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Prediction and Judgmental Adjustments of Supply-Chain Planning in Festive Season

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Prediction and Judgmental Adjustments of Supply-Chain Planning in Festive Season

Megha Chhabra [α], Deepti Sahu [σ] & Gunjan Agarwal [ρ]

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I. Introduction

Supply-chain holds a huge planning propaganda as a baseline to project sales and revenue generation based on it. Specially a case of modern era, where the comfort to customer can help an organization to retain the customer and thereby increase more sales and generate more business of the products. In addition to it, the planned resource production prediction helps generating less of the cost of production and more of the effort on quality productivity. Supply chain managements involve huge planning horizon for demand forecasting. For the purpose they use forecast systems for initial forecast followed by judgmental adjustment by the company experts to adjust exceptional events in the planning process. The manual adjustments made raise questions related to improvement of accuracy and type of adjustments made. Effective Short-term forecasting is important for improving supply chain management [26], irrespective of the type of business. Multiple applications of the prediction analysis and adjustment behavior in prediction accuracy can be seen in past few years [14]-[16], [18]-[20]. According to the literature of economic forecasting, accuracy of the statistical decisions can be improved when experts consider the changes in the statistical models according to the changes coming from occurrence of special events [1]-[8], [10], [11] and [22]-[23] showed that the suggested judgmental adjustments tend to improved accuracy marginally but may also introduce bias. Since it's a human added knowledge as a judgement factor, it is more likely to make error in level of adjustment and make room for error as experimental evidences suggest [24]-[26]. Forecasters make decisions on the basis of noisy and randomly fluctuating events in time series [9].

Several methods, techniques have been used in literature to forecast load demands. We used exponential smoothing technique and trend fitting for prediction.

This study presents effect of seasonal demand on prediction methodology of above mentioned models using reference data of handlooms business sector for predicting shipment load for four different Handlooms companies. The proposed methods are used to predict one month's demand. The outcome of both models is analyzed and accuracy is compared.

II. Time Series Models

A time series is sequential nature of data produced during a certain period of time. Assuming no major disrupting to critical parameters of a recurring event, the future prediction is always related to past data. Two time-series analysis models, namely, multiplicative decomposition and the smoothing technique use the dependency of future data to the past events, and model the behavior as follows:

a) *Smoothing Techniques*

Smoothing techniques are used to smoothen out random variations in the data due to irregular components of the time series. They provide a clearer and better view of data and it is easy to understand.

1) *Moving averages:* A moving average (MA) is an average of the data provided for certain number of time period. The method is called "moving" because it is obtained using summing and averaging the values from a given number of periods say n, each time deleting the oldest value and adding the new one. The moving average is calculated as:

$$MA_{t+1} = \sum_{i=1}^{n-1} \quad (1)$$

Where t= current period.

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D= actual data exchanged each period.
n = length of the time period.

2) *Weighted moving Average (WMA):* In MA each observation is given equal weightage, which in real situations is less likely to occur. It may be desired to place more weight on certain period of time than others. When certain inputs are weighted differently than others, the moving average outcome of those inputs is called weighted moving average(WMA). In this case, different values may be assigned to compute a weighted average of the most recent n values.Hence, Weighted Moving average is given as:

$$WMA_{t+1} = \sum(\text{Weight for period n})(\text{data value in period n})/\sum\text{Weights} \quad (2)$$

3) *Exponential smoothing Technique:* An exponentially weighted moving average is a means of smoothing random fluctuations that has the following desirable properties: (1) declining weight is put on older data, (2) it is extremely easy to compute, and (3) minimum data is required [18]. Exponential smoothing methods are widely used in industry. Their popularity is due to several practical considerations in short-range forecasting [21]. A type of MA forecasting technique which weighs past data from previous time periods with exponentially decreasing importance in the forecast so that the most recent data carries more weight in the moving average. For finding trend effect, adjusted exponential smoothing gives a better answer. Hence,

