ECE 412 MTE

PREDICTING BULLWHIP EFFECT IN A 4-STAGE SUPPLY CHAIN USING MACHINE LEARNING

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PREDICTING THE BULLWHIP EFFECT

IN A 4-STAGE SUPPLY CHAIN MODEL USING MACHINE LEARNING

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Abstract

For organisations to keep up with the increasing demand, the supply chain requires efficiency. However, due to the unpredictable nature of demand, the bullwhip effect is a highly prominent in all industries. The role of AI and machine learning has been investigated in managing the risk which is accompanied by the bullwhip. The purpose of this study is to determine the effectiveness of various machine learning models in the prediction of the bullwhip effect. A 4-stage supply chain model was used to predict the value of bullwhip observed. The bullwhip effect was predicted using the linear regression, KNN and MLP-Regressor based on variables - Demand, Receive, Forecast, Net stock, Lead-Time-Delivery, Safety Stock, Order-up-to-Level, Order and cost. The results provide us with a benchmark to understand the performance of these algorithms to predict the bullwhip effect and can further help fast moving consumer goods firms prevent shortages or overproduction of stocks.

Keywords: Bullwhip Effect, KNN algorithm, NLP Algorithm, Supply Chain, Risk Management

1. Introduction

With the arrival of the coronavirus pandemic, organisations around the world suffered a major decrease in demand. The world moved into a recession (World Bank, 2021). Organisations realised the importance of having a lean system in order to prevent losses. The supply chains of various industries are moving towards a more resilient and lean structure. However, the threat posed by the bullwhip effect still looms large as information sharing is not viable in the highly competitive economies, moreover, poor demand forecasting methods contribute substantially to the bullwhip effect. (Prakash et al 2014) Implementation of artificial intelligence techniques in the supply chains of various industries can help forecast the demand with a higher accuracy and prevent the demand amplification phenomenon. (Amin et al 2008)

This paper aims to model a 4 stage supply chain using the principles laid down by Forrester (1961) and Sternman’s beer game (1983). Using this model, the demand amplification is modelled using the variables such as The model is based on factors such as Demand, Receive, Forecast, Net stock, Lead Time Delivery, Safety Stock, Order up to Level, Order and cost. Consequently, three artificial intelligence algorithms would be implemented on the dataset generated and the algorithms would be compared based on the accuracy they offer.

The system dynamics model laid down by forester in 1961 for the supply chain gives us a highly correlated dataset. The value of variables are derived from one another. Consequently, certain algorithms would perform better at predicting the bullwhip effect than the rest. The paper compares Decision Tree Regressor, MLP regressor and KNN algorithms and their ability to predict the bullwhip effectively.

The paper further investigates whether algorithms which deal with multi-collinearity can better predict the bullwhip effect than those which are simple regressors.

In the following sections, the paper explains the 4 stage supply chain model, and the various variables used in the system. Subsequently, it explains the process behind the data collection, data processing and the experimental results and findings.

2. Modelling and understanding the Bullwhip effect

2.1 Four stage supply chain simulation

An R based program was used to model a supply chain with four stages. The 4 stages are namely retailer, wholesaler, distributor and factory.

Each stage in the system is the customer of upstream and a supplier of downstream stage in the supply chain. For instance, the retailer observes customer demand and based on its current inventory situation places orders to its supplier, in this case the wholesaler. It receives orders made after a delivery lead time. The system is non-coordinated that is there is no information being shared between the stages of the supply chain. The decisions made by each stage are based on the simple moving average forecasting method. Each stage tries to predict the demand by averaging the last five demands of the stage downstream.

In the subsequent section it can be seen that no external factors affect the supply chain. Only the decisions made by each stage using the formulae mentioned contribute to bullwhip.

Time	Demand	Receive	Forecast	NS	LTD	SS	OUT	Order	Cost	Bullwhip
1	100	100	100	0	100	0	100	100	0	
2	100	100	100	0	100	0	100	100	0	
3	105	105	105	0	105	0	105	105	0	
4	105	105	105	0	105	0	105	105	0	
5	110	110	110	0	110	0	110	110	0	

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Table 1: Variables in the Supply chain Model

The table of data generated by model for each stage is shown in the table 1. As mentioned earlier, the demand of each stage is the order of the stage downstream. The other variables in the table are explained briefly in this section.

Net stock (NS) is defined here as a current inventory level. This is given by,

$NS_t = NS_{t-1}$ + Receive – Demand

Safety stock (SS) is the amount of inventory that companies keep in order to protect themselves against stock out situations during lead time. The safety stock is given by the following formula:

SS = Z*STD*√L

The SS was rounded off to 2 decimal places. Z is the safety factor, which is a constant associated with the service level. Service level is the probability of not running out of stock during the next replenishment cycle.

