STUDY OF TRADITIONAL & NON-TRADITIONAL FUELS IN INDIA

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INTRODUCTION

- Over a century Automobile Industry is gearing up for transformations. The fossil fuel price spike and the impact of its emission on environment have called for a change in individual transportation habits. The sector, propelled by Internal Combustion Engines, is gravitating gradually towards Electric Vehicles. But still we see use of most of the fuels like CNG, LPG, Petrol, and Diesel etc. We need to study that which vehicles cannot easily replaced by EV, what is their count.
- Though electric vehicle (EV) with its zero-emission guarantee is the future of transportation. For a country with a population of 1.4 billion ease of transport is a necessity. Indian transport contributes to around 10% of India carbon emission. India is ready to branch out in a new sustainable way of transportation through the means of an electric vehicle. But still some fuels are not easily replaceable by EV.
- EV Market is currently noticing a Boom in vehicle Market which raises a question about the approval of EV technology and design by the buyers. Simultaneously, all other fuels are still steady in their count.

MOTIVATION

We observed mostly used modes of transports on the roads, most of them were fuel based. The rising price of fuels in global economy and the rising pollution with it had an adverse our minds. We tried to observe some alternatives among different types of Vehicles. Electric vehicles was the only outstanding solution to all the major arising problems. They produce zero tailpipe emissions, reducing air pollution and dependence on fossil fuels. EVs are generally cheaper to operate than traditional internal combustion engine vehicles due to lower fuel and maintenance costs. Electric motors are much quieter than internal combustion engines, which leads to less noise pollution. But in our day to day life we are so used to other fuels that it is not possible to adapt EV easily. we need to study how much time will we will take to see EV as good mode of transportation then how will it effect on other fuels will their count increase or decrease. Highly used fuels like CNG, LPG, Petrol, Diesel, etc may be not get highly affected by it so easily. The large amount of data when studied properly and analysed carefully can be used in many future predictions and may help to avoid loss over period of time. We selected this project to get glimpse of many statistical techniques. We can study future values of all fuels and take voluntary actions to increase number of vehicles running on Non-Traditional fuels count

ABSTRACT

From the past behaviour of traditional fuels in India we conclude that it is not possible to replace them very soon because of people are not sure and aware about the electric vehicle and their benefits related to their cost, reduction in pollution etc.

As we know EV belong to zero carbon emission group so we have Consider top 10 states having most no. of RTO station for our correspondence analysis and we have Conclude in which state we have to increase the awareness of EV.

OBJECTIVES

1) Check which Vehicle Category is mostly used and which Fuel is mostly used in it.

2) To observe growth of Traditional fuels & Non-Traditional fuels in India.

3) To do comparable study of EVS and other fuels like CNG, Petrol, Diesel, LPG for India.

4) To analyse in which States of India we need to spread awareness of Electric Vehicles.

5) To study the increase in count of Traditional & Non-Traditional fuels in next 5 years in India.

Data Source (Link) :

https://vahan.parivahan.gov.in/vahan4dashboard/vahan/dashboardview.xhtml;jsessionid=4C3A86ADE94A8F88702116553FB2A13F

KEYWORDS:

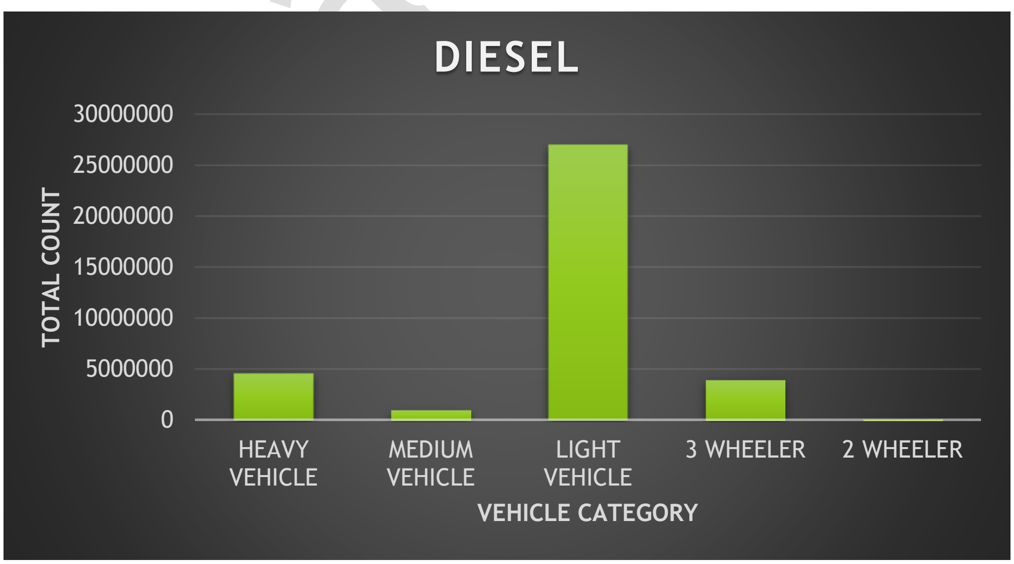
- *Exploratory Data Analysis*
- *Forecasting*
- *Time Series Analysis*
- *Correspondence Analysis*

EXPLORATORY DATA ANALYSIS:

We have firstly Perform graphical analysis of fuels Petrol, Diesel, CNG, Electric Vehicles on vehicle categories like Heavy vehicle(Bus, Truck), medium vehicle(Mini Bus, Tempo), light vehicle(Car) ,3 wheelers & 2 wheelers.

1)DIESEL

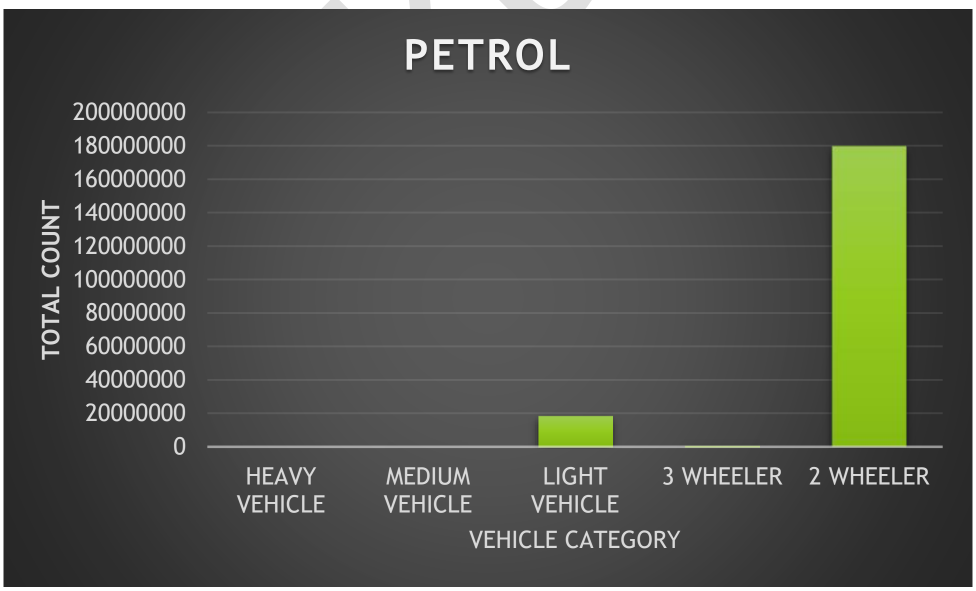
VEHICLE CATEGORY	DIESEL COUNT
HEAVY VEHICLE	4560791
MEDIUM VEHICLE	930292
LIGHT VEHICLE	27000595
3WHEELER	3920193
2WHEELER	78732



INTERPRETATION: - We can clearly see that Diesel is highly used in light vehicle.

2)PETROL

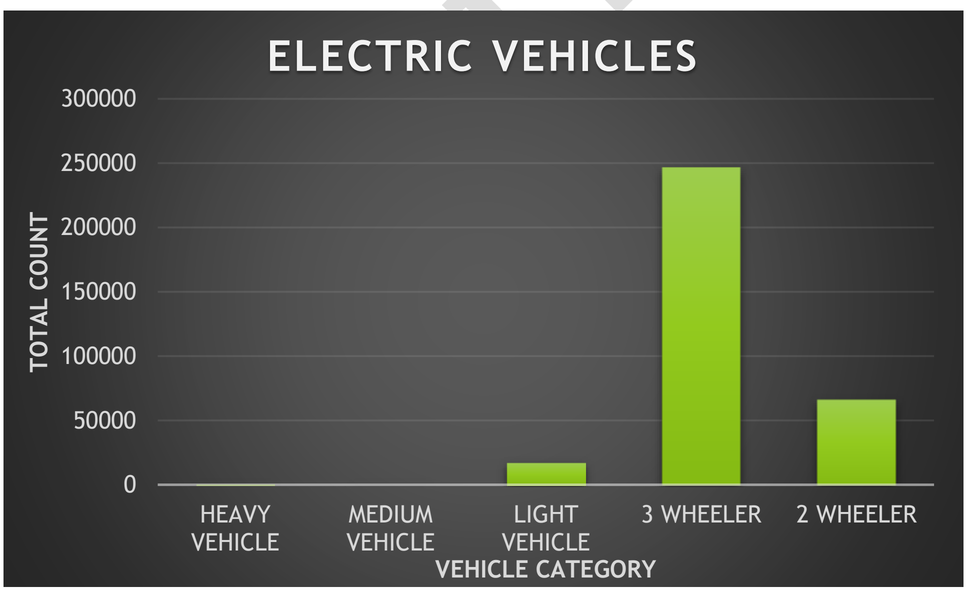
VEHICLE CATEGORY	PETROL COUNT
HEAVY VEHICLE	5298
MEDIUM VEHICLE	2192
LIGHT VEHICLE	18173864
3 WHEELER	703054
2 WHEELER	179630386



INTERPRETATION:-From above graph we come to know that Petrol is highly used in 2wheeler

3)ELECTRIC VEHICLE

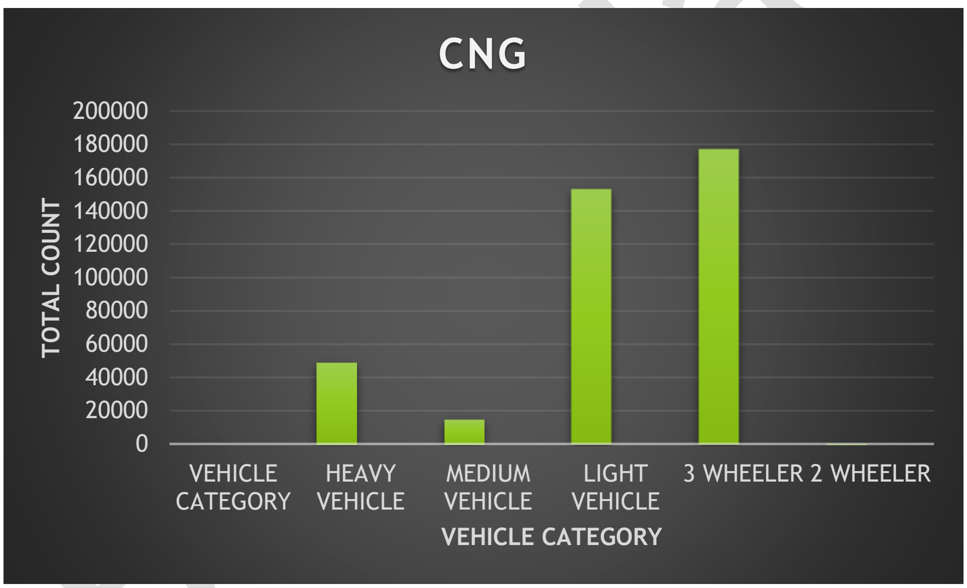
VEHICLE CATEGORY	EV COUNT
HEAVY VEHICLE	379
MEDIUM VEHICLE	90
LIGHT VEHICLE	16886
3 WHEELER	246347
2 WHEELER	65726



INTERPRETATION :- we can see that in 3wheelers electric vehicles are mostly used.

4)CNG

VEHICLE CATEGORY	CNG COUNT
HEAVY VEHICLE	48784
MEDIUM VEHICLE	14683
LIGHT VEHICLE	152837
3 WHEELER	176897
2 WHEELER	355



INTERPRETATION :- From above graph we can observe that in 3wheelers CNG is mostly used.

VEHICLE CATEGORY	TOTAL COUNT	FUEL	EV
HEAVY VEHICLE	4615307	DIESEL	379
MEDIUM VEHICLE	947264	DIESEL	90
LIGHT VEHICLE	45367587	DIESEL	16886
3 WHEELER	5100807	DIESEL	246347
2 WHEELER	179776242	PETROL	65726

From above table we can see that highly used vehicle category is 2wheeler in which petrol is highly used. while Diesel is mostly used in other vehicle categories.

Till now mostly EV is used in 3 Wheelers than other any vehicle category. This can be because of government schemes for Auto rickshaw.

