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Demand Forecasting and Budget Planning for Automotive Supply Chain

Anand Limbare[1, *] and Rashmi Agarwal[2]

[1,2,] REVA Academy for Corporate Excellence, Bengaluru, India

Abstract

Over the past 20 years, there have been significant changes in the supply chain business. One of the most significant changes has been the development of supply chain management systems. It is now essential to use cutting-edge technologies to maintain competitiveness in a highly dynamic environment. Restocking inventories is one of a supplier's main survival strategies and knowing what expenses to expect in the next month aids in better decision-making. This study aims to solve the three most common industry problems in Supply Chain – Inventory Management, Budget Fore-casting, and Cost vs Benefit of every supplier. The selection of the best forecasting model is still a major problem in much research in literature. In this context, this article aims to compare the performances of Auto-Regressive Integrated Moving Average (ARIMA), Holt-Winters (HW), and Long Short-Term Memory (LSTM) models for the prediction of a time series formed by the dataset of Supply Chain products. As performance measures, metric analysis of the Root Mean Square Error (RMSE) is used. The main concentration is on the Automotive Business Unit with the top 3 products under this segment and the country United States being in focus. All three models, ARIMA, HW, and LSTM obtained better results regarding the performance metrics.

Keywords: ARIMA, Holt-Winters, LSTM

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*Corresponding author. Email: anand.ba05@reva.edu.in

1. Introduction

Organizations are changing to create a more effective supply chain that is driven by demand and to quickly respond to changing demand in today's competitive industrial market. Due to consumers' growing intelligence and needs, the market has changed into a "pull" environment where consumers tell providers what things they want and when they need them supplied [1].

Demand forecasting is crucial to inventory management. The quantity of inventory on hand is determined by demand projections. In practice, inaccurate demand forecasts may lead to significant costs, which indicates that the procedure has not been improved. Many systems invest a lot of money in their inventory to avoid "stock-outs." The problem is made more difficult by the possibility that some demands are intermittent meaning that a user may experience times of no demand and subsequent periods of desire. When attempting to predict demand using traditional statistical methods, there are many difficulties to overcome [2]. Most firms struggle to control demand since it is impossible to forecast with accuracy what customers will desire in the future. More than 74% of respondents to a study sur-vey identified poor forecasting accuracy and demand volatility as the two key reasons restricting supply chain flexibility [3]. The most prosperous companies often improve forecasting accuracy to boost the flexibility of their extensive supply networks. The top management in these companies must link projections to improvement goals and draw on past performance to reach a high degree of efficiency [4]. This succinct assessment of the literature demonstrates that ARIMA is a powerful tool for modelling any time series. However, as an a priori study, this report tests the ARIMA model to show that it can produce reliable forecasts in the supply chain sector. There are currently at least 70 linear and nonlinear methods for quantitative demand forecasting models [5]. The models adhere to various paradigms but have the same fundamental idea. It is well accepted in the literature that while predicting, no quantitative model would be perfect in all scenarios and under all conditions. Although several comparative studies have discussed in the literature, the conclusion makes no

mention of the circumstances under which one method is superior to another. Therefore, complicated, seasonal, and perishable scenarios, which are common in the supply chain business, a need for research into the best approach for each circumstance. Additionally, to strengthen the model, this study compares three forecasting models: the HW model, LSTM, and the ARIMA model. The primary concentration is on supply chain data from 2019 to 2022 YTD obtained from the organization that works in the Supply Chain Management field across the globe, with the main focus being on the Automotive Business Unit since this particular Business Unit has the most spending and would deep dive into how much each product in the sector contributes to the spend and inventory management.
To minimize or maximize the overall production of units and better plan the spending for the upcoming month, it is necessary to develop an optimal production plan based on reliable projections. These estimates should result in lower/higher inventory, less downtime, more asset returns, higher customer satisfaction, and shorter lead times.

