990s-2000s)

APS systems introduced more advanced algorithms and simulation capabilities, enabling businesses to create more detailed and nuanced demand forecasts. These systems could consider a wider range of variables, including seasonal trends, promotional activities, and supply chain constraints[9].

2.5 Integration of Big Data and Analytics (2010s)

The rise of big data analytics allowed companies to harness large volumes of data from diverse sources, including social media, market research, and IoT devices. Advanced analytics, including predictive and prescriptive analytics, enabled businesses to gain deeper insights into market trends and customer behaviors, further enhancing demand forecasting accuracy[3][31].

2.6 AI and Machine Learning (Late 2010s-Present)

The integration of AI and machine learning technologies marked a significant leap in demand planning. These technologies can process and analyze vast datasets in real-time, identify complex patterns, and make predictions with a high degree of accuracy. Machine learning algorithms continuously improve over time, learning from past predictions and outcomes to refine future forecasts.

2.6 Collaborative and Integrated Planning (Present-Future)

Today, demand planning is becoming increasingly collaborative and integrated with other supply chain functions. The focus is on creating a connected and responsive supply chain ecosystem where demand planning is closely aligned with real-time market conditions. The use of cloud-based platforms and collaborative tools facilitates greater transparency and coordination among stakeholders, including suppliers, manufacturers, and retailers.

In summary, the evolution of demand planning practices reflects a journey from manual, simplistic approaches to sophisticated, data-driven processes powered by advanced technologies like AI and machine learning. This evolution has enabled businesses to achieve greater accuracy, efficiency, and strategic agility in their demand planning efforts. The decision to use the traditional techniques of demand planning and latest methods depends upon numerous factors. Fig 2 provides high-level outlines to make the decision judiciously.

	Traditional Forecasting	*Machine Learning Forecasting*
Ability to consider numerous variables and data sources	Adding extra variables and sources requires substantial effort	Multiple variables and sources can be smoothly incorporated thanks to the high level of automation
Volume of manual work	High	Low
Amount of data required	Small	Large
Maintenance complexity	Low	High
Technology requirements	Low	High
Best fit	Mid/long-term planning Established products Stable demand	Short/mid-term plan New products Volatile demand scenarios

Figure 2. Traditional Vs ML models usage

3. Traditional Statistical Models for Demand Planning

Traditional demand forecasting models are workhorses in the business world, relying on historical data to predict future demand."" Here are some of the most common ones:

3.1 Moving average of demand forecasting

Moving average is a statistical technique used in time series analysis to smooth out short-term fluctuations and highlight longer-term trends or cycles in data. It involves calculating the average of a specific number of data points within a defined window or period. By averaging out fluctuations, moving averages help in identifying patterns, trends, and changes in data over time.

There are different types of moving averages, such as simple moving average (SMA), exponential moving average (EMA), and weighted moving average. The choice of moving average type depends on the specific characteristics of the data and the desired level of responsiveness to changes. Simple Moving Average (SMA) calculates the mean of a set number of data points over a specified period. It gives equal weight to all data points within the window. Exponential Moving Average (EMA) assigns more weight to recent data points, making it more responsive to recent changes compared to SMA. Weighted Moving Average assigns different weights to data points based on their importance or relevance.

Weighted Moving Average (WMA) at time t:

$$\boldsymbol{WMA_{t+1}} = \sum_{i}(\boldsymbol{w_i} \cdot \boldsymbol{Y_{t-i+1}}) / \sum_{(i)} \boldsymbol{w_i}$$

Y_t = demand at time t
n = number of periods in the average
w_i = weight assigned to data point Y_{t-i+1}

Overall, moving averages are valuable tools in analyzing time series data, providing insights into trends, seasonality, and overall patterns by smoothing out noise and short-term fluctuations. This technique smooths out fluctuations in historical data by taking the average of a set number of past periods."" It's good for identifying trends but can miss sharp changes.

3.2 Exponential smoothing

Exponential smoothing is a popular technique used in time series forecasting to assign exponentially decreasing weights to past observations. It is a simple and effective method that gives more weight to recent data points while gradually decreasing the influence of older observations. This approach helps in capturing trends and seasonality in the data, making it valuable for short to medium-term forecasting.

Exponential smoothing is particularly useful when there is a need to generate forecasts quickly and efficiently, without the complexity of more advanced forecasting methods. By adjusting the smoothing parameter, users can control the level of responsiveness to recent data changes, allowing for flexibility in forecasting based on the specific characteristics of the time series data.