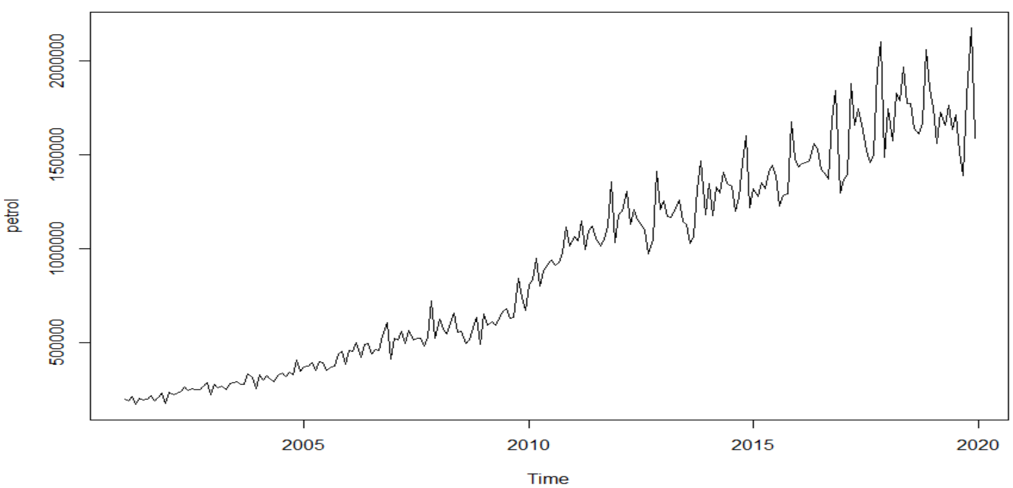
TIME SERIES ANALYSIS

We have performed Time series analysis on ELECTRIC VEHICLE, CNG, PETROL, DIESEL and LPG.

We have fitted models for each fuels & predicted count for next 5 – 10 yrs.

1)PETROL

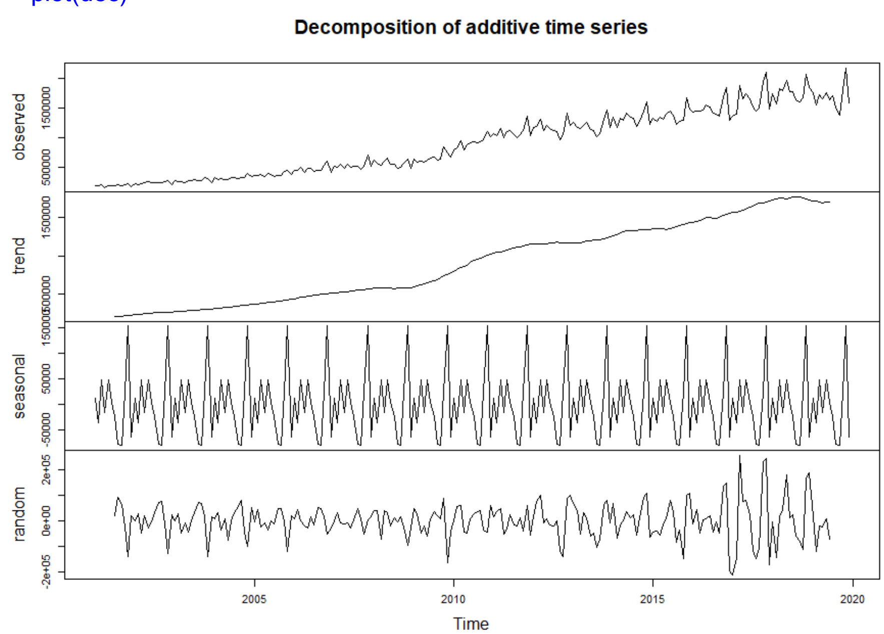
```
> plot.ts(petrol)
```



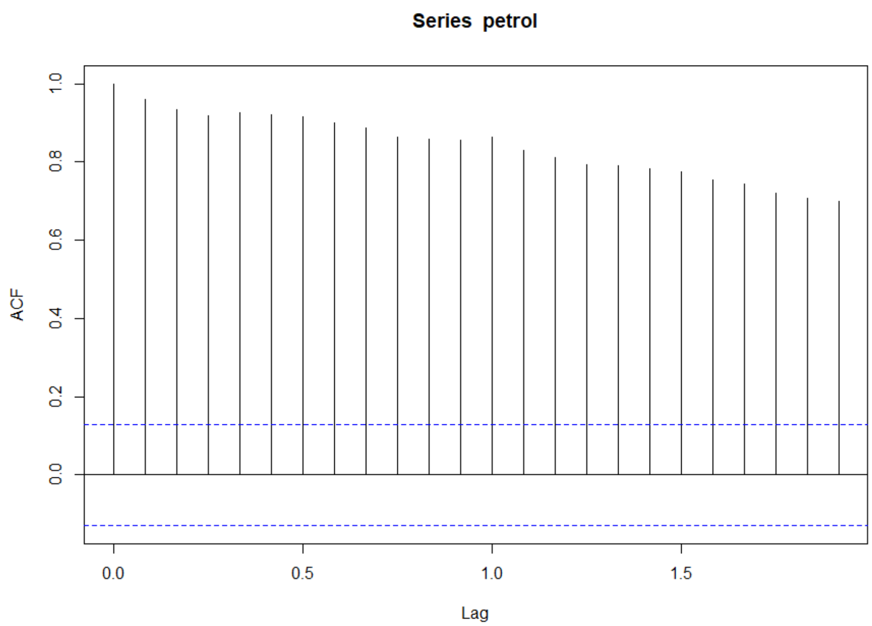

```
> kpss.test(petrol)

        KPSS Test for Level Stationarity

data:  petrol
KPSS Level = 4.6166, Truncation lag parameter = 4, p-value = 0.01

> adf.test(petrol)

        Augmented Dickey-Fuller Test
```

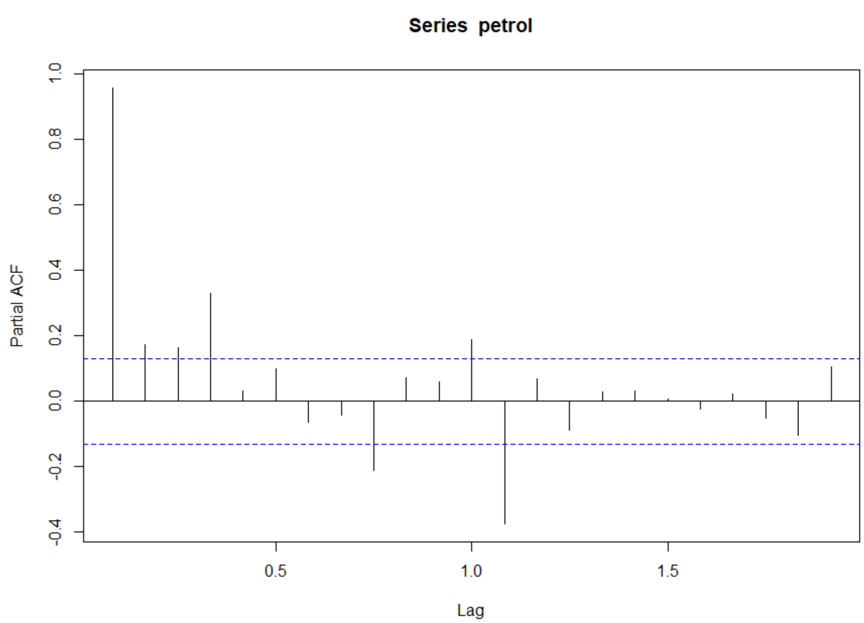
```
data:   petrol
Dickey-Fuller = -2.1839, Lag order = 6, p-value = 0.4987
alternative hypothesis: stationary
```

```
> train=window(petrol,start=(2001),end=c(2015,12))
> train
> test=window(petrol,start=(2016),end=c(2019,12))
> test
> dec=decompose(petrol)
> dec

> plot(dec)
```




```
> acf(petrol,type="correlation")
> acf(petrol,type="partial")
```

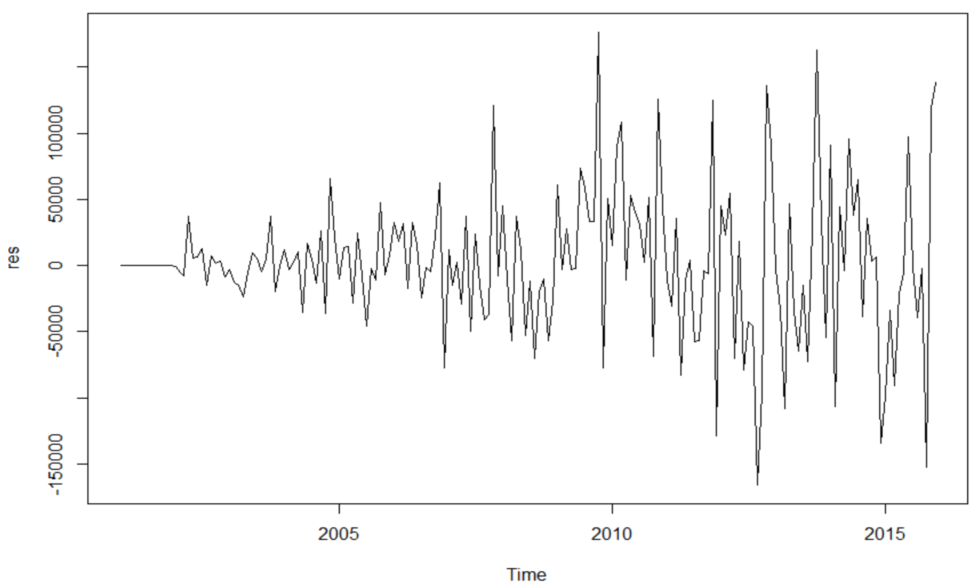





```
model_pt=auto.arima(train,ic="aic",trace = TRUE)
```

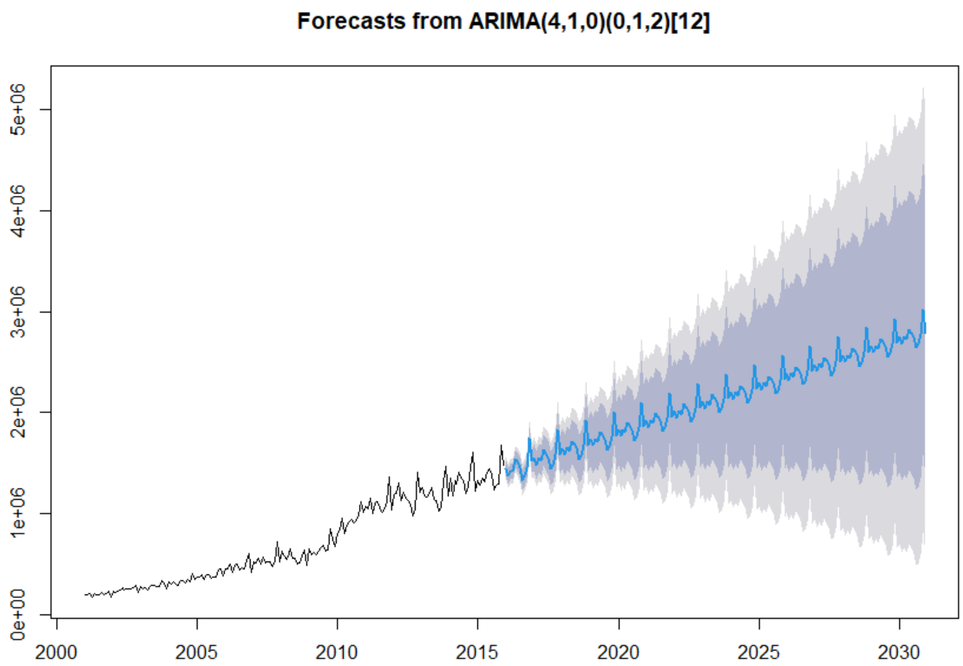
```
Fitting models using approximations to speed things up...

Now re-fitting the best model(s) without approximations...

ARIMA(4,1,0)(0,1,2)[12]                    : 4144.001
```

```
 Best model: ARIMA(4,1,0)(0,1,2)[12]

> model_pt
Series: train
ARIMA(4,1,0)(0,1,2)[12]

Coefficients:
          ar1      ar2      ar3      ar4     sma1     sma2
      -0.5454  -0.5437  -0.3993  -0.3128  -0.4208  -0.2089
s.e.   0.0758   0.0852   0.0872   0.0776   0.0922   0.0927

sigma^2 = 3.221e+09:  log likelihood = -2065
AIC=4144   AICc=4144.71   BIC=4165.83
> forcast=forecast(model_pt,h=132)
> forcast
> res=forcast$residuals
> res


> plot.ts(res)
```




```
> Box.test(res)

        Box-Pierce test
```