Trend adjusted forecast:

$$(F_t)_{adj} = F_t + (1-\beta)/\beta * T_t \quad (3)$$

For which; $F_t = F_{t-1} + \alpha(Y_{t-1} - F_{t-1})$, and Trend factor: $T_t = \beta (F_t - F_{t-1}) + (1-\beta)* T_{t-1}$
Where
$(F_t)_{adj}$ = trend-adjusted Forecast,
F_t = New forecast, F_{t-1} = Old forecast, Y_{t-1}= Observed data
α= Simple exponential smoothing factor
β = Smoothing constant for trend
T_t = exponentially smoothed trend factor

b) *Trend Projections*

When a time series reflects a change from a consistent pattern to a real time increase or decrease in the variable of interest example shipping load or admissions in school etc, trend component of the series is demonstrated in that pattern. The trend projection model is:

$$Tt = b0 + b1*t$$

$$\text{And } b0 = (\sum Y/n) - b1*(\sum t/n) \text{ and } b1 = (\sum t*Y_t - (\sum t\sum Y_t)/n) / (\sum t^2 - (\sum t)^2/n) \quad (4)$$

Where,
Tt= Trend value for the variable of interest in period t.
b0= Intercept of the trend projection line.
b1= Slope of the line.

c) *Trend and seasonal component*

To occupy the Seasonal festive pattern, time series decomposition model breaks down, analyzes and forecasts the seasonal and the trend components. The method is often referred as Time series decomposition, since the technique is analyzing seasonal indexes after decomposing the series in order to identify seasonal components called as seasonal indexes. These helps deseasonalize the series. This deseasonalized series helps in projecting trend projection line. Lastly, seasonal indexes are used to seasonalize the trend projection. [27].The steps involved are as follows:

1. Identify the quarters, months etc. and calculate centered moving averages (CMA).
2. Determine seasonal and Irregular factorsStIt= Yt / CMAt.
3. Determine average seasonal factors corresponding to the seasons At.
4. Scale the seasonal factors St and then determine the deseasonalized dataYt' =Yt/St .
5. Determine trend line of deseasonalized data.
6. Determine deseasonalized predictions.

III. Experimentation

The data is input to both the methods with and without tuning the seasonal effects. In order to fit the seasonal component, extent of seasons is fixed for a month's duration. For example, Ludhiana manufacturers tend to see a huge impact on sale during Diwali, Baisakhi etc. Data is selected and analyzed from four Ludhiana-based handloom manufacturers. For a better accuracy rate, last three years data is analyzed. In the given market trend of last three years, Each festive month's shipment load is recorded and analyzed to forecast next festive season's shipment load.

a) *Data*

The data is collected for the festive season's months of Punjab for Ludhiana based four Handlooms manufacturers for the last three years. Table 1 is organized structure of observed shipment load for the festive season of Lohri (Jan), Holi (March), Vaisakhi (April), Rakhsha-Bandhan (August), Krwachauth(Sep-Oct), Diwali and E-id (Oct-Nov), Guru-Nanak Jayanti (Nov) and finally Christmas(Dec) for all four handlooms. Along with these values, table1 also contains one last entry as observed value of Lohri (Jan'17).

The graphical representation of the observed data along with its linear trend fitting is shown in graph1. The graph shows observed shipment lad of all four handlooms over the seasonal period of last three years along with one last entry as observed shipment load of Jan'17 which is value of interest here.

b) *Results*

All three Smoothing averages and trend fitting with and without tuning the trend effect are applied on the data collected and outcome is predicted for festive season of Lohri (Jan'17). The results are compared with already observed value for Lohri (Jan'17).

i. *Smoothing Technique*

- *Moving averages:* Here the moving average (MA) is an average of the data provided for observed shipment load of all four Handlooms for festive seasons of past three years. Table 2 shows 3-month and 4-month MA. The outcome MA_3 and MA_4 are the two averages predicting the shipment load for festive season of Lohri (Jan'17) using Moving averages. $MA_3 = 2150$ and $MA_4 = 2543.77$. In comparison to the observed value of Lohri (Jan'17) as 2250, the question arises which moving average gives better result. For finding the accuracy level, Sum of squares SSE, mean square error MSE and root mean square error RMSE are found. Table 7 shows the overall comparison.

