

ARTIFICIAL INTELLIGENCE DRIVEN FORECASTING AND RECOMMENDATION MODEL FOR VARIOUS PARAMETER OF A PROCUREMENT FUNCTION ACROSS INDUSTRIES

Authors

Prashant Laxman Pandit

Assistant Professor
Department of Mechanical Engineering
P E S College of Engineering
Aurangabad, Maharashtra, India.

Dr. Siddharth K. Undirwade

Professor & Dean
Department of Mechanical Engineering
IQAC, P E S College of Engineering
Aurangabad, Maharashtra, India)

I. INTRODUCTION

A forecast, like a weather forecast, is a statement about the future, which is unpredictable. Since predictions are mostly used in business to anticipate wants, we concentrate on this area.

Why forecasting is important?

Basic answer lies below:

1. If Schedule goes down

- Excess inventory cost
- Fund flow blockage
- High Inventory Turnover ratio
- Working Capital shortage
- B2B relationships

2. If Schedule goes Up

- Loss in Market share
- Higher cost for expedition
- Premium Freights
- Quality levels may go down
- Increased turbulence in supply chain

In every area of significant technological advancement, artificial intelligence (AI) is unquestionably leading the pack amongst a fiercely competitive market. It is acknowledged that AI will usher in a new era of technology with unprecedented levels of enabling. Its applications and uses are extensive and encompass all domains. Virtually

every aspect of a modern corporation is being impacted by AI, including finance, pharmaceuticals, logistics fleets, and community relations.

The idea and creation of systems capable of carrying out activities that typically require human intelligence is a suitable definition of artificial intelligence. Technologies are created to automate processes that need human perceptual skills, such as face identification or handwriting recognition. Artificial intelligence can also be used to automate jobs that need requisite skills, such as learning, planning, and reasoning from ambiguous or incomplete information. In practical terms, this entails designing systems that are optimized, allowing for entirely new degrees of operational efficiency through algorithmic decision-making and constant information flow.

For businesses, forecasting accuracy is crucial for planning, directing, and making decisions. Forecasts are used in purchasing, production, and supply chain management. Employing appropriate techniques to enhance their forecasting skills presents significant hurdles for medium-sized businesses.

II. LITERATURE SURVEY

In all industries, precise forecasting is necessary for flawless planning, flawless decision-making, and flawless system control. Forecasts are used in the supply chain, purchasing, and manufacturing domains. Despite the fact that predicting implies statistical procedures. Businesses find it extremely difficult to apply appropriate techniques to enhance their forecasting capabilities.

As statistical method is very much dependent on the human ability so a system which will forecast and sometimes take correct decision without any error or mood fluctuation is desirable.

1. The Arima algorithm, a traditional statistic, is a tried-and-true technique for basic linear forecasts, and is employed by numerous businesses. John McCarthy coined the phrase "artificial intelligence" in 1956 while attending Dartmouth College in the United States. AI algorithms have the capacity to operate and optimize on their own, and numerous practical commercial and industry applications have already demonstrated this technology's promise. The most crucial aspect of market analysis is the forecasting of future demand based on historical demand as well as variables like economic growth, demand projections, and buyer socioeconomic status. The application of a forecast model for an agricultural spare parts provider is a specific example. Here, a model that forecasts which tractor parts would malfunction or break was created. The customer's internal and external data was utilized for this. Aside from the tractor model, daily running time, and GPDS data were also used to get this internal data. The external data was information gathered from outside sources, including temperature, humidity, and operating season. This guaranteed the necessary components would arrive on time, which decreased downtime. (Source:)
2. The manufacturing industry is being impacted by the growing global competitiveness because it is placing a demand on limited resources, which affects material availability and cost effectiveness. The continuous logistics/information flow and transparency that

can power CE operations will be aided by Internet of Things (IoT) based technologies like radio-frequency identification (RFID) tags and sensors, global positioning systems (GPS), smart mobile devices, shelf moving robots, and automated guided vehicles. 2, 3]

