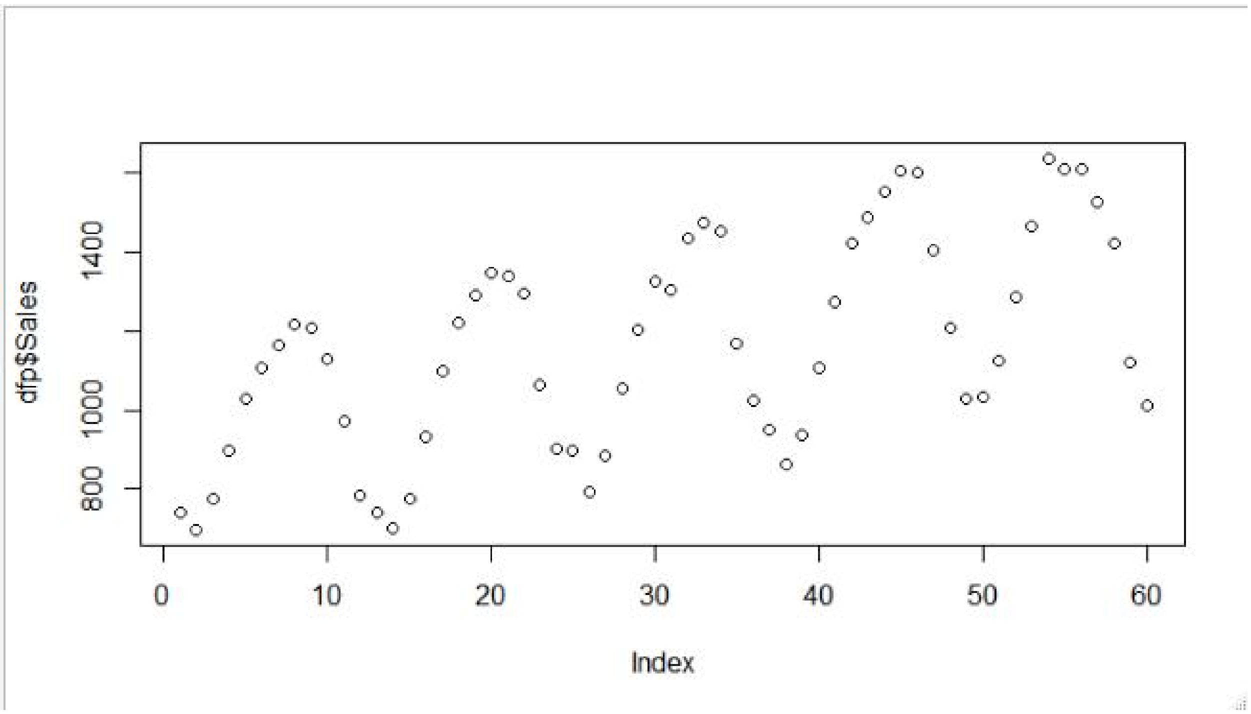
Forecasting

Example- Plastic Sales

Dataset contains 60 observations and 2 variables with Sales is our target variable.

No missing values and outliers are present in our dataset.



From the above plot sales is in purely cyclic is nature, with weak sign of tradeline in sales data.