2. Literature Review

In its broadest sense, a supply chain is made up of two or more entities that are legally separate yet linked by flows of goods, data, and cash. These businesses could be clients themselves, logistic service providers, or firms that produce parts, components, and completed goods. As a result, the aforementioned definition of a supply chain includes the target market or the eventual customer [6].
Several studies have been conducted on Forecasting Budget and Demand albeit for other areas of the field like Highway construction projects [7], federal budgets [8], budget forecasting related to a particular country [9].
As seen, most of the study related to demand and budget forecasting uses time series forecasting models like ANN, Moving Average, Exponential Smoothing, etc, but the combination usage of LSTM, ARIMA, and HW is a rare sight to see.
Time series forecasting is a method for predicting future events by examining historical trends, with the underlying premise being that prior trends will continue to hold true for the foreseeable future. To anticipate future values, forecasting includes fitting models to historical data. Time series forecasting is necessary for prediction problems with a time component since it offers a data-driven method for effective and efficient planning [10].
For several applications, such as business, the stock market and exchange, the weather, electrical demand, cost, and usage of items like fuels and energy, etc., and in any situation where there are periodic, seasonal variations visible, time series analysis and forecasting are crucial [11].
There are several Time Series techniques available notably HW, ARIMA, LSTM, etc.
Another iteration of the exponential smoothing method is referred to as Holt-Winters after its creators. The Holt-Winters exponential smoothing performs well when the data has both a trend and seasonality. For time series displaying additive seasonality and multiplicative seasonality, respectively, the two main HW models are multiplicative and additive [12].
For the same amount of data, an LSTM multivariate machine learning model occasionally performs better than a Holt- Winters univariate statistical model [13]. In order to achieve cutting-edge results on temporal data, LSTM networks can get over the limitations of traditional time series forecasting techniques by making use of the nonlinearities of a specific dataset [14].
From the perspective of statistical modelling, ARIMA is another time series technique that yields reliable results for short-term prediction. Box and Jenkins first presented the ARIMA model in 1970. The Box-Jenkins approach is a set of procedures for identifying, calculating, and analysing ARIMA models using time series data. A well-re-searched paper avail- able in this context is [15], which shows ARIMA's strength in predicting future stock prices. The limitation of the ARIMA model is however the number of periods. It is recommended to employ at least 50 and ideally 100 observations [16]. Ghosh et al. (2023) embarked on a comprehensive study to assess water quality through predictive machine learning. Their research underscored the potential of machine learning models in effectively assessing and classifying water quality. The dataset used for this purpose included parameters like pH, dissolved oxygen, BOD, and TDS. Among the various models they employed, the Random Forest model emerged as the most accurate, achieving a commendable accuracy rate of 78.96%. In contrast, the SVM model lagged behind, registering the lowest accuracy of 68.29% [17].Alenezi et al. (2021) developed a novel Convolutional Neural Network (CNN) integrated with a block-greedy algorithm to enhance underwater image dehazing. The method addresses color channel attenuation and optimizes local and global pixel values. By employing a unique Markov random field, the approach refines image edges. Performance evaluations, using metrics like UCIQE and UIQM, demonstrated the superiority of this method over existing techniques, resulting in sharper, clearer, and more colorful underwater images [18]. Sharma et al. (2020) presented a comprehensive study on the impact of COVID-19 on global financial indicators, emphasizing its swift and significant disruption. The research highlighted the massive economic downturn, with global markets losing over US $6 trillion in a week in February 2020. Their multivariate analysis provided insights into the influence of containment policies on various financial metrics. The study underscores the profound effects of the pandemic on economic activities and the potential of using advanced algorithms for detection and analysis [19].

3. Objectives

In today's firms, demand forecasting and budget planning are growing more and more crucial because they are both essential to survival and the global language of business. Even the most well-established structures inside these organizations are susceptible to sudden, huge changes, and

all business sector requirements call for precise, useful projections into the future. Buyers need to anticipate how much expense they will be incurring in the near future and suppliers must be expecting how much stock they will be selling in the coming weeks so that they can adequately stock up the inventory.
In the beginning, businesses usually buy goods from a variety of suppliers to find the best one, but they usually decide to stick with the same ones because most of them are averse to switching and uncertain of whether another supplier will offer comparable goods at a comparable price.
The focus is on the following 3 short-term forecasting methods to predict the budget and demand for buyers and suppliers.
The main objectives are:
1) Demand Forecasting - Aims at solving the inventory management of suppliers.
2) Budget Planning - Aims to figure out the expenses that will be incurred in the coming months.
3) Supplier Cost vs Benefit - Aims to understand the cost vs benefit of every supplier that way a high cost, low supply vendor can be eliminated.