3. The primary focus in the era of Industry 4.0 revolves around the replacement of manual procurement processes with automation through the utilization of digital technologies. This transition aims to establish a highly efficient procurement system. One of the significant advantages of digitization is the reduction of uncertainties through enhanced transparency of information among supply chain partners. Automation of the procurement process leads to a substantial reduction in procurement cycle time. The simulation conducted in this study provides compelling evidence in favor of the automation and integration of two critical business processes. Furthermore, the overall integration and automation of the entire business system have a similar positive impact. The application and integration architecture proposed in this paper align with the principles of Industry 4.0, contributing to enterprise advancement. The simulation results shed light on the time-saving benefits of operating within an integrated environment, as facilitated by Industry 4.0. These findings find theoretical support in the Organization Information Processing Theory. Multinational companies stand to gain significant advantages by enhancing their information processing capabilities, thereby meeting the information processing requirements of the dynamic and uncertain Industry 4.0 environment. This enhancement not only helps reduce supply and demand uncertainties within the global business network but also directly contributes to optimizing business processes. In the realm of business activities, mistakes are unfortunately inevitable. One of the most common and costly issues faced by sales or service companies is an imbalanced stock inventory (or incorrect capacity planning in the case of service providers). Companies allocate a substantial portion of their resources to inventory and/or service capacity, and even minor errors in resource planning can have a profound impact on ROI, revenue, and profitability.
4. Big data analytics is increasingly gaining prominence in the realm of supply chain management. This growing attention is driven by the versatile applications of big data analysis within supply chain management, encompassing areas such as customer behavior analysis, trend analysis, and demand prediction. Forecasting models have found extensive use in precision marketing, enabling a deeper understanding of customer needs and expectations. In this context, there is a continuous focus on scrutinizing consumption behavior and preferences. This scrutiny leverages forecasts derived from customer data (whether internal or external) and transaction records to effectively manage product supply chains.

Supply chain management is primarily concerned with orchestrating the flow of goods, services, and information from their origins to the end customers through a network of interconnected entities and activities. In conventional supply chain management scenarios, it is typically assumed that parameters such as capacity, demand, and costs are known with certainty. However, reality presents a different picture, as uncertainties arise from various sources, including fluctuations in customer demand, transportation of supplies, organizational risks, and lead times.

Historically, a range of statistical analysis techniques has been employed for demand forecasting in supply chain management, including time-series analysis and regression analysis. However, with the advancements in information technologies and enhanced computational capabilities, big data analytics has emerged as a powerful tool for generating more accurate predictions. These predictions align closely with customer needs, enable a comprehensive assessment of supply chain performance, enhance supply chain efficiency, reduce response times, and provide valuable support for supply chain risk assessment.

5. The rise in supply chain digitization techniques, globalization, and heightened market competitiveness are all contributing factors to the growing requirement for demand forecasting and customer behavior analysis.

Mahya Seyedan and Fereshteh Mafakheri conducted a comprehensive evaluation of predictive big data analytics applications in supply chain demand forecasting in this work. The study emphasized the use of big data analytic techniques in supply chain demand forecasting and offered a classification that was comparative. In order to better understand the strategies and tactics employed in demand prediction, they gathered and examined these studies. Pros and disadvantages of seven popular strategies were found and examined. Regression analysis and neural networks are noted as the two methods that are most frequently used, among others. The analysis also highlighted the fact that by creating and refining a cost function for the fitting of the predictions to the data, simulation or optimization models can be utilized to increase forecasting accuracy. A significant discovery made during the examination of the body of literature is the dearth of study on the use of BIG DATA ANALYSIS in reverse logistics and closed loop supply chains (CLSCs). Adopting a data-driven approach to CLSC design and administration has several important advantages. These days, a huge amount of returned or used products of all kinds and conditions are gathered and processed at several collection places due to growing environmental consciousness and government incentives. The demand for these products, the ultimate cost of the refurbished products, and the cost-effectiveness of the remanufacturing procedures are all directly impacted by these uncertainties.(5)

6. Javad Feizabadi He conducted an examination of past sales in his research, but the results did not show any clear trends or seasonality in demand in the retail market segment. This suggests that the time series is stationar and that ARIMA models can be used to predict it. The company uses the Damped Trend Method and Holt-Winter's Method as its two conventional forecasting techniques. To estimate the parameters of the ARIMAX and ANN models, the dataset was split into training, testing, and prediction sets. The parameters were utilized to predict the demand using ARIMAX and ANN techniques after being obtained from the training dataset and tested using testing datasets. His research has supported two research hypotheses: first, a hybrid approach to demand forecasting is established, merging time series models with machine learning-enabled leading indicators. Second, and perhaps more importantly, this study shows how much performance may be improved by using sophisticated forecasting techniques. Even if the research environment and time series data are not as complex as those used in earlier studies to create a novel and ideal forecasting technique, this study nevertheless adds to the continuous endeavor to enhance machine learning techniques for demand prediction.

