A Review on Machine Learning Models for Supply Chain Management and Forecasting

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Abstract: Supply chain management is critically important for streamlining and optimizing business logistics. Supply chain forecasting plays a vital role in ensuring that businesses are able to meet customer demand while optimizing their inventory levels and reducing costs. This literature review examines the various forecasting methods used in supply chain management over the past decade, from 2010 to 2020. The review covers time-series forecasting, causal forecasting, judgmental forecasting, and collaborative forecasting. The review also explores the impact of new technologies such as artificial intelligence and machine learning on supply chain forecasting. The findings of this review can help businesses and researchers better understand the current state of supply chain forecasting and identify areas for further research.in the forefront for supply chain forecasting. This paper presents a review of latest evolutionary algorithms in the domain of supply chain forecasting with its salient features.

Keywords:-Supply Chain Management, Supply Chain Forecasting, Evolutionary Algorithms, Forecasting Error, Accuracy.

I.Introduction

Supply chain management (SCM) is the process of managing the flow of goods and services from the point of origin to the point of consumption. SCM involves the coordination and integration of various activities such as procurement, production, logistics, and distribution to optimize the overall performance of the supply chain.

Planning and forecasting: SCM begins with planning and forecasting to determine the demand for goods and services, and to ensure that the supply chain is aligned with the demand.

Sourcing and procurement: Sourcing and procurement involve identifying and selecting suppliers, negotiating contracts, and managing the procurement of goods and services from suppliers.

Production and operations: Production and operations involve managing the production and assembly of goods, ensuring quality control, and managing inventory levels.

Fig.1 Functionalities of Supply Chain Management

Logistics and transportation: Logistics and transportation involve managing the movement of goods and services from suppliers to customers, including transportation, warehousing, and distribution.

Inventory management: Inventory management involves monitoring and controlling Due to the need of large data sets to be analyzed, it is necessary to use computational tolls which are fast, accurate and can handle copious amounts of data. Evolutionary algorithms are a set of such algorithms which show the aforesaid characteristics. Supply chain forecasting is the process of predicting future demand for goods and services in order to optimize supply chain management. This involves analyzing historical data, market trends, customer behavior, and other factors that can impact demand.

Forecasting is an important tool for supply chain management because it enables businesses to plan their production and inventory levels more effectively. By accurately predicting demand, businesses can reduce the risk of overstocking or understocking, which can result in lost sales or excess inventory costs.

There are several different methods for forecasting demand in a supply chain, including:

Time-series forecasting: This method uses historical data to identify patterns and trends in demand over time.

Causal forecasting: This method considers the factors that influence demand, such as changes in the economy, competitor behavior, or marketing efforts.

Judgmental forecasting: This method relies on the expertise and intuition of supply chain managers to make predictions about future demand.

Collaborative forecasting: This method involves collaboration between supply chain partners, such as suppliers, retailers, and distributors, to share information and insights about demand.

II. Introduction to Evolutionary Algorithms.

Evolutionary algorithms try to mimic the human attributes of thinking which are [3]:

1) Parallel data processing
2) Self-Organization
3) Learning from experiences

Some of the commonly used techniques are discussed below:

1) Statistical Regression: These techniques are based on the time series approach based on the fitting problem that accurately fits the data set at hand. The approach generally uses the auto-regressive models and means statistical measures. They can be further classified as:

a) Linear
b) Non-Linear

Mathematically [4]:

Let the time series data set be expressed as:

$$Y = \{Y1, Y2 \ldots\ldots\ldots\ldots\ldots\ldots..Yt)$$

Here,

Y represents the data set

t represents the number of samples

Let the lags in the data be expressed as the consecutive differences.

The first lag is given by:

$$\Delta Y_1 = Y_{t-1}$$

Similarly, the j^{th} lag is given by:

$$\Delta Y_j = Y_{t-j}$$

2) Correlation based fitting of time series data: The correlation based approaches try to fit the data based on the correlation among the individual lags. Mathematically it can be given by [5]:

$$A_t = corr(Y_t, Y_{t-1})$$

Here,

Corr represents the auto-correlation (which is also called the serial correlation)

Y_t is the t^{th} lagged value

Y_{t-1} is the $(t-1)^{st}$ lagged value

The mathematical expression for the correlation is given by

$$corr(Y_t, Y_{t-1}) = \frac{conv(Y_t, Y_{t-1})}{\sqrt{varY_t, varY_{t-1}}}$$

Here,

Conv represents convolution given by:

$$conv\{x(t), h(t)\} = \int_{t=1}^{\infty} x(\vartheta)h(t-\vartheta)d\vartheta$$