Table 1: Observed shipment load for the festive season of 2016 for Ludhiana based four Handlooms supply-chain companies

Year	1		2			3		
Festive Month	Season (t)	Observed Shipment Load (Units per pack of Handlooms)(Y)	Festive Month	Season (t)	Observed Shipment Load (Units per pack of Handlooms)(Y)	Festive Month	Season (t)	Observed Shipment Load (Units per pack of Handlooms)(Y)
(Jan'14)	1	2500	(Jan'15)	1	2200	(Jan'16)	1	2300
(March'14)	2	1130	(March'15)	2	1145	(March'16)	2	1130
(April'14)	3	2200	(April'15)	3	2500	(April'16)	3	2400
(August'14)	4	2250	(August'15)	4	2300	(August'16)	4	2250
(Sep-Oct'14)	5	3450	(Sep-Oct'15)	5	3400	(Sep-Oct'16)	5	3350
(Oct-Nov'14)	6	3000	(Oct-Nov'15)	6	2800	(Oct-Nov'16)	6	3000
(Oct-Nov'14)	7	3330	(Oct-Nov'15)	7	2850	(Oct-Nov'16)	7	3150
(Nov'14)	8	1100	(Nov'15)	8	1200	(Nov'16)	8	1400
(Dec'14)	9	1700	(Dec'15)	9	1950	(Dec'16)	9	1900
Year			4			(Jan'17)	1	2250

- *Weighted moving Average (WMA):* The expert planner/ analysts of the companies decide to weigh the past three month's sales. WMA calculated using average weightage given to past values for the combined data is shown in table 3. Using observed Shipment load for the last three months from table1, WMA is calculated for festive season of Lohri (Jan'17) as follows: WMA for Lohri'17= 2233.33.

Graph 2 shows Observed Vs Forecasted shipment load with 3period moving average for the festive season of past three years for Ludhiana based four Handlooms supply-chain companies. The graph illustrates that with 3 period moving average the next forecasted value that is Jan'17 reduced than observed value. Where as in graph 3 shows with the 4-period moving average the forecast increases.

- *Exponential smoothing Technique:* Since trend is expected out of festive season demands of the handlooms in the market hence, adjusted exponential smoothening $(F_t)_{adj}$ is obtained as a result. Therefore using eq 3, trend adjusted forecast is calculated with $\alpha = 2/(n+1)$ i.e.= $2/(27+1) = 0.1$, and initial $T_t = 0$ and $\beta = 0.1$. The adjusted forecast in table4 gives final $(F_t)_{adj}$ =2280.922 which is close to simple exponential smoothing without any tuning for trend effects F_t =2312.219

Accuracy of forecast is better judged by finding mean square error for different values of smoothing constant α ($0< \alpha\leq 1$). In order to get which smoothing factor gives better result, comparison between forecasts for α=0.1 and α=0.8 is shown in table 5. Result shows for α=0.8 is relatively gives more root mean square error hence less accurate forecast for large data set. It is observed that the data with larger fluctuations over the period of time more than a year does not predict accurate using exponential smoothing.

ii. *Trend Fitting:* Using eq6 the model can be fitted using table1 data. To occupy the Seasonal festive pattern, time series decomposition model breaks down, analyzes and forecasts the seasonal and the trend components. The given data set has distinct nine seasons hence the forecast is effected by the trend and seasonal component. Table 6 shows before and after seasonal and trend decomposition effect comparison of trend fitting. The forecasted value comes out to be T = 2378and 2322 resp. for Jan'17.

The accuracy so measure for all the methods applied are shown in table 7. Accuracy is compared by calculating MSE and RMSE of all the forecasts so far applied in this work. The lesser the RMSE better is the forecast. As shown in table 7, Trend fitting after trend deseasonalization gives least RMSE and hence is the best forecast seen.

IV. Conclusion

The techniques used in this case study shows following results based on forecast and the measure of error based on MSE and RMSE:

- The moving average method is simple to use. It works well with time series that do not have trend or seasonal components. With little data, limited to on period ahead, it works better. It this case study, with the data for past three years which included trend effects, it does not give effective result. The outcome of the smoothing Technique shows results for the moving averages MA_4 gives lesser RMSE and hence is better forecast than MA_3.

