A Hybrid Demand Forecasting for Intermittent Demand Patterns using Machine Learning Techniques

Praveena S
Department of Computer Science and Engineering
SRM Institute of Science and Technology
Chennai, India
ps4851@srmist.edu.in

Prasanna Devi S
Department of Computer Science and Engineering
SRM Institute of Science and Technology
Chennai, India
hod.cse.vdp@srmist.edu.in

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***Abstract*—Intermittent demand forecasting is a major obstacle to the digital supply chain revolution and accurate demand forecasting (DF) enhances the overall productivity of enterprises and minimizes expenditures. Random and low-volume demand is referred to as intermittent demand. It appears erratically between demand periods, with a high percentage of zero values. Companies managing complex inventory systems face difficulties due to intermittent demand's unexpected nature, which results in expenses associated with excess inventory or stockouts. This research aims to present an integrated forecasting strategy for intermittent demand problems using Long Short-Term Memory (LSTM) and parametric methods to assist new range of management decisions as a vital element of intelligent supply chain. This can be achieved by two biggest e- commerce companies' dataset and the results showed that hybrid forecasting framework results are more accurately than traditional forecasting techniques. The hybrid Intermittent forecasting can be used as an alternate technique for anticipating intermittent demand since its ease of computing of forecasting results accurately than the classical forecasting methods.**

Keywords— Intermittent Demand, Demand Forecasting, Machine Learning, LSTM, Time series, Traditional Forecasting.

I. INTRODUCTION

Demand forecasting is an essential component of any business or supply chain. It aims to forecast and predicting future product demand to facilitate in improved decision-making. One of the primary reasons for using demand forecasting in operations management is to improve supply chain efficiency, Maintain Adequate Cash Flow, Enhance Labor Management, Make an Accurate Budget. Demand planning establishes the basis for supply chain management for product distribution and replenishment. Based on stability and uncertainty, Demand patterns can be ccategorized as intermittent, lumpy, smooth, and erratic [2]. DF is based on data using time series analysis and accurate forecasting can be done by ad-hoc forecasting methods and Model based forecasting methods. A product has many periods of zero demand, which is known as intermittent demand (sometimes referred to as sporadic demand). When demand does arise in these circumstances, it frequently has a tiny and occasionally very unpredictable size. Intermittent demand patterns are common phenomenon in spare sparts, automotive industries SKUs, and in the defence and aaviation industries.

It can be difficult to predict intermittent demand. The complexity of forecasting demand arises by two factors. The first is that the real demand is inconsistent, and the second is that the demand timespan is unpredictable [3]. Therefore, it is necessary to forecast demand in terms of both amount and frequency. Numerous Techniques for predicting sporadic demand have been developed, such as Croston (CR) method [4], Adjusted Croston methods [2], Bootstrapping technique [5], Aggregate- disaggregate intermittent demand approach (ADIDA) [6]. The exhaustive research will be needed for forecasting of intermittent demand in retail sector.

This system will employ robust forecasting techniques to deal with a wide range of products and their intrinsic demand patterns., as well as forecast demand for products that are new and for which there is no prior demand data. Consequently, the following features of the new forecasting technique are suggested: (1) Predict the product demand at store level in a weekly and monthly basis, (2) to take care of sporadic demand for goods that are slow moving and predict the possibility of obsolescence and (3) estimating the new product with its future demand without knowledge of past demand.

II. BACKGROUND AND LITERATURE REVIEW

A. Demand Pattern Categorization

According to a number of experts, selecting an appropriate forecasting approach can be facilitated by a precise classification of the demand. Nikolopoulos, K. (2021) [3] modelling fast-moving time series has received a lot of attention, whereas intermittent time series and intermittent demand forecasting have received far less. Croston [4] proposed exponential smoothing method for forecasts in stock control system. The results provided that irregular demand always results in inadequate stock levels. The Croston's method was biased sometimes so that, by comparing sporadic demand dataset from the auto market with conventional techniques, Syntetos and Boylan et al. (2005) [7] found that the new method is more efficient altogether. The four varieties of demand are periodic occurrence and low variation in volume (smooth), periodic occurrence and high variation in volume (erratic), non-periodic occurrence and low variation in volume (intermittent), and non-periodic occurrence and high variation in volume (lumpy). One of the most difficult demand forecasting issues is the prediction of intermittent and lumpy demand.

