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Impact of Promotion on FMCG

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Abstract- Due to rapid changes in demands from customers, particularly in Fast Moving Consumer Goods (FMCG) segment, it becomes essential that methods for the forecasting chosen for predicting demands should have acceptable level of accuracy. Accurate forecasting in FMCG, turns out to be more tough, when the businesses use promotional activities in form of discounting, price reductions, providing s with purchase of specified number of units on selective week days on selective items. This paper studies the effect of promotions on FMCG. It compares a promotional enabled forecasting with the existing forecasting techniques on a real life FMCG data. The findings of the study reveal that the LSTM-based model significantly improves forecasting accuracy compared to the SES method. Specifically, the Mean Square Error (MSE) is reduced by approximately 94%, while the Mean Absolute Deviation (MAD) decreases by nearly 74%, indicating the model's strong capability in capturing complex demand patterns and reducing forecasting errors.

Keywords– Promotion, FMCG, Forecasting, Accuracy.

1. INTRODUCTION

The FMCG market experiences demand fluctuations, which increases when companies use promotional activities. The role of appropriate selection of forecasting technique becomes highly significant in promotional scenarios, for proper planning of inventories, correct scheduling and proper distribution decisions. Small errors in forecasting can also leads to notable losses due to inventory understocking or overstocking.

The use of promotions benefit organisations in short term by improving sales or market penteration, but leads to increase in demand variability and changes the patterns of demand that earlier easily captured with the past data. As majority of the existing and traditional methods of forecasting are based on assumption that both trend as well as seasonality remains stable, while considering promotional demand as random noise. It leads to underforecasting during promotion days and overforecasting during regular days.

2. LITERATURE REVIEW

The literature shows that FMCG segment holds 71% share of total retail sales in India. Consumer literature indicates that fast-moving consumer goods account for approximately 71% of all retail sales in India [1]. In FMCG market around 65% consumers resides in rural areas, which accounts for nearly 50% of daily expenses on FMCG [2]. It has been observed that 50% sales in FMCG comes from personal care and household items [3].

Pervasive use of promotional activities for influencing demand and efforts to mitigate bullwhip effect has found in the works of [4], [5] and [6]. In spite of important contributions on promotional activities, recent studies still shows a significant research gap on majority of organisations, small scale and micro small scale industries inability to correctly determine the promotion impact on management of inventories [6].

Prominent studies [6], [7], [8] and [9] suggests to incorporate promotional campaigns which cause in the time series forecasting models to avoid stockouts and minimise overstocking of inventories.

The ignorance of post promotional phase by traditional forecasters, leads to overstocking, when demand generally reduces, that requires new and advanced forecasting approaches based on artificial intelligence (AI) and machine learning (ML) [10].

AI and ML based forecasting methods anticipated demand fluctuations, better in retail industry than existing quantitative (time series) forecasting models [11].

As per the studies [12], the industries are second largest contributor of GDP in India after agriculture (Fig. 1). The literature [13, 14] shows that FMCG contribues nearly 3% of India's GDP (Fig. 2).

The Figure 1 shows the sector wise contributor of India's GDP. The Figure 2 highlights industry wise GDP contibution.

3. TRADITIONAL FORECASTING

Existing forecasting techniques are usually the quantitaive methods, i.e., Time Series forecasting models where the methods of exponential smoothing, Holts Winter model generally used, along with naïve method as per the requirement. In addition to it, three period and four period averaging methods and in some scenarios use of weighted method of averaging is recommended.

Time series quantitative method of ARIMA have capability to create forecasts considering moving average and as well as the autocorrelation [15-17].

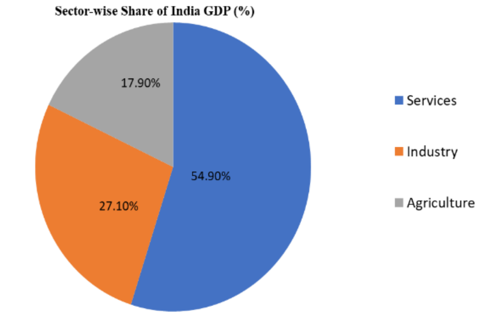

Figure 1: Sector wise India GDP

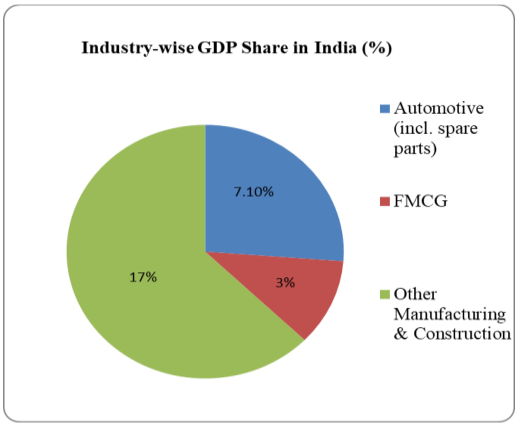

Figure 2: Industry wise GDP share in India

The selection of most suitable forecasting method among various quantitative techniques is made by comparing error. The prominent error checking methods are mean square error (MSE), mean absolute percentage error (MAPE), mean absolute deviation (MAD). Besides this, bias and tracking signal are also used for error determination.

