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Research Article

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Machine Learning-Expert Opinion Hybrid Model for Supply Chain Demand Forecasting

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Abstract
Supply chain management places a significant emphasis on forecasting. A good demand forecast leads to the neutralization of the bullwhip effect, which reduces losses and increases profits. A hybrid model is proposed by this study, which employs four machine learning algorithms and four conventional forecasting methods to predict units sold in a chain store data set while also estimating them using the mean squared error (MSE). The paper examines the effectiveness of these predictions. We also benchmark each other using our Fulfillment Ratio (FR), which is the number of orders that can be filled at any one time without backorders or inventory. This is useful in determining how efficiently and quickly your business receives orders from customers. Finally, the value predicted by the lower MSE and correct FR method is the input of the mathematical model to which the expert opinion is applied. The purpose of this model is to reduce the cost of the organization due to the forecasting error and if the threshold is correct, then the demand for the following seasons is decided. In addition to allowing the use of different demand forecasting methods and taking into account occupancy, this process uses expert opinion, which has received little attention in other decision models.

Keywords: Demand Forecasting, Supply Chain, Machine Learning, Expert Opinion, Bullwhip Effect.

1. Introduction

The flow of information, products, and capital through the supply chain is continuous throughout the process [1]. Post-forecasting plays the most important role in this structure. A company's profitability and efficiency can be determined by demand forecasting, which is the core of inventory management. By increasing forecasting accuracy, you can design better products, and reduce wastage and wastage, etc. The significance of forecasting is heightened by the variety and competition between companies and stores that impact demand. There have been significant advancements in machine learning techniques in recent times. These methods are now employed due to technical progress and a surge in data availability. The reasons for choosing these methods include their speed in computation, accuracy, and network functionality. These methods are based on information from previous questions that we can easily apply. By identifying disparate demand factors and mapping them to demand, we can provide a precise forecast.

The process facilitates the integration of all components, resulting in greater flexibility in the supply chain. Due to the importance of information flow across supply chain components, enhancing forecasting accuracy leads to improved information quality and better supply chains ultimately reducing shock effects [2, 3].

In the beginning, the customer places an order with the retailer, while the wholesaler and the warmer work together to place their orders, as shown in Figure 1. Ultimately, the distributor issues orders to the manufacturer, leading to this chain. Valuable insight can be obtained by analyzing demand forecasts at every stage of the chain, as changes in disparities between real and projected demand result in the bullwhip effect [4]. The more accurately we predict customer demand, we will avoid bigger fluctuations in the next stages and this shows the importance of more accuracy in predicting customer demand.

The demand forecasting study relied only on data and forecasts and no expert help was used in this study. This study suggests that after forecasting the demand, the quantity is converted into a mathematical model determined by expert judgment. This model aims to minimize the cost of predictable error and can lead to error reduction through error reduction and manipulation. Chain costs are covered. Prediction, least squares, and expert opinion are the necessary steps in a continuous cycle to solve this process.

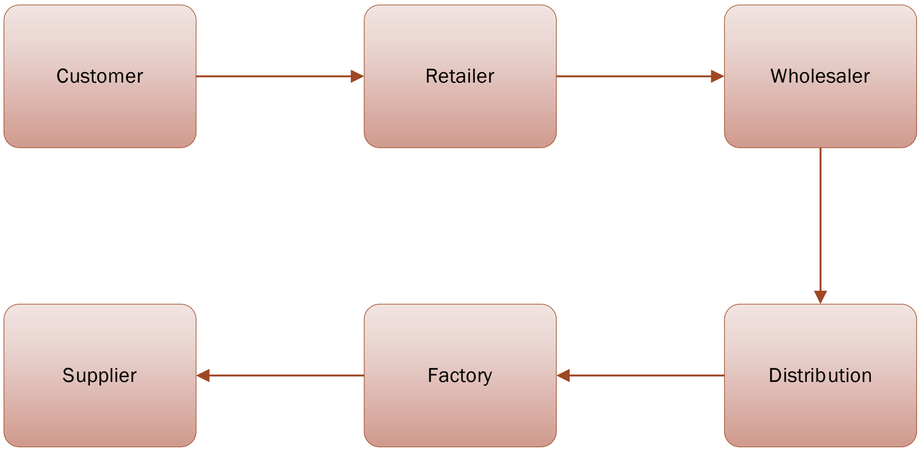

Figure 1: Supply Chain Schematic

2. Literature Review

Carbonneau et al. in an article entitled "Using machine learning techniques to predict supply chain demand" analyzed and researched the application of advanced machine learning techniques such as neural network (NN), recurrent neural network (RNN), and support vector machine (SVM) to predict supply chain demand [5].

