

Report on Demand forecasting of Mess-1 All Nighter's Canteen ( ANC1 )

Prepared under the guidance of

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As a part of the course,

**MF F421 : SUPPLY CHAIN MANAGEMENT**

**Birla Institute of Technology and Science, Pilani**



By

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### Acknowledgement

I would like to express my sincere gratitude to Dr. C P Kiran for providing me with his valuable time and resources whenever required. His input provided were vital to the project.

## **Introduction**

ANC1 is a night canteen in Bits pilani, Hyderabad campus where students can place orders through an app called smart campus or through cash. The orders that were placed through smart campus will be directly billed from the student's other advances paid at the beginning of the semester. ANC1 works from 10:00 pm to 2:00 am.

Objective:

ANC1 offers 40 different items in their menu but out of them they were good at making paneer paratha, paneer 65, veg fried rice, egg fried rice, chicken fried rice, dosa. They receive orders from these items regularly so it is important for them to maintain the availability of these items so that they can make more profit as the demand can be predictable with less error compared to other items.

Problem solving approach:

As ANC1 starts working hours after Mess1 working hours, Impact of the mess menu on the orders will be high compared to the other factors. As the mess menu repeats every week seasonal factors were calculated based on day. As the demand projected is mainly used to maintain the inventory, so the projection of each dish and estimating amount of ingredients will have a high error due to bullwhip phenomenon. So to tackle this problem for an ingredient let's just say paneer, to estimate the amount to keep in the inventory we can add all the items that share the paneer as the ingredient based on the weightage. So the estimated demand tells about how much paneer they need to have in their inventory and they also need to maintain the safety stock too as there are possible chances of getting higher orders than expected. To make it simple, quantities were used at the same amount across all dishes ex: the amount of chicken used in chicken schezwan rice is the same as the amount used in chicken fried rice. ANC1 was not in operation on many of the Sundays so I have ignored sundays. To forecast demand I have used moving average, weighted moving average, simple exponential smoothing, holt's model, winter's model and Error from the models were calculated in terms of mean squared error( MSE ), mean absolute deviation( MAD ), mean absolute percentage error( MAPE ).

## Converting RAW INPUT DATA to Organized input for forecasting:

### 1. Classifying items to decrease error in forecasting:

As most of the recipes share common ingredients and process we can merge their orders ex: chicken schetzwan rice and chicken fried rice shares almost all the ingredients as same and even their process of making is same. So orders that were merged are all dosa types into one, all chicken starters into chicken 65, all chicken fried rice related dishes into chicken fried rice, all veg fried rice related dishes into veg fried rice, all paneer fried rice related dishes into paneer fried rice.

### 2. Finding cumulative sum of all orders of a same item:

As data is too large with different varieties it is not recommended to do with excel sheets. Instead we can use python to solve this problem.

```
df = pd.read_csv("anc1.csv")
df['date'] = pd.to_datetime(df['date'])
df['day'] = df['date'].dt.day_name()
```

Above python code is used to load anc1.csv data into a dataframe named df and with help of dates mentioned in the csv we are finding which day it is using 2nd and 3rd lines this creates the another column with name day and mentions the corresponding day.

```
df_merged = df.groupby(['date', 'item']).sum()
df_merged.to_csv('anc1_merged.csv')

total = df.groupby('date').sum()
total.to_csv('total_merged.csv')
df_merged
```

Above python code creates a new dataframe called df\_merged where the cumulative orders for specific date of a particular item is calculated and it also exports that data to anc1\_merged.csv . It also calculates the total number of orders on a particular date and stores it into a dataframe named total .

### 3. We need to find the most frequently ordered items so that we can project demand for them to do that we have used python code

```
dt = {}
for i in df_merged.index:
    item = df_merged['item'][i];
    if ( item in dt):
        dt[df_merged['item'][i]] += 1
    else:
        dt[df_merged['item'][i]] = 0
k = []
```

```

for key, value in dt.items():
    if(value > 80):
        print(key, " : ", value)
    else:
        k.append(key)
for i in k:
    del dt[i]

```

This finds the frequency of orders and outputs items that have frequency of more than 80 days. So the output is

```

Chicken Fried Rice : 102
Egg Fried Rice : 95
Paneer 65 : 98
Veg Fried Rice : 102
Paneer Paratha : 96
Dosa : 99

```

So I have forecasted demand for these 6 items as these are more frequent orders.

4. To forecast the demand of each item we need to separate the data of each item so we need the six separate excel sheets to forecast the demand of each item. so we need to separate data basing on the item name and save it into the dataframe and export it to the csv file. to do that i have used the python programme before that we need to save the data of operational dates of ANC1 and non-operational dates.

```

idx = pd.date_range('2021-10-18', '2022-04-27')

o_dates.index = pd.DatetimeIndex(o_dates.index)

o_dates = o_dates.reindex(idx, fill_value=0)
o_dates

```

This saves the operational dates into o\_dates dataframe and inserts the non-operational datasets with a filling value as 0.

```

cfr = df_merged[df_merged.item == "Chicken Fried
Rice"].set_index('date')
cfr.index = pd.DatetimeIndex(cfr.index)
cfr = cfr.reindex(idx, fill_value=0)
cfr.reset_index()
cfr.to_csv('cfr.csv')
vfr = df_merged[df_merged.item == "Veg Fried
Rice"].set_index('date')
vfr.index = pd.DatetimeIndex(vfr.index)
vfr = vfr.reindex(idx, fill_value=0)
vfr.reset_index()
vfr.to_csv('vfr.csv')
dosa = df_merged[df_merged.item == "Dosa"].set_index('date')
dosa.index = pd.DatetimeIndex(dosa.index)

```

```

dosa = dosa.reindex(idx, fill_value=0)
dosa.reset_index()
dosa.to_csv('dosa.csv')
efr = df_merged[df_merged.item == "Egg Fried
Rice"].set_index('date')
efr.index = pd.DatetimeIndex(efr.index)
efr = efr.reindex(idx, fill_value=0)
efr.reset_index()
efr.to_csv('efr.csv')
pp = df_merged[df_merged.item == "Paneer
Paratha"].set_index('date')
pp.index = pd.DatetimeIndex(pp.index)
pp = pp.reindex(idx, fill_value=0)
pp.reset_index()
pp.to_csv('pp.csv')
p65 = df_merged[df_merged.item == "Paneer 65"].set_index('date')
p65.index = pd.DatetimeIndex(p65.index)
p65 = p65.reindex(idx, fill_value=0)
p65.reset_index()
p65.to_csv('p65.csv')

```

The above code separates data based on the item name and exports that data into csv format.

5. The last step is to make the data continuous and make minor changes to get started with the forecasting. I removed sundays as i mentioned before that the number of operational days on sunday were less. On some days anc was operational but didn't offer some of the items so i have filled that value with the previous same day orders and upcoming same day orders.
6. ANC1 was not in operation for a few months and the number of orders, pattern are different. We cannot compare both of them. And the main reason for not considering the same is because the number of people on the campus were continuously varying.

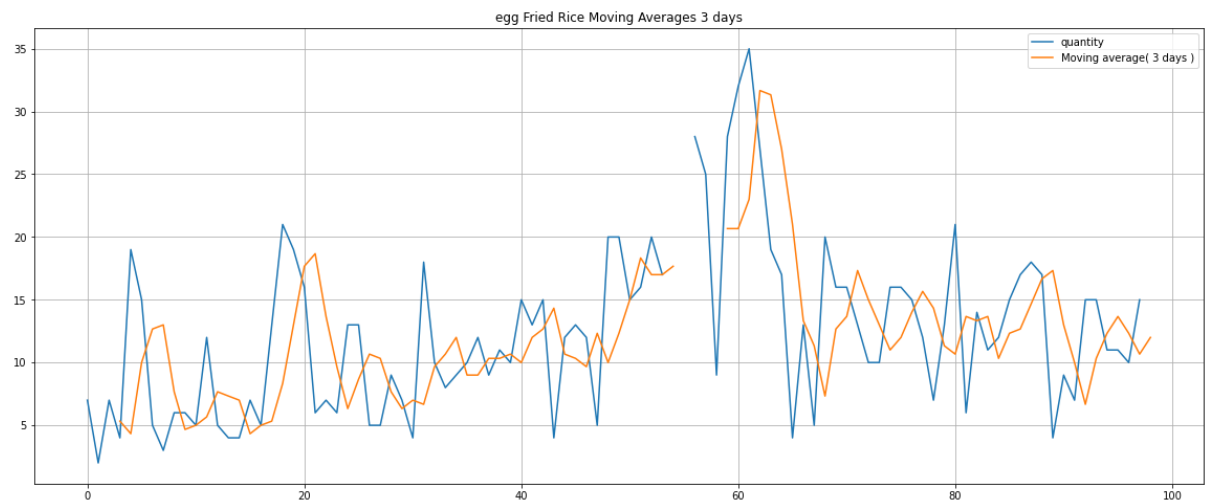
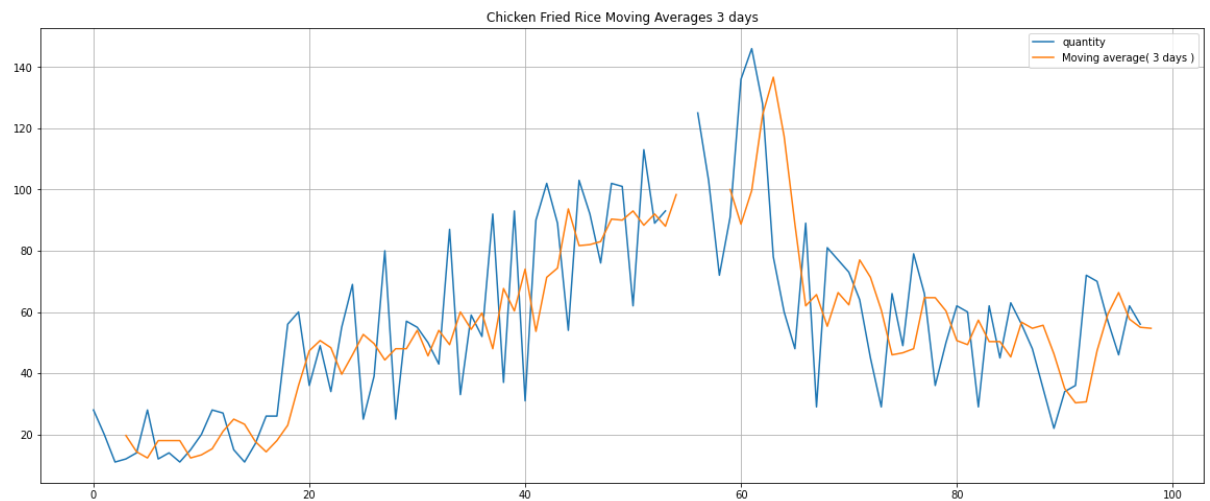
## Forecasting of Demand:

