Optimizing the Manpower Planning with better utilization in E-commerce

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Abstract-- **Accurate forecasting and manpower planning as per the demand is one of the critical success factors of any e-commerce businesses. In a typical e-commerce business, to meet call demand without understaffing or over-staffing, we need to deploy robust techniques which are analytics-driven. A contact centre needs to come up with a solution, which can precisely predict how many agents are needed to handle the tickets. Proper forecast leads to proper staffing, meeting the service level, better cost management and hence, better customer experience.**

Current methods hardly can solve this problem since they either focus on short-term forecasting for the next day, week, or ignore call-holding time for call traffic prediction, hence this paper is to introduce analytically driven forecasting models with better accuracy and simultaneously provide the manpower required to be staffed.

The sample data used for this research papers is taken from a retail e-commerce company with an in-house contact centre (customer support) in three locations (Pune, Bangalore & Hyderabad) with more than 1500 employees. Customer contacts the centre via calls/email/chats for any query/request/complaints. The company receives approximately 40000 tickets from these three channels.

Currently the forecasting is done on excel based on the number of orders planned for the month against tickets received from customers. This leads to inconsistency in hiring manpower posing a risk of either less utilization or added pressure on the employees. So, this is one of the key challenges the companies face in the forecasting of calls/chats/emails in an hourly/daily/monthly basis as it tends to give higher deviation in the forecast, the accuracy level drops during the seasonal cycles (holidays, special events, promotional activities, etc.).

Applying forecasting brings in many challenges like erratic business growth, seasonal factors, promotions/marketing events, unusual trends in purchases and tech-related issues which lead to incorrect forecasting. Different Time Series models (ARIMA, Holt-Winters, and Linear Regression along with Simple moving average) have been investigated to achieve the best prediction or accuracy, and which is dynamic in nature. The proposed forecasting model will be deployed in production using web application. This will give the output of the model providing the best accuracy, which is taken as an output to predict the no. of agents required to be staffed for the day. The application will predict the calls/chats/emails for a given date (with peak and non-peak time) and provides the concurrent logins required with 75%-80% utilization. This will also help in moving the employees from one queue to another queue for better utilization. With this type of approach, call centre workforce management (WFM) can arrange staffing availability efficiently based on volume predictions, hence optimizing the manpower and reducing the cost to company by around 10%-20%. The results suggest that call centre managers should invest in the use of forecast models which describe dynamically changing volume and utilizing the agents in better productivity.

Keyword's: **forecasting, seasonality, e-commerce, call centre, manpower utilization, ARIMA, Holt-Winters, Linear Regression, Workforce management, prediction,**

I. INTRODUCTION

Demand forecasting has become a buzz word in e-commerce companies, which ensures to forecast the inventory management and hence results in optimizing the stock and supply leading to minimal impact on cost. This is true for customer service as well. Different companies use different types of analytic tools to forecast the demand in sales and post-sales in calls. Accurate forecasting and manpower planning as per the demand is one of the critical success factors of any e-commerce businesses.

In a typical e-commerce business, in order to meet call demand without understaffing or over-staffing, we need to deploy robust analytical methods. A contact centre need to come up with a solution, which can precisely predict how many agents are needed to handle the tickets. Proper forecast leads to proper staffing, meeting the service level, better cost management and hence, better customer experience.

Current methods hardly can solve this problem since they either focus on short-term forecasting for the next day, week, or ignore call-holding time for call traffic prediction[1], hence this paper is to introduce analytically driven forecasting models with better accuracy and simultaneously provide the manpower required to be staffed.

Why is forecasting required in the call centre? The very reasons for forecasting of manpower in the call centre are:

- They are non-profit making teams and are a cost to the company.
- It takes at least 1 month to hire and train the agent on the product and process.
- Unpredictable call patterns at different intervals of the day, and to ensure there are adequate agents logged in to take the calls in

those intervals.

The main objective of this paper is to predict the nature of call patterns on a Weekly/Daily/hourly and give the recommendations of concurrent logins required for the day/hour. This way it will help the business to ensure that they are neither overstaffed nor under-staffed, hence ensuring that the cost is under control and at the same time customer experience is not compromised.