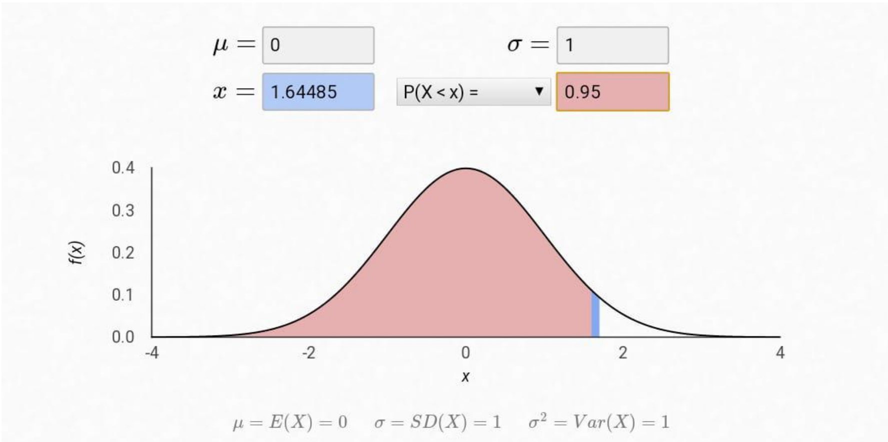

Figure 1 : Service level in normal distribution

The service level was taken to be 0.95 in the simulation. Let us see how service level and safety factor are related. Since service level is a probability, it can be expressed as the area under the curve of a standard normal distribution curve. So, safety factor can be defined as the z-score at which the probability of not running out of stock during the next replenishment cycle is equal to the service level. As an example, if Z=1.645 (approx.) then stock will not run out of stock 95 times out of 100.

STD is the standard deviation of the demand. L is the Lead time, which is the number of days between the time an order is placed and the time it is received.

Lead time demand (LTD) is the average demand during lead time. This is given by,

LTD = Forecast*L

Here, lead time was taken as 1 time period.

Order Up to Level (OUT) is a replenishment policy. Each period companies review stock levels and place an order to bring its stock levels up to a target level.

OUT = LTD + SS

Order (O), stocks ordered but not yet arrived, is given by,

O = OUT - NS

For the calculation of bullwhip, operation research model is used. The formula for calculating bullwhip is given by,

Bullwhip = Variance of Order/Variance of Demand

Cost, it is the cost incurred in storing the product in inventory and back ordering in the case when the stock is not sufficient to fulfil the demand. It is calculated as:

Cost = (Holding cost/piece) x (Net stock), if Net Stock > 0

In other cases,

Cost = (Backordering cost/piece) x (Quantity of unfulfilled order)

Back ordering and holding cost are 0.5 and 2 respectively.

Therefore, it can be said that no factors other than service level, demand, lead time, number of periods used for forecasting in Simple moving average affect the bullwhip.

3. Data collection

The data is generated using the bullwhip model above. This section shows plots of demand of each of the stage of the supply chain. To implement variability in the demand, the customer demand is simulated using a sinusoidal curve as shown in the figure 2.

3.1 Data Preparation

In order to use the data, data pre-processing is required. The process of data pre-processing has the three steps namely: Data Exploration, Data Cleaning, Data Processing

3.2. Data Exploration:

In this process, the data is checked for any inaccuracies such as missing values, typographical errors etc.

3.3. Data Cleaning:

In this process, all the unnecessary and incorrect data points are removed in order to increase the accuracy of the data table.

3.4 Data Processing: In this process, all the labelled data is encoded with a numerical value. The data table is scaled for the machine learning algorithms. The dataset is further split into testing and training data sets.

	Demand	Receive	Forecast	NS	LTD	SS	OUT	Order	Cost	Bullwhip
0	1.079815	0.794282	1.471047	2.013201	1.471047	0.086524	0.904166	0.805220	0.013808	1.000
1	1.130718	0.805220	1.498303	1.984658	1.498303	0.092601	0.923528	0.850255	0.084502	1.098
2	1.181621	0.850255	1.540425	1.965815	1.540425	0.105478	0.955231	0.894883	0.131172	1.287
3	1.224040	0.894883	1.585024	1.961857	1.585024	0.152212	1.005705	0.938755	0.140975	1.405
4	1.266459	0.938755	1.642013	1.972059	1.642013	0.170877	1.049232	0.962378	0.115708	1.530

Figure 2: Dataset after processing and scaling the data point

4. EXPERIMENTAL RESULTS AND FINDINGS

This section describes the result of experiments of various machine learning algorithms on the datasets described earlier using jupyter notebook. Exactly same datasets have been used for all the machine learning models for valid comparisons.