The existing qualitative (time series) forecasting models can capture trend and seasonaity, but fails to predict promotional demand accurately.

4. MACHINE LEARNING TECHNIQUES FOR FORECASTING

Machine learning (ML) usually preferred where requirement for more accurate and precise forecast has to be prepared and as well as degree of difficulty increases. ML techniques generally used for making predictions, particularly in FMCG products are Long-Short Term Memory (LSTM), Random Forest, Neural Network, XGBoost and Extra Tree Regressors [18-21]. Non linearity can be easily addressed through ML techniques. In addition to it ML techniques are capable to compute variance in demand because of promotion activities for example price discounting, seasonality, in contrast to existing forecasting techniques, for example Time Series.

LSTM a Deep learning (DL) model, formulated using recurrent neural network (RNN) records a better accuracy over existing time series models. It has been found that demand in which the promotional component is present, is very easily computed through LSTM. The choice of the LSTM-based model is based on its ability to understand patterns in data that change over time. In FMCG demand forecasting, sales are not constant and are affected by factors such as seasonal trends, consumer behaviour, and promotional activities. LSTM is designed to remember past information for a longer period, which helps in identifying these patterns more effectively than traditional methods.

Unlike simpler forecasting techniques that depend mainly on recent values, LSTM can adjust to sudden changes and variations in demand. This makes it more suitable for real-world situations where data is not stable or linear [22,23]. Previous research has also shown that LSTM models generally provide better accuracy in time-based predictions. Hence, its use in this study is appropriate for capturing complex demand behaviour and improving forecasting results.

5. METHODOLOGY

The real time data gathered from a fruit retail shop in Jaipur. Data of demand occurs at the shop is recorded for the four weeks. The predicting techniques adopted are (i) existing time series technique, i.e., simple exponential technique (SES) and (ii) LSTM Neural Network approach. The objective of the study has now been clearly stated. It mainly focuses on improving forecasting accuracy by comparing different models, while also considering how promotional activities influence demand patterns.

5.1 Mathematical Formulation of Simple Exponential Smoothing (SES)

$$S_t = \alpha\, y_t + (1 - \alpha)\, S_{t-1}, \quad 0 < \alpha < 1 \qquad (5.1)$$

One step ahead forecast:

$$\hat{y}_{t+1} = S_t \qquad (5.2)$$

Multi step ahead forecast:

$$\hat{y}_{t+h} = S_t, \quad h = 1, 2, \dots, H \qquad (5.3)$$

Where:

y_t = actual demand at time t

S_t = smoothed level at time t

α = smoothing parameter (0 to1)

5.2 Mathematical Formulation of Long-Short Term Memory (LSTM)

Input Feature Vector:

$$x_t = [y_t, \mathrm{Weekend}_t, \mathrm{Promo}_t, \mathrm{DOW}_t] \qquad (5.2.1)$$

Forget Gate:

$$f_t = \sigma(Wf\,[h_{t-1}, x_t] + bf) \qquad (5.2.2)$$

Input Gate:

$$i_t = \sigma(Wi\,[h_{t-1}, x_t] + bi) \qquad (5.2.3)$$

Candidate Cell State:

$$\hat{C}_t = \tanh(Wc\,[h_{t-1}, x_t] + bc) \qquad (5.2.4)$$

Cell State Update:

$$C_t = f_t \odot C_{t-1} + i_t \odot \hat{C}_t \qquad (5.2.5)$$

Output Gate:

$$o_t = \sigma(Wo\,[h_{t-1}, x_t] + bo) \qquad (5.2.6)$$

Hidden State:

$$h_t = o_t \odot \tanh(C_t) \qquad (5.2.7)$$

Multi-Step Forecast (7-Day Horizon)