The research findings regarding the economic value size of using these approaches for researchers and practitioners are more significant than the established method. Using objective pieces of evidence, this study discovered that applying ML-based demand forecasting method is likely to result in a considerable improvement in supply chain efficiency. This finding is consistent with earlier research that elucidated the benefits of this approach and made it easier for supply chain planners to understand.(6)

III. NOTEWORTHY CONTRIBUTIONS IN THE FIELD

In general, the ability to comprehend demand behavior and establish an effective method for predicting it is recognized as a vital organizational capability. A well-refined demand forecasting process offers substantial performance advantages. For instance, improvements in the demand forecasting process have led to a doubling of inventory turnover and a 50% reduction in on-hand inventory. Likewise, there is documented evidence of a 25% reduction in days of inventory for Coca-Cola Inc. In recent decades, due to the phenomenon of globalization and the prevailing trend of outsourcing and offshoring, businesses have begun sourcing products from distant global markets, primarily to achieve cost savings in production. This shift has resulted in significantly longer lead times for product production and procurement. As lead times extend, demand forecast accuracy tends to decrease. To counteract these effects, it has become increasingly imperative for firms to precisely forecast demands. Additional factors, such as the pressures of time-based competition and the proliferation of products, further underscore the significance of achieving a more precise demand forecast.

There are three fundamental principles underpinning demand forecasting: 1) forecasting is inherently imperfect, 2) as the forecast horizon extends, accuracy tends to diminish, and 3) forecasts become more precise as demand becomes more aggregated. The primary objective in supply chain management is to align supply with demand. The occurrence of supply-demand mismatches depends on factors such as the nature of products within a supply chain, the length of the supply chain, and the effectiveness of the forecasting and planning procedures. In recent years, the availability of extensive data and the development of sophisticated methods for harnessing big data have significantly contributed to mitigating the risks associated with mismatches. The complexity and abundance of data, along with advanced processing engines, have empowered supply chain planners to conduct more detailed analyses and enhance forecasting outcomes, both for frequently and infrequently demanded time series. Research and practical experience have underscored the importance of integrating human judgment and statistical models to enhance the effectiveness of the forecasting process [6].

In his research and experimentation conducted within a multinational steel company, J. FEIZABADI followed a specific methodology and reported his findings. The company had recently ventured into the retail market segment, characterized by standardized products. This particular market segment was experiencing rapid global growth, with a year-on-year volume increase of over 5%. It encompassed a wide range of product types that represented the entirety of the company's product portfolio. As is customary for standardized products, the company employed a finished goods inventory buffer to respond to fluctuations in demand, essentially operating on a make-to-stock basis within this market segment. The key decision in this system was to anticipate demand accurately and produce steel accordingly, with this

decision occurring within a short-term planning horizon (typically spanning 1 to 3 months). The reliability of demand forecasting was crucial at both the product family and individual SKU (Stock Keeping Unit) levels. This study primarily focused on addressing the challenges within this specific market segment. The research design comprised two main phases: 1) the development of hybrid machine learning-based demand forecasting methods, and 2) the application of statistical analysis to assess the impact of these new methods on performance [6].

In 2014, Walmart organized an online competition on Kaggle to select employees. Walmart supplied sales data covering the years 2010-2012 and tasked participants with forecasting the data for 2012-2013. Most statisticians addressed this challenge by employing conventional forecasting methods. In 2017, an endeavor was made to tackle the identical problem, this time employing artificial neural networks. The dataset, furnished by Walmart and outlined in Table 1, comprised approximately 420,000 entries. The data was extracted and employed to construct various neural network models for the analysis.

Table 1: Sample Interpretation of Input Factors after Data Processing.

Store	Date	Temperature	Fuel price index	Discount marker 1	Discount marker 2	Discount marker 3	Discount marker 4	CPI	Unemployment index	Is Holiday	Rank
1	5/2/2010	42.31	2.572	-2000	-500	-100	-500	0.964	8.106	0	13
1	12/2/2010	38.51	2.548	-2000	-500	-100	-500	0.2422	8.106	1	13
1	19/2/2010	39.93	2.514	-2000	-500	-100	-500	0.2891	8.106	0	13
1	26/2/2010	46.63	2.561	-2000	-500	-100	-500	0.3196	8.106	0	13
1	5/3/2010	46.5	2.625	-2000	-500	-100	-500	0.3501	8.106	0	13
1	12/3/2010	57.79	2.667	-2000	-500	-100	-500	0.3806	8.106	0	13
1	19/3/2010	54.58	2.72	-2000	-500	-100	-500	0.2156	8.106	0	13