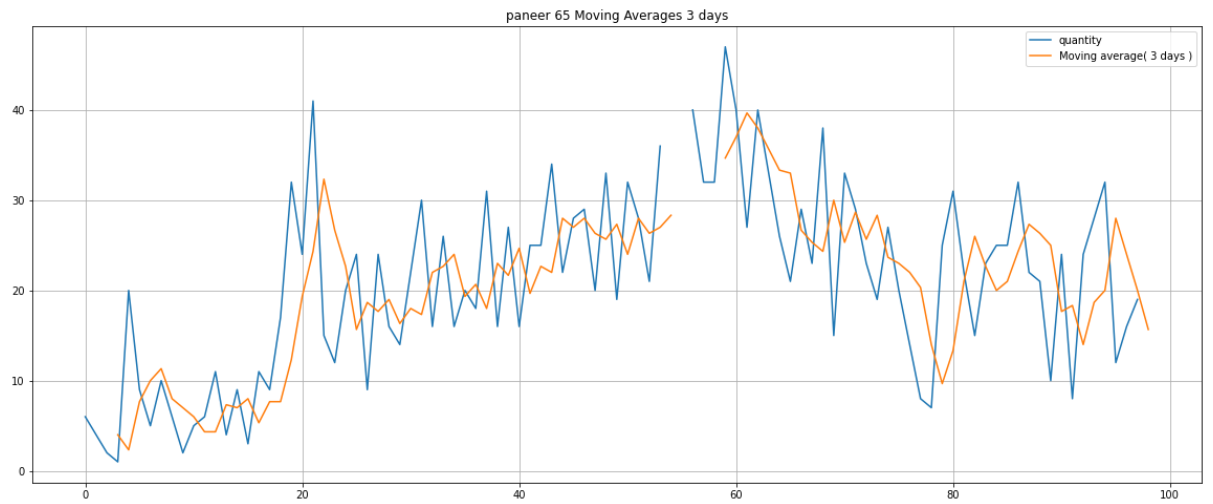
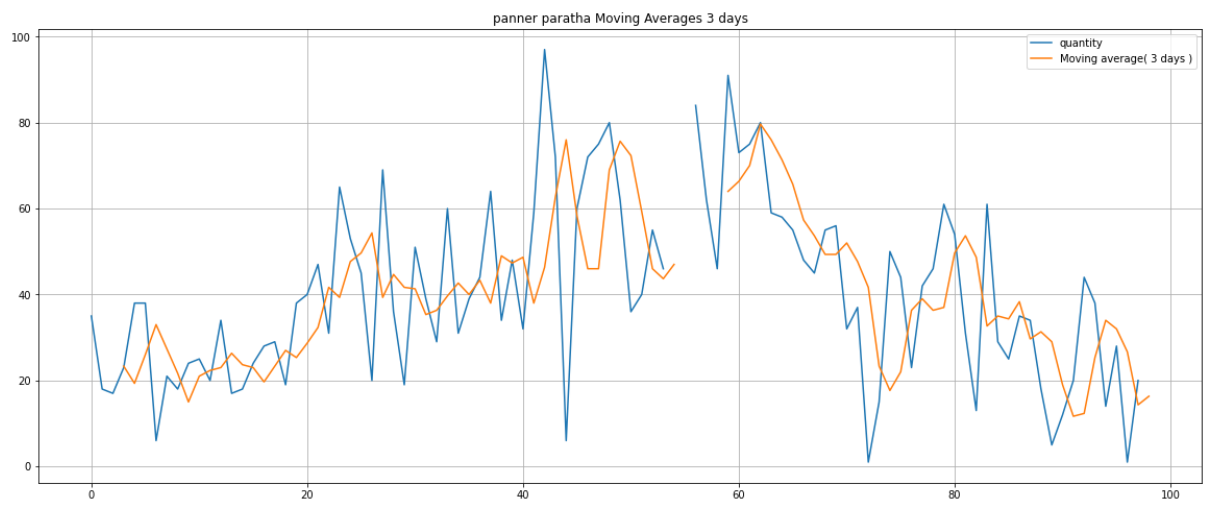
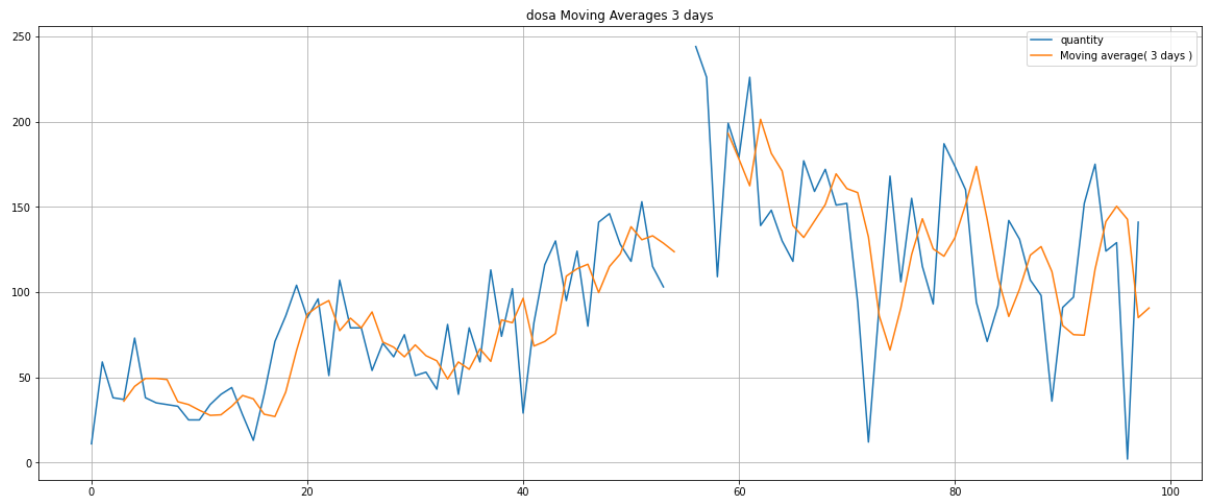
### 1. Moving Average

- Moving Average ( 3 days ) :

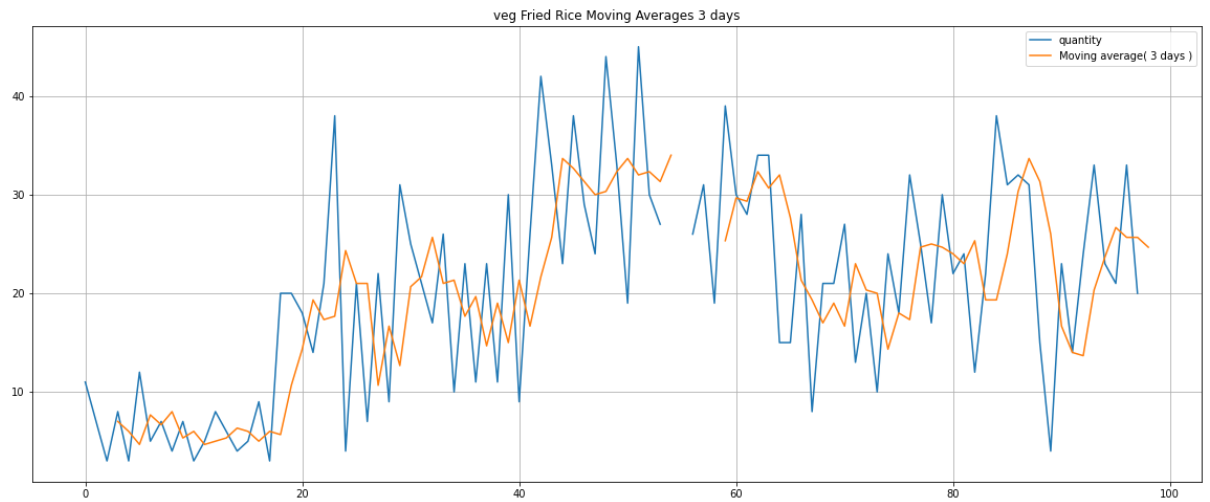
In this method we forecast demand by average of recent previous 3 orders. No Changes can be done to this model. Reason for taking 3 days is that the mess menu feels repeating itself after 3 days according to types of dish.