Literature Review:

The call centre team constitute an important part of every product/service based company which support the post-sales/purchase queries/issues of customer's. Before staffing or scheduling is done by first predicting the call arrivals, which might mostly have patterns. Accurate forecasting would result in optimizing the operational efficiency, avoiding any under-staffing or over-staffing leading to hit the service levels or cost of over-staffing [7].

Statistical studies have proved that there is a direct impact on customer satisfaction and customer loyalty, which can lead to better revenue generation. Also, workforce salary accounts for roughly 60% to 70% of the operating cost of a call centre [8]. It is hence important to optimize the manpower in the call centre and maintaining good customer satisfaction.

It is the job of a workforce management team to ensure that manpower optimization and solve the problem of staffing from days to weeks to months in advance. It is a known thing that call centre patterns are unpredictable due to multiple factors like holidays, marketing campaigns, level of business [9].

A few authors have optimized the traditional staffing challenges for cross-skill or multi-skill agents. When it comes to the staffing of a single period, Cez¸ik and L'Ecuyer [12] have adopted the simulation-based cutting-plane algorithm of Atlason, Epelman, and Henderson [14]. This method, when used for a single queue, has the shape of a sigmoid function, which is concave above a certain threshold in particular, as the number of agent's increases. The operation managers' main objective is to minimize the total staffing cost and expected abandonment penalties for the various customer classes. That is not the standard view of optimal staffing in the call centre industry. Customer service managers are much more comfortable with planning based on percentiles of the waiting time distribution. [12]

It is indicated by Gans et al. [14], that both staffing and dynamic assignment problems in multiskill call centres are essentially outside the reach of exact analytical methods (for an exception. Hence, most of the research done is divided into two parts. The first is the so-called "conventional" high-traffic regime. Here, the number of servers is held fixed while service and arrival rates are accelerated linearly in such a way that system utilization approaches one.

Different Time Series models (ARIMA[3], Holt-Winters, Linear Regression along with Simple moving average[5]) have been investigated to achieve the best prediction or accuracy, and which is dynamic in nature.

II. Experimental Design

A. *Objective of the Study:*

a) Segmenting the calls into monthly/weekly/daily/hourly.
b) Identifying the trend in call patterns and if there are any external factors involved in any unusual patterns.
c) Run different models on the data and select the one with the highest accuracy.
d) Performance measurement and result analysis.
e) Based on the results, recommend the concurrent agents required to log in for the day/hour.

B. *Data Collection:*

Calls Data has been collected from one of the leading retail eCommerce company.

The required data is of the number of inbound calls received from 1st June 2017 to 31st Sep 2019. Considered data have been received from appropriate teams from .csv files.

C. *Data Understanding:*

The sample data contains the below variables.

Variables	Legend
CS Calls	Inbound Calls from customers
Ops Calls	Inbound Calls from CEE's
Answered Calls	No. of successfully answered calls
Unanswered Calls	No. of dropped calls without answering
Service Level	Percentage of answered calls to offered calls
Orders	No. of order received for the day
Total Calls	Day wise Total inbound calls received in all three Centre's

Fig. 1. Data Metrics

The variable used for the forecasting is "Total Calls" on a weekly basis.

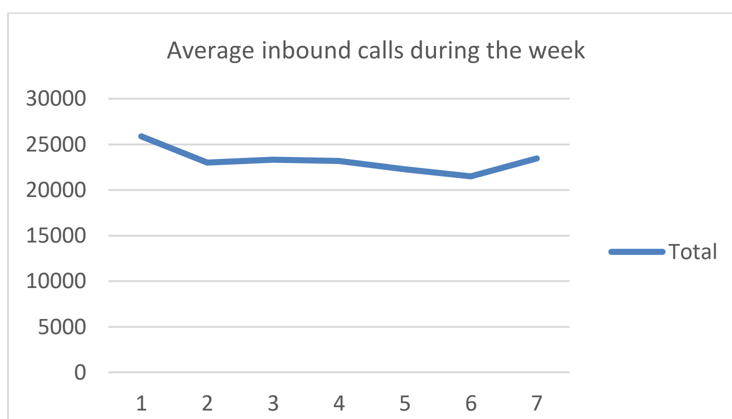

Fig.2. Average calls for the week

Fig.2 depicts the average calls received throughout the week for 2 years. It is observed that the volume pattern on all the days of the week is similar except on Sunday and Saturday with a slight increase in the calls. Hence this can be used to proportionate the calls of the week into days wise by using average distribution for all 7 days of the week based on the last 2-3 months inflow.