4. Business Understanding

A supply chain company has two aspects: the suppliers of the parts they purchase and the price they plan to pay for the items. Every day, the firm needs products to run its operations, but more crucially, the company may not be aware of the quantity of products it will require or the cost of those products. The relationship established between the customer and the supplier typically begins to deteriorate when the supplier is unable to meet a demand set by the buyer.
In the early stages, businesses often compile all their suppliers into a database before making purchases from them, and occasionally they continue to do so despite knowing that there are better suppliers out there who can offer the same parts for less money. Thus, based on the method and volume of sales, this study selects the top providers. It is recommended to purchase from a supplier if they are offering more products for less money as opposed to purchasing from someone who is charging a higher price. This process is achieved via the Cost vs Benefit Quadrant Analysis.

5. Data Understanding

By using the expertise of working in a supply chain industry, the data is to be used for Demand Forecasting, Budget Planning and Cost vs Benefit of each supplier. The data contains the following variables.
1. Date – The time spans from May 2019 to June 2022 and is weekly statistics.
2. Supplier Number – Each line entry has a supplier number that identifies the supplier to whom this invoice was raised.
3. Business Unit – Refers to which business unit the invoice posted belongs to. A single line entry talks about which unit ordered the products from the supplier.
4. Country – Refers to the country the supplier belongs to.
5. Product – Refers to the product name which is being bought by the buyer from the supplier.
6. Month – This column states the month when the invoice was posted.
7. Year – This column states the year when the invoice was posted.
8. Quantity – Refers to the number of products that were sold to the buyer in this week.
9. Amount Spent – Refers to the amount spent buying the products from the supplier for that week.
The only currency used in the data collection is US dollars.
Along with the columns for quantity and amount spent, the date column is the most crucial variable that is required.
Date is required since the model deals with conducting a time series forecast. It also doubles as an index column to feed the data into the model.
Since demand forecasting is one of the main focus, the quantity column is necessary because it is used to project how much quantity will be needed over the following four weeks so that the supplier can be informed and they can prepare the volume.
Since a budget prediction is being made, an amount column is needed. This projection is primarily for purchasers since they need to know how much money they will need in the future weeks, so they can keep it on hand.
A quadrant analysis is also needed by combining both quantity and amount spent to identify which supplier has the best cost vs benefit ratio.

6. Data Modelling

Modelling is performed by splitting train and test data for BM, HIBE Materials, and PT for all 3 models used in the study. With the dataset being 165 rows, the data is split at 161 for Training and 4 for Testing.
ARIMA – While performing the ARIMA model on the datasets, it is imperative to check the data information first. Getting rid of all columns and keeping only what is necessary. In this case, columns ‘business unit’, ‘country’, ‘month’, ‘year’, ‘product name’ is removed to keep the data trimmed and only ‘date’, ‘qty’ and ‘amt’ is retained.
Plotting the data on a line chart helps visualize the data much more efficiently and to check if it is following some pattern. This step is done for all Products for quantity and amount.
The data is run through an Augmented Dickey-Fuller Test to check whether the data is stationary or not.
The model helps capture important information like ADF, P-Value, Number of Lags, Number of Observation Used for ADF Regression, and Critical Values Calculation. Once the test is run, the concentration is mostly on the p-value, and it is preferred the p-value should be as <0.05. If it turns out to be more than 0.05 then it means the data is not stationary.

Fig.1 states that the p-value is greater than 0.05 so the data has to be stationary. For that to happen, the data has to be differentiated with the period = 2. Post this, it is clear that the data is stationary as shown in Fig. 2.

```
1. ADF :  -1.801318519567991
2. P-Value :  0.3798072820079655
3. Num Of Lags :  9
4. Num Of Observations Used For ADF Regression: 155
5. Critical Values :
        1% :  -3.4732590518613002
        5% :  -2.880374082105334
        10% :  -2.5768120811654525
```

Fig. 1. ADF Test prior to data becoming stationary.

The data is run through the ARIMA model and Auto ARIMA will iterate through every step to figure out the best combination of order and it will assign a score called the Akaike's Information Criterion (AIC). The goal is to minimize the AIC.

Once the AIC is figured out, the best combination is fit into the ARIMA model on the training dataset and the performance is checked on the test section.

Holt-Winters - The data is plugged into the python note-book ready to be processed for the Holt-Winters model. All variables are removed except date, quantity, and amount.