Error for set1 of chicken fried rice is:

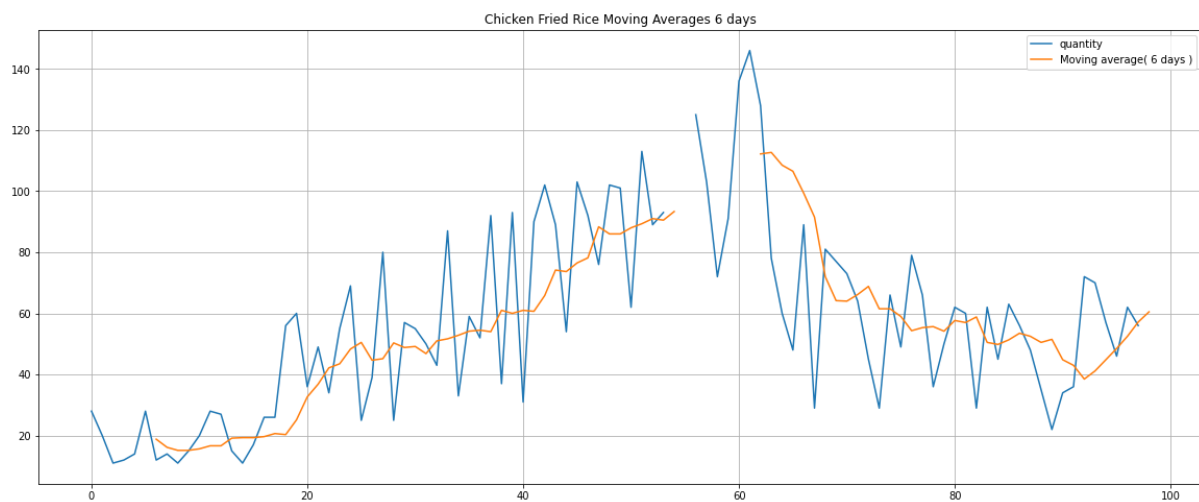


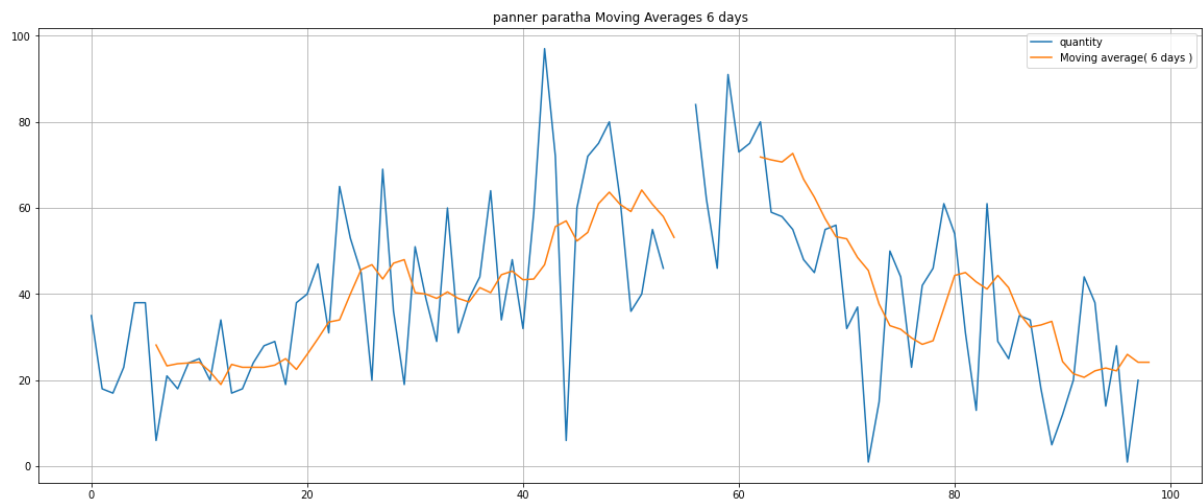
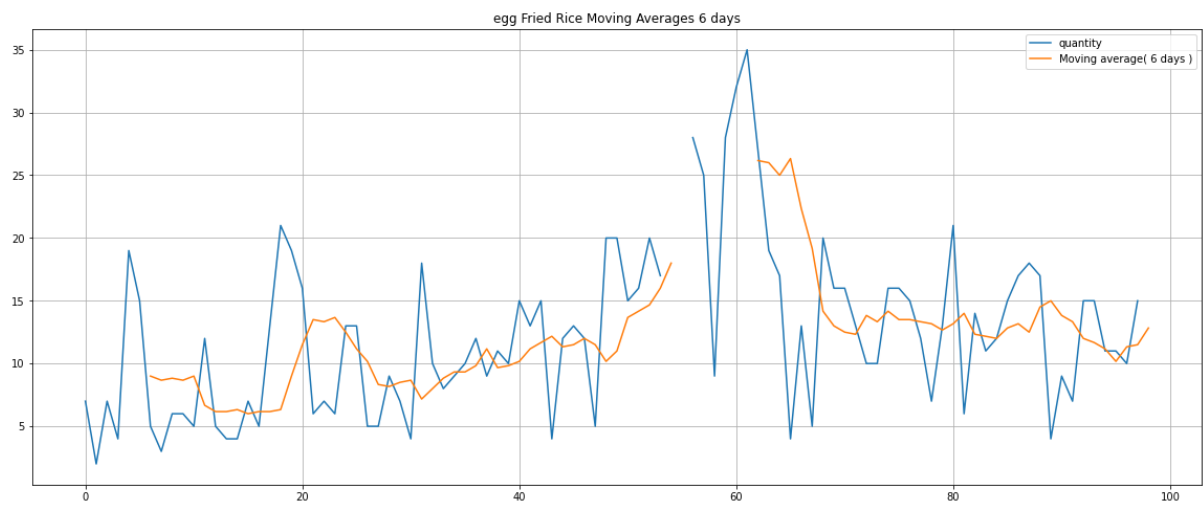
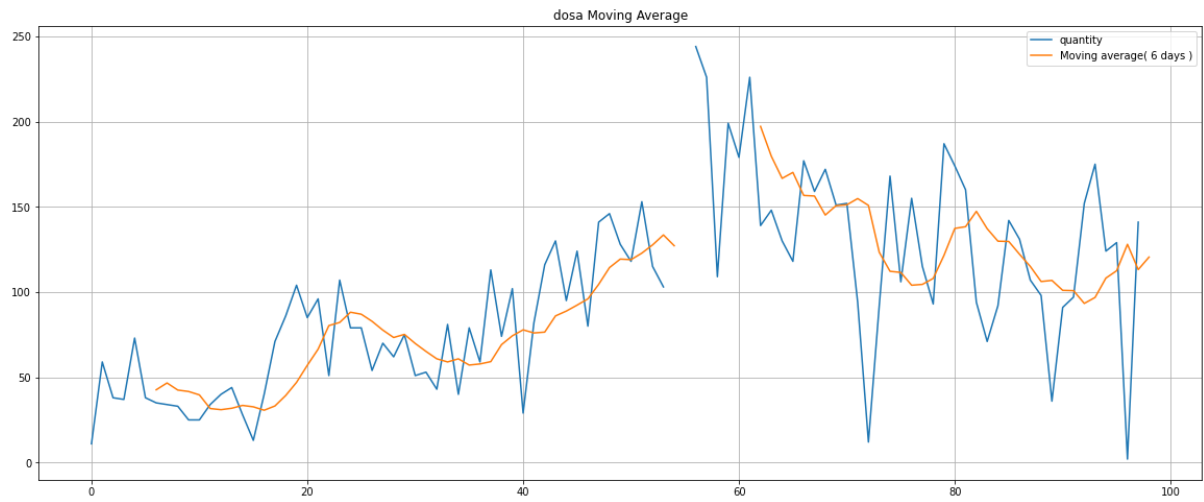






- Moving Average ( 6 days ) :**  
 In this method we forecast demand by average of recent previous 6 orders. No Changes can be done to this model. Reason for taking 6 days is as the sunday is removed from the data mess menu repeats after every 6 days.