The proposed machine learning model has nine inputs namely Cost, Order, OUT, SS, LTD, NS, Forecast, Receive and Demand. Bullwhip will be the forecasted output of the model. The computed output, is the numerical value of the bullwhip effect for that Stock position

Sno	Algorithm	Accuracy
1	Decision Tree Regressor	24.52%
2	MLP Regressor	25.32%
3	KNN Algorithm	54.64%

Table 2: Accuracies for machine learning algorithms applied

A correlation Matrix was also constructed to understand the correlation between bullwhip and the various inputs. A multi-correlation matrix was obtained. This explains why the Decision tree regressor gave a poor prediction score (Il-Gyo Chong et al 2005) of 24.25%. The MLPRegressor algorithm resulted in a prediction score of 25.32%. This can be explained by the fact that the value of bullwhip has a small resolution of upto 2 decimal places. Due to this small resolution, the algorithm is unable to differentiate and predict the bullwhip effect with a high degree of accuracy. (Yi-Chung Hu et al 2014)

The KNN algorithm was also used. The algorithm took the projection of the 9 input variables and plotted it against the numerical value of bullwhip. Consequently, the machine tried to look for clusters which can further predict the bullwhip. The machine found the most accurate result at K=5 or 5 clusters. This resulted in a prediction score of 54.64%. The prediction can further be enhanced by increasing the resolution of the numerical value of bullwhip.

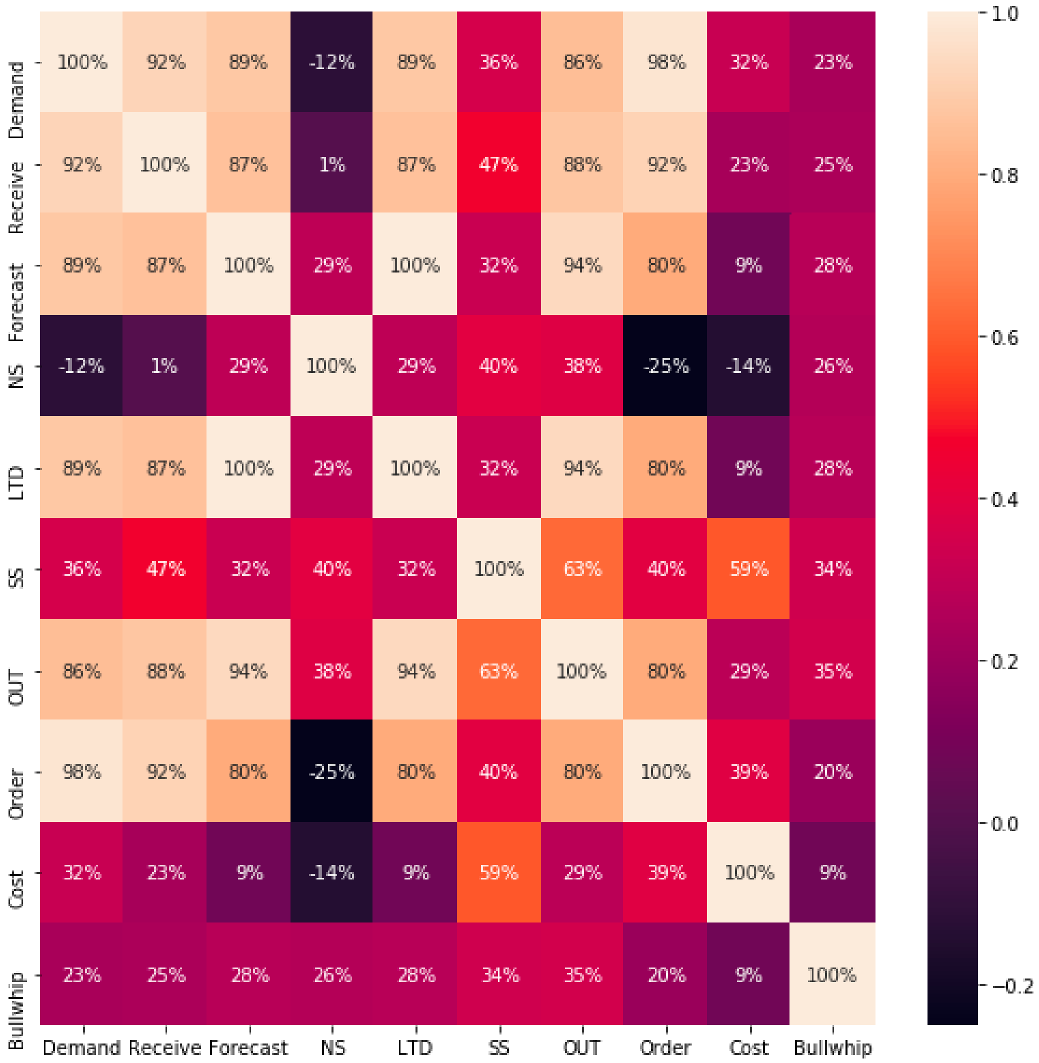

Figure 3: Correlation Matrix between the 9 Input variables and the output Bullwhip

5. CONCLUSION

The paper's objective was to model the bullwhip effect, understand its underlying causes and model a prediction artificial intelligence algorithm. We concluded that the advanced demand forecasting techniques which use regressors and perform poorly with multi collinearity must not be used to predict the bullwhip effect. Algorithms which use the projection of the data points such as KNN algorithms are effective for its prediction (Rinkaj Goyal et al 2014). Future research could be aimed at exploring algorithms which handle high degrees of collinearity. Moreover, research with a larger dataset can also be conducted to verify the results of this paper

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