A Review on Data Driven Models for Supply Chain Forecasting

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Abstract: Supply chain Management has remained an active area of research due to its widespread applications in several domains of manufacturing business. Supply Chain Management is a broad domain of business analytics with each sub-domain having its own importance. Off late, supply chain forecasting has emerged as a very effective tool which is useful in streamlining production, logistics and manpower thereby critically affecting the profit margin. 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. The current supply has a critical impact on the future demands. Due to the enormity of data to be analysed, supply chain forecasting is prone to errors in forecasting. Off late, machine learning based algorithms typically termed as evolutionary algorithms have been 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

The processing and storage of products is prone to high risks due to the limited shelf life. They generally bear a very limited shelf life and hence meticulous management is mandatory for the industries relying on aquatic products [7]-[8]. Moreover, substantial involvement of manpower and limited automation makes profitability more challenging. Supply chain management plays a pivotal role for such industries in streamlining the processes and deciding the profits. Supply chain management can be defined as the management of the flow of goods and services including all processes which are intertwined with the transformation of raw materials into final products. Supply chain management is critical for relating the demand and supply of products and services. Supply chain forecasting has come up as an extremely powerful toll for supply chain management [9]. Figure 1 depicts the functionalities of Supply Chain Management.

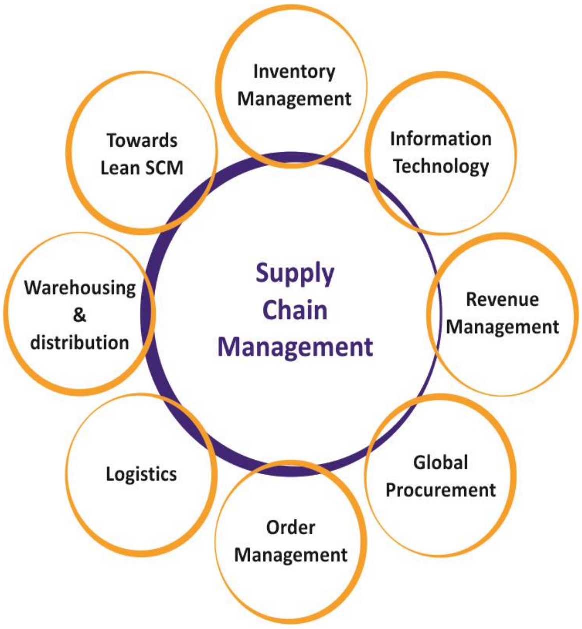

Fig.1 Functionalities of Supply Chain Management

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.

II. Introduction to Evolutionary Algorithms.

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

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:

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:

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

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

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

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.

The approach uses the ANN and works by training and testing the datasets required for the same. The general rule of the thumb is that 70% of the data is used for training and 30% is used for testing. The neural network can work on the fundamental properties or attributes of the human brain i.e. parallel structure and adaptive self-organizing learning ability. Mathematically, the neural network is governed by the following expression:

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

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.

The relation f is often difficult to find being highly random in nature.

The neural network tries to find the relation f given the data set (D) for a functional dependence of x(t).

The data is fed to the neural network as training data and then the neural network is tested on the grounds of future data prediction. The actual outputs (targets) are then compared with the predicted data (output) to find the errors in prediction. Such a training-testing rule is associated for neural network. The conceptual mathematical architecture for neural networks is shown in the figure below where the input data is x and fed to the neural network.

III. Previous Work

The survey of existing literature in the domain has been domain has been of extensive help in foreseeing the methodologies and gaps in existing work.

Oglu et al. in [1] 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.

Amalnick et al. in [2] 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.

Fildes et al. in [3] 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 [4] 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.

Viegas et al. in [5] 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.

Chen et al. in [6] consider a pharmaceutical supply chain composed of one pharmaceutical manufacturer and one pharmacy. Authors investigate how price cap regulation affects pharmaceutical firms' pricing decisions. It also evaluates the economic and social performance of the pharmaceutical supply chain and assess the risks associated with price cap regulation. The derived equilibriums under different price cap regulations, including retailer price cap regulation, manufacturer price cap regulation and linkage price cap regulation, are compared to that without regulation. The results show that one-sided price cap regulation will damage the economic performance of the regulated firm, whereas the unregulated firm may gain a financial advantage. The regulation may increase the risk of a supply shortage if pharmaceutical firms cannot cope with the financial loss. In contrast, linkage price cap regulation can be an effective policy for improving both the economic and social performance of the pharmaceutical supply chain.