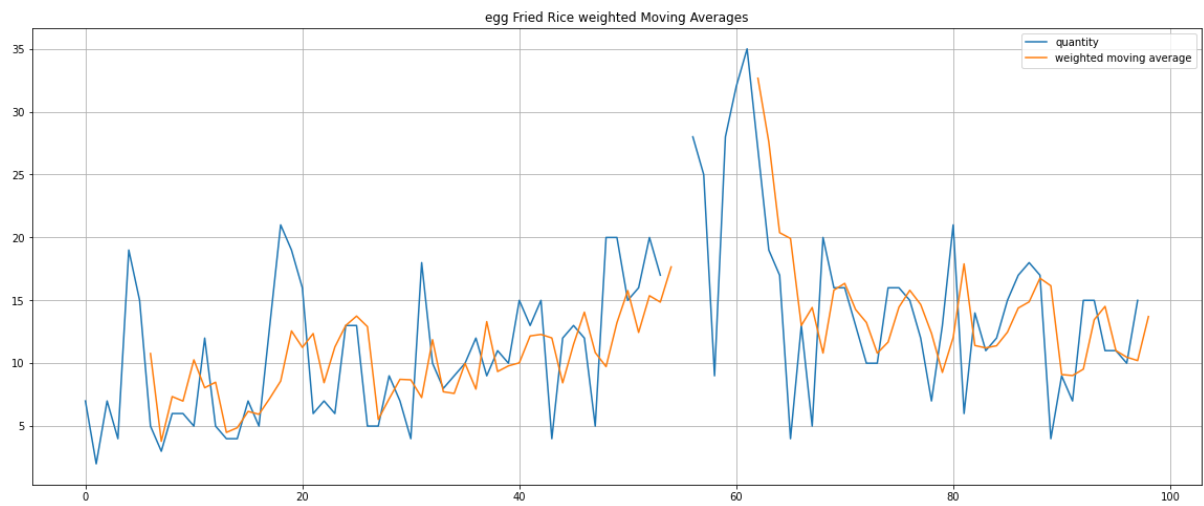
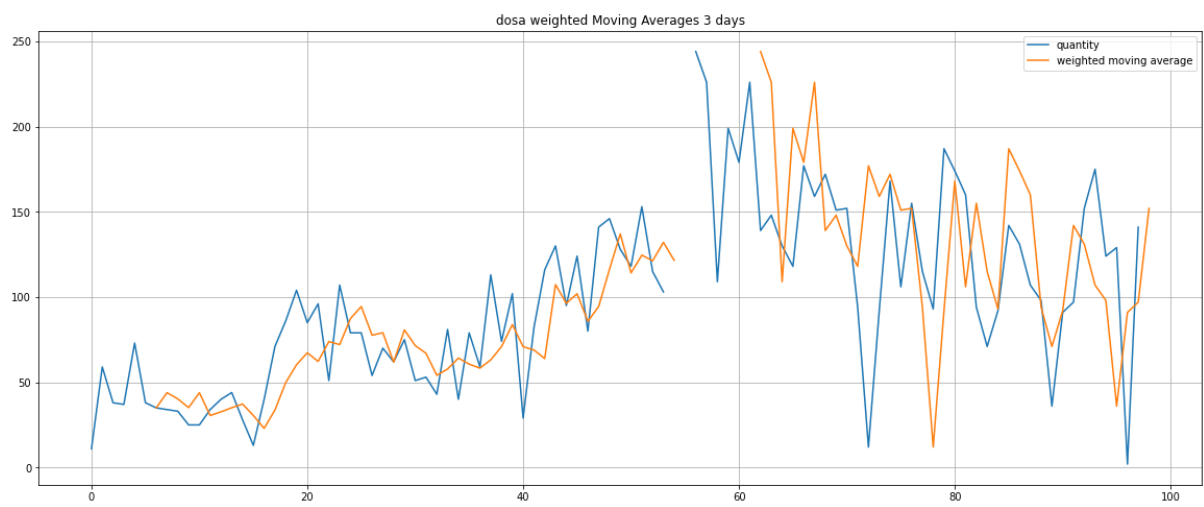
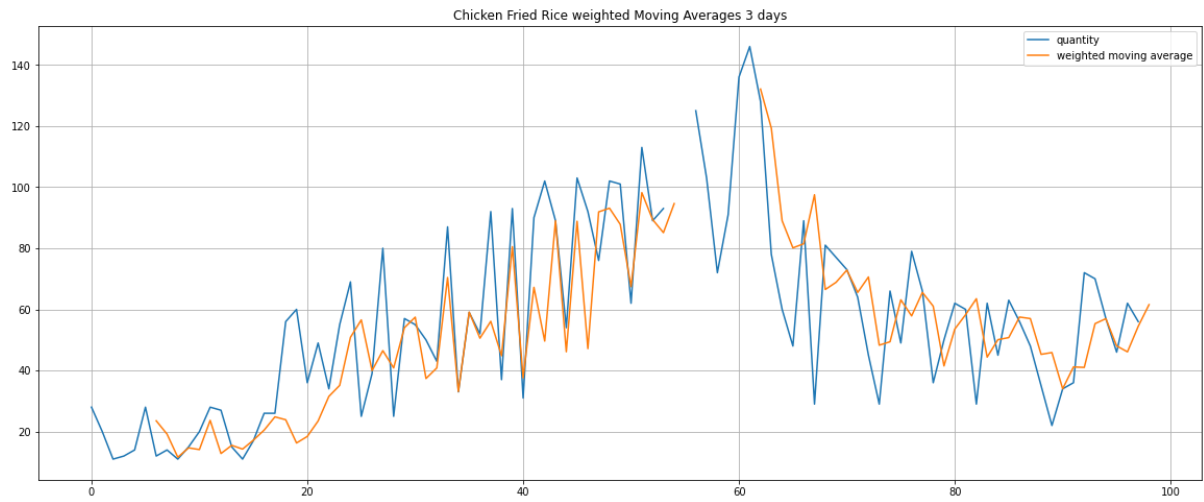


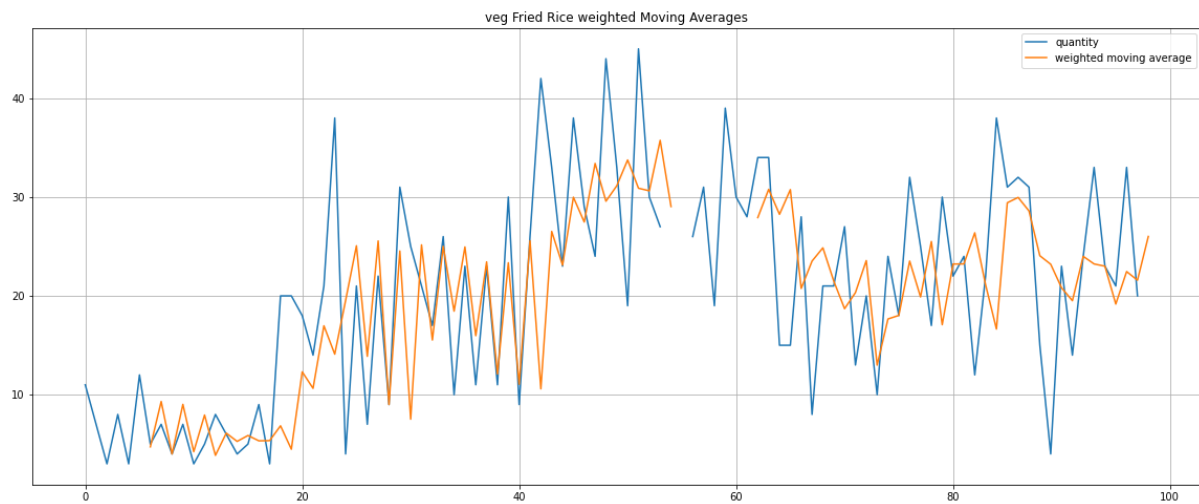
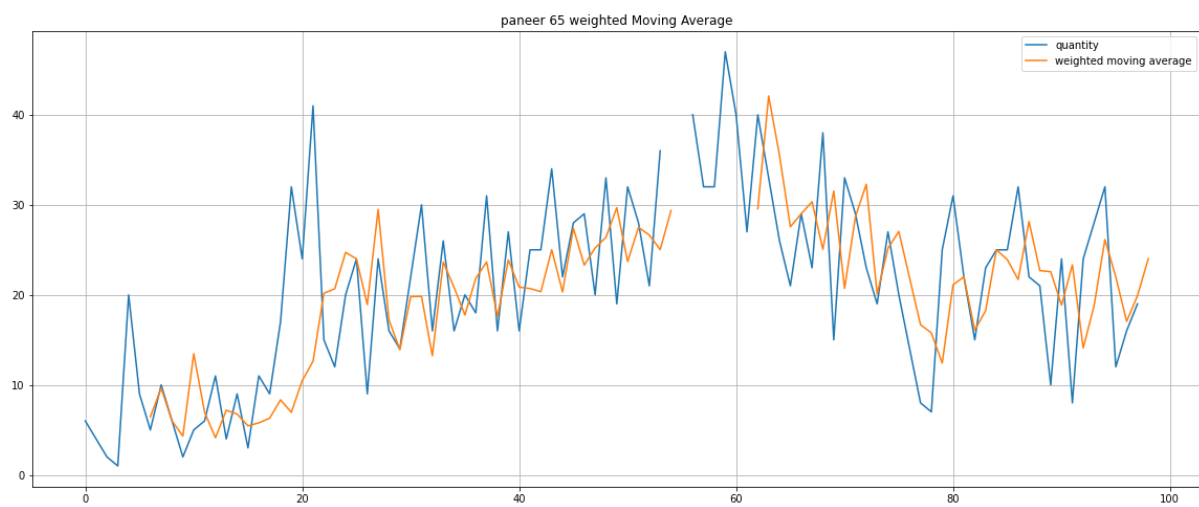
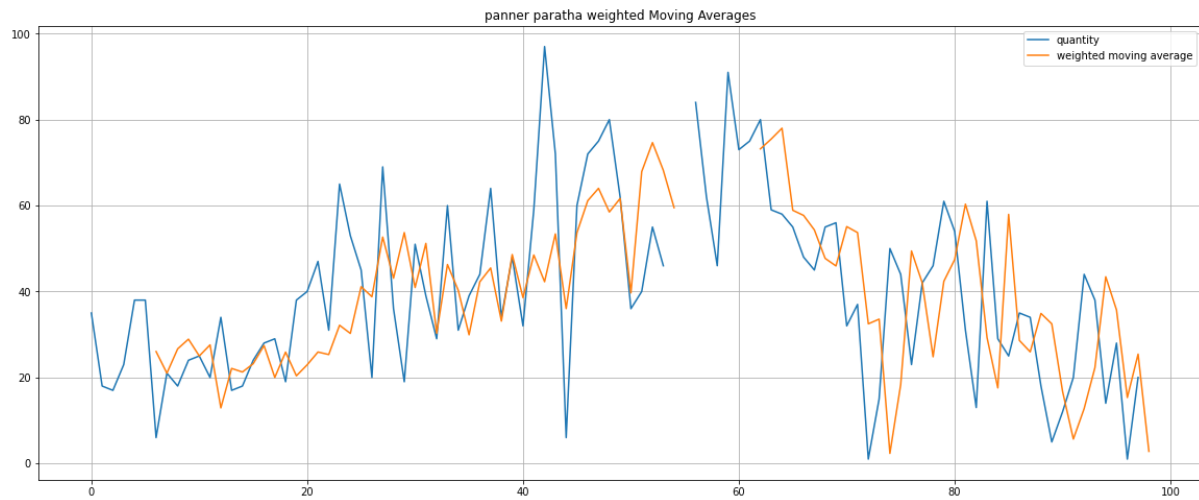




## 2. Weighted moving Average

It is similar to the moving average but we add some weights accordingly so that the error is minimized and possibly we can get better results compared to the moving average as the weights are added accordingly so that the relevant data gets more weight.