Ali and Azad in their article, "Demand Forecasting in Small Grid" used support vector regression to estimate daily household electricity consumption. They compared the efficiency of this model with two other models, nominal linear regression and multi-layer perceptron. They showed that support vector machine is the best choice for this task. The result of their research shows that machine learning techniques can be used to predict demand in an intelligent environment [6].

In their research, Burger and Moura proposed a general model for predicting electricity consumption. Their proposed model validates the model's efficiency and selection using a real-time corridor function. The time series data used in this model are related to 8 buildings located in the campus of the University of California and recorded hourly over two years are the authors of this. The researchers believe that their proposed model will be able to help accurately predict the multivariate electricity demand of buildings [7].

Kilimci et al. with a case study on the SOK data, a Turkish store, succeeded in developing an intelligent demand forecasting system. During this study, 11 different methods of forecasting were employed to integrate them: time series processes, support vector regression models, and deep learning models for demand forecasts [8].

By utilizing deep learning techniques like ANN, CNN, and LSTM, Husna et al were able to predict the unit sales of products sold in chain stores across multiple countries, including Ecuador. Finally, the performance of the implemented models is evaluated and compared [9].

Feizabadi utilized machine learning methods like neural networks to create a mixed model for forecasting supply chain demand. This model is also powered by time series. This method is applied and evaluated about the work product and the steel manufacturer.

There were statistically significant differences between traditional and ML-based demand forecasting methods when it came to improving supply chain performance [10].

3. Problem Description

In this process, we first sorted the data related to the demand of the previous periods that was collected and is available in the data set and measured the correlation of each feature with the amount of demand. Then, we divided the dataset into two parts of training and validation completely randomly. We use the training section to map a predictor and the validation section to calculate the accuracy of the prediction, which prevents overfitting of the predictor.

The process is forecasted by continuously comparing the machine learning method with the conventional method. Compared to neural networks and support vector regression methods, the machine learning regression technique is more appropriate and the time series method is more suitable compared to other traditional methods such as mode, mean, and naive errors. assessment If it is smaller, we apply it to the test data above, after which we select the best prediction method by comparing the mean squared error (MSE). A mathematical model is used to calculate the value of the forecasted demand, with input from expert opinion.

The general schematic of the process is given in the following figure:

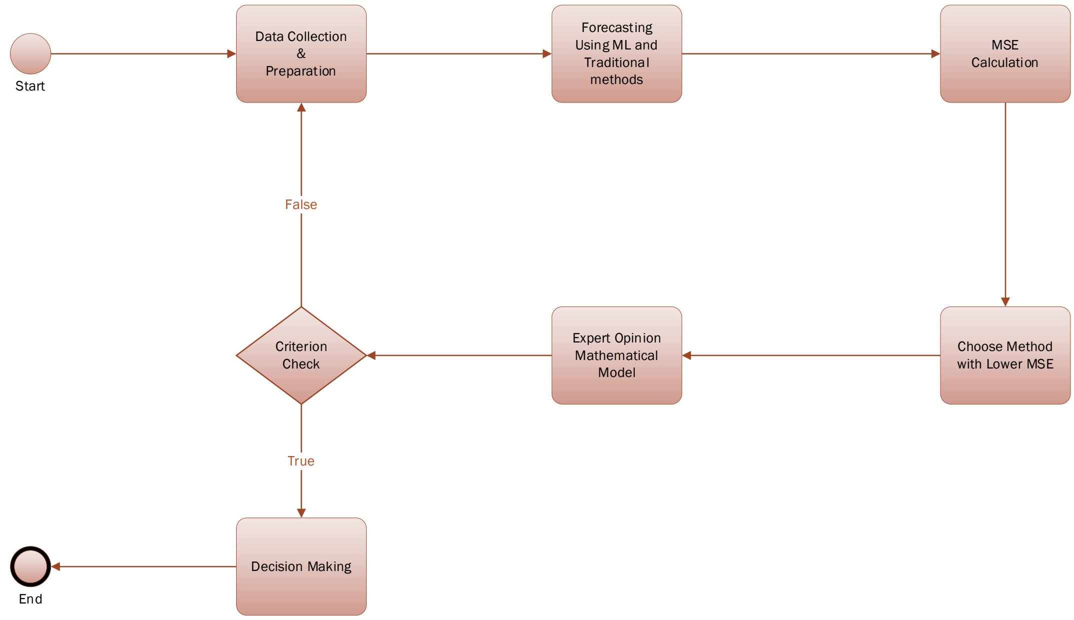

Figure 2: Decision-Making Process

3.1 Mathematical Model

The establishment of two demand management values is based on environmental feedback, seasonal changes in demand due to conditions, and the growth and decline in demands, as determined by an expert or manager. The first value is the constant value of *fce*. This value states that on average each unit of difference between the actual amount and the predicted amount will cost the organization. In other words, if the expected amount is greater than what we have, we will be responsible for the expenses of perishable goods and their storage, while a smaller amount means that we are responsible for fulfilling its demand. Given e(t) as the second constant, what is the maximum difference between the actual quantity and the projected amount within period t? This number signifies the orders placed during this period to store, store ,or cover more than anticipated.$y(t)$: the actual amount of demand in period t.

$yp(t)$: the predicted amount of demand for period t

T: Number of periods

fce: The amount of fixed cost that the expert considers per unit of difference between actual and predicted demand (lost sales, storage, perishable materials, etc.).

$e(t)$: The maximum amount of difference between forecast and actual allowed for the period t, which is determined by the expert (or management). It means the amount of predicted capacity to control fluctuations and differences.

$$Min \sum_{t=1}^{T} |y(t) - yp(t)| * fce$$

$$st:$$

$$|y(t) - yp(t)| < e(t)$$

$$y(t), yp(t), e(t) > 0$$

$$T > 0, Int$$

If the criterion is not established in a period, we can imagine two main situations:

1. The initial phase refers to a phase in which the target value is affected by one or more factors, either decreasing or increasing.
2. Another case is the case where some features or characteristics are not considered in the data set but influence the target value. for example, environmental or financial indicators that may have influenced the target value.

The two situations are characterized by the expert knowing the factors and parameters that impact the demand, as well as having determined the constant values.

This model's advantage lies in its ability to predict events using data and demand methods, as well as expert guidance and monitoring that can reduce supply chain error costs. The model minimizes the costs of shortages or corruption of surplus materials by adjusting for both actual demand and predicted adjustment limits. Additionally, this model takes into account these factors.

4. Experimental Results

In this section, four machine learning algorithms including Linear Regression, Support Vector Regressor (SVR), Random Forest and Multi-Layer Perceptron (MLP), and also four traditional forecasting methods including Moving Average (MA), Auto Regression (AR), Auto Regressive Integrated Moving Average (ARIMA) and Simple Exponential Smoothing (SES) has applied on the experimental dataset.

The dataset is associated with one of the biggest retail chain SKUs and contains weekly sales data from 2011 to 2013. The target is to predict sold units for each record using time data, the total price for the customer, and the base price for the retailer, which is featured in SKU, and displayed in SKU. A brief statistical analysis is brought in Table 1. The Density of sold units, the relationship between sold units and total price, and the relationship between sold units and base price and sold units over time can be seen in Figures 3, 4, and 5.