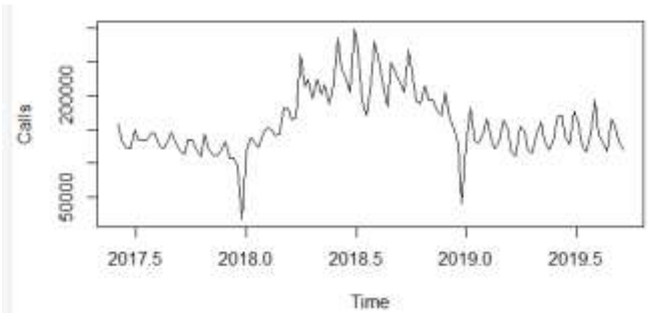

Fig.3. Call received from June’17 till Sep’19

We see from Fig.3 that there seems to be an unusual pattern in year 2018 compared to 2017 and 2019 and there seems to be a sharp dip at the end of the year.

D. Modelling Techniques

Three modelling techniques have been used using R for the predictions (ARIMA, Holt-Winters, Linear regression).

1. ARIMA with and without seasonal effect.
2. Holt-Winters
3. Linear Regression

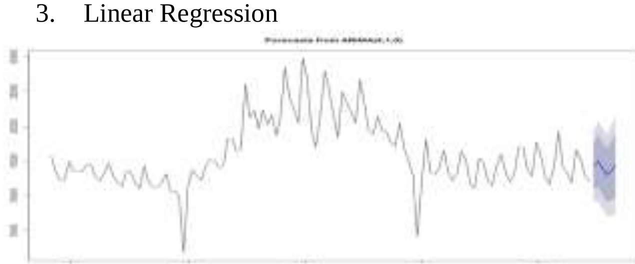

Fig. 4 ARIMA

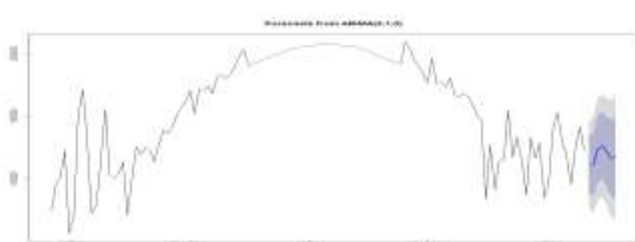

Fig. 4.1 Deseasonal ARIMA

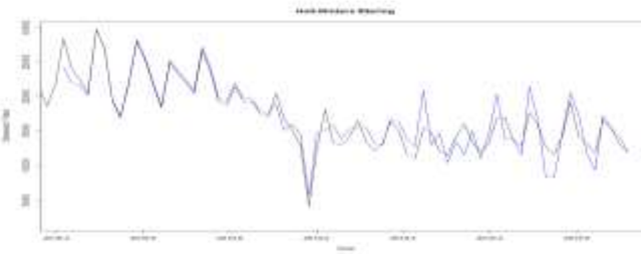

Fig. 4.2 Holt Winters

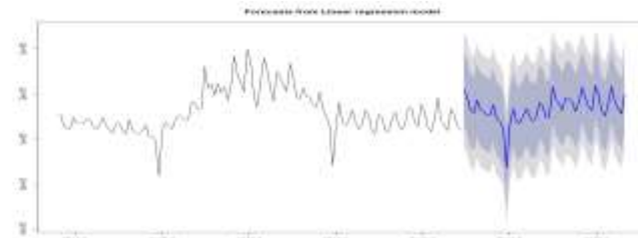

Fig. 4.3 Time Series Regression

In this paper, de-seasonality factor has been applied to reduce the MAPE.

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	-196.4082	25869.72	17709.32	-6.856052	16.68338	0.7103051	0.004101731

Fig.4 error before de-seasonality

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	778.2618	17270.41	11372.05	-1.185709	9.619129	0.8644146	0.002562136

Fig.4.1 Error after de-seasonality

Results and Discussion

The forecasted result via ARIMA method is used to predict the calls received on weekly basis, and hence distributing the weekly volume into daily volume using the percentage of average volume received in the last 8 weeks. And this is hence used for splitting the day’s volume into hourly volume.