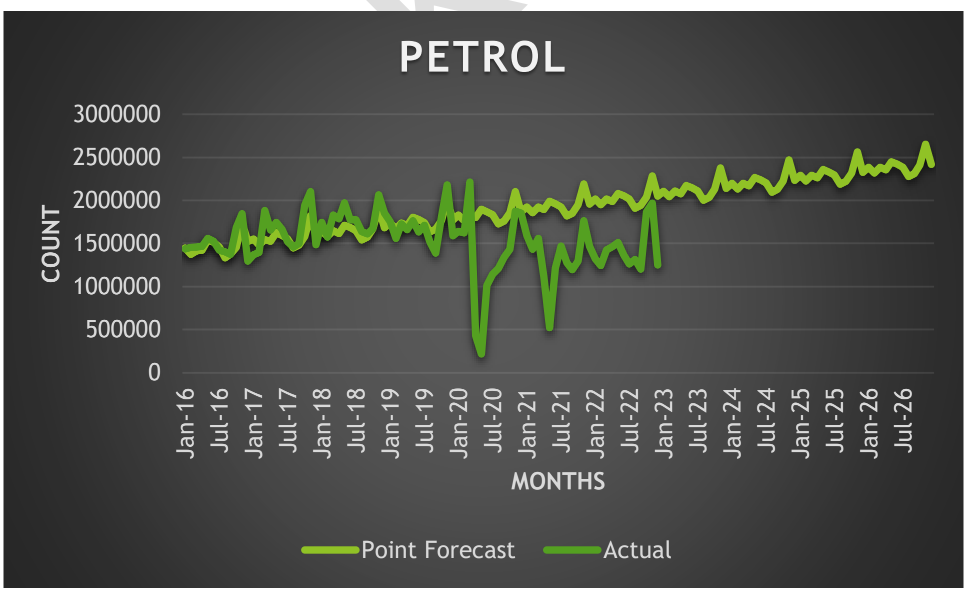
```
data:   res
X-squared = 0.017144, df = 1, p-value = 0.8958

> acf(res,type="correlation")
> acf(res,type="partial")
> plot(forcast)
```




```
> kpss.test(res)

        KPSS Test for Level Stationarity

data:   res
KPSS Level = 0.074624, Truncation lag parameter = 4, p-value = 0.1

> adf.test(res)

        Augmented Dickey-Fuller Test

data:   res
Dickey-Fuller = -4.3074, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

> mres=auto.arima(res,max.p=5,max.q=5)
> mres
Series: res
```

```
ARIMA(0,0,0) with zero mean

sigma^2 = 2.881e+09:   log likelihood = -2215.75
AIC=4433.49     AICc=4433.52     BIC=4436.69
```

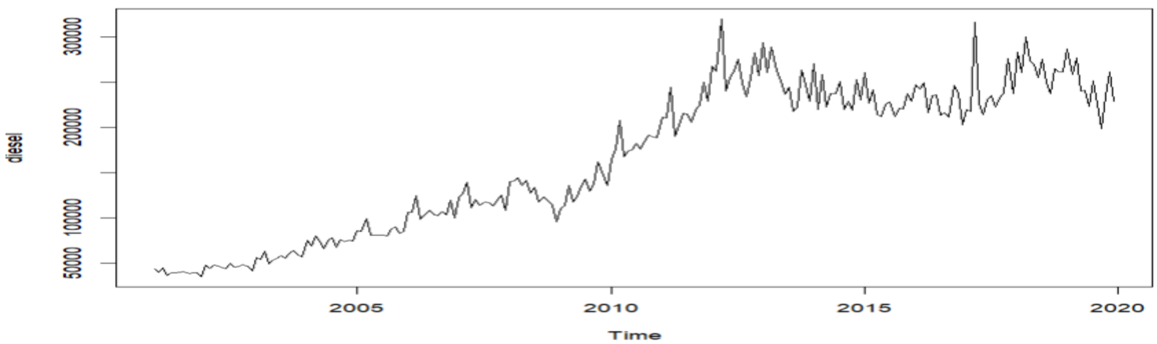
```
>
forc_test=forecast(model_pt,h=length(test))

forc_test

train_accuray=accuracy(model_pt$fitted,x=train)

train_accuray

                    ME      RMSE      MAE       MPE     MAPE         ACF1 Theil's U
Test set 2161.816 53678.24 36924.85 0.1213557 4.906469 -0.009759455 0.5367327
test_accuray=accuracy(forc_test$mean,x=test)

test_accuray

               ME     RMSE      MAE      MPE     MAPE      ACF1 Theil's U
Test set 39511.65 141744.7 108168.3 1.716811 6.408898 0.2751183 0.6352163
```



Hence,from above graph we can interpret that we get good predictions of Petrol.

2)DIESEL

plot.ts(diesel)



kpss.test(diesel)

KPSS Test for Level Stationarity

data: diesel

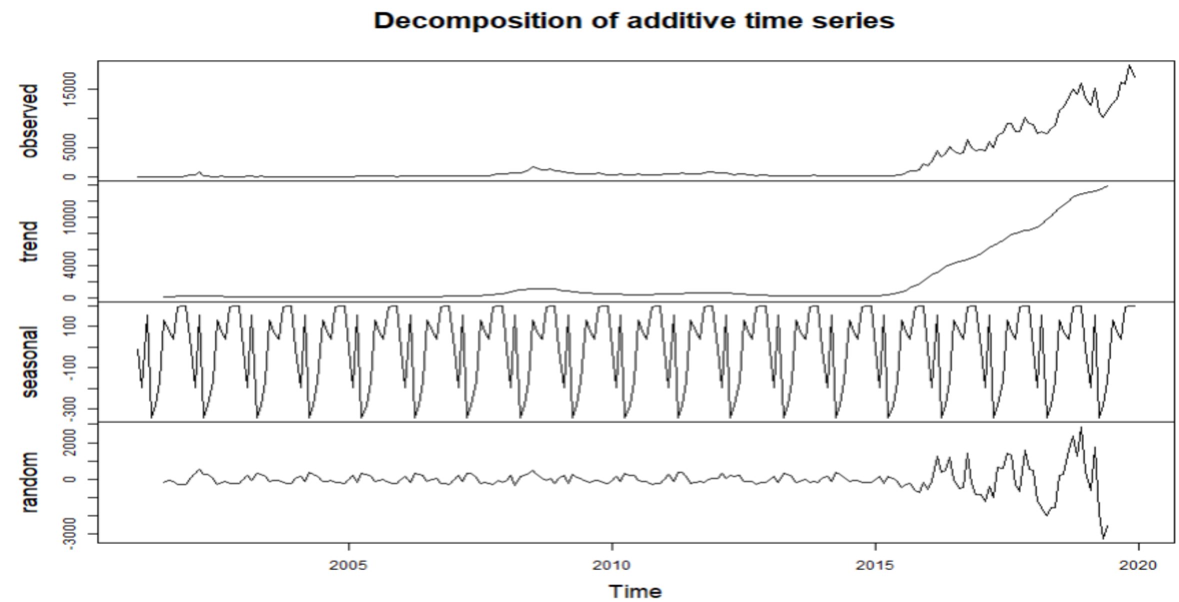
KPSS Level = 4.2854, Truncation lag parameter = 4, p-value = 0.01

Conclusion : Since p value <0.05 . Hence The Diesel Time Series is not Trend Stationary

dec=decompose(ev)

dec

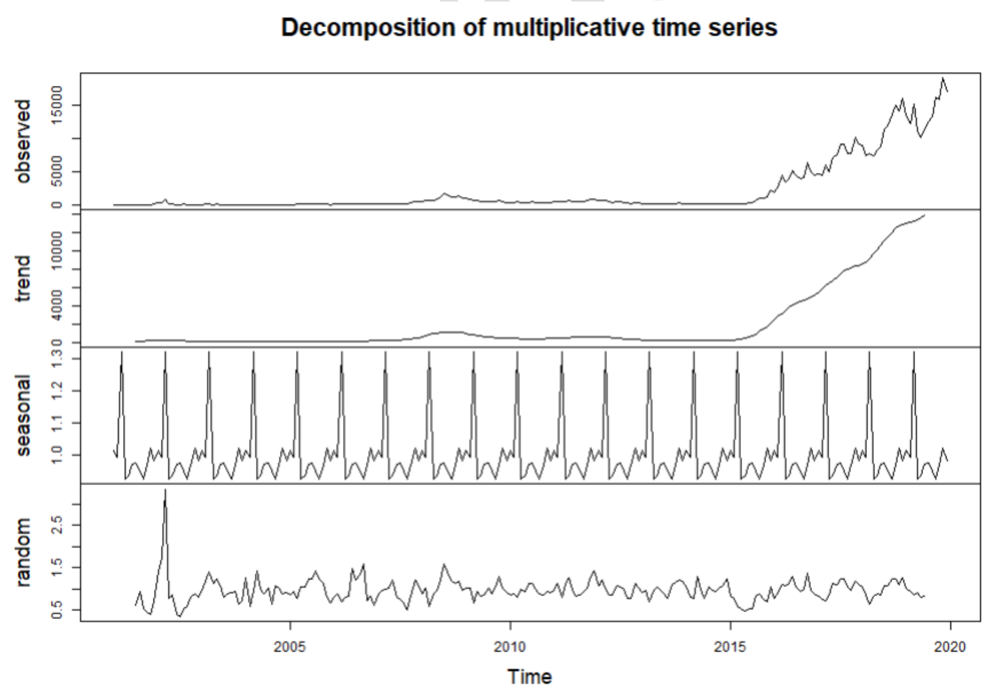
plot(dec)




```
dec1=decompose(ev,type = "multiplicative")
```

```
dec1
```

```
plot(dec1)
```



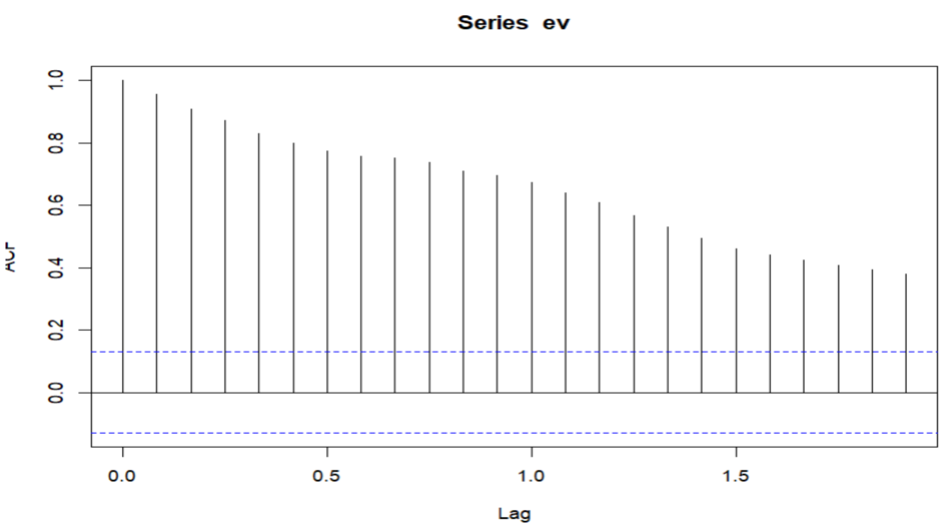

```
adf.test(ev)
```

Augmented Dickey-Fuller Test

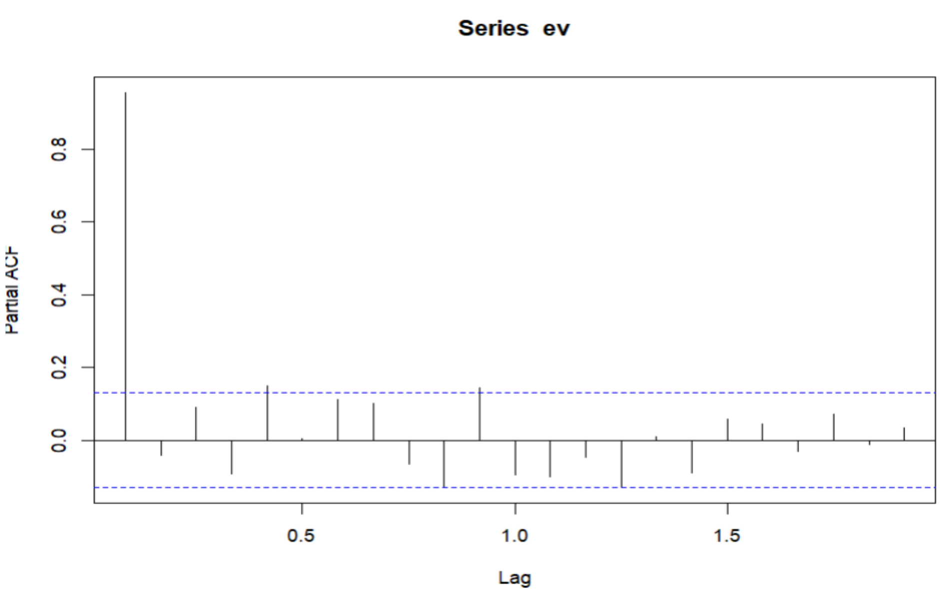
data: ev
Dickey-Fuller = 0.98551, Lag order = 6, p-value = 0.99
alternative hypothesis: stationary

Conclusion: Hence the time series has unit root .Hence not Stationary

acf(ev,type="correlation")