The data is checked for seasonal decompose with the additive model as the magnitude of the data remains the same throughout. Since the data is weekly data, the period selected is 4. The seasonal decompose chart helps to visualize the data if there is a trend, seasonality and noise. The data is split into train and test and the Holt-Winters Exponential Smoothing technique is processed through the training dataset by testing it with trend as additive or multiplicative and seasonal as additive or multiplicative. Trying different combinations helps the model achieve better performance.

LSTM – Long Short-Term Memory networks are a type of recurrent neural network capable of learning order dependence in sequence prediction problems.

The data is plugged into the model ready to be processed for LSTM. All variables are removed except date, quantity, and amount. The data is run through the seasonal decompose technique to visualize the data better. As stated in the above HW section, the decompose technique decomposes different parts of the time series by providing the column which needs to be taken action on.

The data is split into train and test and the training data is plugged into the LSTM model. Post this the data is sent for preprocessing. This is an important step for Recurring Neural Network models. The preprocessing that is being done is called as MinMaxScaler as shown in Fig. 3. This converts the data into a scale of 0 to 1 to not confuse the model due to the high magnitudes of data. Both the train and test data are run through the MinMaxScaler preprocessing.

```
amt
ADF Statistic: -9.926454554541317
p-value: 2.8983333570950085e-17
```

Fig. 2. ADF Test post data becoming stationary with diff = 2

```
array([[0.30395858],
       [0.13457702],
       [0.5765549 ],
       [0.65034885],
       [0.36568425],
       [0.29609227],
       [0.73388827],
       [0.75262102],
       [0.5081914 ],
       [0.21298646]])
```

Fig.3. MinMaxScaler in LSTM

The model needs an input number. The procedure of LSTM in terms of input number is, it takes the number of rows in which the input number is stated, learns the pattern and then predicts the next number in the sequence. This technique is achieved through TimeSeriesGenerator technique.

Post that, from Keras library, the Sequential, Dense, and LSTM classes are called. The Sequential class helps the layers add one after the other. LSTM class is called with 100 neurons with activation function as 'relu'. The model is compiled with the optimizer selected as 'adam' and the loss as 'mse'.

The model is run for 50 epochs. Plotting the loss per epoch helps better understand at which stage the loss is at its lowest for which the model learns on its own. The training data is run through the model and is tested against the performance on the test data.

Quadrant Analysis for Cost vs Benefit – This analysis is mostly an EDA. The data pulled for this is for all 3 products but only change is to get the supplier number too along with quantity and amount. The analysis is divided into 4 categories.

1. High Cost - Less Products – Suppliers which have a high amount but less products sold to the buyer. These suppliers are the ones that this study proposes to the management team to get rid of.

2. High Cost - More Products – Suppliers which have a high amount and also more products sold by them. These are the suppliers the management team would be willing to keep.

3. Low Cost - Less Products – Suppliers which are cheap but also are selling less products. While this is not a preferred category for the management, most suppliers fall into this category. It is advised to get most of the suppliers from this category moved to the next sector which is,

4. Low Cost - More Products – The best of the lot. This is the preferred supplier list since the cost is low and they sell more products to the buyer.

Fig. 4, 5 and 6 shows the Quadrant Analysis for PT, HIBE and BM respectively. The bottom right section of the Quadrant Analysis is considered to be the Preferred supplier and the top left section is considered as non-Preferred suppliers.