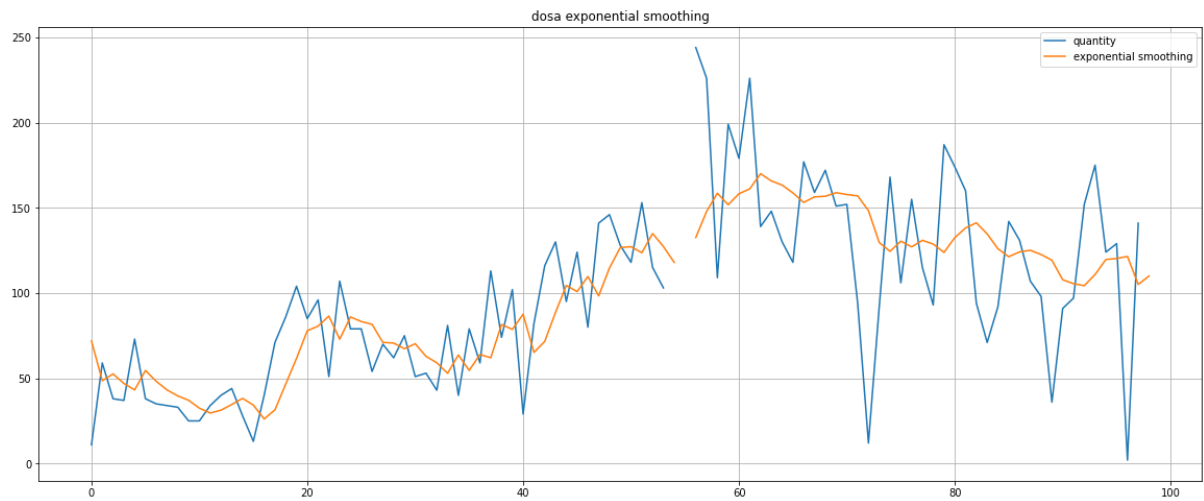
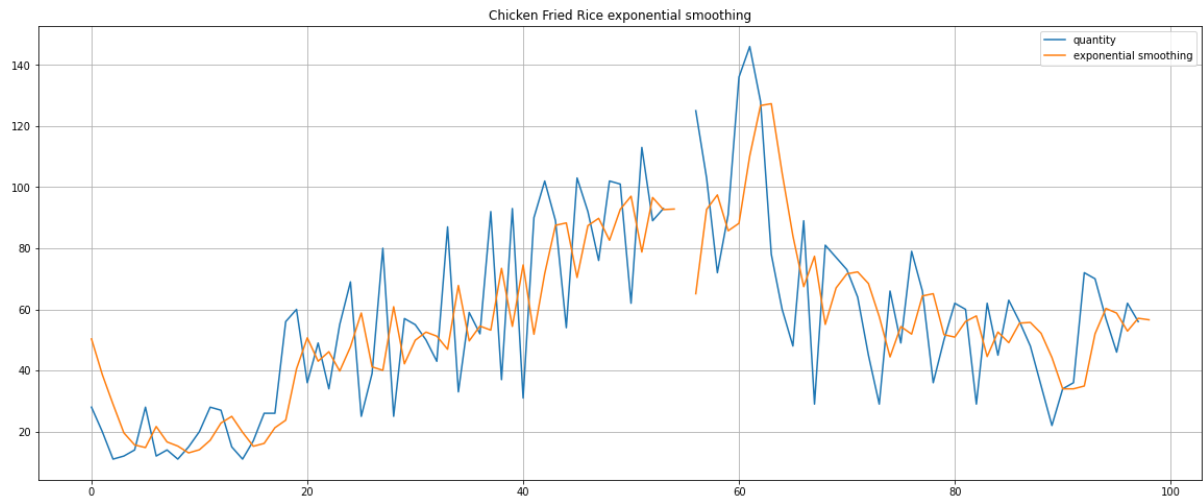


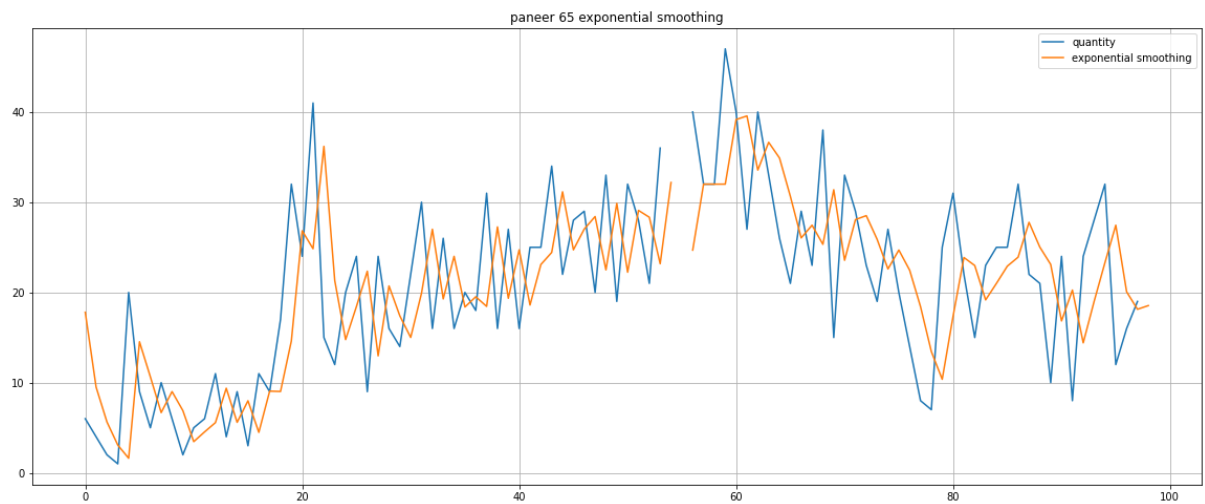
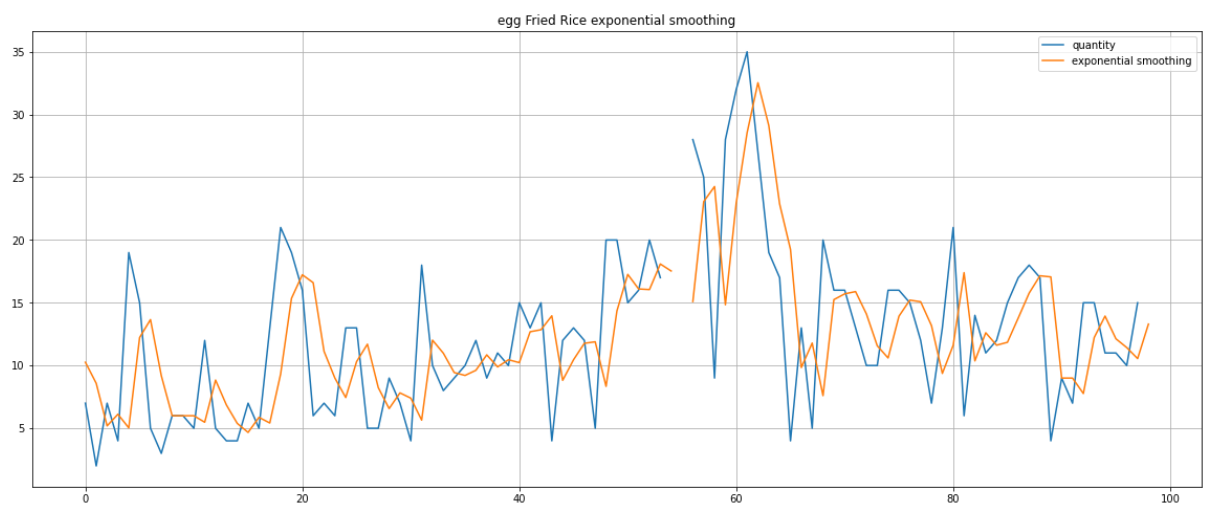
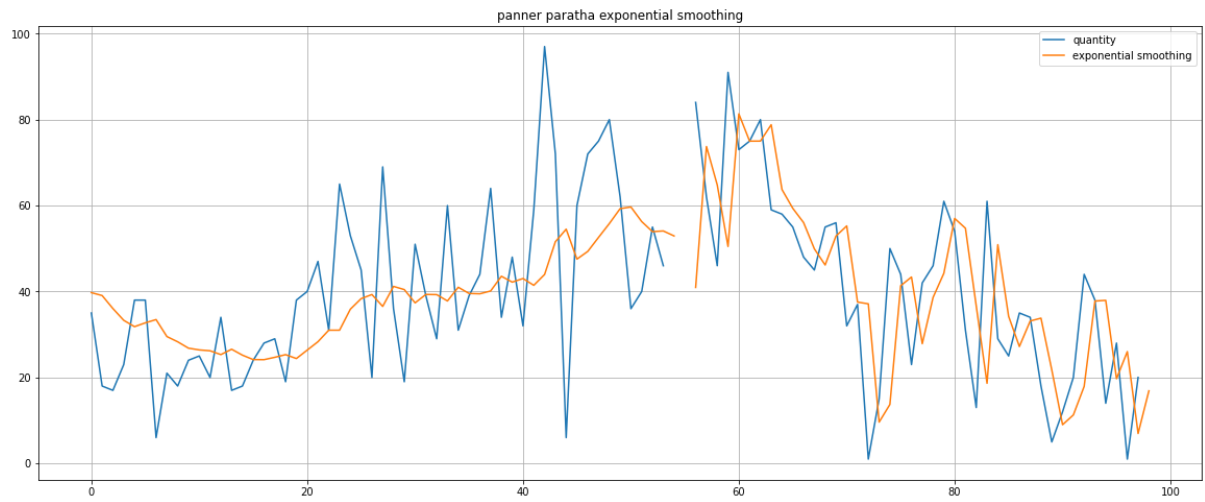