	Total_price	base_price	units_sold
count	130	130	130
mean	126.16	129.92	29.11
std	7.99	6.58	11.39
min	112.57	114	2
25%	118.27	130.39	21
50%	131.81	133.24	28
75%	133.77	133.95	37.75
max	136.08	136.09	63

Table 1: Brief statistical analysis of dataset

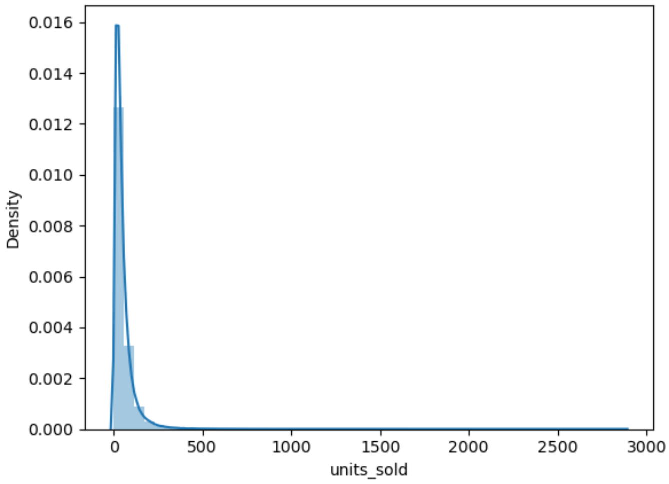

Figure 3: Sold Units Density

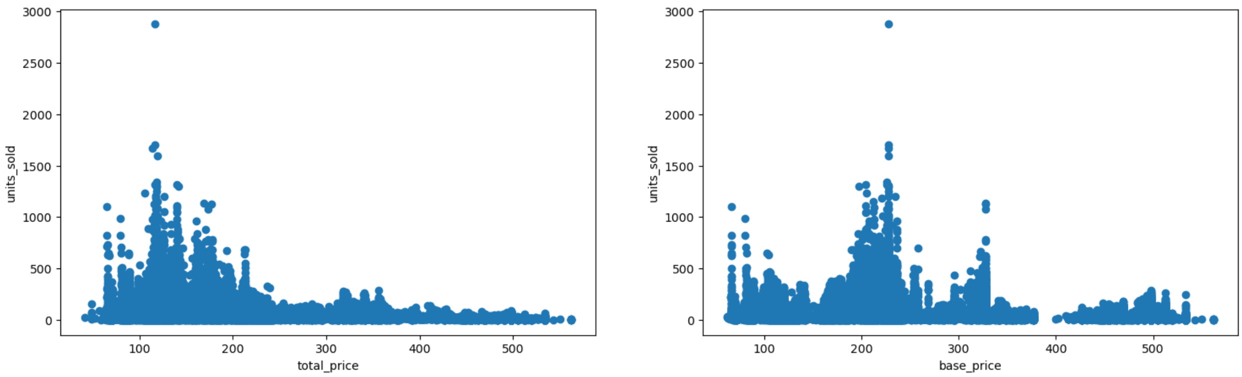

Figure 4: sold units vs. base price and total price

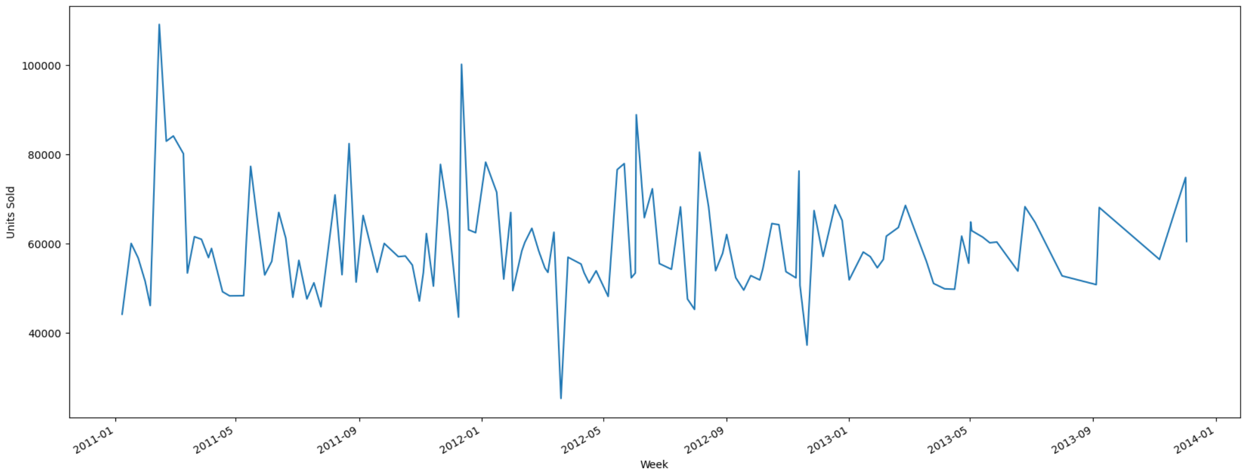

Figure 5: Sold Units Over Time

To evaluate our forecasting model, we used Mean Squared Error as below:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$$

In which n equals to number of data points, Y_i is the observed value and $\hat{Y}_i$ is the predicted value. Also, the Fill Rate (FR) is calculated as below:

$$FR = \frac{Total\ Demand\ Fulfilled}{Total\ Demand} * 100$$

that we have considered the filled demand equal to the predicted demand and the total demand equal to the actual demand in a given period. Results are according to table.2.

	Algorithm	MSE	FR
Machine Learning	Linear Regression	85	106.00%
	Support Vector Regreesor	93.37	118.00%
	Random Forest	90.62	119.00%
	Multi-Layer Perceptron	138.25	131.00%
Traditional	Moving Average	80.2	99.00%
	AR	10.54	88.00%
	ARIMA	139.76	84.00%
	SES	33.07	107.00%

Table 2: Comparative Results

As illustrated in Table 2, the MSE of traditional methods of AR and machine learning algorithms is the lowest among all approaches, but the FR of AR is not precise enough, so the next SES has the correct corresponding FS except for the low one. MSE. and it does not lead to unsatisfied demand or a decrease in demand. Then we apply them to our mathematical model to decide the next demand and potential units to sell. If the expert claims that e(t) equals 10 and fce equals 5$, so the Linear Regression method is discarded because the constraint according to the values determined by the expert is not true, in the other hand, we can use SES because it has the condition and total cost in this situation will be about 2$.

5. Conclusion