Overall, exponential smoothing provides a straightforward yet powerful tool for generating accurate forecasts by striking a balance between incorporating historical data and adapting to new trends or patterns in the time series.

Similar to moving averages, this method assigns weights to past data points, with more recent data having a higher weight."" This allows it to react faster to changing trends.

$$F_t = \alpha * Y_t + (1 - \alpha) * F_{t-1}$$

Where Ft = forecast at t
α = smoothing constant $(0 < \alpha <= 1)$

3.3 ARIMA (Autoregressive Integrated Moving Average)

The Autoregressive Integrated Moving Average (ARIMA) model is a popular time series forecasting method that combines autoregressive (AR) and moving average (MA) components with differencing to handle non-stationary data. ARIMA models are widely used in various fields, including finance, economics, and weather forecasting, to predict future values based on past observations.

The AR component in ARIMA captures the relationship between an observation and several lagged observations, while the MA component models the error term as a linear combination of error terms observed at previous time points. The integration part of ARIMA involves differencing the data to make it stationary, removing trends and seasonality[10].

ARIMA models are characterized by three main parameters: p, d, and q.
- *p* represents the order of the autoregressive component.
- *d* represents the degree of differencing needed to make the data stationary.
- *q* represents the order of the moving average component.

By adjusting these parameters, analysts can tailor ARIMA models to suit different types of time series data and improve forecasting accuracy. ARIMA models are valuable tools for capturing complex patterns in time series data and making reliable predictions for future values. These traditional models are relatively easy to understand and implement. However, they can struggle with highly volatile demand or external factors that significantly impact sales.

4. Advancements in AI for Demand Planning

AI technologies have significantly transformed demand planning by enabling more accurate, timely, and nuanced predictions. Here's a detailed discussion of various AI technologies used in demand planning:

4.1 Data Type for Demand Planning

Demand planning requires understanding complex patterns and predicting future outcomes based on historical data. AI, particularly machine learning (ML) and predictive analytics, plays a crucial role in this. At its core, AI involves creating algorithms that can learn from and make decisions based on data. In demand planning, AI uses historical sales data, market trends, and external variables to forecast future demand.

	Data Velocity	
Reaction time	**High**	**Low**
Real time	Sales data, Inventory levels, Social trends, Advertisement, Promotional activities, Internet of Things devices	Customer segmentation, Network Constraints, Lead times, Supplier's Contracts, Price Changes, Product Life Cycle
Less Frequent	Seasonality trends, Competitor price changes, Competitor promotions,	Economic Indicators, Industry Trends, Unemployment, Weather information

Table 1: Type of data used for demand forecasting

Table 1 shows that classification of the data sets requirements for the modern demand forecasting systems. the advancement in technology has reduced the cost of capturing and processing the high velocity internal transactions at fast speed. Many internal and external data sources required for demand forecasting are now available at near real time such as sales data, inventory data. Now organizations are also capturing the competitor's data by website crawling at real time to react to competitors quickly.

4.2 Big data with High velocity

The main reason companies move over to the cloud is cost savings. However, the cloud also drives speed, agility, and visibility, providing a range of benefits for your business. The impact of the cloud computing has been multi-facets on supply chain. Cloud technology adoption has been a game changer for supply chain operation in general and on demand planning in particular. Due to ongoing automation in supply chain using IoT, real-time data stream, block-chain technology, senor based fulfilment centres, the scale of data has been humongous[11], [12]. Large scale organization are currently deploying these automations and marketing intelligence to gather relevant data to improve the velocity and accuracy of the demand forecasting to make automate decisions. Large ecommerce companies are on forefront of deployment of the technology to automate the decision making based on demand forecasts. These systems are adaptive and can auto-corrected their decision making using latest Reinforce Learning techniques and continue causal inference.

4.3 Driver based forecasting models

A range of studies have explored the use of multiple features in demand forecasting. Amazon developed a two-stage feature selection algorithm for e-commerce demand forecasting, achieving significant accuracy improvements[13]. Even, new forecasting approaches are explored of including drivers in an AR model for multiple products, incorporating associated product demand as predictors [14]. The driver-based approaches are not limited to parametric models but these are explored for demand forecasting models using a probabilistic multidimensional data model, capturing uncertainty and manipulating large amounts of data[15]. There are several techniques that address the challenge of heterogeneous factors in demand forecasting, using support vector regression and feature selection to eliminate calendar effects.