Table 2: Forecasting Jan'17 using 3-Month moving average and 4-Month moving average

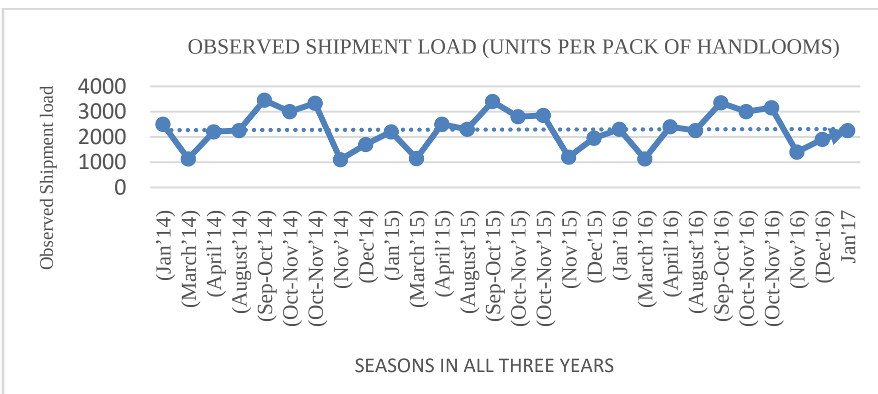
Festive Month	Year	Season(t)	Observed Shipment Load (Units per pack of Handlooms) *(y)*	MA_3	MA_4	CMA_4
(Jan'14)	1	1	2500			
(March'14)		2	1130	1943.333		
(April'14)		3	2200	1860	2020	2138.75
(August'14)		4	2250	2633.333	2257.5	2491.25
(Sep-Oct'14)		5	3450	2900	2725	2866.25
(Oct-Nov'14)		6	3000	3260	3007.5	2863.75
(Oct-Nov'14)		7	3330	2476.667	2720	2501.25
(Nov'14)		8	1100	2043.333	2282.5	2182.5
(Dec'14)		9	1700	1666.667	2082.5	1809.375
(Jan'15)	2	1	2200	1681.667	1536.25	1711.25
(March'15)		2	1145	1948.333	1886.25	1961.25
(April'15)		3	2500	1981.667	2036.25	2186.25
(August'15)		4	2300	2733.333	2336.25	2543.125
(Sep-Oct'15)		5	3400	2833.333	2750	2793.75
(Oct-Nov'15)		6	2800	3016.667	2837.5	2700
(Oct-Nov'15)		7	2850	2283.333	2562.5	2381.25
(Nov'15)		8	1200	2000	2200	2137.5
(Dec'15)		9	1950	1816.667	2075	1860
(Jan'16)	3	1	2300	1793.333	1645	1795

(March'16)		2	1130	1943.333	1945	1982.5
(April'16)		3	2400	1926.667	2020	2151.25
(August'16)		4	2250	2666.667	2282.5	2516.25
(Sep-Oct'16)		5	3350	2866.667	2750	2843.75
(Oct-Nov'16)		6	3000	3166.667	2937.5	2831.25
(Oct-Nov'16)		7	3150	2516.667	2725	**2543.75**
(Nov'16)		8	1400	**2150**	2362.5	
(Dec'16)		9	1900			
Jan'17	4	1	2250			

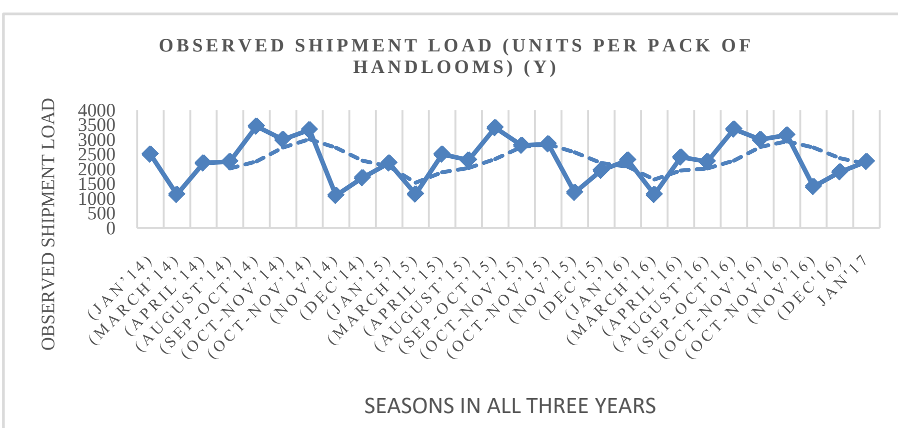
Table 3: Weighted moving average for last three months