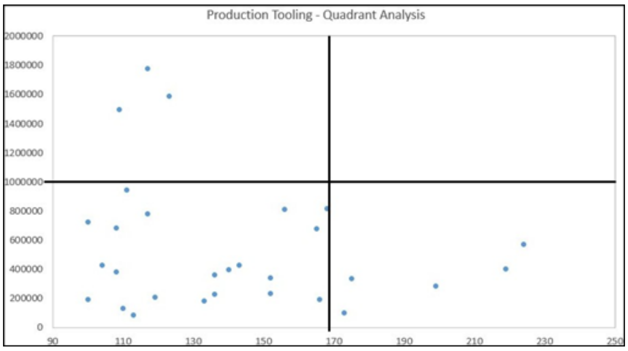

Fig. 4. Quadrant Analysis of PT

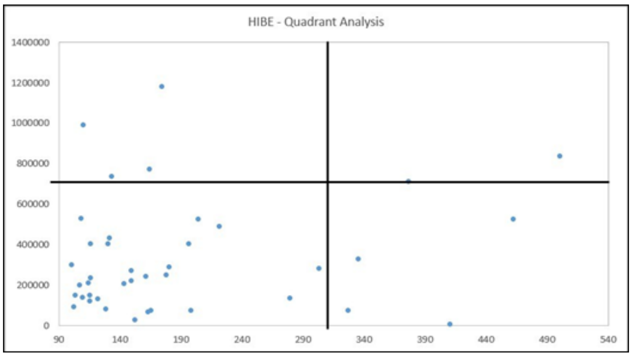

Fig. 5. Quadrant Analysis of HIBE

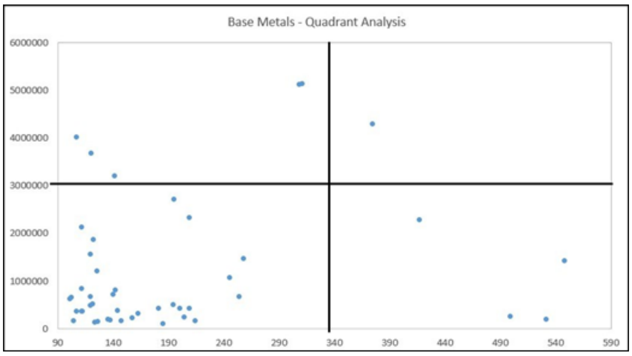

Fig. 6. Quadrant Analysis of BM

7. Model Evaluation

Many statistical methods and components are used to pro-vide enough quantifiers and charts to support the buyers and suppliers to make better decisions and derive useful insights. All tables viewed are for every product matched with amount and quantity. Every combination of data is run through all 3 models.

Base Metals: LSTM performs well, as stated in Figure 7 with the blue trend line rep-resenting the test data and the orange trend line representing the predicted data for Budget Planning with an accuracy of 94.69% as shown in Figure 7.1.

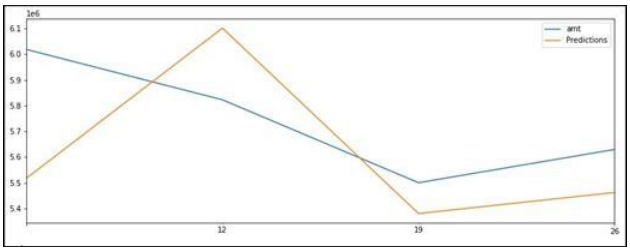

Fig. 7. LSTM Predictions for Base Metals – Budget Planning

Model	Dataset	Variable	RMSE	Mean of Test Data	Accuracy
ARIMA	Base Metals	Amount	3,96,897.00	57,42,659.00	93%
Holt-Winters	Base Metals	Amount	5,55,800.70	57,42,659.00	90%
LSTM	Base	Amount	3,04,792.00	57,42,659.00	95%

Fig.7.1 Model Comparison for BM – Budget Planning

HIBE: ARIMA performs well on HIBE for Budget Planning with the orange trend line representing the test data and the blue trend line representing the predicted data as shown in Figure 7.2 with an accuracy of 97.28% as stated in Figure 7.3.

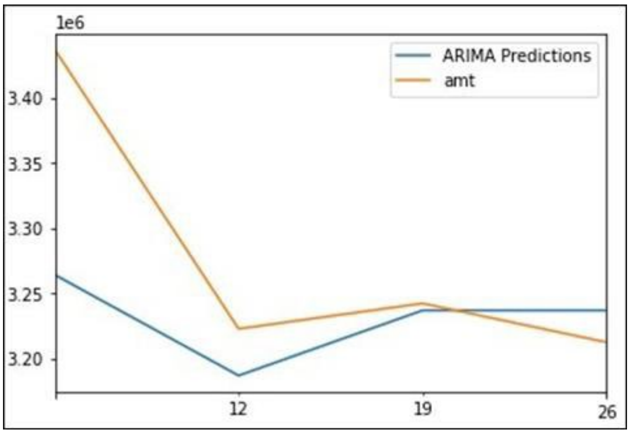

Fig. 7.2 ARIMA Predictions on HIBE – Budget Planning

Model	Dataset	Variable	RMSE	Mean of Test Data	Accuracy
ARIMA	HIBE	Amount	89,054.30	32,78,600.50	97%
Holt-Winters	HIBE	Amount	3,84,228.70	32,78,600.50	88%
LSTM	HIBE	Amount	2,87,358.60	32,78,600.50	91%

Fig. 7.3 Model Comparison for HIBE – Budget Planning

Production Tooling: ARIMA performs well on Production Tooling for Budget Plan-ning with the orange trend line rep- resenting the test data and the blue trend line rep-resenting the predicted data as shown in Figure 7.4 with an accuracy of 98.51% as stated in Figure 7.5.