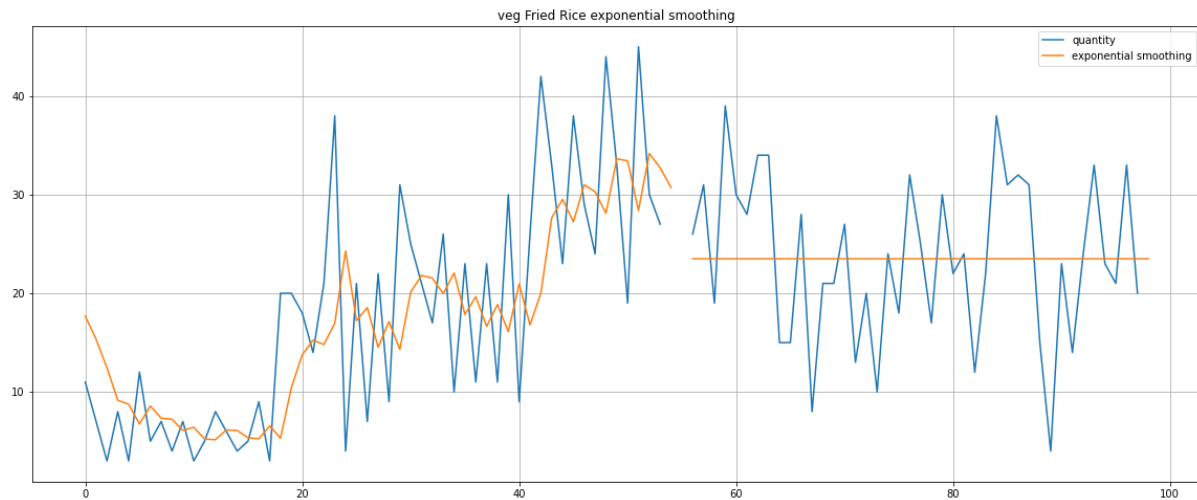
### 3. Simple Exponential smoothing

In simple exponential smoothing we use a constant smoothing factor alpha so that the forecast is equal to previous forecast plus error in previous

forecast multiplied by smoothing constant. Alpha is calculated using solver in excel to minimize the forecast error.

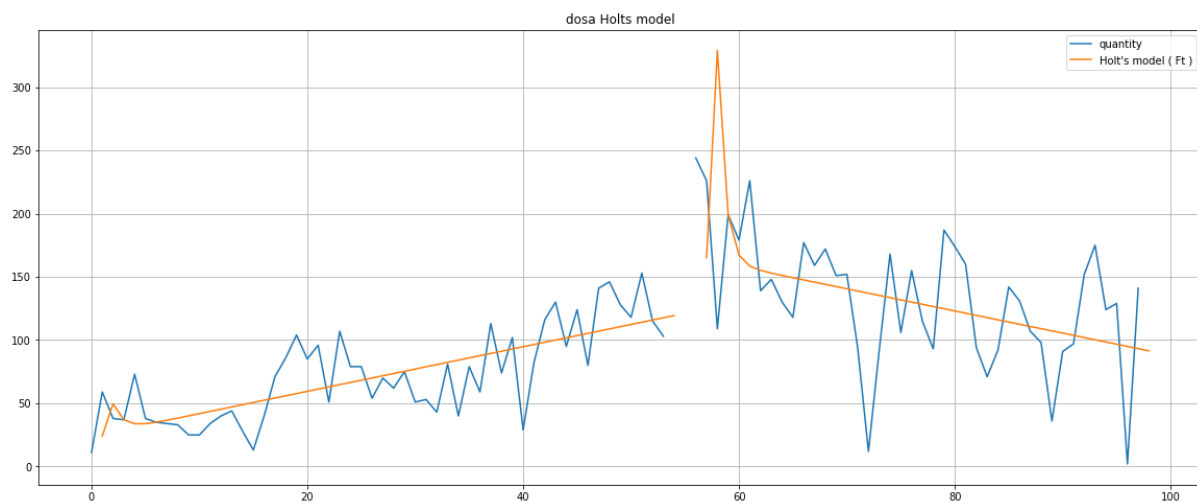




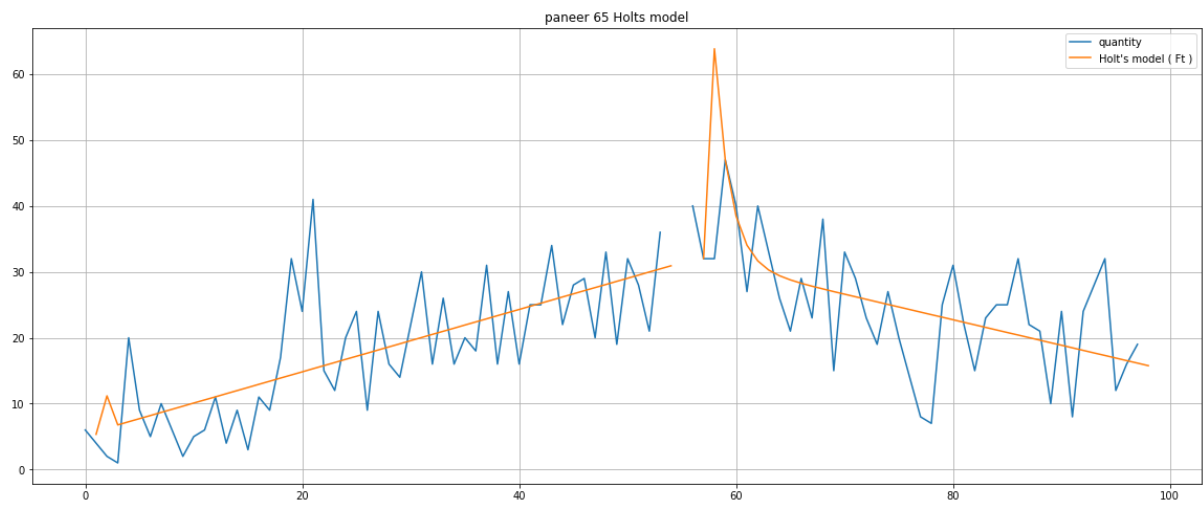
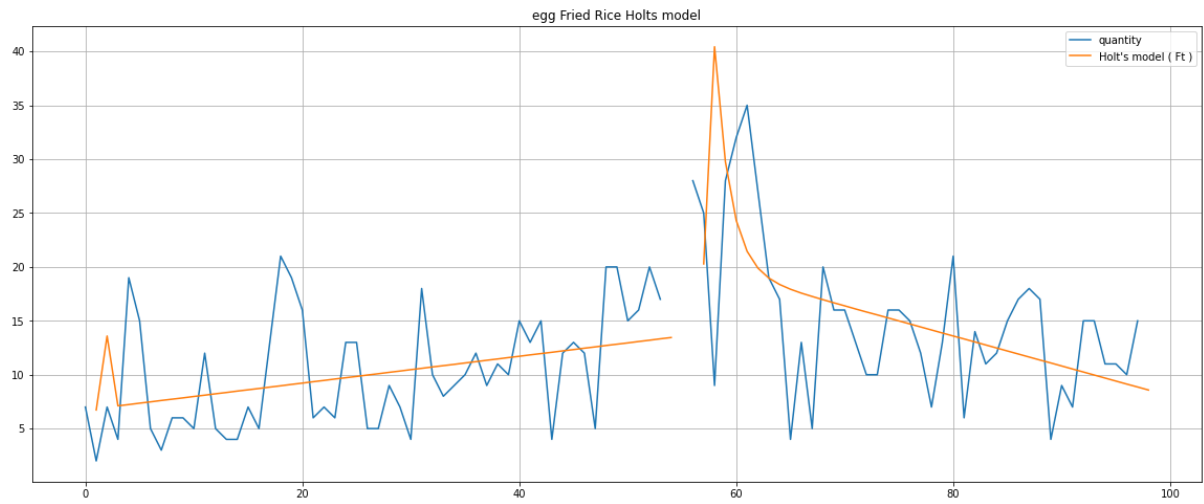


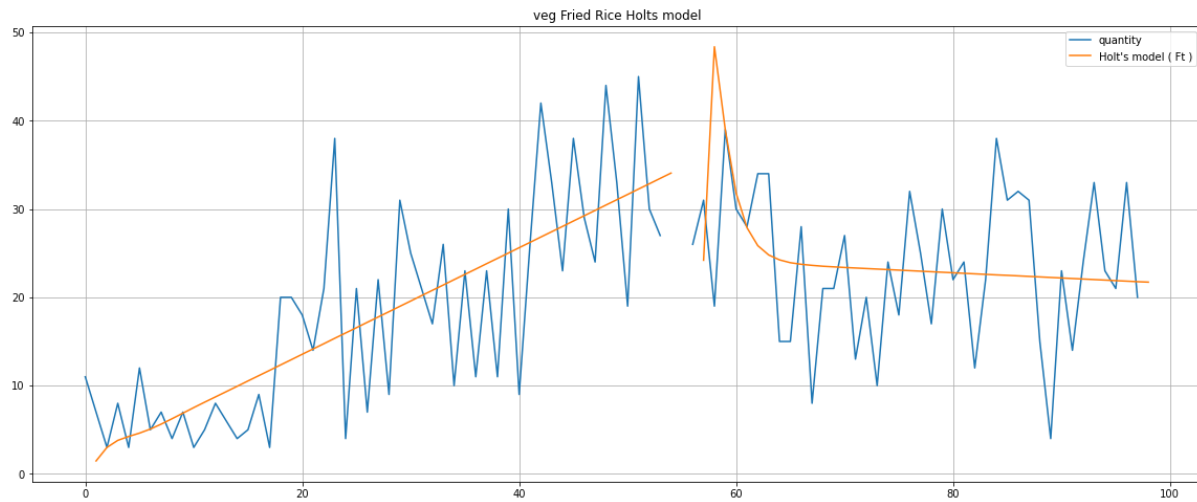
#### 4. Holt's model

In Holt's model we consider smoothing both level and trend. It is also called trend-corrected Exponential smoothing. we get the values of the alpha and beta using solver in excel.