.Season (t)	Weights (w)	Values (y)	weights*value	Festival
Last Month	1/2	1900	950	Christmas
Two months ago	1/6	1400	233.33	Gurunanak Jayanti
Three Months ago	1/3	3150	1050	Eid
Forecasted value			**2233.33**	Lohri(Jan'17)

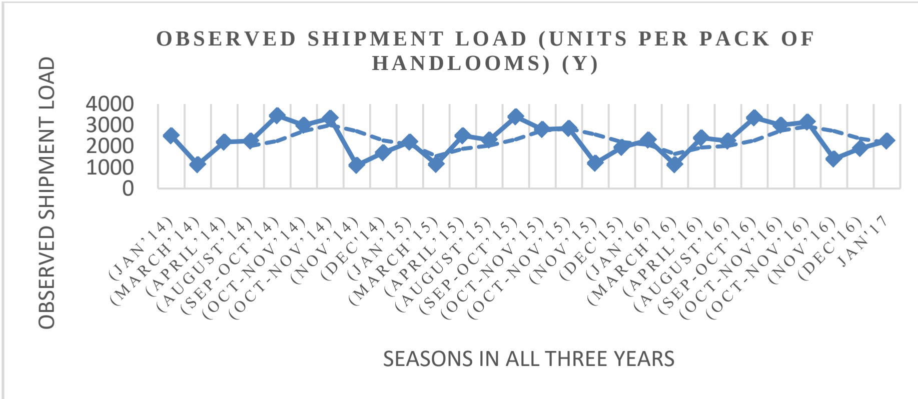
Graph 1: Observed shipment load for the festive season of 2016 for Ludhiana based four Handlooms supply-chain companies.



Graph 2: Observed Vs Forecasted shipment load with 3period-moving average for the festive season of past three years for Ludhiana based four Handlooms supply-chain companies.



Graph 3: Observed Vs Forecasted shipment load with 3period-moving average for the festive season of past three years for Ludhiana based four Handlooms supply-chain companies.



- Using Weighted moving averages, given the understanding of the owner of the sales-market head, the weights assigned to the various months of certain period 'n' hugely impacts the forecast value accuracy level. In the given data set, the weights assigned by the stakeholder proves to give best outcome of all forecasts. WMA is the best suited outcome for the dataset.
- Due to large variation of shipment load in various sequential months, Exponential smoothing technique could not predict better results for data with such huge variation. Setting α=0.8 gives poor forecast of the observed shipment load of Lohri (Jan'17).
- The trend adjustments made in data due to seasonal effect of festivals dramatically improves projection using trend line projection. RMSE comparison between other techniques and trend projection shows trend projection with trend deseasonalization gives best of all results and closest forecast to actual observation.

Table 4: Forecasting Jan'17 using exponential smoothing average with α= 0.1

Festive Month	Year	Season(t)	Observed Shipment Load (Units per pack of Handlooms) (*y*)	Old Forecast F_{t-1}	New Forecast ($F_t = F_{t-1} + 0.1(y_{t-1} - F_{t-1})$)	Adjusted forecast $(F_t)_{adj} = F_t + (1-\beta)/\beta * T_t$
(Jan'14)		1	2500	2500	2500	2500
(March'14)		2	1130	2500	2363	2239.7
(April'14)		3	2200	2363	2346.7	2221.06
(August'14)		4	2250	2346.7	2337.03	2215.251
(Sep-Oct'14)		5	3450	2337.03	2448.327	2438.893
(Oct-Nov'14)		6	3000	2448.327	2503.494	2544.654
(Oct-Nov'14)		7	3330	2503.494	2586.145	2697.575
(Nov'14)		8	1100	2586.145	2437.53	2404.064
(Dec'14)	1	9	1700	2437.53	2363.777	2267.28
(Jan'15)		1	2200	2363.777	2347.4	2245.812
(March'15)		2	1145	2347.4	2227.16	2027.515
(April'15)		3	2500	2227.16	2254.444	2099.319
(August'15)		4	2300	2254.444	2258.999	2123.487
(Sep-Oct'15)		5	3400	2258.999	2373.099	2353.828
(Oct-Nov'15)		6	2800	2373.099	2415.789	2436.867
(Oct-Nov'15)		7	2850	2415.789	2459.211	2517.259
(Nov'15)	2	8	1200	2459.211	2333.289	2272.204