In driver-based forecasting model, the forecast is estimated as function of driver variables that are lagged by t time period. Due to large number of variants of driver variables, the feature space can easily explode. These models are generally trained with penalty terms to select the most important feature variants. Below is the linear formulation of a driver-based forecasting model.

$$F_t = \sum_i \sum_m (\beta_{t-i}^m * X_{t-i})$$

Where X_t^m = driver variable variant m at time t
β_t^m = Coefficient of m variable at time t

The set of feature variates also consists of dummy variables to model various external factors such as competitors marketing and promotional events. Driver based forecasting models are highly popular in industry due to expandability of demand forecast. These models also provide flexibility of running simulation for future forecast by playing out different market and economic scenarios.

4.4 Forecasting with Neutral Net

Neural networks, especially deep neural networks (DNNs), are powerful tools for modeling complex non-linear relationships in data. The DNN model could be a very large, fig 3 captures a small simple DNN model's architecture. In demand planning, they can process vast amounts of data, including unstructured data like social media sentiments, **to** predict demand more accurately. They can capture intricate patterns that traditional statistical methods might miss[16].

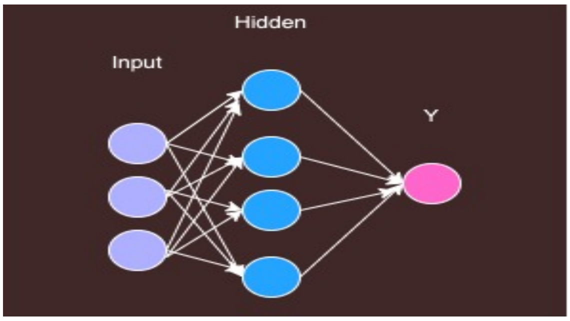

Figure 3: FNN model architecture

The document (Deep Sequential Models for Forecasting Time Series Data) provides a comprehensive review of deep sequential models, focusing on their applications in forecasting time series data. It discusses the significance of deep learning in time series forecasting, highlighting the use of artificial neural networks (ANN), long short-term memory (LSTM), and temporal-conventional neural network (TCNN). The review compares these models in terms of application fields, model structures, activation functions, optimizers, and implementation. It emphasizes the widespread use of LSTM models, especially in hybrid forms, for accurate predictions. Additionally, the paper addresses challenges and future perspectives in the development of deep sequential models.

4.4.1 Sequence Models

Sequence models such as LSTM (Long Short-Term Memory) models have emerged as powerful tools for demand planning in various industries. These models, known for their ability to capture long-term dependencies in sequential data, are increasingly utilized to forecast demand accurately. For instance, in the context of logistics demand forecasting for fresh food e-commerce enterprises, the LSTM model has been employed to predict market demand based on sales data and factors like time and meteorological conditions [17]. Similarly, in supply chain management, LSTM neural networks are integrated with hyperparameter tuning and hybrid models like CNN-LSTM to enhance the accuracy of demand forecasting for products such as medicinal drugs. These applications highlight the significance of LSTM models in improving forecast accuracy, aiding in inventory control, production planning, and strategic decision-making processes within businesses [18], [19].

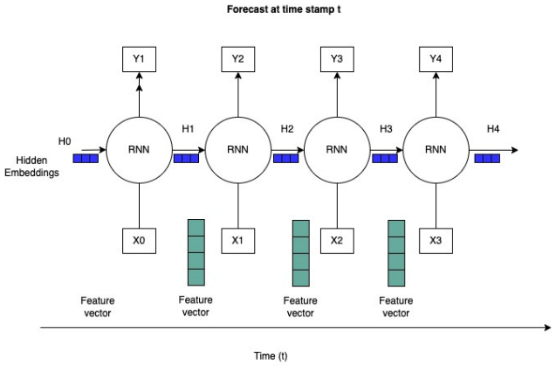

Figure 3: RNN model architecture

The working of RNN model is complicated as show in fig 3. At a high level, these models takes feature vectors at previous time stamps to forecast the demand for next time stamps. RNN models have capability of remembering the useful pattern that can be useful to make prediction now. Similarly, these can ignore the erroneous patterns if those are not useful.

4.4.2 TCNN model

Another deep learning architecture that is used for time series modeling is Temporal Convoluted Neural Networks (TCNN). Unlike, RNN based models that parse the short-and-long-term dependencies in time series data, TCNN models parse the features using different size of kernels.

A simple example of kernel that TCNN can learning is Sin curve that models the seasonality in the time series data. With multiple hidden layers, these models can look back to several time stamps without dealing with large window size for kernels. For example, with 7 window size kernels and 4 hidden layers, the model can look back 28 data points in time series. Instead of having a continuous kernel, model can use a kernel with stride (skipping the consecutive time stamp data) to increase its vision of historical data points. TCNN models are highly useful for high velocity data used for short term demand forecasting[19], [20].