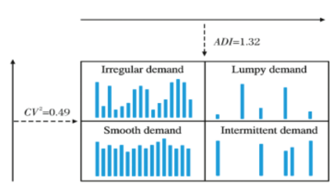

Fig. 1. Syntetos Boylan Croston (SBC) Demand Pattern Classification

B. Intermittent Demand Forecasting

To deal with obsolescence issues and to forecast intermittent demand, the new method proposed by Teunter, R et. al (2011) [9] smoothes exponentially the demand probability and size after each positive demand period. The existing approaches for forecasting intermittent demand are compiled as follows. Hong et al. [10] explored machine learning vs Croston's method to predict intermittent demand. Neural network (NN), Quarntile-Random-Forest (QRF), and Gradient-Boosting-Machines (GBM) were trained and tested by three different single-stage model sets respectively. Aggregated Single stage model was hard managing several models for various goods might be challenging and also building a model that can fit the all-time series provided as soon as in aggregate because training and managing several models for various items takes a lot of time. Moreover, in the meta-Model, the classification taken in the 1st stage using NN, Logit, RF, and its performance were assessed and optimized on ROC curves. Prediction output was fed into 2nd stage meta-model to predict temporal demand. They investigated and concluded that no assurance combining the highest-performing model with the second-stage models would produce the best outcomes. There is a lack of meeting unexpected demand arising from some business scenarios and therefore, Future research might examine how to improve the forecast by better capturing the irregular variations. On the contrary, the intermittent demand in industrial retail has received less attention. The SKU types are increasingly varied and customer needs are becoming more refined, intermittent demand may become more prevalent in today's retail market. Tian et al. [11] proposed a forecasting method with the Markov-Combined Method which incorporates inventory data. The efficiency of MCM is investigated in this study through three accuracy measures by datasets from JD and Alibaba, and its performance is compared using three benchmark models. MCM may increase the reliability of intermittent demand product forecasts, lowering inventory management expenses and enhancing business profits. According to this study, businesses need to take inventory data into account when predicting sales. The previous research primarily depends on the properties of time series and does not take into account the characteristics of demand occurrence. Zhuang et al. [12] proposed a two-level framework for predicting sporadic demand patterns from an ML aspect. The intermittent-demand-forecasting problem was broadly categorized into two, initially it addresses the prediction of demand's existence and later its quantity of demand. These methodologies used in this study were assessed and validated across a number of aspects using real data from the auto after-sales industry. Two forecasting methods (BTIDCF and TBIDCF) were employed to make more accuracy of spare part predictions.

C. Metrics for intermittent demand forecasting

To determine a model's strengths and flaws after training, we must employ evaluation measures. Measurement of intermittent series is challenging. Typically, typical forecast accuracy measurements do not apply to such issues. So, Hydman et al. [13] provided a number of evaluation measures for regression prediction that correspond to these sequences. Scaler dependent metric is calculated by $e_t = Y_t - F_t$ indicates that the variation among the forecasted value and the actual-value, where the forecasted-value is F_t and the actual-value obtained is Y_t.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - F_i)^2 \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - F_i| \tag{2}$$

The main drawback of the approaches is that they are reliant on magnitude values and it is impractical to calculate the comparison of time series with magnitudes that are different. Additionally, the MAE makes a difficult-to-implement prediction containing a series with intermittency that is high will consist of a value of zero at every stage if it is used as a loss function. The Mean Absolute Scaled Error (MASE) is the most widely used assessment indicator for this type of analysis. The Naive forecasting method, which uses the recent past actual sales as the basis for tomorrow's demand, can be seen as the denominator. MASE is seen to be the best option meant for sporadic prediction evaluation metrics as it is not concerned with the denominator being 0 or being infinite until the historical demand is equal in all circumstances. The equation is given below:

$$MASE = \frac{1}{n}\sum_{i=1}^{n}\frac{|Y_i - F_i|}{\frac{1}{n-1}\sum_{i=2}^{n}|Y_i - Y_{i-1}|} \tag{3}$$