(Dec'15)		9	1950	2333.289	2294.961	2205.488
(Jan'16)		1	2300	2294.961	2295.464	2215.392
(March'16)		2	1130	2295.464	2178.918	2001.961
(April'16)		3	2400	2178.918	2201.026	2061.663
(August'16)		4	2250	2201.026	2205.924	2084.904
(Sep-Oct'16)		5	3350	2205.924	2320.331	2314.38
(Oct-Nov'16)		6	3000	2320.331	2388.298	2444.113
(Oct-Nov'16)		7	3150	2388.298	2464.468	2583.255
(Nov'16)		8	1400	2464.468	2358.021	2369.127
(Dec'16)	3	9	1900	2358.021	2312.219	**2280.992**
Jan'17	4	1	2250			

Table 5: A comparative study of forecasts by setting α=0.1 and α=0.8 for all four handlooms for the last three years data

Festive Month	Year	Season (t)	Observed Shipment Load (Units per pack of Handlooms) *(y)*	Old Forecast α=0.1	New Forecast α=0.1	Old Forecast α=0.8	New Forecastα=0.8
(Jan'14)		1	2500	2500	2500	2500	2500
(March'14)		2	1130	2500	2363	2500	1404
(April'14)		3	2200	2363	2346.7	1404	2040.8
(August'14)		4	2250	2346.7	2337.03	2040.8	2208.16
(Sep-Oct'14)		5	3450	2337.03	2448.327	2208.16	3201.632
(Oct-Nov'14)		6	3000	2448.327	2503.494	3201.632	3040.326
(Oct-Nov'14)		7	3330	2503.494	2586.145	3040.3264	3272.065
(Nov'14)		8	1100	2586.145	2437.53	3272.06528	1534.413
(Dec'14)	1	9	1700	2437.53	2363.777	1534.413056	1666.883
(Jan'15)		1	2200	2363.777	2347.4	1666.882611	2093.377
(March'15)		2	1145	2347.4	2227.16	2093.376522	1334.675
(April'15)		3	2500	2227.16	2254.444	1334.675304	2266.935
(August'15)		4	2300	2254.444	2258.999	2266.935061	2293.387
(Sep-Oct'15)		5	3400	2258.999	2373.099	2293.387012	3178.677
(Oct-Nov'15)		6	2800	2373.099	2415.789	3178.677402	2875.735
(Oct-Nov'15)		7	2850	2415.789	2459.211	2875.73548	2855.147
(Nov'15)		8	1200	2459.211	2333.289	2855.147096	1531.029
(Dec'15)	2	9	1950	2333.289	2294.961	1531.029419	1866.206
(Jan'16)		1	2300	2294.961	2295.464	1866.205884	2213.241
(March'16)		2	1130	2295.464	2178.918	2213.241177	1346.648
(April'16)		3	2400	2178.918	2201.026	1346.648235	x2189.33
(August'16)		4	2250	2201.026	2205.924	2189.329647	2237.866
(Sep-Oct'16)		5	3350	2205.924	2320.331	2237.865929	3127.573
(Oct-Nov'16)		6	3000	2320.331	2388.298	3127.573186	3025.515
(Oct-Nov'16)		7	3150	2388.298	2464.468	3025.514637	3125.103
(Nov'16)		8	1400	2464.468	2358.021	3125.102927	1745.021
(Dec'16)	3	9	1900	2358.021	**2312.219**	1745.020585	**1869.004**
Jan'17	4	1	**2250**				

Table 6: A comparative study of forecasts before and after seasonal and trend decomposition effect comparison of trend fitting for all four handlooms for the last three years data