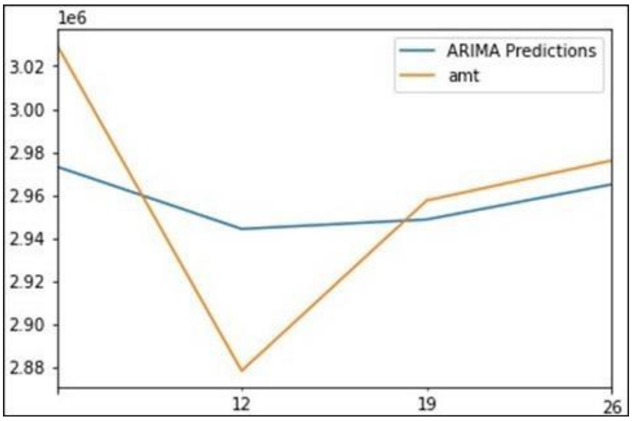

Fig 7.4. ARIMA Predictions on PT – Budget Planning

Model	Dataset	Variable	RMSE	Mean of Test Data	Accuracy
ARIMA	Production Tooling	Amount	44,101.50	29,60,431.30	99%
Holt-Winters	Production Tooling	Amount	64,750.30	29,60,431.30	98%
LSTM	Production Tooling	Amount	77,695.30	29,60,431.30	97%

Fig 7.5. Model Comparison for PT – Budget Planning

Demand Forecasting

Base Metals: LSTM performs well, as stated in Figure 7.6 with the blue trend line rep-resenting the test data and the orange trend line representing the predicted data for Demand Forecasting with an accuracy of 98.80% as shown in Figure 7.7.

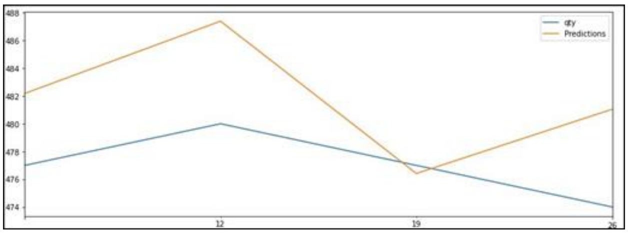

Fig 7.6. LSTM Predictions for BM – Demand Forecasting

Model	Dataset	Variable	RMSE	Mean of Test Data	Accuracy
ARIMA	Base Metals	Quantity	7.6	477.0	98%
Holt-Winters	Base Metals	Quantity	7.2	477.0	98%
LSTM	Base Metals	Quantity	5.7	477.0	99%

Fig 7.7. Model Comparison for BM – Demand Forecasting

HIBE: HW performs well, as stated in Figure 7.8 with the orange trend line representing the test data and the blue trend line representing the predicted data for Demand Forecasting with an accuracy of 99.24% as shown in Figure 7.9.

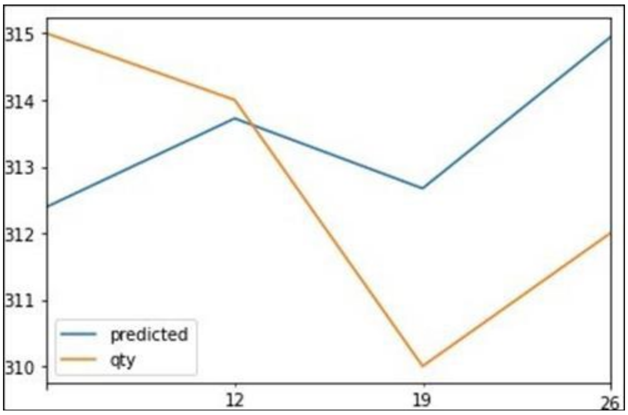

Fig 7.8. HW Predictions for HIBE – Demand Forecasting

Model	Dataset	Variable	RMSE	Mean of Test Data	Accuracy
ARIMA	HIBE	Quantity	3.2	312.8	99%
Holt-Winters	HIBE	Quantity	2.4	312.8	99%
LSTM	HIBE	Quantity	4.0	312.8	99%

Fig 7.9. Model Comparison for HIBE – Demand Forecasting

Production Tooling: ARIMA performs well, as stated in Figure 7.10 with the orange trend line representing the test data and the blue trend line representing the predicted data for Demand Forecasting with an accuracy of 98.41% as shown in Figure 7.11.