Data Preprocessing ➔

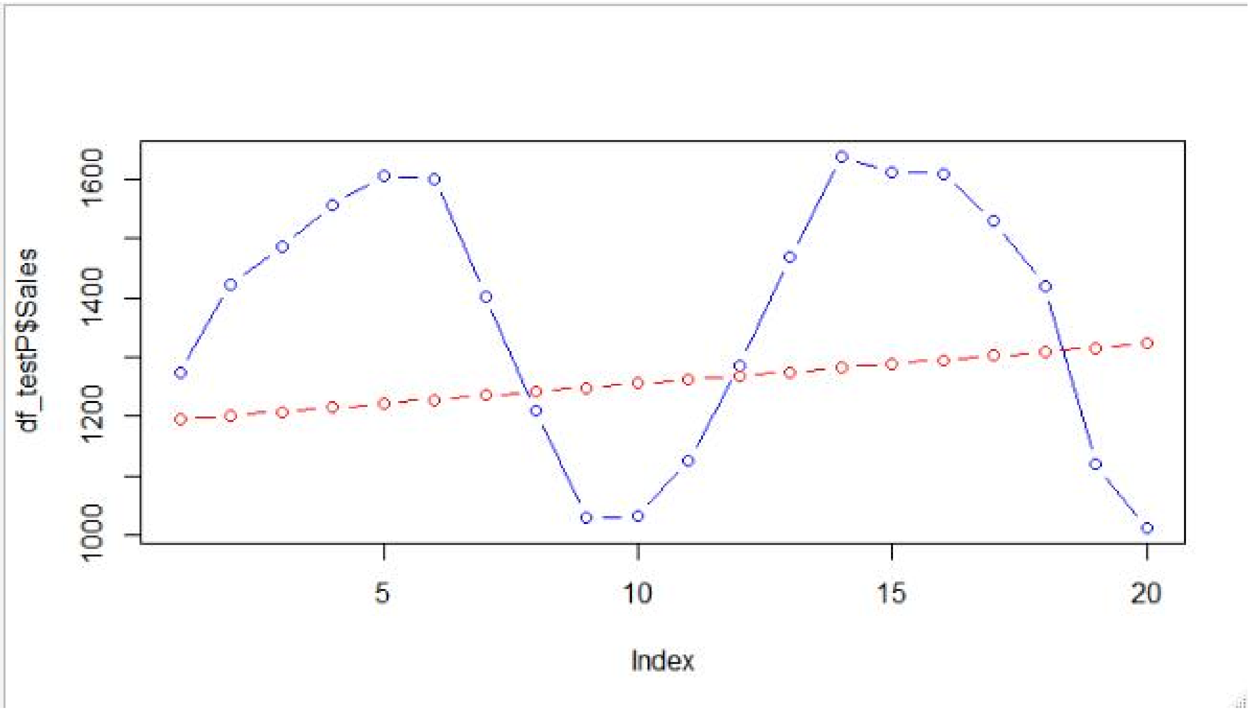
Created dummy variables from 1949 to 1953 for all the months.

Considered first 40 records as train data and balance 20 records as test data.

Linear Trend Model ➔

`Multiple R-squared:  0.1211,   Adjusted R-squared:  0.09802`

RMSE ➔ 248.924

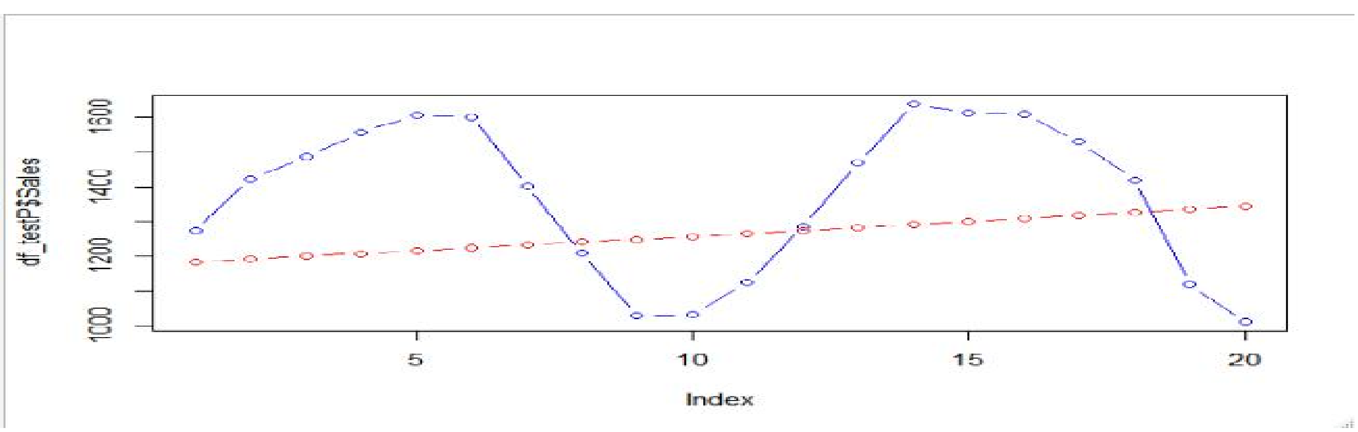


From the above plot predicted values are not in cyclic pattern in our data.