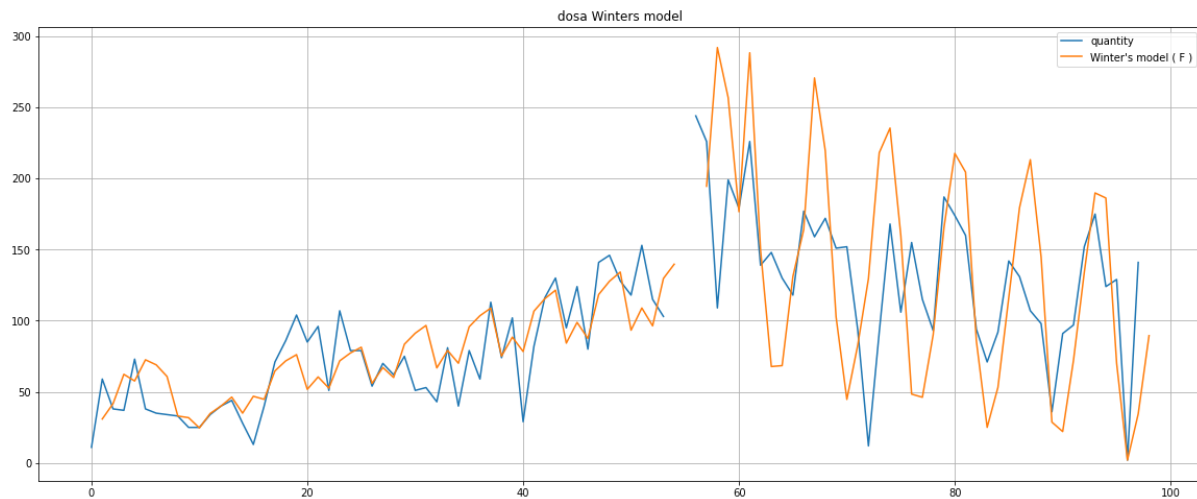


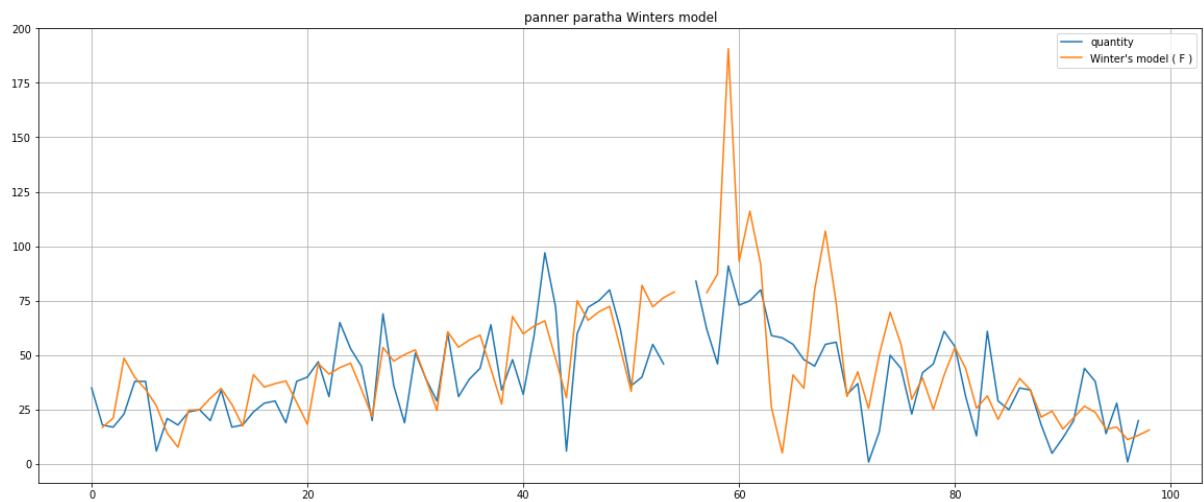
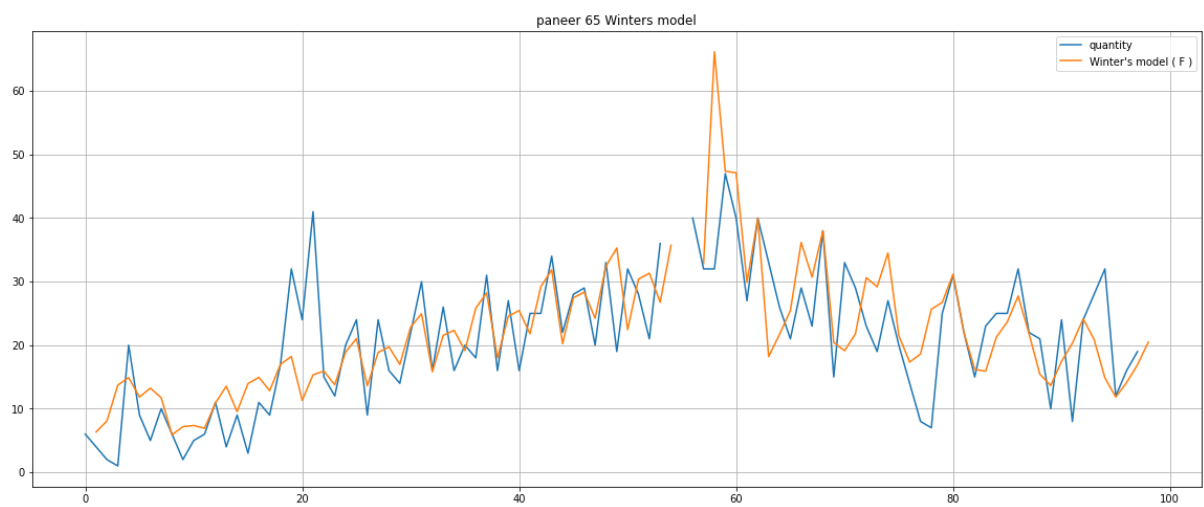
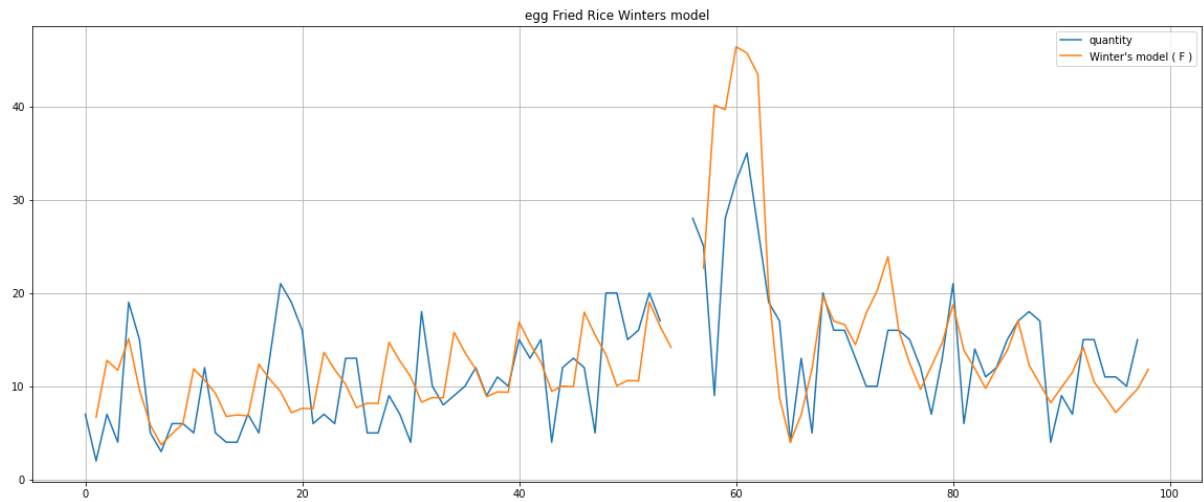