Below are the results from different models.

Model	Accuracy	MAPE
ARIMA	83.317	16.683
De Seasonal ARIMA	90.49	9.51
Holt Winters	87.39	12.61
Linear Regression	79.464	20.536

While ARIMA gives the best accuracy with a MAPE of 16.683, and accuracy of 84.4%, we notice that there seems to be a seasonal factor that was impacting the forecasting. Deseasonal is applied to the model and the MAPE reduces to 9.181.

Volume Percentage Split															
Date	Weekly Split	Inflow	7:00:00	8:00:00	9:00:00	10:00:00	11:00:00	12:00:00	13:00:00	14:00:00	15:00:00	16:00:00	17:00:00	18:00:00	19:00:00
9/29/2019	11.29%	14285	4.17%	7.41%	8.38%	7.97%	7.39%	6.97%	4.80%	4.21%	3.49%	3.69%	5.71%	7.06%	8.11%
9/30/2019	10.16%	12853	5.37%	7.61%	8.30%	8.15%	7.28%	6.41%	4.60%	4.32%	3.19%	3.74%	6.21%	7.82%	9.03%
10/1/2019	8.68%	10976	4.94%	7.95%	8.58%	8.05%	7.16%	5.71%	4.37%	4.00%	3.25%	3.28%	7.25%	9.07%	9.84%
10/2/2019	8.68%	10983	4.79%	8.10%	8.09%	7.75%	7.08%	5.51%	4.98%	4.25%	3.40%	3.59%	5.85%	8.46%	10.97%
10/3/2019	8.37%	10587	5.06%	7.43%	7.97%	8.66%	6.01%	5.56%	4.54%	4.17%	3.24%	3.64%	7.25%	8.50%	10.78%
10/4/2019	7.67%	9703	5.74%	8.82%	9.25%	8.75%	6.44%	5.24%	4.41%	3.77%	2.95%	4.11%	7.52%	8.78%	9.82%
10/5/2019	7.67%	9704	6.07%	8.48%	9.23%	8.08%	7.46%	6.20%	5.48%	4.30%	3.64%	4.14%	7.95%	7.97%	9.55%
10/6/2019	9.08%	11023	5.42%	8.17%	8.78%	8.35%	7.19%	6.63%	5.40%	5.22%	3.95%	4.28%	6.83%	7.84%	9.19%
10/7/2019	7.95%	9652	5.09%	8.03%	8.44%	7.63%	6.70%	5.47%	4.22%	3.90%	3.32%	3.72%	6.29%	9.66%	10.45%
10/8/2019	7.89%	9585	5.37%	8.05%	8.78%	8.18%	7.73%	5.50%	4.57%	4.19%	3.34%	3.83%	6.73%	8.88%	10.33%
10/9/2019	6.89%	8369	5.53%	8.26%	8.24%	7.91%	6.45%	4.71%	3.70%	3.67%	3.33%	3.63%	8.50%	10.83%	11.22%
10/10/2019	6.51%	7901	5.94%	9.45%	9.06%	8.20%	6.52%	4.96%	3.70%	3.61%	3.49%	4.44%	7.83%	9.56%	10.72%
10/11/2019	6.07%	7369	6.89%	8.78%	9.42%	7.60%	6.45%	4.78%	3.38%	4.40%	2.97%	3.98%	9.15%	9.46%	10.01%
10/12/2019	6.38%	7745	7.19%	9.18%	9.09%	8.60%	7.27%	5.20%	4.03%	4.14%	3.50%	4.13%	8.03%	8.90%	8.92%
10/13/2019	7.57%	8791	6.35%	9.26%	8.25%	8.47%	6.97%	5.98%	4.97%	4.57%	3.57%	4.11%	7.53%	8.68%	8.61%
10/14/2019	7.17%	8323	5.48%	7.93%	7.83%	7.70%	6.62%	5.00%	4.05%	3.08%	2.88%	3.62%	7.91%	9.59%	11.51%
10/15/2019	6.92%	8036	5.61%	9.12%	7.93%	8.29%	6.74%	4.83%	3.47%	3.29%	3.14%	4.02%	8.10%	9.88%	11.51%
10/16/2019	6.55%	7608	5.77%	9.21%	9.58%	7.61%	6.11%	5.02%	3.39%	3.86%	3.51%	4.15%	8.58%	8.36%	10.30%
10/17/2019	5.99%	6958	6.41%	9.73%	8.80%	7.96%	5.59%	4.61%	3.68%	3.13%	3.00%	3.98%	8.85%	9.18%	11.28%
10/18/2019	5.86%	6799	6.50%	9.50%	9.28%	7.49%	5.22%	5.35%	3.12%	3.50%	3.57%	3.84%	9.19%	9.32%	10.99%
10/19/2019	6.17%	7160	7.22%	9.23%	8.21%	7.68%	6.69%	5.68%	4.87%	3.55%	3.60%	4.29%	7.77%	9.83%	9.97%
10/20/2019	6.81%	8012	5.47%	7.85%	9.96%	9.24%	7.49%	6.38%	4.28%	3.97%	3.93%	4.24%	7.41%	9.02%	8.94%
10/21/2019	6.48%	7632	5.82%	8.02%	9.29%	7.97%	6.76%	4.80%	3.83%	2.74%	3.55%	3.79%	7.81%	9.46%	10.64%
10/22/2019	6.58%	7743	6.13%	8.30%	8.50%	7.41%	6.66%	5.02%	4.06%	3.33%	3.36%	3.67%	8.34%	9.01%	10.65%
10/23/2019	6.50%	7649	4.92%	8.00%	9.31%	7.45%	6.71%	5.27%	4.34%	3.35%	3.78%	4.13%	8.75%	10.28%	9.90%
10/24/2019	6.09%	7168	5.94%	10.11%	9.51%	8.02%	6.04%	4.38%	3.32%	3.21%	3.06%	3.99%	7.74%	10.94%	9.60%
10/25/2019	5.74%	6754	7.45%	9.70%	9.33%	8.19%	4.92%	4.83%	3.35%	4.38%	3.21%	4.19%	8.05%	10.48%	9.31%
10/26/2019	6.29%	7398	6.53%	10.77%	8.88%	8.48%	6.38%	5.00%	4.20%	3.88%	3.73%	4.68%	7.64%	9.11%	9.22%

