

A Review on Supply Chain Forecasting Methods Based on Evolutionary Algorithms

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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:

$$Y = \{Y_1, Y_2, \dots, Y_t\}$$

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 jth 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:

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

Here,

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

Y_t is the tth lagged value

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

The mathematical expression for the correlation is given by

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

Here,

Conv represents convolution given by:

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

Here,

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

t represents time

Y_t is the tth 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:

$$\text{var}(X) = X_i - E(X)$$

Here,

X_i 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:

$$Y_t = \alpha_t + \delta_1 z_1 + \dots \delta_t z_t + \mu_t$$

Here,

Y_t is the time series data set

α_t is a time dependent variable

δ₁ 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:

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

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

Oglu et al. showed that that employing advanced demand forecasting, such as machine learning, could mitigate the effect and improve the performance; however, it is less known what is the extent and magnitude of savings as tangible supply chain performance outcomes. In this research, hybrid demand forecasting methods grounded on machine learning i.e. Fuzzy Logic and Neural Network is developed. Both time series and explanatory factors are feed into the developed method. The method was applied and evaluated in the context of functional product and a steel manufacturer. The statistically significant supply chain performance improvement differences were found across traditional and ML-based demand forecasting methods. The implications for the theory and practice are also presented.

Rajesh R. et al. presented the indicators of firm resilience based on indicators from secondary data. These indicators can be measured on a regular basis based on performance in flexibility, responsiveness, quality, productivity and accessibility. Since source information for the data is often unknown, a methodology that is suited for prediction needs to be used. An improved grey prediction model is proposed in this research for forecasting the periodic

indicators of resilience performance. This research shows that error measures ensure the best fit of the data to achieve strong prediction capability. A prediction model is applied to the supply chain of an Indian electronics manufacturer to forecast the measures of its resilience.

France R.A. et al. proposed that many companies struggle with justifying the cost of quality within their supply chain. Outsourcing suppliers to countries such as These outsource decisions do not effectively determine the impacts of quality defects. In this paper we demonstrate a method for evaluating the systemic supply chain risk of poor quality. We introduce a multi-objective stochastic model that uses Six Sigma measures to evaluate financial risk. Results from modeling suggest quality, profit, and customer satisfaction can be evaluated. The authors used a deep neural network for supply chain prediction.

Singhry et al. proposed that despite the importance of collaborative planning, forecasting, and replenishment (CPFR), its influence on supply chain innovation capability (SCIC) and supply chain performance (SCP) has not been sufficiently examined. Through cluster and stratified random sampling, 286 responses from top managers of 1,574 Nigerian manufacturing companies were analyzed. Data analysis was performed using structural equation modeling with AMOS graphics. The results show that SCIC has a full mediating effect on the relationship between CPFR and SCP. Specifically, CPFR has a significant relationship with both SCP and SCIC, and SCIC also relates significantly to SCP.

Bojarssky et al. proposed that a concerted effort along the supply chain (SC) entities is needed which poses another important challenge to managers. This work addresses the optimization of SC planning and design considering economical and environmental issues. The strategic decisions considered in the model are facility location, processing technology selection and production–distribution planning. A life cycle assessment (LCA) approach is envisaged to incorporate the environmental aspects of the model. IMPACT 2002+ methodology is selected to perform the impact assessment within the SC thus providing a feasible implementation of a combined midpoint–endpoint evaluation. The proposed approach reduces the value-subjectivity inherent to the assignment of weights in the calculation of an overall environmental impact by considering endpoint damage categories as objective function.

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

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

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

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

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

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

Here,

N is the number of predicted samples

V is the predicted value

\bar{V}_t is the actual value

e is the error value

It is desirable to attain high values of prediction accuracy.

VI. CONCLUSION

It can be concluded from 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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