The common measurement in many forecasting studies employs the measure of MAPE (Mean Absolute Percentage Error). However, when demand is sporadic, Y_t is frequently equal to zero, and interpreting MAPE will be inappropriate. MAAPE (Mean Arctan Absolute Percentage Error) is based on MAPE and has more symmetric for overstock and understock penalties. The Eqs. are shown below

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}p_t \tag{4}$$

$$MAAPE = \frac{1}{n}\sum_{i=1}^{n}\arctan(p_t) \tag{5}$$

III. Methodology

To address the lack of downstream information and the occurrence of intermittent demand for electronic goods, we developed a hybrid framework for intermittent demand forecasting for products in the E-Commerce field of the supply chain, which is depicted in Fig.2. Long Short-term Memory (LSTM) and SBA (Syntetos Boylan Approximation) are used in the forecasting technique construction stage based on artificial intelligence and time-series models for intermittent-demand forecasting. Then, to categorize products according to demand features, we employ RFQV (Recency, Frequency, Quantity, and Variance analysis). It is based on the RFM (Recency, Frequency, and Monetary Value) model [12]. Each product is divided into a single subset, which is subject to change as time passes. Three accuracy metrics are lastly carried out for result interpretation and analysis.

A. *Problem definition for intermittent demand forecasting (IDF)*

The two largest Chinese e-commerce giants, JD and Alibaba, provided two of the datasets that were used. Inventory data of Alibaba is available from January 1, 2020, through July 1, 2021, whereas the inventory data from JD's can be obtained from 1st January 2021 until 31st December 2021. JD and Alibaba datasets, respectively, each contains 6890 and 7845 entries from various categories and time spans. To avoid the influence of promotional activities, JD's statistics between June and November was omitted. Four patterns of demand can be identified: erratic, smooth, lumpy and intermittent. The coefficient of variations (CV) and average demand interval are the indicators used to classify items (ADI). Building a demand forecasting mechanism that is reliable for all the products with different features is currently difficult because no existing model can manage the range of product demand features.

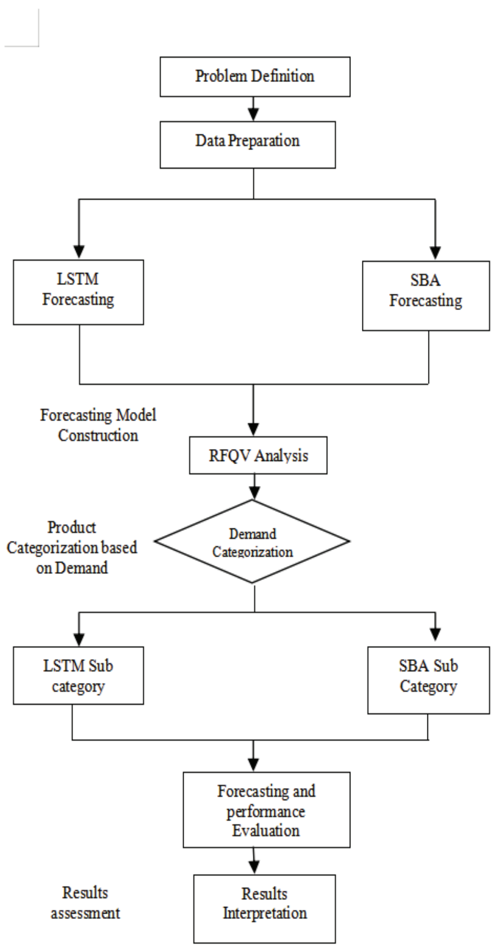

Fig. 2. Hybrid Demand Forecasting Framework

B. *Hybrid Intermittent Demand Forecasting Model Construction*

In our approach, two original forecasting models were employed during the building of the forecasting model. For anticipating time series demand, the first method is Recurrent Neural Network (RNN). And the other classic Technique for parametric time series method is Syntetos-Boylan Approximation (SBA).