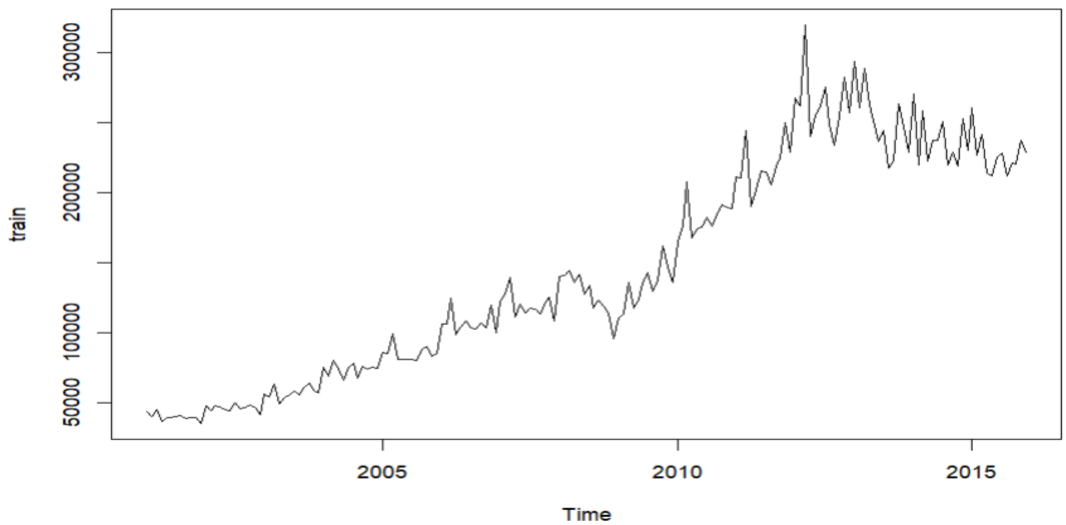


acf(ev,type="partial")



train=window(diesel,start=c(2001),end=c(2015,12)) train

plot.ts(train)



m1=auto.arima(train,seasonal = TRUE)

> m1

Series: train

ARIMA(0,1,1)(0,1,1)[12]

Coefficients:

	ma1	sma1
	-0.4427	-0.5594
s.e.	0.0635	0.0820

sigma^2 = 1.21e+08: log likelihood = -1792.36

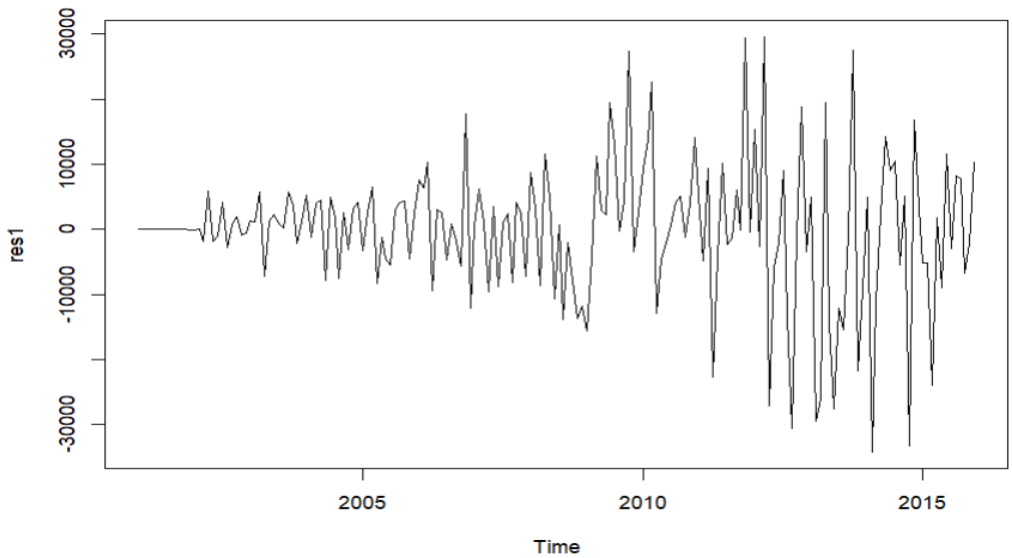
AIC=3590.72 AICc=3590.86 BIC=3600.07

fm1=forecast(m1,h=132)

fm1

res1=fm1$residuals

plot.ts(res1)

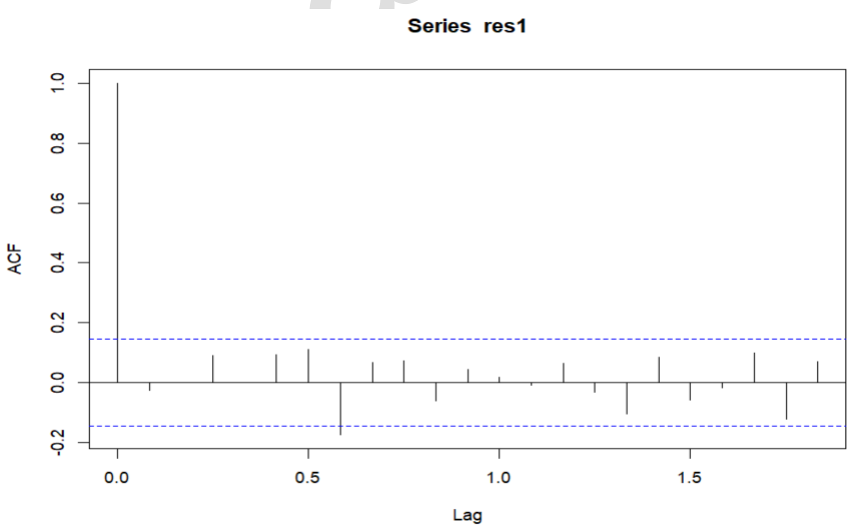


Box.test(res1)

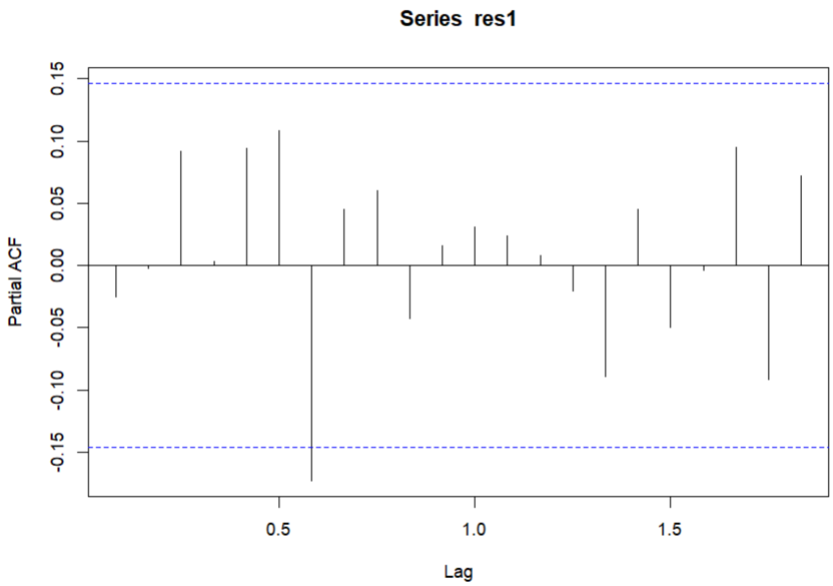
Box-Pierce test

data: res1
X-squared = 0.11406, df = 1, p-value = 0.7356
Conclusion: Hence the residuals follow White Noise Seq.

acf(res1,type="correlation")



acf(res1,type="partial")



kpss.test(res1)

KPSS Test for Level Stationarity

data: res1
KPSS Level = 0.2041, Truncation lag parameter = 4, p-value = 0.1

Hence the residuals seq is trend Stationary

adf.test(res1)

Augmented Dickey-Fuller Test

data: res1

Dickey-Fuller = -4.2211, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

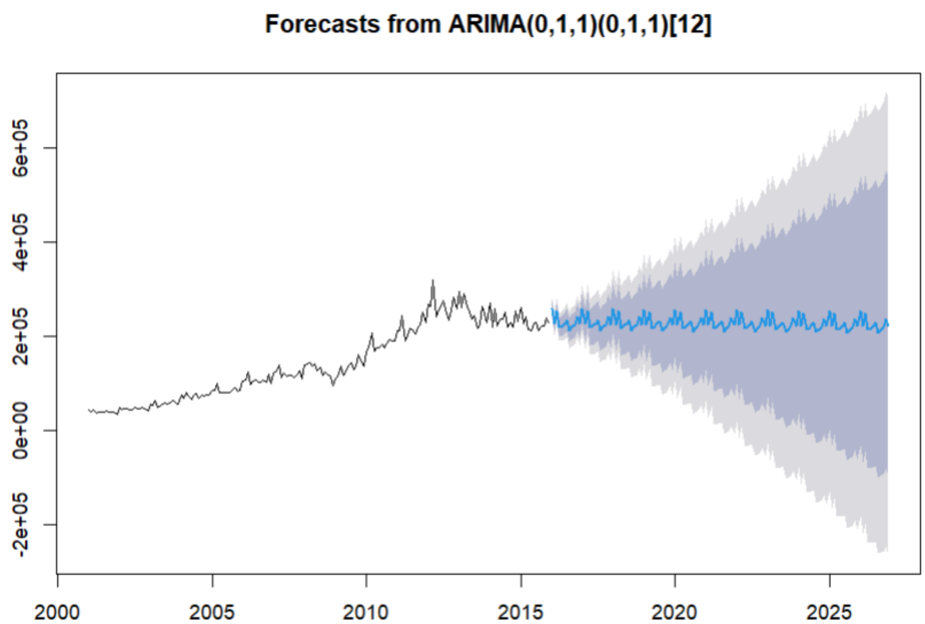
Hence the residuals seq is unit root Stationary mres1=auto.arima(res1,max.p=5,max.q=5)

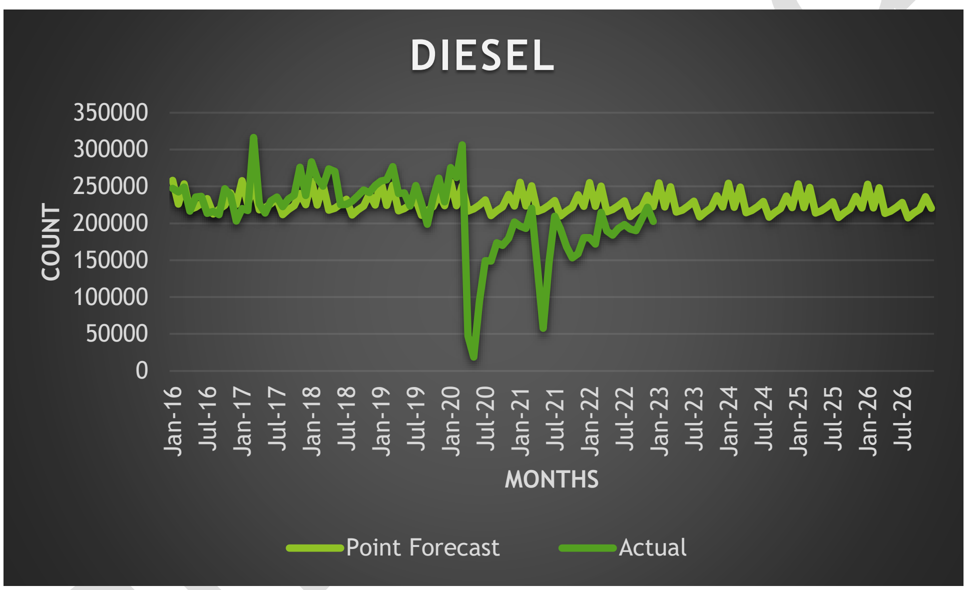
mres1

Series: res1

```
ARIMA(0,0,0) with zero mean

sigma^2 = 110911915:  log likelihood = -1922.59
AIC=3847.18   AICc=3847.2   BIC=3850.38
```

```
test=window(diesel,start=(2016),end=c(2019,12))
> test
> forc_test=forecast(m1,h=length(test))
> forc_test
 train_accuray=accuracy(m1$fitted,x=train)
> train_accuray
                ME     RMSE      MAE         MPE     MAPE        ACF1 Theil's U
Test set -149.5837 10531.47 7217.679 -0.04463883 4.768957 -0.02517276 0.5584861
> test_accuray=accuracy(forc_test$mean,x=test)
> test_accuray
               ME     RMSE   MAE      MPE     MAPE      ACF1 Theil's U
Test set 15423.28 26268.19 21431 5.620251 8.411365 0.4759261  0.873657
```

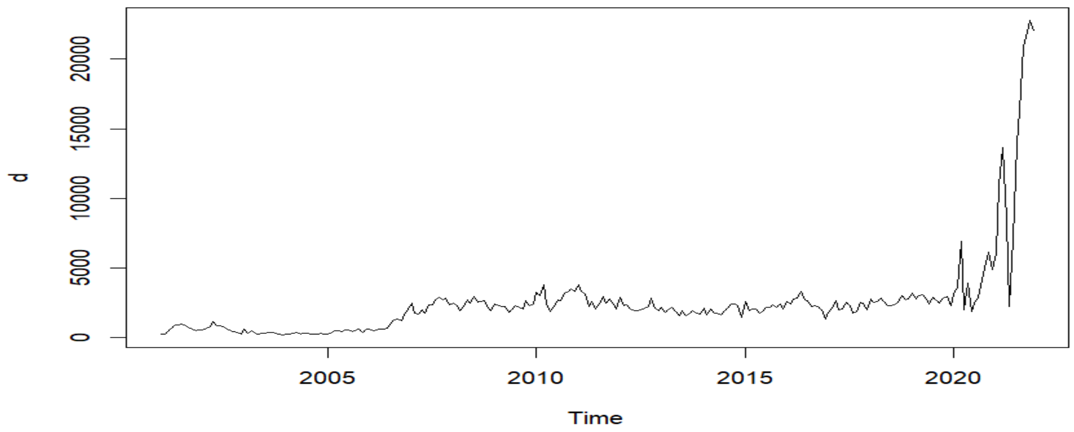




Hence,from above graph we can say that for next 5 yrs count of Diesel will be stable.