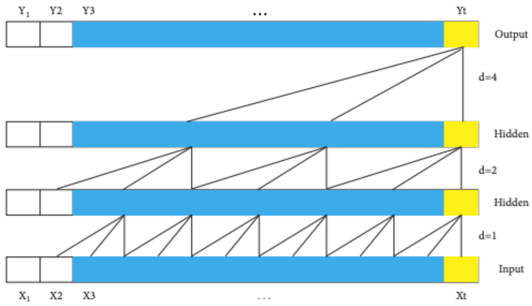

Fig 4: TCNN model architecture

Generally, the deep learning models such as Bi-LSTM use the past and future time stamps to make predictions. However, TCNN models are generally trained with causal mask that hides the data points of future time stamps. Fig 4 shows how several hidden layers increases the coverage of past data points of forecasting model.

We propose to explore the TCNN in demand planning due to some inherent benefits of this model. The TCNN model is simpler than other deep learning framework such as RNN. They can easily have very long window to consider previous trends back in time by adding more layers or using skip filters. Another benefit of TCNN is better interpretability of the results by examining of the filters.

4.5 Demand forecasting using social data

The use of social media data in demand forecasting has proven to be highly valuable and beneficial across various industries. Research studies have demonstrated that leveraging insights from social media big data can significantly enhance the accuracy of predicting future product demand, leading to improved supply chain performance. By analyzing sentiment, trends, and word analysis results from platforms like Twitter and Facebook, organizations can gain valuable information to supplement traditional forecasting models. The incorporation of social media data has shown to have a significant predictive power in forecasting color trends, fit demands, and product demands months in advance of the sales season. This fine-grained social media information greatly aids in making critical decisions such as setting the initial shipment quantity for items, which is crucial for fashion retailers. The use of social media data has been validated through various frameworks and case studies, showcasing its positive impact on improving the accuracy of demand forecasting within supply chains[21].

Social media data can be effectively used for demand forecasting. Research is this area explored the framework, which incorporates sentiment, trend, and word analysis from social media data, has been shown to improve the accuracy of demand forecasting in a supply chain. This approach has been particularly successful in the fashion industry, where the use of social media text data has been found to be predictive of demand [22], [23].

5. Challenges in demand forecasting

Forecasting models face significant challenges and limitations, particularly in the context of time series data. Another challenge is the need for configurable models and analyst expertise to reach desired precision without making model unnecessary complex. The practioners stress the importance of performance analysis and evaluation in addressing these challenges. More challenges come into picture due to inclusion of several type of datasets in forecasting which differ at granularity in space of economic datasets and agency datasets. There are studies that underscore the need for robust, adaptable, and expert-driven forecasting models[3], [24].

In recent time, the main challenges with demand forecasting processes and models can be categorized into followings:

- *Uncertainty and Unforeseen Events*: External factors such as extreme weather conditions, global crises like the COVID-19 pandemic, or sudden market shifts can introduce uncertainties that traditional forecasting models may struggle to account for. These unforeseen events can significantly impact demand patterns, making accurate forecasting challenging[25].

- *Data Quality and Quantity:* Demand forecasting models heavily rely on historical data for accuracy. However, issues related to data quality, incomplete datasets, or insufficient historical information can hinder the effectiveness of forecasting models. Ensuring data accuracy and sufficiency is crucial for reliable predictions[26][34].

- *Model Complexity and Selection*: Choosing the appropriate forecasting model from a wide range of options like ARIMA, LSTM, or XGBoost can be challenging. Each model has its strengths and limitations, and selecting the most suitable one for a specific industry or dataset requires expertise and careful consideration[26].

- *Dynamic Market Trends*: Markets are constantly evolving with changing consumer preferences, new product introductions, and competitive landscape shifts. Forecasting models need to adapt to these dynamic trends to provide accurate predictions, which can be a significant challenge in fast-paced industries[27].

- *Integration of New Technologies*: Incorporating advanced technologies like machine learning algorithms or social media data into demand forecasting processes requires expertise and resources. Ensuring seamless integration of these technologies while maintaining model accuracy poses a challenge for organizations aiming to leverage cutting-edge tools for forecasting[21], [22].