Data: $z= [z_1, z_2 .... z_N]^T$: demand time series of a given retailer;
H: the forecasting horizon:
Product ID: the ID of the product variant;
M= (LSTM, SBA) the considered models for hybrid forecasting framework
Result: $X= [y_1, y_2, y_3 .... yh]^T$ forecasts vector (h-step ahead forecasts)
1.Subset the dataset corresponding to the product variant.
Y=subset (product ID):
2. Pre-process Y. pre-processed demand series can be obtained by the fitted model based on the specific model
3. Divide the dataset Y into a pair of training and validation subsets Y_{train} and $Y_{validation}$, respectively as follows:
$Y_{train} = [y_1, y_2, y_3 .... yh]^T$
$Y_{validation} = [y_{\alpha+1}, y_{\alpha+2}, y_{\alpha+3} .... y_{\alpha+h}]^T$
Such as $_\alpha$ is the training set size and h is the testing set size ($\alpha+h = N$) ;
4. Train SBA and LSTM on $Y_{train;}$
5. Train each model M_i(i=1,2,3) on $Y_{train;}$ and generate the h-step ahead forecast for each one of them ($Y\ Mi= [y_{1'}, y_{2'}, y_{3'} .... Yh']\ Mi)^T$
6. Perform product value analysis using RFQV (recency, frequency, quantity and co-efficient of variation).
7. Separate the demand patterns of products using decision tree classification.
8. customize the both forecasting techniques SBA and LSTM with RFQV features.
9. Measure the MAE of SBA model using $Y_{validation}$
10. Measure the MAE of LSTM model using $Y_{validation.}$
11. Return SBA and LSTM forecasts
$X= [y_{1'}, y_{2'}, y_{3'} .... Yh']^T{}_{SBA}$
$X= [y_{1'}, y_{2'}, y_{3'} .... Yh']^T{}_{LSTM}$

Fig. 3. Hybrid Demand Forecasting Pseudo-Algorithm

C. *Product Demand Categorization*

It is essential to choose the proper demand characteristics from the historical sales recording dataset for the demand categorization of E-Commerce products. Recency and frequency are advantageous for inventory managers in the measurement of product value, although quantity is more significant than revenue in the E-Commerce business due to cheap unit prices. It is observed that the given coefficient of demand variation and the inter-demand interval are often used in the categorization of parts (spare), we adapt RFM to recency, frequency, quantity, and coefficient of variation (RFQV) for analyzing and evaluating future possible product demand. [7]. By using a decision tree classification with RFQV characteristics, we divided the products according to demand patterns. The accuracy obtained individually between SBA and LSTM, respectively, is the response aim for demand pattern categorization. SBA and LSTM in RFQV features were used to modify the forecasting techniques to meet the two categories. As a result, various product types are integrated with the appropriate forecasting technique and is combined as a hybrid-forecasting framework (HFF) using more than two models.

IV. Results and Discussion

Three distinct accuracy metrics were utilized to evaluate and understand the demand forecasting model: MSE (Mean Square Error); AE (Absolute Error), and MASE (Mean Absolute Scaled Error). The standard metric for demand prediction accuracy is called RMSE (root mean square error), which calculates the Mean of the squares of the errors or deviations. Since RMSE increases the calculation error at the absurd level, we use mean absolute error (MAE), which is generally a value that occurs from robust to extreme, to help with the balancing of the performance. We compared the forecasting outcomes using the suggested model's hybrid of LSTM and SBA.

To prevent overfitting, we provide data-driven adaptive parameter choices for those models' constants. In Table 1, the performance comparison for the various approaches on the testing period dataset is shown using three predicting accuracy measures on average. The findings demonstrate that the suggested hybrid technique outperforms LSTM in each of the three accuracy criteria while requiring significantly less processing time. As a result, product demand pattern categorization can increase current prediction accuracy while limiting computation costs.