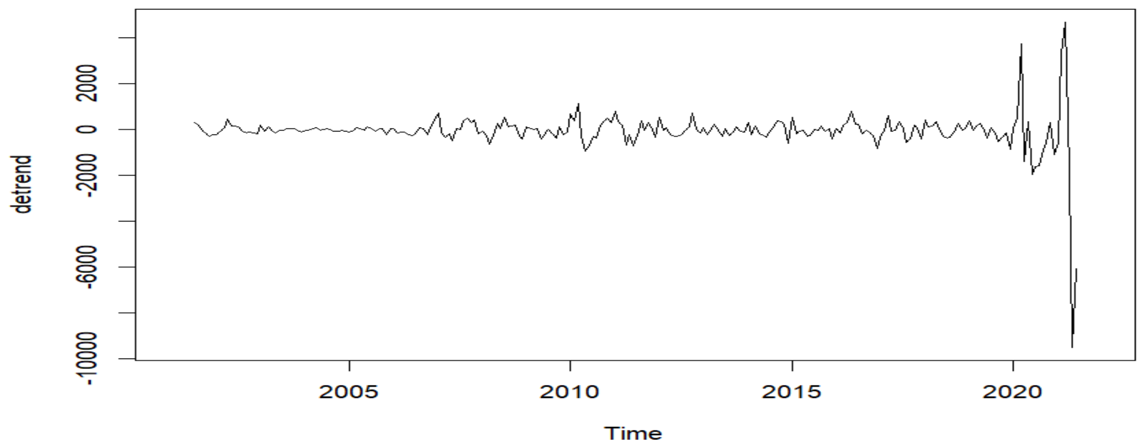
3)CNG

```
> plot.ts(d)
```

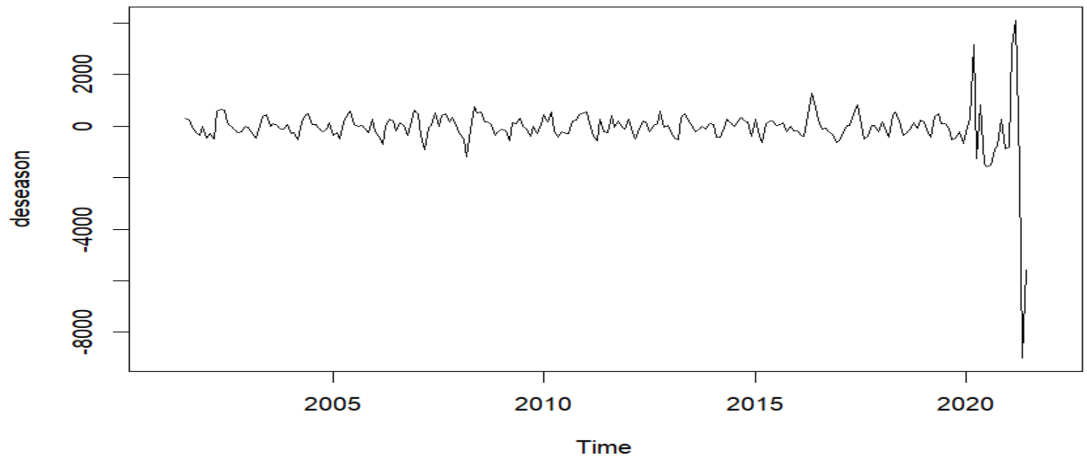


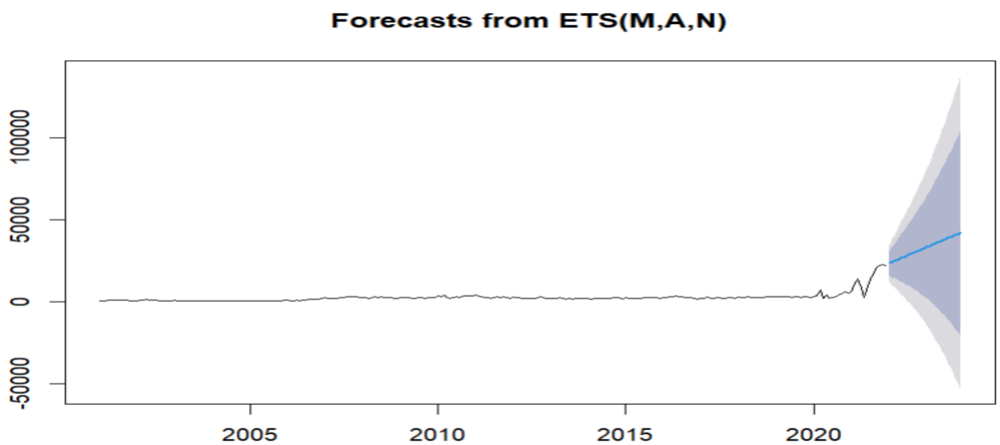

```
kpss.test(d)

        KPSS Test for Level Stationarity

data:  d
KPSS Level = 1.5232, Truncation lag parameter = 5, p-value = 0.01
```

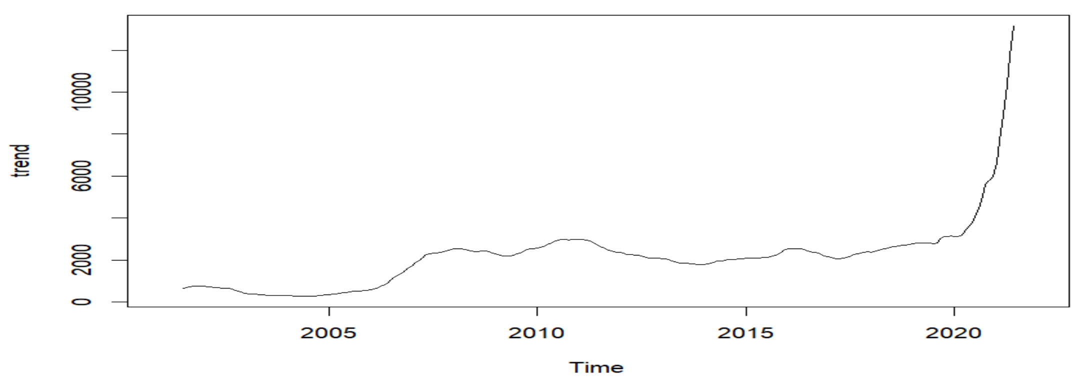
```
> ### Estimating and eliminating  trend
> trend=ma(d,order=12)
> trend
> detrend=d-trend
> detrend
> plot.ts(detrend)
```




```
### Deseasonalizing data
> season=decompose(d)
> s=season$figure
> s
 [1]  252.44774  227.95399  588.69983 -108.67101 -495.08976 -461.23351    1.59566  -52.90434
 [9]   20.36024  146.97066   69.60399 -189.73351
> deseason=detrend-s
> deseason
> plot.ts(deseason)
> kpss.test(deseason)

          KPSS Test for Level Stationarity

data:  deseason
KPSS Level = 0.34303, Truncation lag parameter = 5, p-value = 0.1
### Hence Now the Stationarity is achieved.
```








```
> m1=auto.arima(deseason,max.p=7,max.q=7)
```

```
> m1
```

```
Series: deseason
ARIMA(3,0,1) with zero mean
Coefficients:
         ar1      ar2      ar3     ma1
      0.0716  -0.2610  -0.6570  0.4839
s.e.  0.1381   0.1017   0.0973  0.1502
sigma^2 = 440572:
 log likelihood = -1899.42
AIC=3808.84   AICc=3809.09   BIC=382
```

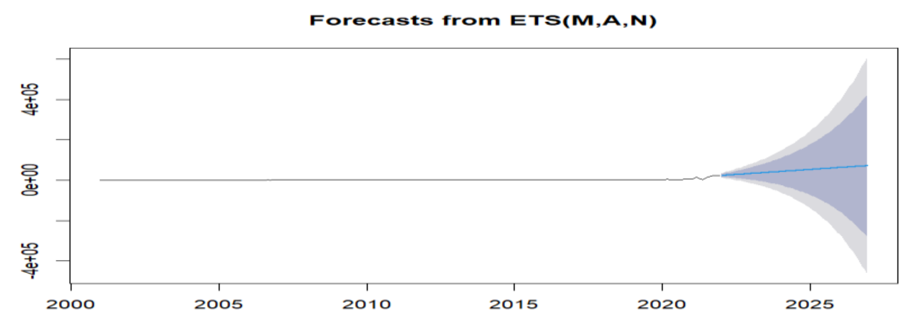
```
forc=forecast(d,h=12)
> forc=forecast(d,h=24)
> forc
> forc_arima=forecast(m1,h=24)
> forc_arima
> df_forc=as.data.frame(forc_arima)
> df_forc
> df_forc["Point Forecast"]
> plot.ts(forc_arima)
> resid_arima=residuals(m1)
> resid_arima
> plot.ts(trend)
> plot.ts(resid_arima)
> Box.test(resid_arima)

        Box-Pierce test

data:  resid_arima
X-squared = 1.63e-05, df = 1, p-value = 0.9968

>
> forc=forecast(d,h=24)
> forc
> plot(forc)
> mt_trend=as.matrix(trend,start=c(2001,1))
> ###b Accuracy
> accuracy(forc)
                   ME     RMSE      MAE       MPE     MAPE      MASE      ACF1
Training set 76.35875 1107.064 471.5562 -5.153044 19.70939 0.4821042 0.3290804
> accuracy(forc_arima)
```

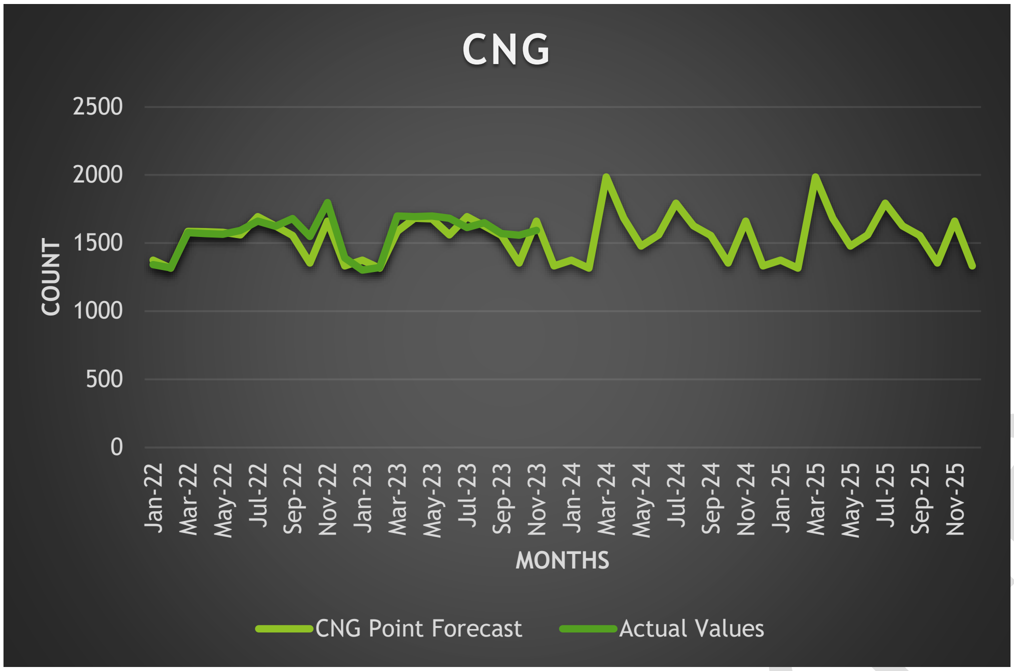
	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	-43.33682	658.2015	372.1162	82.34837	450.4103	0.9741335	0.0002606121