Exponential Model ➔

`Multiple R-squared:  0.1269,   Adjusted R-squared:  0.104`

RMSE ➔ 250.1071

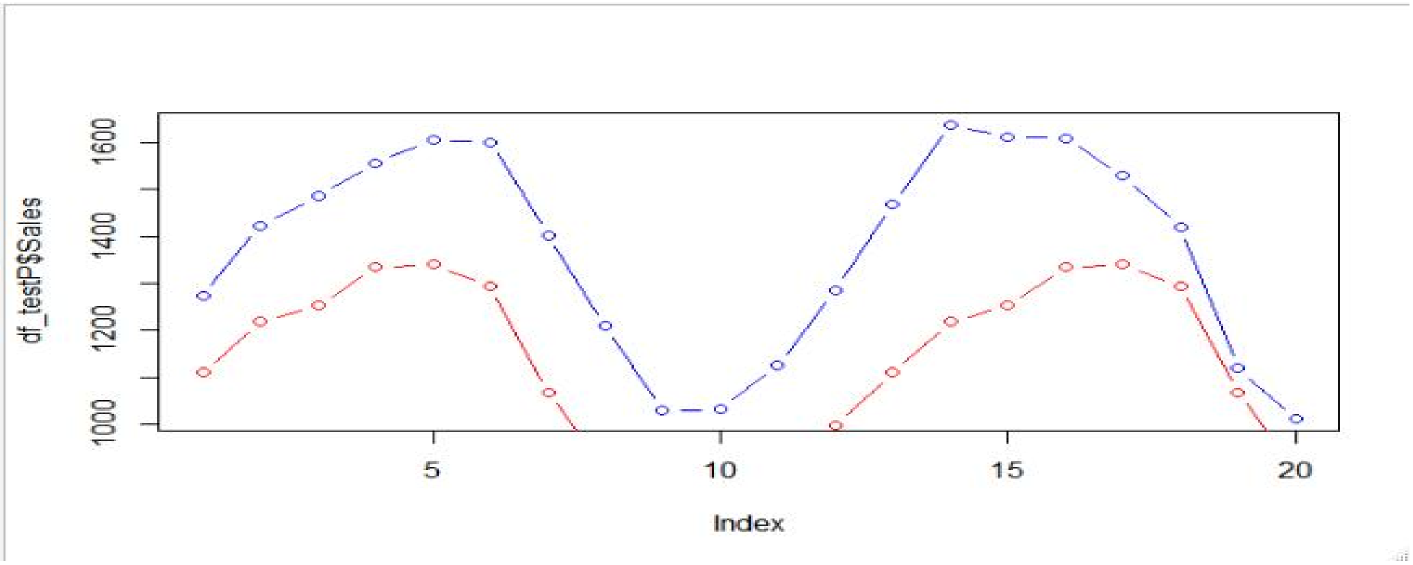


There are no changes in this model as compared to previous model.