Festive Month	Year	Quarters (t)	Observed Shipment Load (Units per pack of Handlooms) Y_t	Season	3 period	Seasonal irregular factor	Scaling factor	Deseasonalized data	Deseasonalized trend projection	Trend line	Trend projection	Trend line
				t	CMA	S_tY_t	S_t	$Y_t/S_t = Y'_t$	Y'_t*t	T'_t=b0+b1*t	Y_t*t	Tt=b0+b1*t
(Jan'14)		1	2500	1			1.238	2018.96	2018.96	2228.92	2500	2264.1
(March'14)		2	1130	2	1943.3	0.581	0.594	1903.16	3806.32	2234.45	2260	2266.2
(April'14)		3	2200	3	1860	1.183	1.229	1789.53	5368.59	2239.98	6600	2268.4
(August'14)		4	2250	4	2633.3	0.854	0.846	2659.24	10636.94	2245.51	9000	2270.5
(Sep-Oct'14)	1	5	3450	5	2900	1.19	1.185	2910.24	14551.19	2251.05	17250	2272.7
(Oct-Nov'14)		6	3000	6	3260	0.92	0.931	3220.8	19324.8	2256.58	18000	2274.8
(Oct-Nov'14)		7	3330	7	2476.7	1.345	1.31	2542.5	17797.5	2262.11	23310	2277
(Nov'14)		8	1100	8	2043.3	0.538	0.544	2021.34	16170.69	2267.64	8800	2279.1
(Dec'14)		9	1700	9	1666.7	1.02	1.122	1515.61	13640.48	2273.17	15300	2281.3
(Jan'15)		1	2200	10	1681.7	1.308	1.238	1776.68	17766.81	2278.7	22000	2283.4
(March'15)		2	1145	11	1948.3	0.588	0.594	1928.42	21212.63	2284.24	12595	2285.6
(April'15)		3	2500	12	1981.7	1.262	1.229	2033.56	24402.7	2289.77	30000	2287.7
(August'15)		4	2300	13	2733.3	0.841	0.846	2718.33	35338.29	2295.3	29900	2289.9
(Sep-Oct'15)	2	5	3400	14	2833.3	1.2	1.185	2868.06	40152.86	2300.83	47600	2292
(Oct-Nov'15)		6	2800	15	3016.7	0.928	0.931	3006.08	45091.2	2306.36	42000	2294.2
(Oct-Nov'15)		7	2850	16	2283.3	1.248	1.31	2176.01	34816.21	2311.89	45600	2296.3
(Nov'15)		8	1200	17	2000	0.6	0.544	2205.09	37486.59	2317.43	20400	2298.5
(Dec'15)		9	1950	18	1816.7	1.073	1.122	1738.49	31292.87	2322.96	35100	2300.6
(Jan'16)		1	2300	19	1793.3	1.283	1.238	1857.44	35291.34	2328.49	43700	2302.8
(March'16)		2	1130	20	1943.3	0.581	0.594	1903.16	38063.16	2334.02	22600	2304.9
(April'16)		3	2400	21	1926.7	1.246	1.229	1952.22	40996.54	2339.55	50400	2307.1
(August'16)		4	2250	22	2666.7	0.844	0.846	2659.24	58503.19	2345.08	49500	2309.3
(Sep-Oct'16)	3	5	3350	23	2866.7	1.169	1.185	2825.88	64995.33	2350.61	77050	2311.4
(Oct-Nov'16)		6	3000	24	3166.7	0.947	0.931	3220.8	77299.2	2356.15	72000	2313.6
(Oct-Nov'16)		7	3150	25	2516.7	1.252	1.31	2405.07	60126.68	2361.68	78750	2315.7
(Nov'16)		8	1400	26	2150	0.651	0.544	2572.61	66887.84	2367.21	36400	2317.9
(Dec'16)		9	1900	27			1.122	1693.92	45735.73	2372.74	51300	2320
Jan'17	4	1	**2250**	28				b1	5.532	b1	2.152	
								b0	2223.39	b0	2261.91	
								T'(28)	2378.27	T(28)	2322.17	

Table 7: Comparison of accuracy of forecast using SSE, MSE and RMSE for all techniques applied

Error measure	Smoothing techniques				Trend fitting	
	Moving averages		Exponential smoothing		Normal	Deseasonalized
	MA3	MA4	$\alpha = 0.1$	$\alpha = 0.8$		
SSE	21470355.56	15913144.53	16949382.13	22536138.72	15230927.11	6568052.846
MSE	795198.3539	589375.7234	627754.8936	834671.8046	564108.4115	243261.2165
RMSE	891.7389494	767.7080978	792.309847	913.6037459	751.0715089	**493.2151828**
Forecasted value	2150	2544	2358	1745	2378	**2322**

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