>

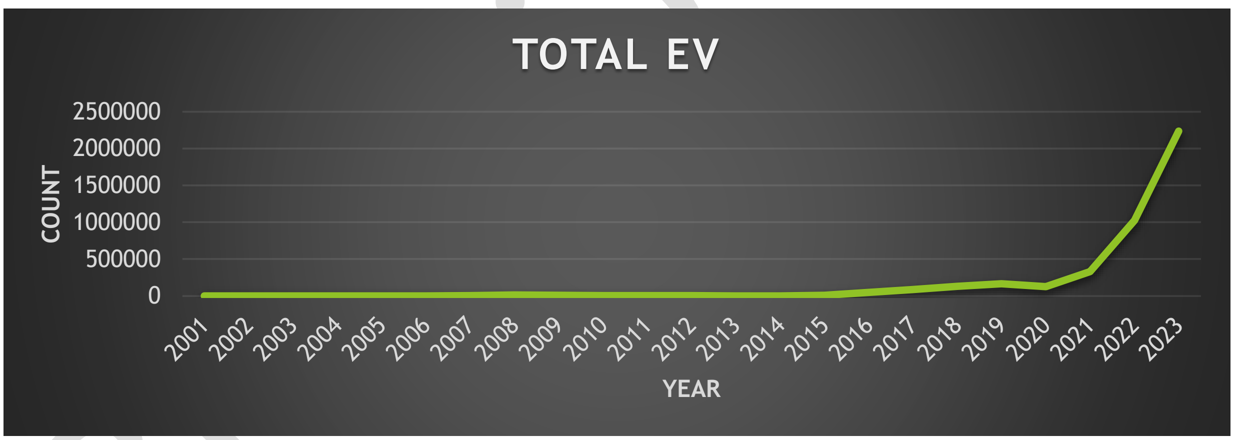
ACTUAL PREDICTIONS-

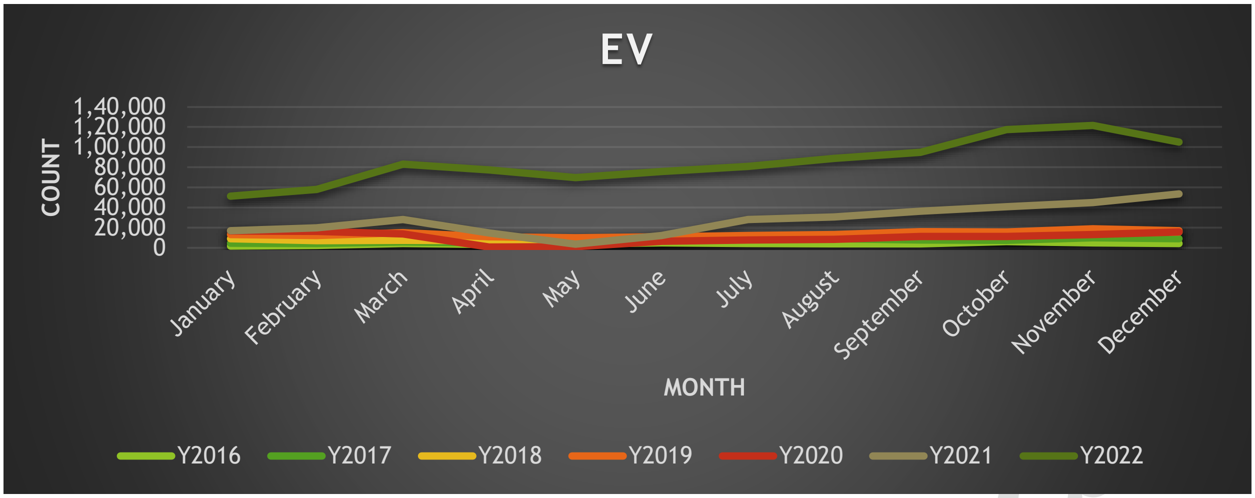
```
forc=forecast(d,h=60)
> forc
> plot(forc)
```

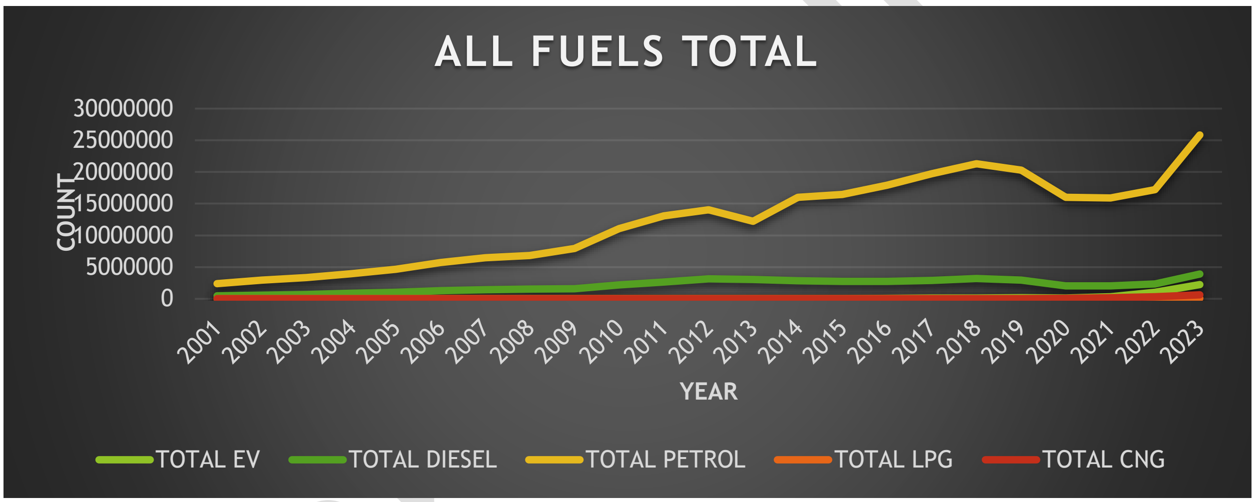




4)ELECTRIC VEHICLE

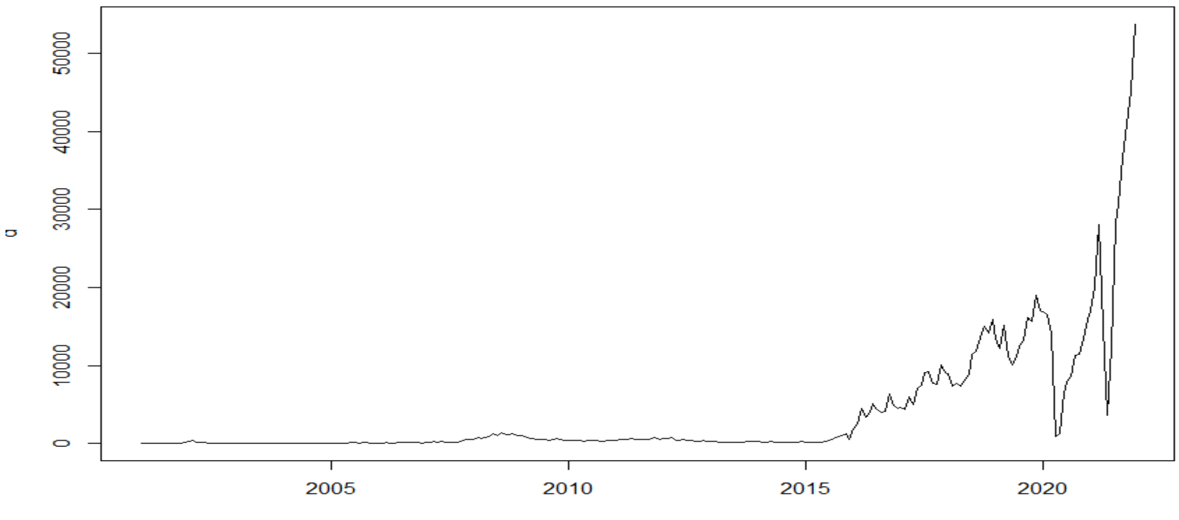




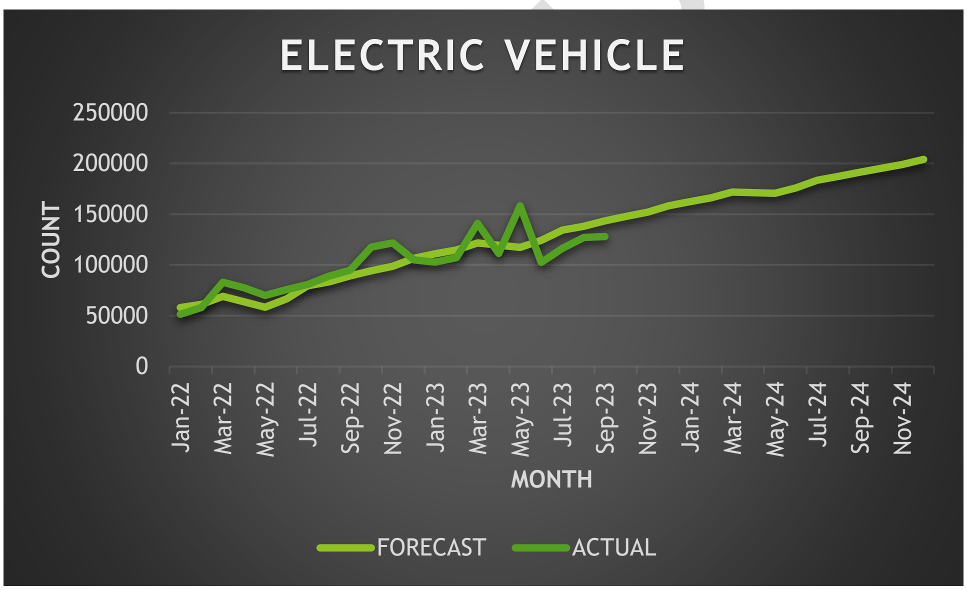



```
KPSS Test for Level Stationarity

data:  d
KPSS Level = 2.3359, Truncation lag parameter = 5, p-value = 0.01
> train=window(d,start=(2010),end=c(2021,12))
> train
> m2=auto.arima(train,ic="aic",trace =TRUE)

 Best model: ARIMA(3,1,1)(1,0,0)[12] with drift

> m2
Series: train
ARIMA(3,1,1)(1,0,0)[12] with drift

Coefficients:
         ar1      ar2     ar3      ma1    sar1     drift
      0.9926  -0.4887  0.4137  -0.7677  0.6789  1313.631
s.e.  0.1187   0.1083  0.0803   0.1066  0.0901  1536.980

sigma^2 = 5352501:  log likelihood = -1312.04
AIC=2638.09   AICc=2638.92   BIC=2658.83
> forc_m2=forecast(m2,h=120)
```

```
> forc_m2


>
```



50000
40000
30000
20000
10000
0
2005
2010
2015
2020
Time

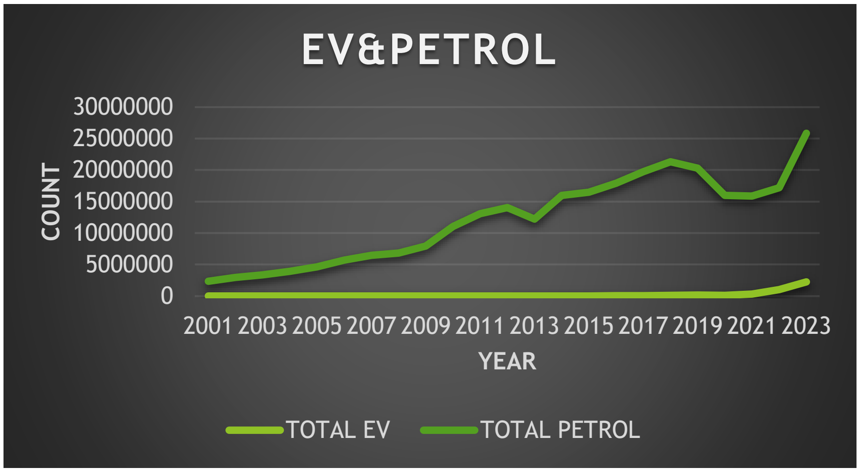


ELECTRIC VEHICLE
COUNT
250000
200000
150000
100000
50000
0
Jan-22
Mar-22
May-22
Jul-22
Sep-22
Nov-22
Jan-23
Mar-23
May-23
Jul-23
Sep-23
Nov-23
Jan-24
Mar-24
May-24
Jul-24
Sep-24
Nov-24
MONTH
FORECAST
ACTUAL

Hence, from all graphs given below we can say that count of EV is increasing highly. Future of India is being seen good with EV. In future, their will be boom in EV market.