(Source: Walmart)

Any problem has the potential for mathematical modeling, and the Artificial Neural Network (ANN) represents one such approach. Neural networks, akin to the human brain, possess the essential capacity for learning and can assimilate new knowledge gained from fresh and analogous situations. While ANNs do not equate to the complexity of the human brain, they exhibit distinct attributes that confer advantages in certain applications. These capabilities encompass pattern recognition and adaptability to acquire knowledge through linear and nonlinear mappings as necessitated by the task at hand. Much like the human brain, a neural network can acquire skills through diverse methods, including memory-based learning, parameter adjustment following random predictions, classification, and more. However, for the effective deployment of a neural network in practical scenarios, it is imperative to construct a highly accurate mathematical model of it.

Artificial neural networks offer significant value to statisticians in demand forecasting, yielding highly precise results. However, it is essential that the demand forecasting problem is meticulously modeled. All potential factors influencing demand must be thoroughly considered, and efforts should be made to ensure their independence as much

as possible. MATLAB and R generate feature-optimized outcomes that can be employed for working with larger datasets, optimizing neural network hyperparameters, and leveraging GPU acceleration to achieve superior accuracy in demand forecasting, thus benefiting Supply Chain Management. Numerous studies emphasize the meticulous modeling of practical problems to align with ANN applications as accurately as feasible. The results demonstrate that ANN's can be effectively applied even to extensive datasets, yielding minimal errors. While R offers superior accuracy, it comes at the cost of longer processing times. In contrast, MATLAB accelerates neural network computations and offers better parameter optimization. Although these software tools may not be suitable for handling large-scale industrial data directly, they serve as a valuable means to identify optimal parameters for subsequent industry-scale demand forecasting utilizing neural networks.

Mahya Seyedan and Fereshteh Mafakheri conducted research addressing the growing demand for customer behavior analysis and demand forecasting. This demand is primarily attributed to globalization, intensified market competition, and the increasing adoption of supply chain digitization practices. Their study involved an extensive examination of the applications of predictive big data analytics in the context of supply chain demand forecasting. The research provided an overarching survey of various Big Data Analytics (BDA) methods applied to demand forecasting within the supply chain domain, categorizing them comparatively. The collected studies were thoroughly analyzed, considering the methods and techniques employed for demand prediction. The analysis revealed the existence of seven prominent techniques, each accompanied by its respective advantages and disadvantages. Notably, neural networks and regression analysis emerged as the two most frequently utilized techniques. Additionally, the review highlighted the potential for optimization models or simulations to enhance forecasting accuracy by formulating and optimizing cost functions for aligning predictions with data.

In their research titled "Overcoming Bottlenecks with Artificial Intelligence," Julia Feldt, Henning Kontny, and Axel Wagenitz emphasize the potential of machine learning (ML) as a foundation for assembly planning. This is particularly relevant due to the frequent and dynamic changes in information, leading to a high volume of repetitive planning tasks associated with each material number. ML offers an efficient way to leverage historical data with minimal effort. The study sheds light on how AI-driven digital solutions within the supply chain can enhance adaptability and resilience, benefiting both researchers and company executives. It suggests a transformation of the planning process, shifting from repetitive Excel-based calculations to an autonomous Real-Time Digital Twin of Assembly. While this transformation may necessitate a restructuring of the planning department, the overall value gained throughout the Supply Chain underscores the significance of such a change.

IV. PROPOSED METHODOLOGY

Proposed methodology or work flow of the research work depends upon the problem statement. I have approached four companies with this idea and expecting a positive response from them. They work flow operates by enabling a sequence of data to be transformed and correlated together in a model that can be tested and evaluated to achieve an outcome, whether positive or negative.

Machine learning (ML) pipelines encompass multiple stages for model training. These pipelines are iterative in nature, with each step being repeated to continually enhance model accuracy and attain a successful algorithm. In order to construct more effective ML models and extract maximum value from them, it is crucial to have accessible, scalable, and resilient storage solutions. This underscores the importance of on-premises object storage as a foundational element for enabling these advancements.