Ahmadi et al. in [7] showed sustainable development of a nation greatly depends on the health of individuals. The emergence of the diseases caused by unhealthy lifestyle as well as the growth and aging of the population have faced the pharmaceutical industry with an increasing demand for drugs and the related products over time. This increase in demand has made the pharmaceutical industry as an important and large industry which constitutes a considerable portion of the healthcare expenditures. This sector is grappling with many challenges and inefficiencies in research and development activities, introducing new products, procurement, manufacturing, storage, and distribution affairs. Such issues have resulted in the inability of pharmaceutical companies to satisfy market demand in an efficient while effective manner. These problems alongside the dynamic and complex nature of a pharmaceutical supply chain (PSC) necessitate the employment of efficient optimization techniques to provide these companies with informed decision making by relying on available data. Hence, this chapter aims to identify the prevalent challenges of PSCs at three different decision levels, i.e., long-term (strategic), mid-term (tactical), and short-term (operational) decisions; as well as presenting various ways to deal with such problems. Accordingly, first, the characteristics of a PSC are presented and discussed. In order to provide a tangible perspective for application of Operations Research in PSC, an exhaustive mathematical programming model is presented.

Sabouhi et al.in [8] present an integrated hybrid approach based on data envelopment analysis (DEA) and mathematical programming method to design a resilient supply chain. First, the efficiency of potential suppliers is evaluated by a fuzzy DEA model. Afterwards, using the obtained efficiency, a two-stage possibilistic-stochastic programming model is developed for integrated supplier selection and supply chain design under disruption and operational risks. The model incorporates partial and complete disruptions of suppliers as well as quantity discount for procurement of various raw materials. Furthermore, we utilize several proactive strategies such as fortification and pre-positioning emergency inventory at fortified suppliers, and using multiple sourcing to enhance the resiliency of supply chain. Atra pharmaceutical company (APC) is used as a case study to investigate the applicability of the proposed model and analyze the solution results. The results indicate the validation of proposed model and the impact of various resiliency strategies.

Settanni et al. in [9] evaluated the evaluates reconfiguration opportunities in Pharmaceutical Supply Chains (PSC) resulting from technology interventions in manufacturing, and new, more patient-centric delivery models. A critical synthesis of the academic and practice literature is used to identify, conceptualise, analyse and categorise PSC models. From a theoretical perspective, a systems view of operations research is adopted to provide insights on a broader range of OR activities, from conceptual to mathematical modelling and model solving, up to implementation.

Mehralian et al. in [10] showed that managing independent members who share common goals is a frequent concern in any supply chain. More specifically, due to the critical role of the pharmaceutical industry in producing and delivering the right product to the right people at the right time, coordination of pharmaceutical supply chain (PSC) members is a critical factor. Therefore, the purpose of this study (PSC) is to identify and prioritise factors affecting coordination of a PSC. The analytic hierarchy process (AHP) is used to prioritise six strategic criteria, with 26 sub-criteria, for coordinating PSC operations. To run AHP, 44 interviews were performed to collect data for deep analysis. In this study 26 factors affecting coordination in a PSC were grouped to the six strategic factors. The results showed that, of these factors, organisational structure is perceived as the most important factor, followed by information technology, relationship and decision making, mutual understanding, management commitment, and regulatory affairs.

Mueller et al. in [11] evaluated the potential impact and value of applications (e.g. adjusting ordering levels, storage capacity, transportation capacity, distribution frequency) of data from demand forecasting systems implemented in a lower-income country's vaccine supply chain with different levels of population change to urban areas. Implementing a computer aided mechanism, authors generated a detailed discrete event simulation model of Niger's entire vaccine supply chain, including every refrigerator, freezer, transport, personnel, vaccine, cost, and location. They introduction of a demand forecasting system to adjust vaccine ordering that could be implemented with increasing delivery frequencies and/or additions of cold chain equipment (storage and/or transportation) across the supply chain during varying degrees of population movement.

Laan et al. in [12] showed that getting aid items to those in need can be challenging, long-term projects provide an opportunity for demand planning supported by forecasting methods. Based on standardized consumption data of the Operational Center Amsterdam of Médecins Sans Frontières (MSF-OCA) regarding nineteen longer-term aid projects and over 2000 medical items consumed in 2013, authors describe and analyze the forecasting and order planning process. Authors find that several internal and external factors influence forecast and order planning performance, be it indirectly through demand volatility and safety markup. Moreover, we identify opportunities for further improvement for MSF-OCA, and for humanitarian logistics organizations in general.

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

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

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

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

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

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

Here,

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

It is desirable to attain high values of prediction accuracy.

Conclusion:

It can be concluded form the previous discussions that it is challenging to predict the demand which

however is critically important to manage economics and logistics simultaneously. This paper focusses on the need and relevance of supply chain forecasting. The various approaches used for the purpose off late, have been highlighted with their salient features. The performance metrics to evaluate the performance of the techniques is also presented.

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