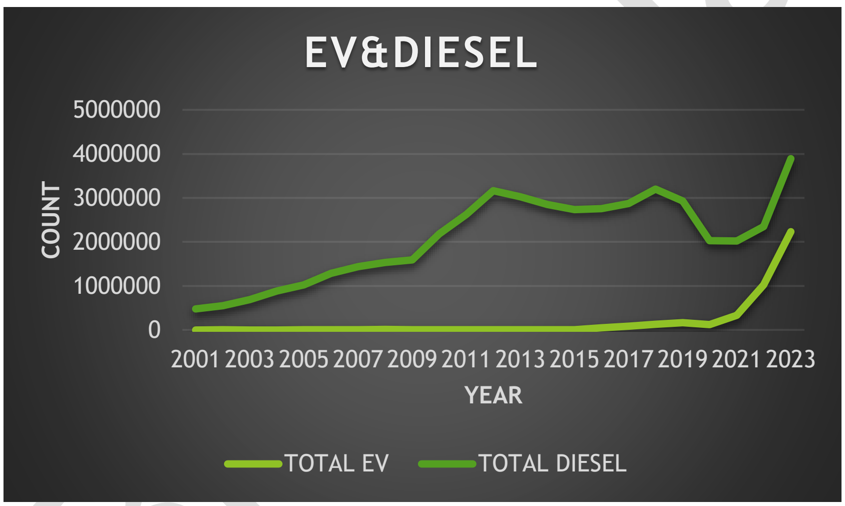
COMPARATIVE STUDY OF EV & OTHER FUELS

1)EV & PETROL



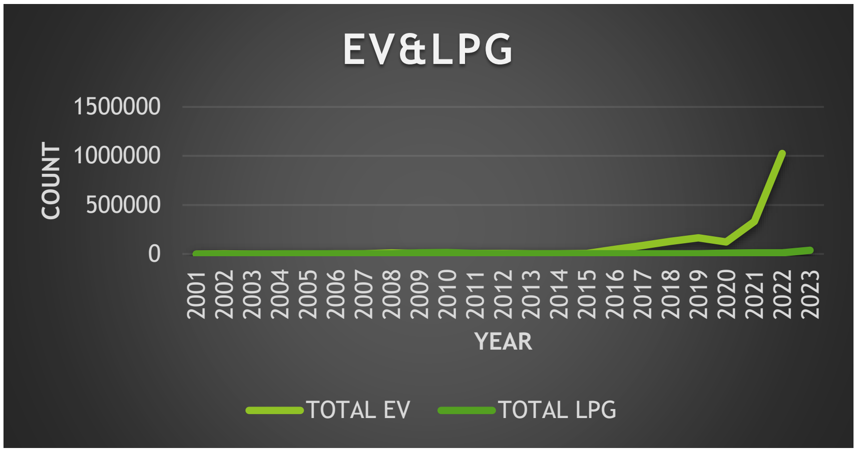
We can interpret that it will not be easy for EV to overtake petrol. But count of EV is rising.

2)EV & DIESEL



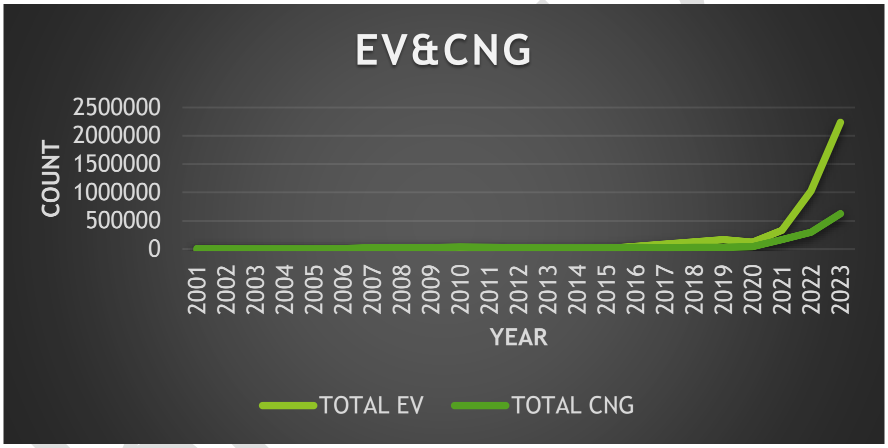
We can interpret that it will not be easy for EV to overtake DIESEL but EV is increasing.

3) EV & LPG



We can interpret that it will not be easy for EV to overtake DIESEL but EV will increase increasing.

4)EV & CNG

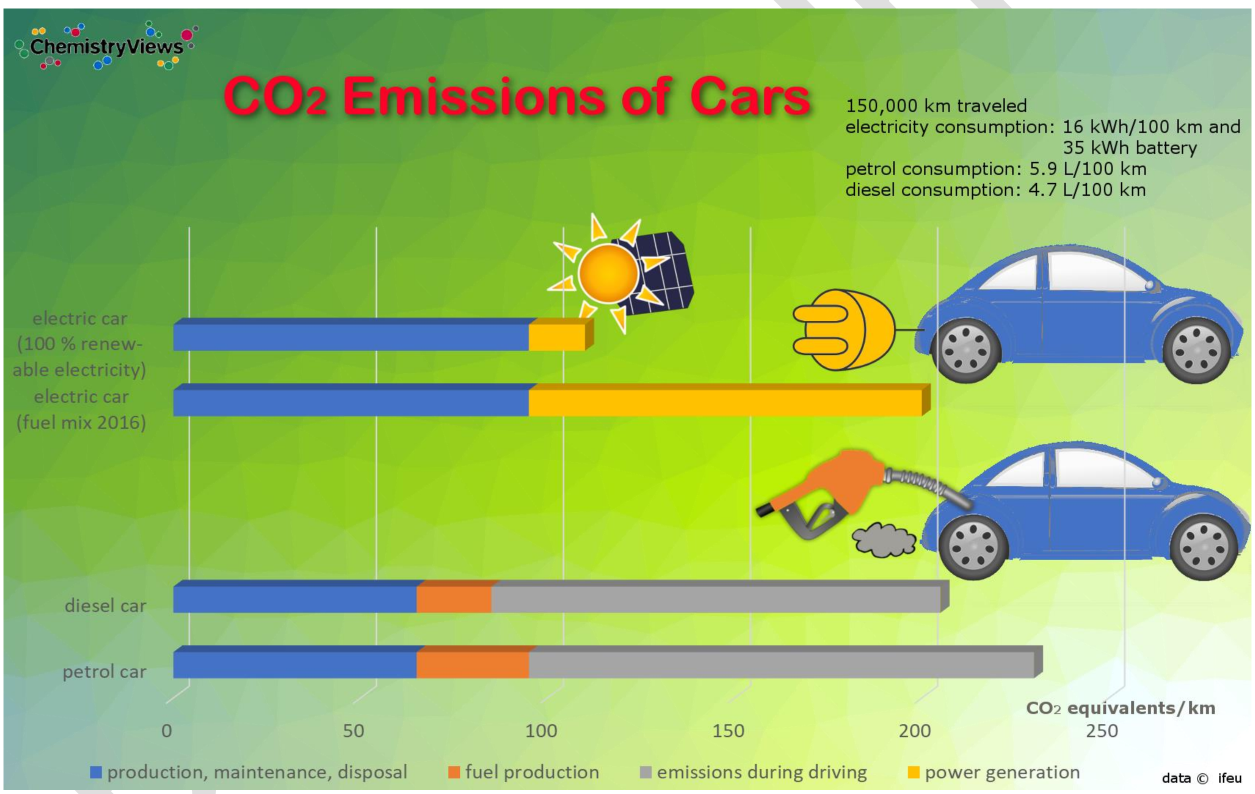


We can interpret EV is increasing and CNG will remain constant.

Parameters	**CNG**	**EV**
Emission	Lower emission	zero emission

Initial Investment	More costly than fossil fuel	More costly than CNG
Maintenance Costs	Higher than petrol cars	Less than CNG

Hence, from above chart we can say that EV is more beneficial than CNG. We should increase awareness of EV.



CORRESPONDENCE ANALYSIS

Correspondence analysis is also called as RECIPROCAL AVERAGING, is a useful data science visualization technique for finding out and displaying the relationship between categories. It uses that plots data, visually showing outcome of two or more data points.

FUELWISE CLUSTERING OF STATES:-

Here, we have taken data of ten states of India namely Maharastra, Tamilnadu, Kerala, Karnakata, Himachal Pradesh, Haryana, Uttar Pradesh, Andra Pradesh, Punjab & Rajasthan. Based on high number of RTO's present in states. Here, we have Analyse which states needed to be get aware about EV.

Code:

```
library("FactoMineR")

library("factoextra")

library("gplots")

library("ca")

data=read.csv("C:\\Users\\Ishwari\\Desktop\\EV CLUSTERING DATA.csv",row.names = 1)

data

names(data)

attach(data)

head(data)

df=as.data.frame(data)

df

res.ca=ca(df,graph=FALSE)

res.ca
```

```
chisq.test(df)

EV=get_eigenvalue((res.ca))

EV

fviz_screeplot(res.ca,addlabels=TRUE,ylim=c(0,50))

row=get_ca_row(res.ca)

row

head(row$coord)

head(row$cos2)

head(row$contrib)

fviz_ca_row(res.ca,repel = TRUE)

fviz_ca_biplot(res.ca,repe=TRUE)

fviz_ca_biplot(res.ca,map="rowprincipal",arrow=c(TRUE,TRUE),repel=TRUE)
```

```
              EV   CNG  PETROL  DIESEL
MAHARATRA   3260  1371  150789   24118
TAMILNADU   1733   353  129084   14261
RAJASTHAN   1905   262   87508   17129
HARYANA      715  1066   44678   10861
HIMACHAL      24     2    8769    1619
PUNJAB       387   127   47074    8942
KERALA      1071   261   61675    7567
AP           666   136   68593   11874
UP          6106  1483  205788   22834
KARNATAKA   2591   518  103020   16511
```

```
Principal inertias (eigenvalues):
               1         2         3
Value       0.00768  0.003173  0.001034
Percentage  64.61%   26.69%    8.7%
```

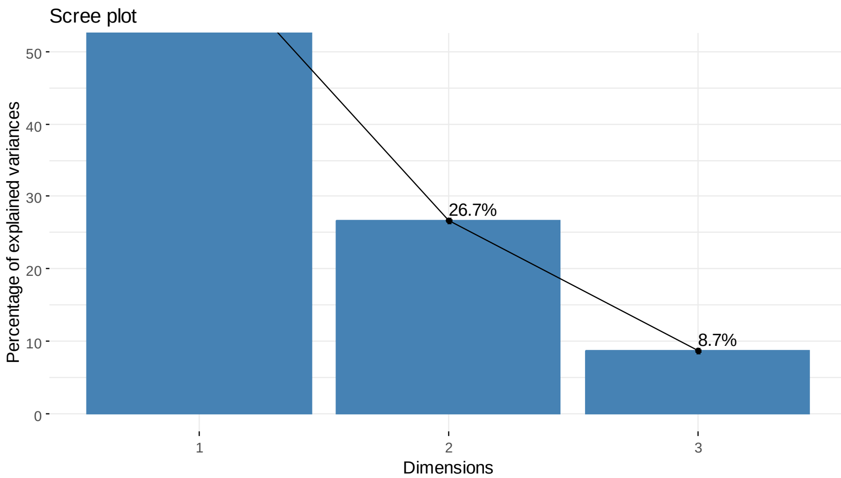
chisq.test(df)

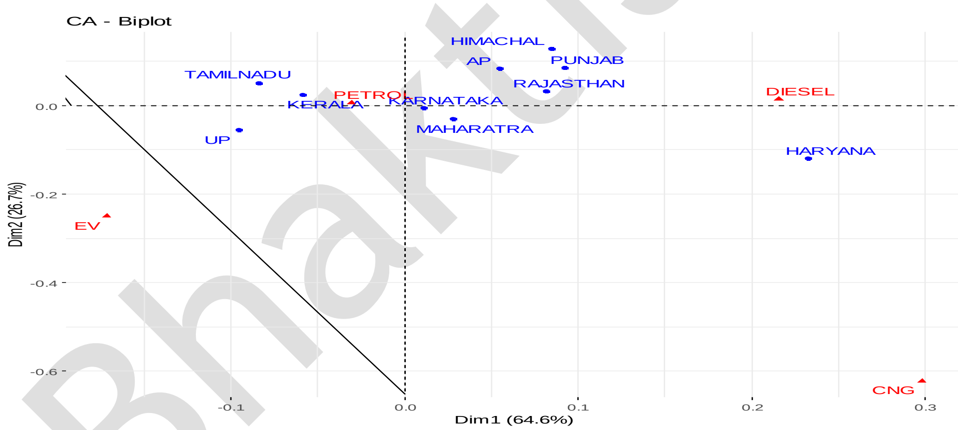
Pearson's Chi-squared test

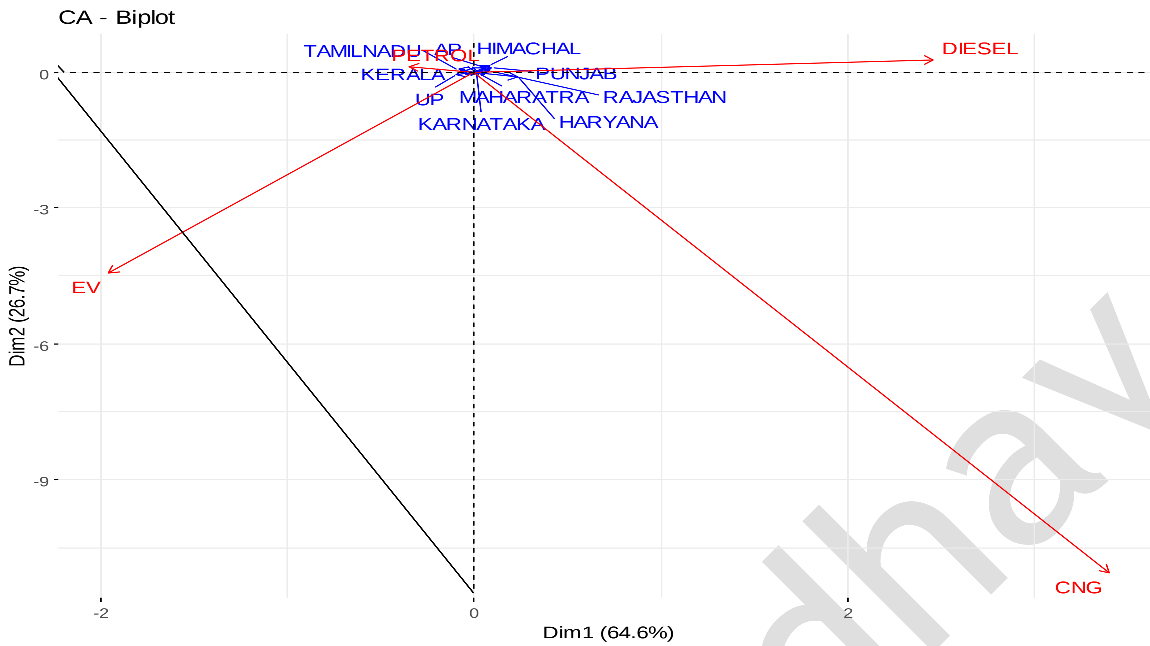
data: df

X-squared = 126

81, df = 27, p-value < 2.2e-16







INTERPRETATION :- From above plots we can see that petrol & Diesel are highly used in all states but CNG & EV need to be get more aware among population of respective states.