TABLE I. SALES FEATURES OF ONLINE RETAILERS (JD AND ALIBABA)

	ALIBABA	*JD*
Data Features		
No.series	964	4130
Mean obs/series	110.269	152.341
% zero values		
Mean	0.469	0.835
S.D	0.105	0.115
Maximum	0.98	0.995
Minimum	0.548	0.652
Average of non zero demand		
Mean	1.556	1.394
S.D	0.913	0.617
Maximum	48.5	510.000
Minimum	1	1
CV of non zero demand		
Mean	1.556	1.394
S.D	0.913	0.617
Maximum	48.5	510.000
Minimum	1	1
ADI		
Mean	7.52	21.86
S.D	15.54	35.84
Maximum	174	212
Minimum	1.34	1.356

NOTE: ADI (AVERAGE DEMAND INTERVAL), CV (THE COEFFICIENT OF VARIATION); S.D (STANDARD DEVIATION)

TABLE II. PERFORMANCE FOR ROLLING FORECASTING – JD AND ALIBABA DATASET

	MAE	*RMSE*	*SMAPE*	***PROPOSED METHOD (% ENHANCEMENT)***		
				MAE	***RMSE***	***SMAPE***
Forecast Horizon =1 (observation= 927*1*7)						
SES	0.474	0.598	1.823	30.802	-2.508	77.619
	(0.565)	(0.713)	(0.204)			
Croston	0.491	0.610	1.1816	33.198	-0.462	77.533
	(0.569)	(0.679)	(0.206)			
SBA	0.495	0.617	1.800	33.737	0.648	77.333
	(0.469)	(0.620)	(0.268)			
proposed	0.328	0.613	0.408			
	(0.560)	**(0.880)**	**(0.362)**			
Forecast Horizon =3 (observation = 927*3*7)						
SES	0.476	0.576	1.925	29.25	-2.507	74.514
	(0.574)	(0.724)	(0.314)			
Croston	0.491	0.615	1.191	33.17	-0.562	75.533
	(0.746)	(0.564)	(0.216)			
SBA	0.598	0.516	1.812	34.312	0.548	76.333
	(0.569)	(0.620)	(0.518)			
proposed	0.328	0.494	0.408			
	(0.545)	**(0.875)**	**(0.352)**			
Forecast Horizon =5 (observation= 927*5*7)						
SES	0.464	0.589	1.723	30.801	-3.5	77.51
	(0.545)	(0.613)	(0.224)			
Croston	0.491	0.610	1.1816	33.298	-0.462	77.533
	(0.469)	(0.679)	(0.206)			
SBA	0.485	0.517	1.810	34.737	0.548	74.333
	(0.568)	(0.520)	(0.268)			
proposed	0.318	0.513	0.508			
	(0.460)	**(0.980)**	**(0.462)**			
Forecast Horizon =7 (observation = 927*7*7)						
SES	0.464	0.498	1.923	30.802	-2.518	75.619
	(0.555)	(0.613)	(0.104)			
Croston	0.491	0.610	1.1816	33.198	-0.462	77.533
	(0.569)	(0.679)	(0.206)			
SBA	0.495	0.617	1.800	33.737	0.648	77.333
	(0.469)	(0.620)	(0.268)			
proposed	0.328	0.613	0.408			
	(0.560)	**(0.990)**	**(0.460)**			

NOTE: OBSERVATIONS= ITEM NUMBER * FORECASTING HORIZON(S) * ROLLING ROUNDS.

V. CONCLUSION

To facilitate flexible decisions in inventory management, which is a crucial component of an intelligent supply chain, a hybrid forecasting strategy using Long Short-Term Memory (LSTM) and a time series method is proposed in this paper.

Based on the findings of an empirical investigation, it is possible to manage demand for E-Commerce platform products more accurately by using the hybrid forecasting approach that includes product categorization. This study is also an example of how artificial intelligence can be used in conjunction with traditional models to make decisions. In some cases, this strategy can be even more effective than using AI alone. Future research may alter the forecasting technique to better account for different scenarios (such as those with enough or inadequate historical data) or may substitute new ensemble operators for categorization at the combining prediction stage.

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