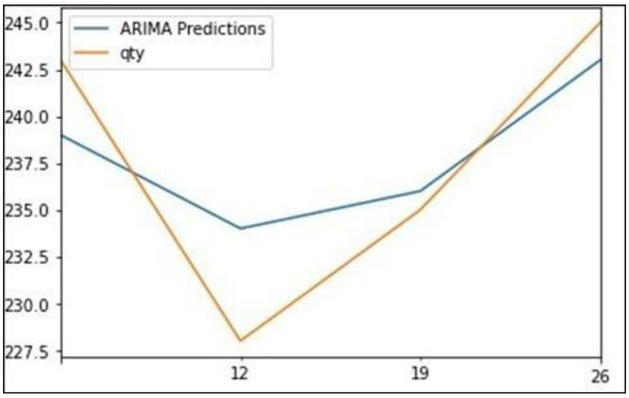

Fig 7.10. ARIMA Predictions for PT – Demand Forecasting

Model	Dataset	Variable	RMSE	Mean of Test Data	Accuracy
ARIMA	Production Tooling	Quantity	3.8	237.8	98%
Holt-Winters	Production Tooling	Quantity	6.8	237.8	97%
LSTM	Production Tooling	Quantity	5.9	237.8	98%

Fig 7.11. Model Comparison for PT – Demand Forecasting

8. Analysis and Results

Multiple Time Series models are processed on the Supply Chain dataset for the weekly range of 2019 to 2022, and insights were incurred from them. During data modelling, it was understood that every dataset had a different model working for it and those models respectively are used to predict the future values for that particular dataset. Figures 8.1, 8.2, 8.3 shows the results that would be taken into consideration for the upcoming month for every dataset.

ARIMA - Production Tooling - Budget Planning		ARIMA - Production Tooling - Demand Forecasting	
Date	Amount	Date	Amount
03-07-2022	29,70,470	03-07-2022	246
10-07-2022	29,76,941	10-07-2022	242
17-07-2022	29,55,513	17-07-2022	236
24-07-2022	29,64,824	24-07-2022	236
Total	1,18,67,748	Total	960

Fig. 8.1 Next 4 weeks value for PT

ARIMA - HIBE - Budget Planning		HW - HIBE - Demand Forecasting	
Date	Amount	Date	Amount
03-07-2022	32,36,435	03-07-2022	313
10-07-2022	32,38,729	10-07-2022	314
17-07-2022	32,37,922	17-07-2022	313
24-07-2022	32,37,922	24-07-2022	315
Total	1,29,51,008	Total	1255

Fig. 8.2 Next 4 weeks value for HIBE

LSTM - Base Metals - Budget Planning		LSTM - Base Metals - Demand Forecasting	
Date	Amount	Date	Amount
03-07-2022	55,23,060	03-07-2022	471
10-07-2022	54,46,661	10-07-2022	469
17-07-2022	53,83,109	17-07-2022	468
24-07-2022	53,28,674	24-07-2022	466
Total	2,16,81,504	Total	1874

Fig. 8.3 Next 4 weeks value for BM

9. Conclusions and Future Work

Demand Forecasting and Budget Planning is an important aspect in the Supply Chain field to know how much inventory is going to be needed and how much amount is going to be spent on those. The overall goal has been worked on thoroughly and the result has been achieved. This study had narrowed down the Business Unit and the country to Automotive and USA respectively and the result achieved has been through the 3 popular time series models called ARIMA, Holt Winters, and LSTM. This helps the buyers and the suppliers significantly to plan for their inventory and expenses.

Considering the above designed Time Series models and output, some recommendations for future work include adding top spend countries like Germany, Japan, Canada, Australia, China, etc. and to expand on more products in the current Business Unit. Building several Time Series models like VARMAX, SARIMA, Facebook Prophet will also help in getting accurate results.

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