Here,

ϑ is a dummy shifting variable for the entire span of the time series data

t represents time

Y_t is the t^{th} lagged value

Y_{t-1} is the $(t-1)^{st}$ lagged value

X is function 1

H is function 2

Var represents the variance given by:

$$var(X) = X_i - E(X)$$

Here,

Xi is the random variable sample

E represents the expectation or mean of the random variable X [6]

3) Finite Distribution Lag Model (FDL): This model tries to design a finite distribution model comprising of lags fitted to some distribution such as the normal or lognormal distributions. Mathematically:

$Y_t = \alpha_t + \delta_1 z_1 + \cdots \ldots \ldots \ldots \ldots . \delta_t z_t + \mu_t$

Here,

Y_t is the time series data set

α_t is a time dependent variable

δ_1 is a time-varying co-efficient

z is the variable (time variable)

t is the time index [7]

μ_t is the time dependent combination-coefficient

4) Artificial Neural Networks (ANN): In this approach, the time series data is fed to a neural network resembling the working of the human based brain architecture with a self-organizing memory technique [8]. Mathematically, the neural network is governed by the following expression [9]

$Y = \sum_{i=1}^{n} X_i . W_i + \theta_i$

Here,

X_i represents the parallel data streams

W_i represents the weights

θ represents the bias or decision logic

The second point is critically important owing to the fact that the data in time series problems such as sales forecasting may follow a highly non-correlative pattern and pattern recognition in such a data set can be difficult. Mathematically:

$x = f(t)$

Here,

x is the function

t is the time variable.

III. Theoretical Background and Literature Review

Supply chain forecasting is a critical function in modern supply chain management. Accurate forecasting helps businesses plan production and inventory levels, reduce costs, and improve customer satisfaction. In recent years, advances in technology have enabled the development of new forecasting methods and tools. Some sub categories are:

Time-series forecasting is a method that uses historical data to identify patterns and trends in demand over time. This method has been widely used in supply chain forecasting and has been found to be effective in predicting demand for many products. Recent research has focused on improving the accuracy of time-series forecasting using machine learning and other techniques.

Causal forecasting considers the factors that influence demand, such as changes in the economy, competitor behavior, or marketing efforts. This method has been found to be effective in predicting demand for products with a strong causal relationship between factors.

Judgmental forecasting relies on the expertise and intuition of supply chain managers to make predictions about future demand. This method is often used when there is limited historical data available or when there are significant changes in market conditions.

Collaborative forecasting involves collaboration between supply chain partners, such as suppliers, retailers, and distributors, to share information and insights about demand. This method has been found to be effective in improving the accuracy of demand forecasting, particularly in complex supply chains with multiple partners.

Advances in technology, such as artificial intelligence and machine learning, have enabled the development of new forecasting tools and methods. These technologies have been found to improve the accuracy of demand forecasting and reduce the time and effort required to analyze large amounts of data.

Oglu et al. in [11] proposed the use of fuzzy logic and a neural network to predict the demand for pharmaceutical products in a distributed network, in conditions of insufficient information, a large assortment and the influence of risk factors. A comprehensive approach to solving forecasting problems is proposed using: the theory of fuzzy logic - when forecasting emerging and unmet needs and a neural network - if there is a lot of retrospective information about the actual sale of drugs and drugs. Using this approach to solve the problems of forecasting demand allows you to get statistics and experience. The general algorithm, mathematical interpretation and examples of forecasting the demand for pharmaceutical products in the face of uncertainty of information are given, and the general structure of the system for forecasting the demand for drugs is described.

Fildes et al. in [12] showed that computer-based demand forecasting systems have been widely adopted in supply chain companies, but little research has studied how these systems are actually used in the forecasting process. Authors report the findings of a case study of demand forecasting in a pharmaceutical company over a 15-year period. Carrying out the judgmental interventions involved considerable management effort as part of a sales & operations planning (S&OP) process, yet these often only served to reduce forecast accuracy. This study uses observations of the forecasting process, interviews with participants and data on the accuracy of forecasts to investigate why the managers continued to use non-normative forecasting practices for many years despite the potential economic benefits that could be achieved through change. The reasons for the longevity of these practices are examined both from the perspective of the individual forecaster and the organization as a whole.