$$\hat{y}_{t+1:t+7} = Wy\, h_t + by \qquad (5.2.8)$$

Table 5.1 : Fruit Retail Shop Data at Jaipur

1	Date	Day	Commodity	Promotion	Promotion Type	Discount in %	MRP Rs. Per kg	Price Rs. per kg	Demand in kg
2	08-12-25	Mon	Banana	No	No Promotion	0	60	60	73.47
3	08-12-25	Mon	Apple	No	No Promotion	0	180	180	52.45
4	08-12-25	Mon	Orange	No	No Promotion	0	100	100	41.81
5	08-12-25	Mon	Grapes	No	No Promotion	0	140	140	41.71
6	08-12-25	Mon	Papaya	No	No Promotion	0	50	50	36.4
7	09-12-25	Tue	Banana	No	No Promotion	0	60	60	83.37
8	09-12-25	Tue	Apple	No	No Promotion	0	180	180	53.94
9	09-12-25	Tue	Orange	No	No Promotion	0	100	100	47.86
10	09-12-25	Tue	Grapes	No	No Promotion	0	140	140	34.94
11	09-12-25	Tue	Papaya	No	No Promotion	0	50	50	38.33
12	10-12-25	Wed	Banana	No	No Promotion	0	60	60	71.86
13	10-12-25	Wed	Apple	No	No Promotion	0	180	180	57.83
14	10-12-25	Wed	Orange	No	No Promotion	0	100	100	42.06
15	10-12-25	Wed	Grapes	Yes	Bundle Offer	14	140	120.4	40.5
16	10-12-25	Wed	Papaya	No	No Promotion	0	50	50	42.33
17	11-12-25	Thu	Banana	No	No Promotion	0	60	60	73.24
18	–	–	–	–	–	–	–	–	–
19	28-02-26	Sat	Banana	Yes	Weekend Price-Off	9	60	54.6	175.36
20	28-02-26	Sat	Apple	Yes	Festival Discount + Display	14	180	154.8	130.84
21	28-02-26	Sat	Orange	Yes	Festival Discount + Display	13	100	87	125.3
22	28-02-26	Sat	Grapes	No	No Promotion	0	140	140	68.13
23	28-02-26	Sat	Papaya	No	No Promotion	0	50	50	77.6
24	01-03-26	Sun	Banana	No	No Promotion	0	60	60	100.2
25	01-03-26	Sun	Apple	No	No Promotion	0	180	180	69.42
26	01-03-26	Sun	Orange	No	No Promotion	0	100	100	53.04
27	01-03-26	Sun	Grapes	No	No Promotion	0	140	140	48.59
28	01-03-26	Sun	Papaya	No	No Promotion	0	50	50	53.46

6. RESULT AND DISCUSSIONS

The forecasting techniques SEA and LSTM shows on using LSTM error of Mean Square Error (MSE) is reduced nearly by 94% on using LSTM in comparison to SES. Similarly, error of Mean Absolute Deviation (MAD) lowers down nearly by 74 % on choosing LSTM over SES. The results of error metrics are presented in Table 6.1.

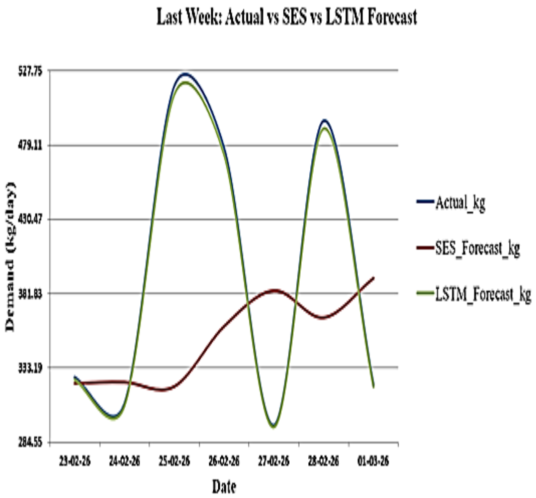

Fig 6.1: Comparison of SES and LSTM

The Figure 6.1 depicts that the ML based LSTM Neural Network approach outperforms the traditional Simple Exponential Smoothing approach.

Table 6.1 : Comparison of Accuracy of Traditional SES and ML based LSTM Forecasting Techniques

Error	Simple Exponential Smoothing	LSTM
MSE	13158.60	705.60
MAD	80.91	21.06

6. CONCLUSIONS

The present study shows that the limitation of time series forecasting to predict demand accurately for FMCG items, when the demand contains combination of promotional and non promotional data. The study concludes that Machine Learning technique LSTM is more suitable for predicting rapidly changing FMCG demand which having both promotional and non promotional components. The study brings out useful practical insights for businesses by showing how better forecasting through LSTM can support more accurate planning of demand and inventory. With improved predictions, companies can avoid overstocking as well as shortages, which helps in reducing costs and improving customer satisfaction.

Promotional activities play an important role in shaping consumer behaviour, especially in markets where customers are exposed to multiple product choices. By drawing attention through discounts, coupons, and bundled offers, promotions make products more attractive and encourage quicker purchase decisions. These offers often create a feeling that the opportunity is limited, which pushes consumers toward impulse buying rather than planned purchasing [24].

In addition, promotions increase brand visibility and help consumers become more familiar with a product, sometimes leading them to try new brands or hybrid brands they might not have considered earlier. Over time, this can influence their perception and preference toward certain brands. However, if promotions are offered too frequently, consumers may begin to focus mainly on price rather than product quality or brand value. As a result, they may switch brands easily depending on the best available deal, which can weaken long-term customer loyalty.

The use of a four-week dataset is recognized as a limitation of the present study. In future work, a longer time period of data will be considered to enable better training of the LSTM model and to provide more reliable and stable forecasting results.

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