Defining demand in the supply chain is crucial to avoid the bullwhip effect, as it generates significant disparities between actual demand and predicted demand. Furthermore, superior prediction precision leads to increased revenues (revenues), improved product design, reduced costs caused by waste and pollution, etc. Managers are frequently weighed down by the need to accurately predict demand in today's competitive market environment. The purpose of this research is to provide a process for better supply chain demand forecasting. The accuracy of forecasts is enhanced by the use of experts' opinions, which are only obtained from experienced sources and through experience and consideration of the environmental factors and it improves prognosis. The purpose of this model is to reduce the cost of the organization due to accurate forecasting. Costs such as maintenance, deterioration of perishable materials, insufficient supplies, and reduced demand are included. In the initial phase of our experimentation, we incorporated machine learning techniques such as linear regression patterns, support vector regression methods, random forests, and multilayer perceptron along with conventional forecasting methods like the moving average, time series method, and simple exponential smoothing. then we calculated the MSE and chose the method with the smallest MSE. There are two limitations to this model, which are cost and maximum allowable error. The application of these limits results in making a decision, while alternative parameters that impact demand are evaluated. However, the data is not always reliable. However, the limitation of the present study is that we have considered only a few price-related parameters while demand may depend on other parameters such as holidays, weekends, weather, etc. The addition of these parameters, in addition to increasing the quality of the study, also creates complexity and machine learning algorithms can provide better predictions in the presence of these parameters and these conditions. Future works can be based on the development of more complex mathematical models that consider more factors. Also, expert review in a specific field and consequently the use of specific parameters can influence the decision-making model. Moreover, examining other artificial intelligence algorithms or using hybrid algorithms to predict demand before entering the mathematical model can be very attractive for development.

Data Availability

Data will be available on request.

Conflict of Interests

The Author declare no conflict of interest.

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