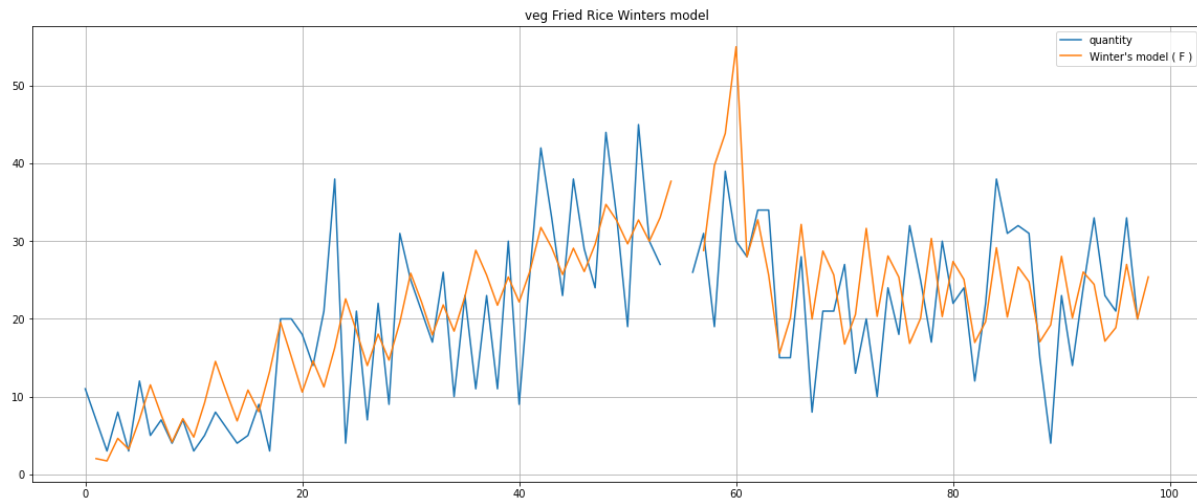


## 5. Winters model

In Winter's model we consider smoothing both level, seasonality and trend. It is also called trend and seasonality corrected Exponential smoothing. we get the values of the alpha, beta and gamma using solver in excel.







### **Errors from different models :**

Error for set1 of chicken fried rice is:

Moving Average 3d	MSE	417.81
	MAD	16.27
	MAPE	0.38
Moving Average 6d	MSE	368.65
	MAD	15.29
	MAPE	0.32
Weighted average model	MSE	329.65
	MAD	12.58
	MAPE	0.25
Exponential smoothing	MSE	475.91
	MAD	17.11
	MAPE	0.43
Holt's model	MSE	288.28
	MAD	13.84
	MAPE	0.37
Winter's model	MSE	264.55
	MAD	12.61

	MAPE	0.34
--	------	------

Error for set2 of chicken fried rice is:

Moving Average 3d	MSE	647.84
	MAD	19.85
	MAPE	0.37
Moving Average 6d	MSE	532.07
	MAD	17.11
	MAPE	0.38
Weighted average model	MSE	423.44
	MAD	14.78
	MAPE	0.33
Exponential smoothing	MSE	597.44
	MAD	18.66
	MAPE	0.34
Holt's model	MSE	825.92
	MAD	19.71
	MAPE	0.36
Winter's model	MSE	1042.29
	MAD	21.20
	MAPE	0.37

Error for set1 of veg fried rice is:

Moving Average 3d	MSE	82.93
	MAD	7.12
	MAPE	0.56
Moving Average 6d	MSE	81.45
	MAD	6.94
	MAPE	0.51
Weighted average model	MSE	79.72

	MAD	5.94
	MAPE	0.39
Exponential smoothing	MSE	82.59
	MAD	7.18
	MAPE	0.62
Holt's model	MSE	62.35
	MAD	6.10
	MAPE	0.55
Winter's model	MSE	55.17
	MAD	5.49
	MAPE	0.54

Error for set2 of veg fried rice is:

Moving Average 3d	MSE	85.30
	MAD	7.15
	MAPE	0.48
Moving Average 6d	MSE	86.96
	MAD	7.26
	MAPE	0.53
Weighted average model	MSE	74.39
	MAD	6.48
	MAPE	0.46
Exponential smoothing	MSE	66.77
	MAD	6.69
	MAPE	0.44
Holt's model	MSE	80.64
	MAD	6.75
	MAPE	0.45

Winter's model	MSE	78.06
	MAD	7.05
	MAPE	0.42

Error for set1 of egg fried rice is:

Moving Average 3d	MSE	31.92
	MAD	4.25
	MAPE	0.54
Moving Average 6d	MSE	25.43
	MAD	3.82
	MAPE	0.47
Weighted average model	MSE	21.00
	MAD	3.47
	MAPE	0.41
Exponential smoothing	MSE	27.19
	MAD	3.89
	MAPE	0.53
Holt's model	MSE	23.72
	MAD	4.00
	MAPE	0.53
Winter's model	MSE	27.34
	MAD	4.19
	MAPE	0.55

Error for set2 of egg fried rice is:

Moving Average 3d	MSE	46.44
	MAD	5.44
	MAPE	0.54
Moving Average 6d	MSE	39.95

	MAD	4.51
	MAPE	0.57
Weighted average model	MSE	30.58
	MAD	3.87
	MAPE	0.47
Exponential smoothing	MSE	46.61
	MAD	5.20
	MAPE	0.51
Holt's model	MSE	53.46
	MAD	4.86
	MAPE	0.51
Winter's model	MSE	58.29
	MAD	5.00
	MAPE	0.42

Error for set1 of Dosa is:

Moving Average 3d	MSE	672.90
	MAD	20.52
	MAPE	0.34
Moving Average 6d	MSE	629.72
	MAD	20.45
	MAPE	0.33
Weighted average model	MSE	536.71
	MAD	18.61
	MAPE	0.30
Exponential smoothing	MSE	645.40
	MAD	20.71
	MAPE	0.43
Holt's model	MSE	591.11



	MAD	19.41
	MAPE	0.36
Winter's model	MSE	502.29
	MAD	17.06
	MAPE	0.32

Error for set2 of Dosa is:

Moving Average 3d	MSE	2806.78
	MAD	41.96
	MAPE	2.37
Moving Average 6d	MSE	2405.85
	MAD	36.80
	MAPE	2.35
Weighted average model	MSE	3426.67
	MAD	45.83
	MAPE	1.95
Exponential smoothing	MSE	2522.52
	MAD	39.64
	MAPE	1.98
Holt's model	MSE	2986.33
	MAD	38.89
	MAPE	1.68
Winter's model	MSE	4477.93
	MAD	53.10
	MAPE	0.64

Error for set1 of Paneer paratha is:

Moving Average 3d	MSE	377.51
	MAD	14.21
	MAPE	0.63
Moving Average 6d	MSE	299.21
	MAD	12.91
	MAPE	0.54
Weighted average model	MSE	281.17
	MAD	12.65
	MAPE	0.46
Exponential smoothing	MSE	308.72
	MAD	13.53
	MAPE	0.56
Holt's model	MSE	257.31
	MAD	12.48
	MAPE	0.51
Winter's model	MSE	248.31
	MAD	12.16
	MAPE	0.46

Error for set2 of Paneer paratha is:

Moving Average 3d	MSE	311.37
	MAD	14.38
	MAPE	2.21
Moving Average 6d	MSE	300.06
	MAD	14.73
	MAPE	2.50
Weighted average model	MSE	445.32
	MAD	17.93
	MAPE	1.98

Exponential smoothing	MSE	360.39
	MAD	14.73
	MAPE	1.91
Holt's model	MSE	389.88
	MAD	12.59
	MAPE	1.88
Winter's model	MSE	693.77
	MAD	18.53
	MAPE	1.34

Error for set1 of Paneer 65 is:

Moving Average 3d	MSE	62.43
	MAD	6.27
	MAPE	0.49
Moving Average 6d	MSE	59.69
	MAD	5.90
	MAPE	0.41
Weighted average model	MSE	61.35
	MAD	5.55
	MAPE	0.35
Exponential smoothing	MSE	73.85
	MAD	7.22
	MAPE	0.61
Holt's model	MSE	50.23
	MAD	5.52
	MAPE	0.64
Winter's model	MSE	47.95
	MAD	4.89
	MAPE	0.70

Error for set2 of Paneer 65 is:

Moving Average 3d	MSE	83.11
	MAD	7.68
	MAPE	0.43
Moving Average 6d	MSE	70.40
	MAD	7.09
	MAPE	0.44
Weighted average model	MSE	69.17
	MAD	6.86
	MAPE	0.40
Exponential smoothing	MSE	76.88
	MAD	7.43
	MAPE	0.40
Holt's model	MSE	76.99
	MAD	6.45
	MAPE	0.37
Winter's model	MSE	79.10
	MAD	6.00
	MAPE	0.33

### **Factors that influencing the error:**

1. There was error in demand projection due to sudden variation of the no of orders placed and number of orders were fluctuating because the people on the campus were changing due to covid restrictions. To solve this problem anc1 should have the data of the number of people on the campus and make an equation that builds positive correlation with no of students on campus.
2. There may be any events like a birthday, getting placed etc. which will add to the number of orders.
3. Examinations will have an impact on the number of orders placed because some people may want to study till late night.

### **Observation:**

1. Even though we are trying to forecast demand for an item in the same category, all items do not fit in the same model well. each has different best models.
2. Items and their best fit models are
  - Chicken fried rice - weighted moving average
  - Veg fried rice - weighted moving average (set - 1)
  - Veg fried rice - winter's model( set - 2 )
  - Egg fried rice - winter's model( set - 1 )
  - Egg fried rice - weighted moving average (set - 2)
  - Paneer paratha - winter's model
  - Paneer 65 - weighted moving average( set - 1 )
  - Paneer 65 - winter's model( set - 2 )
  - Dosa - weighted moving average ( set - 1 )
  - Dose - winter's model ( set - 2 )
3. If holt's model works better than exponential smoothing than winter's model works fit better than holt's model.