The steps involved which give a perfect solution is:

- 1. Data Collection:** Data collection involves the systematic gathering and measurement of information related to variables of interest. This process is conducted in a structured manner, allowing researchers to address specific research questions, test hypotheses, and assess outcomes. The accuracy of our model is contingent on both the quantity and quality of the collected data.
- 2. Data Preparation:** Data preparation refers to the procedure of cleansing and modifying raw data before it undergoes processing and analysis. This crucial step is conducted prior to processing and frequently entails tasks such as reformatting, rectifying errors, and merging data sets to enhance their quality and usefulness.
- 3. Choose a Model:** A machine learning model is a file that has undergone training to identify specific patterns. The training process involves exposing the model to a dataset and equipping it with an algorithm to analyze and learn from the data. The choice of model depends on various factors, including the nature of the problem, dataset size, and other relevant parameters.
- 4. Train the Model:** Training an ML model entails supplying an ML algorithm, also known as the learning algorithm, with training data to acquire knowledge from. The expression "ML model" pertains to the model artefact produced during the training procedure. This represents a significant phase in comprehending and processing the data.
- 5. Evaluate the Model:** The primary metrics employed for assessing a classification model encompass accuracy, precision, and recall. Accuracy is characterized as the proportion of accurate predictions concerning the test data. This can be effortlessly computed by dividing the count of correct predictions by the total number of predictions.
- 6. Make Predictions:** It is used to predict outcomes using the model.

ML Work Flow

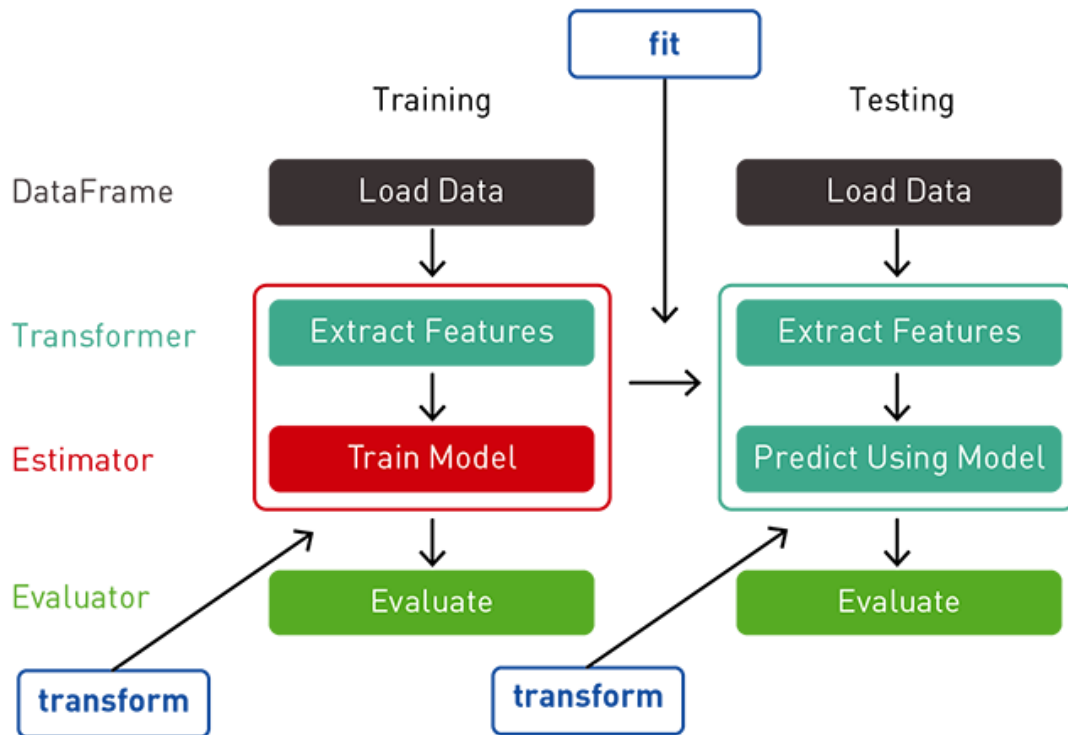


Figure 1: ML Workflow

V. EXPECTED OUTCOME

- Continuous Improvement in forecasting and prediction.
- Increased productivity.
- Accurate prediction of raw material requirement.
- Delivery of material/ raw material on time.
- No stocks in clearance.
- Fund flow.
- No shortage of material.
- Error free forecasting
- Assistance provided to the purchase manager using Artificial Intelligence for correct decision making etc.

Forecasting seeks to lower uncertainty and offer standards for tracking real performance. Artificial intelligence (AI) methods and emerging information technologies are being used to increase forecast accuracy, which helps to enhance the bottom line.

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