Fig. 5 Volume percentage split

Actual Headcount Required														
Date	Inflow	7:00:00	8:00:00	9:00:00	10:00:00	11:00:00	12:00:00	13:00:00	14:00:00	15:00:00	16:00:00	17:00:00	18:00:00	19:00:00
9/29/2019	14285	37	66	75	71	66	62	43	38	31	33	51	63	72
9/30/2019	12853	43	61	67	66	59	52	37	35	26	30	50	63	73
10/1/2019	10976	34	55	59	55	49	39	30	27	22	23	50	62	68
10/2/2019	10983	33	56	56	53	49	38	34	29	23	25	40	58	75
10/3/2019	10587	34	49	53	57	40	37	30	28	21	24	48	56	71
10/4/2019	9703	35	54	56	53	39	32	27	23	18	25	46	53	60
10/5/2019	9704	37	51	56	49	45	38	33	26	22	25	48	48	58
10/6/2019	11023	37	56	61	58	50	46	37	36	27	30	47	54	63
10/7/2019	9652	31	48	51	46	40	33	25	24	20	22	38	58	63
10/8/2019	9585	32	48	53	49	46	33	27	25	20	23	40	53	62
10/9/2019	8369	29	43	43	41	34	25	19	19	17	19	44	57	59
10/10/2019	7901	29	47	45	41	32	25	18	18	17	22	39	47	53
10/11/2019	7369	32	40	43	35	30	22	16	20	14	18	42	44	46
10/12/2019	7745	35	44	44	42	35	25	20	20	17	20	39	43	43
10/13/2019	8791	35	51	45	47	38	33	27	25	20	23	41	48	47
10/14/2019	8323	29	41	41	40	34	26	21	16	15	19	41	50	60
10/15/2019	8036	28	46	40	42	34	24	17	17	16	20	41	50	58
10/16/2019	7608	27	44	46	36	29	24	16	18	17	20	41	40	49
10/17/2019	6958	28	42	38	35	24	20	16	14	13	17	39	40	49
10/18/2019	6799	28	40	39	32	22	23	13	15	15	16	39	40	47
10/19/2019	7160	32	41	37	34	30	25	22	16	16	19	35	44	45
10/20/2019	8012	27	39	50	46	38	32	21	20	20	21	37	45	45
10/21/2019	7632	28	38	44	38	32	23	18	13	17	18	37	45	51
10/22/2019	7743	30	40	41	36	32	24	20	16	16	18	40	44	52
10/23/2019	7649	24	38	45	36	32	25	21	16	18	20	42	49	47
10/24/2019	7168	27	45	43	36	27	20	15	14	14	18	35	49	43
10/25/2019	6754	31	41	39	35	21	20	14	19	14	18	34	44	39
10/26/2019	7398	30	50	41	39	30	23	19	18	17	22	35	42	43