Goodarzian et al. in [13] showed that in the pharmaceutical industry, a growing concern with sustainability has become a strict consideration during the COVID-19 pandemic. There is a lack of good mathematical models in the field. In this research, a production–distribution–inventory–allocation–location problem in the sustainable medical supply chain network is designed to fill this gap. Also, the distribution of medicines related to COVID-19 patients and the periods of production and delivery of medicine according to the perishability of some medicines are considered. In the model, a multi-objective, multi-level, multi-product, and multi-period problem for a sustainable medical supply chain network is designed. Three hybrid meta-heuristic algorithms, namely, ant colony optimization, fish swarm algorithm, and firefly algorithm are suggested, hybridized with variable neighborhood search to solve the sustainable medical supply chain network model. Response surface method is used to tune the parameters since meta-heuristic algorithms are sensitive to input parameters. Six assessment metrics were used to assess the quality of the obtained Pareto frontier by the meta-heuristic algorithms on the considered problems. A real case study is used and empirical results indicate the superiority of the hybrid fish swarm algorithm with variable neighborhood search.

Amalnick et al. in [14] proposed an accurate demand forecasting in pharmaceutical industries has always been one of the main concerns of planning managers because a lot of downstream supply chain activities depend on the amount of final product demand. In the current study, a five-step intelligent algorithm is presented based on data mining and neural network techniques to forecast demand in pharmaceutical industries. The main idea of the proposed approach is clustering samples and developing separate neural network models for each cluster. Using the obtained data, the performance of the proposed approach was assessed in a pharmaceutical factory. The optimal number of clusters for this case was four. Mean arctangent absolute percentage error, average relative variance, and correlation coefficient (R) were used to evaluate the performance of different neural network structures. The results of performing the models once for all data and once for the data of each single cluster showed that the forecasting error significantly decreased thanks to using this approach. Furthermore, the results indicated that clustering products not only raises the prediction accuracy but also enables a more reliable assessment of forecasted values for each single cluster. Such analyses are very important and useful for managers of marketing and planning departments in pharmaceutical units.

Viegas et al. in [15] showed that The Pharmaceutical Supply Chain (PSC) is responsible for considerable environmental and product-value impacts. However, studies on the reverse flows of PSC do not capture the diverse routes of end-of-use and end-of-life medicines (EOU/EOL-M) and how the constraints in the forward supply chain processes and operations impact such reverse flows. This research proposes a classificatory review in which three categories of reverse flows are identified: donations, Reverse Logistics (RL) and Circular Economy (CE). Donations are characterized by explicit philanthropic acts involving corporate reputation or by emergency humanitarian action. RL is boosted by regulatory issues and restricted by business imperatives of the PSC. CE is characterized by informal loops of not expired medicines, mainly due to health professionals' initiatives (although this may not be clear to participants). This classification emerged from content analysis of 2622 references found in six databases, from which 127 were selected.

IV. Evaluation Parameters

Since errors can be both negative and positive in polarity, therefore its immaterial to consider errors with signs which may lead to cancellation and hence inaccurate evaluation of errors. Therefore we consider mean square error and mean absolute percentage errors for evaluation. The other evaluation parameters are [21]:

1) Mean Square Error (mse)
2) Mean Absolute Error (MAE)
3) Mean Absolute Percentage Error (MAPE)
4) Accuracy

$$MSE = \frac{1}{N}\sum_{I=1}^{N}(V_t - \widehat{V}_t)^2 \quad (12)$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N} |V_t - \widehat{V}_t|$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N} |e_t|$$

$$MAPE = \frac{100}{N}\sum_{t=1}^{N}\frac{|V_t - \widehat{V}_t|}{V_t}$$

$$Accuracy = 100 - error(\%)$$

Here,

N is the number of predicted samples
V is the predicted value
$\widehat{V}_t$ is the actual value
e is the error value

It is desirable to attain high values of prediction accuracy.

Conclusion:

Supply chain forecasting predominantly deals with forecasting of demands of the products and goods based on previously available data. The estimation of demands directly impacts the production, which in turn influences the supply. This review has identified several trends, including the increasing use of new technologies such as machine learning and the growing importance of collaborative forecasting. The findings of this review can help businesses and researchers better understand the current state of supply chain forecasting and identify areas for further research. The performance metrics to evaluate the performance of the techniques is also presented.

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