6. Demand planning case studies

The sources provided discuss various aspects of demand forecasting with driver models in different contexts. Here is a summary of the key points from the sources:

6.1 E-Commerce Enterprises Demand Forecasting

A method based on Horizontal Federated Learning and ConvLSTM is proposed for e-commerce enterprise demand forecasting to improve accuracy while avoiding privacy data leakage. The model aims to alleviate the bullwhip effect in the supply chain system and promote sustainable development [28].

6.2 Staff Forecasting

Forecasting the demand for radiology services is crucial for health care organizations. The study demonstrates the construction of a comprehensive and accurate forecasting model using statistical techniques to provide decision support for radiology managers regarding department staffing [29].

6.3 Electricity Demand Forecasting

The Macro Demand Spatial Approach (MDSA) is introduced for electricity demand forecasting, considering location as a key factor. This approach combines qualitative and quantitative methods to forecast electricity demand in different spatial characteristics, such as main development areas and supporting areas, to aid in transmission system planning [30].

6.4 Demand planning with big cloud service providers

In the case of AWS and Azure, demand planning involves analyzing historical usage data, monitoring trends in resource consumption, and forecasting future demand based on factors like seasonality, new project launches, or changes in business operations. By leveraging advanced forecasting models like ARIMA, LSTM, TCNN or XGBoost, organizations can predict their cloud service requirements with greater accuracy, allowing them to scale resources up or down proactively to meet changing demands. Effective demand planning for cloud services to optimize their cloud spending, improve resource utilization, and ensure seamless operations by aligning their cloud infrastructure with actual usage patterns. This proactive approach to demand planning helps businesses leverage the flexibility and scalability of cloud services while controlling costs and maintaining high performance levels[11], [12]

In summary, these sources highlight the importance of using advanced modeling techniques like LSTM, TCNN, ARIMA, other statistical methods, and spatial approaches to forecast demand accurately in various sectors such as e-commerce, healthcare, energy, Cloud computing and environmental planning.

7. Emerging Trends in Demand Planning process

Emerging technologies and trends in AI that could influence supply chain and demand planning processes include:

7.1 Blockchain Technology

Blockchain technology is revolutionizing supply chain management by enhancing transparency, traceability, and security in transactions. By leveraging blockchain for smart contracts and decentralized ledgers, organizations can streamline supply chain operations, improve trust among stakeholders, and ensure the authenticity of products throughout the supply chain.

7.2 Internet of Things (IoT)

IoT devices are increasingly being integrated into supply chain processes to provide real-time visibility and monitoring of goods in transit. By connecting physical objects to the internet, IoT enables data collection on location, temperature, humidity, and other variables, optimizing inventory management, reducing delays, and enhancing overall supply chain efficiency.

7.3 Predictive Analytics and Machine Learning

The use of predictive analytics and machine learning algorithms like LSTM, XGBoost, TCNN and ARIMA is transforming demand forecasting and inventory management within supply chains. By analyzing historical data, market trends, and external factors, organizations can make more accurate predictions, optimize inventory levels, reduce stockouts, and improve overall operational efficiency.

7.4 Robotic Process Automation (RPA)

RPA technologies are automating repetitive tasks in supply chain processes such as order processing, inventory management, and logistics coordination. By deploying robots to handle routine tasks with speed and accuracy, organizations can streamline operations, reduce human error, and enhance productivity across the supply chain.

These emerging technologies in AI are reshaping traditional supply chain practices by introducing automation, data-driven decision-making, transparency, and efficiency into various aspects of supply chain management.

8. Conclusion

This research shows that the need of explanability of machine learning model is as important as the accuracy of the demand. The driver-based models are widely used to ensure the understandability of demand trends specially in financial and retail sector. However, these models suffer when many drivers are included in the model. The deep learning models are more flexible and accurate in forecasting; however, these are not suitable for explanability. The trend of research in this area shows the eagerness to explore more complex models in demand forecast but in combination of the traditional models such as MA and ARIMA.

The practice of integrating the deep learning models is still evolving. This research shows the huge potential of deep learning models such as TCNN in demand planning process due to simplicity in implementation. This approach is highly robust to address common pitfalls in demand planning such as tradeoff between long term and short term forecast accuracy, preprocessing of data, and opaqueness of model predictions.

Recently, generative models such as ChatGPT and Claude have captured the attention of researchers across the fields. Current generative models are suitable for text and image-based tasks where data is not in structured format. As the usage of unstructured data in demand planning is currently limited to social media data, there is a need to come up with the right use cases for application of generative models in demand planning. One area that might emerge as right application for generative models in demand planning process is summarization of the qualitative inputs from different stakeholders. With GenAI models, these inputs can be converted into structured features and included into demand planning machine learning models.

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