Fig. 5.1 Headcount required based on the forecasted volume.

III. Conclusions

The current traditional method of manual forecasting in excel gives us the 65-75% accuracy and whereas based on the forecasted volume using the ARIMA model gives 90%+ accuracy. This same model can be used to recommend the manpower requirement for the future without having a dependency on external factor.

A UI Application is being developed to easy interface to import the files and collect all the forecasted values within minutes and can be used anywhere, anytime. The same format can be used to predict the incoming chats/emails/calls for all the line of businesses.

The code and files are available in the github link: https://github.com/brahma1988/Forcasting/blob/master/Resource-Optimization-master.zip

References

1. Cao L., Ma K., Cao B., Fan J. (2019) Forecasting Long-Term Call Traffic Based on Seasonal Dependencies. In: Wang X., Gao H., Iqbal M., Min G. (eds) Collaborative Computing
2. Bastianin, A., Galeotti, M. & Manera, M. Empir Econ (2019) 57: 923. https://doi.org/10.1007/s00181-018-1475-y
3. Brockwell, P. J., & Davis, R. A. (2016). Introduction to time series and forecasting. springer.
4. Barrow, D., & Kourentzes, N. (2018). The impact of special days in call arrivals forecasting: A neural network approach to modelling special days. European Journal of Operational Research, 264(3), 967-977.
5. Barrow, D. K. (2016). Forecasting intraday call arrivals using the seasonal moving average method. Journal of Business Research, 69(12), 6088-6096.
6. The importance of accurate call center forecasting https://monetsoftware.com/the-importance-of-accurate-call-center-forecasting/
7. Ibrahim, R., et al., Modelling and forecasting call centre arrivals: A literature survey and a case study. International Journal of Forecasting (2016), https://dx.doi.org/10.1016/j.ijforecast.2015.11.012
8. Chan, W., Ta, T. A., L'Ecuyer, P., & Bastin, F. (2016, December). Two-stage chance-constrained staffing with agent recourse for multi-skill call centers. In 2016 Winter Simulation Conference (WSC) (pp. 3189-3200).
9. Gans, N., G. Koole, and A. Mandelbaum. 2003. "Telephone Call Centers: Tutorial, Review, and Research Prospects". Manufacturing and Service Operations Management 5:79–141
10. Channouf, N., P. L'Ecuyer, A. Ingolfsson, and A. N. Avramidis. 2007. "The Application of Forecasting Techniques to Modeling Emergency Medical System Calls in Calgary, Alberta". Health Care Management Science 10 (1): 25–45.
11. Cez¸ik, M. T., and P. L'Ecuyer. 2008. "Staffing Multiskill Call Centers via Linear Programming and Simulation". Management Science 54 (2): 310–323.
12. Atlason, J., M. A. Epelman, and S. G. Henderson. 2008. "Optimizing Call Center Staffing using Simulation and Analytic Center Cutting Plane Methods". Management Science 54 (2): 295–309

13. Harrison, J. M., & Zeevi, A. (2005). A method for staffing large call centers based on stochastic fluid models. Manufacturing & Service Operations Management, 7(1), 20-36.
14. Bassamboo, A., Harrison, J. M., & Zeevi, A. (2006). Design and control of a large call center: Asymptotic analysis of an LP-based method. Operations Research, 54(3), 419-435.