<u>Model to Capture Seasonal variation ➔</u>

`Multiple R-squared: 0.8405,	Adjusted R-squared: 0.7778`

<u>`RMSE ➔263.2362`</u>

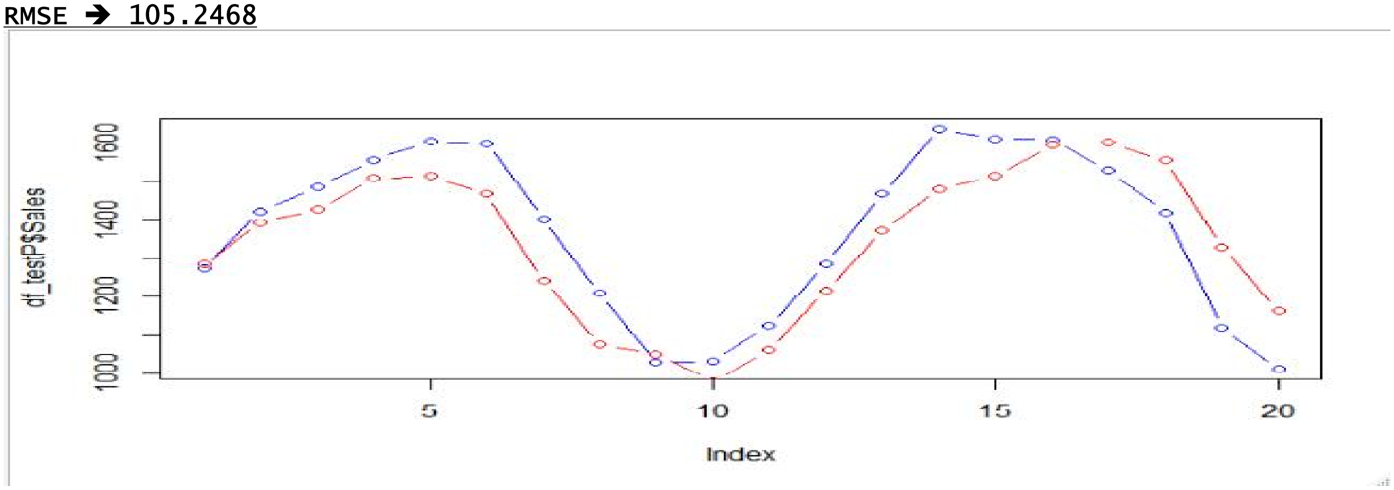


From above plot pattern of actual values is followed by predicted values and Sales is completely depending on seasonal changes.

<u>Additive Seasonality with Linear Trend ➔</u>

`Multiple R-squared: 0.9791,	Adjusted R-squared: 0.9698`

<u>`RMSE ➔ 105.2468`</u>

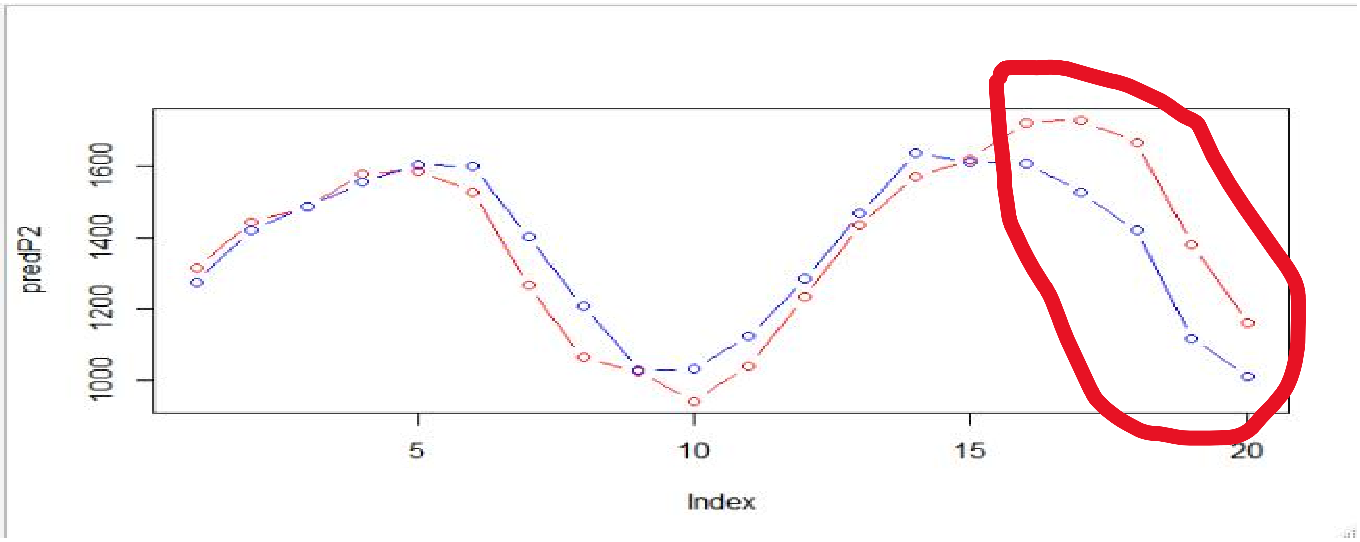


In this plot gap between predicted and actual value is compressed as compared to previous model.

<u>Multiplicative Seasonality →</u>

`Multiple R-squared:  0.9848,   Adjusted R-squared:  0.9781`

<u>`RMSE → 117.115`</u>



<u>In this plot slight problem with last 5 records because difference in quite noticeable.</u>

Model	R^2	RMSE
Linear Model	**0.1211**	**248**
Exponential Model	**0.1211**	**248**
Model to Capture Seasonal variation	**0.8405**	**263.2362**
Additive Seasonality with Linear Trend	**0.9791**	**105.2468**
Multiplicative Seasonality	**0.9848**	**117.115**

<u>From above plots and table, we can infer that Additive Seasonality with Linear Trend Model is our best final model.</u>