CORRESPONDENCE ANALYSIS OF ONLY EV:

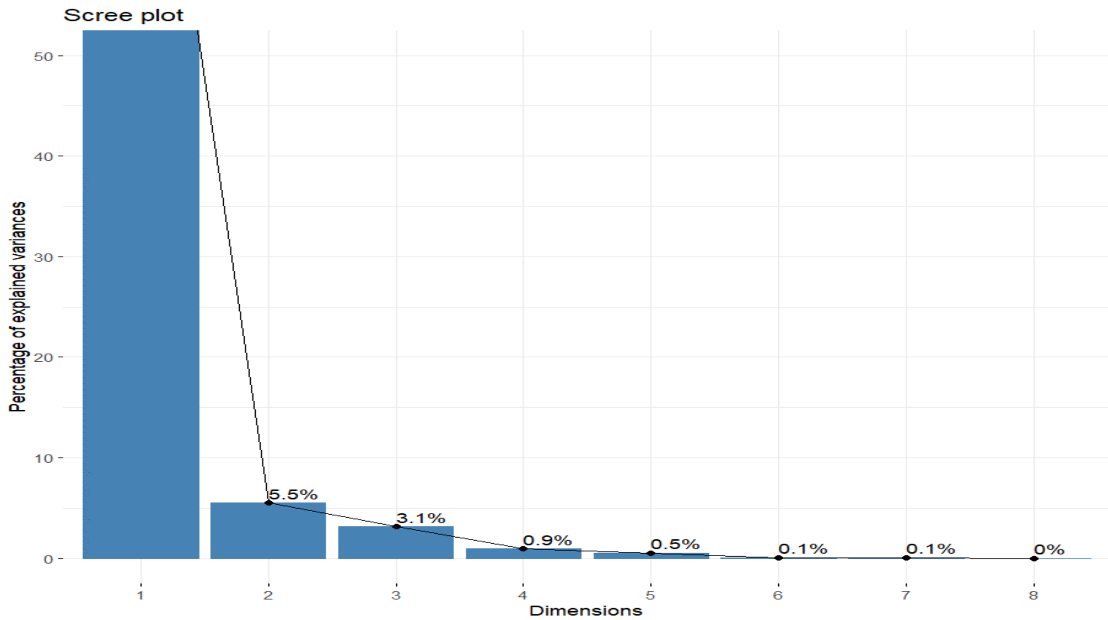
Here,we have taken same states but data of EV count from 2015 till today .to know which states is needed to get aware of EV ,to know about zero carbon emission misson of 2070.

code

```
> library("FactoMineR")
> library("factoextra")
> library("gplots")
> library("ca")
> library("ade4")
> library("amap")
> library("MASS")
> data=read.csv("C:\\Users\\Ishwari\\Desktop\\ONLY EV CLUSTERING.csv",row.names = 1)
> data
     MAHARATRA TAMILNADU RAJASTHAN HARYANA HIMACHAL PUNJAB KERALA     AP     UP KA
RNATAKA
2015      1011        86       676      55        4     18     27      8   1012       682
2016       943        86      3996    1380        4     38     19     20  15310       599
2017       943       118      3945    2488       15    137     77      0  40649       727
2018      4640      1332      4578    4623       62    363    272   1167  53211      2295
2019      7318      3444      6633    5108        5    961    478   2125  55796      6148
2020      7135      5697      5604    2982      181    832   1360   1624  31268      9709
2021     29914     30030     23464    8660      327   4643   8742   9578  66722     33312
2022    136055     66953     78240   25865     1008  14053  39622  29137 162860     95899
2023    160825     77633     76715   25333      941  20382  64034  27629 226511    127882
> names(data)
 [1] "MAHARATRA"  "TAMILNADU"  "RAJASTHAN"  "HARYANA"    "HIMACHAL"   "PUNJAB"     "KERALA"
 [8] "AP"         "UP"         "KARNATAKA"
> attach(data)

> head(data)
     MAHARATRA TAMILNADU RAJASTHAN HARYANA HIMACHAL PUNJAB KERALA    AP     UP KAR
NATAKA
2015      1011        86       676      55        4     18     27     8   1012       682
```

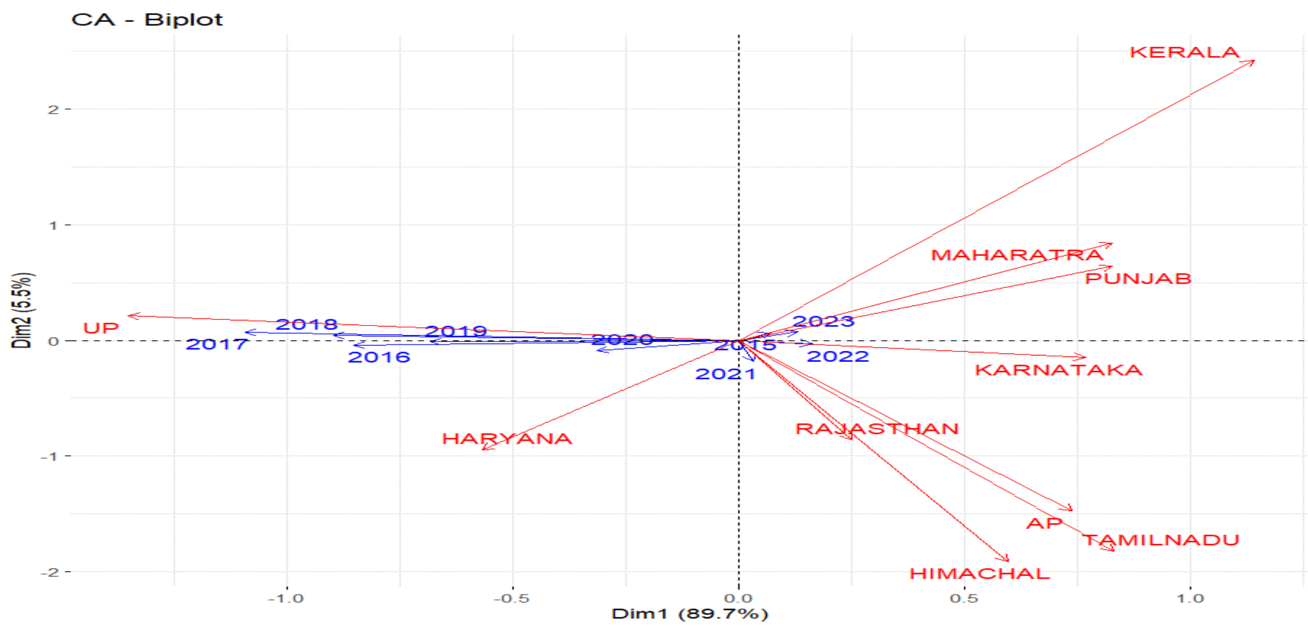
```
2016        943        86      3996    1380       4     38     19    20  15310       599
2017        943       118      3945    2488      15    137     77     0  40649       727
2018       4640      1332      4578    4623      62    363    272  1167  53211      2295
2019       7318      3444      6633    5108       5    961    478  2125  55796      6148
2020       7135      5697      5604    2982     181    832   1360  1624  31268      9709
> df=as.data.frame(data)
> df
     MAHARATRA TAMILNADU RAJASTHAN HARYANA HIMACHAL PUNJAB KERALA    AP     UP KA
RNATAKA
2015       1011        86       676      55        4     18     27     8    1012       682
2016        943        86      3996    1380        4     38     19    20   15310       599
2017        943       118      3945    2488       15    137     77     0   40649       727
2018       4640      1332      4578    4623       62    363    272  1167   53211      2295
2019       7318      3444      6633    5108        5    961    478  2125   55796      6148
2020       7135      5697      5604    2982      181    832   1360  1624   31268      9709
2021      29914     30030     23464    8660      327   4643   8742  9578   66722     33312
2022     136055     66953     78240   25865     1008  14053  39622 29137  162860     95899
2023     160825     77633     76715   25333      941  20382  64034 27629  226511    127882
> res.ca=ca(df,graph=FALSE)
> res.ca

 Principal inertias (eigenvalues):
           1        2        3        4        5       6       7       8
Value      0.107347 0.006564 0.003745 0.001118 0.00065 9.6e-05 8.1e-05 1e-05
Percentage 89.75%   5.49%    3.13%    0.93%    0.54%   0.08%   0.07%   0.01%

 Rows:
            2015      2016      2017      2018      2019      2020      2021      2022
Mass     0.001812  0.011339  0.024860  0.036731  0.044565  0.033616  0.109060  0.328959
ChiDist  0.559805  0.913658  1.097726  0.901634  0.685093  0.353334  0.201439  0.178955
Inertia  0.000568  0.009466  0.029957  0.029860  0.020917  0.004197  0.004425  0.010535
Dim. 1   0.219822 -2.598848 -3.335356 -2.738822 -2.081149 -0.959325  0.102142  0.496669
Dim. 2   0.804094 -0.507505  0.896701  0.533017 -0.158591 -1.068492 -2.252587 -0.355398
            2023
Mass     0.409057
ChiDist  0.153889
Inertia  0.009687
Dim. 1   0.398624
Dim. 2   0.899609


 Columns:
```

```
          MAHARATRA TAMILNADU RAJASTHAN    HARYANA   HIMACHAL    PUNJAB    KERALA
AP
Mass       0.176600   0.093863   0.103216   0.038731   0.001290  0.020976  0.058041   0.036095
ChiDist   0.287234   0.321372   0.174636   0.222375   0.361066  0.289003  0.429107   0.288517
Inertia   0.014570   0.009694   0.003148   0.001915   0.000168  0.001752  0.010687   0.003005
Dim. 1    0.827672   0.829610   0.250392  -0.566436   0.594075  0.827715  1.138329   0.737972
Dim. 2    0.842618  -1.823853  -0.859424  -0.946726  -1.913255  0.641400  2.425780  -1.476730
                 UP  KARNATAKA
Mass       0.330806   0.140382
ChiDist   0.442954   0.263744
Inertia   0.064907   0.009765
Dim. 1   -1.350100   0.768212
Dim. 2    0.211434  -0.147185
> chisq.test(df)
             Pearson's Chi-squared test
data:   df
X-squared = 236232, df = 72, p-value < 2.2e-16
> EV=get_eigenvalue((res.ca))
> EV
          eigenvalue  variance.percent  cumulative.variance.percent
Dim.1  1.073467e-01        89.74611108                        89.74611
Dim.2  6.564114e-03         5.48786018                        95.23397
Dim.3  3.745437e-03         3.13133384                        98.36531
Dim.4  1.118378e-03         0.93500863                        99.30031
Dim.5  6.500482e-04         0.54346614                        99.84378
Dim.6  9.550567e-05         0.07984653                        99.92363
Dim.7  8.131058e-05         0.06797888                        99.99161
Dim.8  1.004107e-05         0.00839473                       100.00000
> fviz_screeplot(res.ca,addlabels=TRUE,ylim=c(0,50))
```




```
row=get_ca_row(res.ca)
> row
Correspondence Analysis - Results for rows
 ===================================================
  Name        Description
1 "$coord"    "Coordinates for the rows"
2 "$cos2"     "Cos2 for the rows"
3 "$contrib"  "contributions of the rows"
4 "$inertia"  "Inertia of the rows"
> head(row$coord)
           Dim.1       Dim.2        Dim.3       Dim.4       Dim.5       Dim.6
2015  0.07202207  0.06514703  0.340945961 -0.19568931 -0.36203141  0.12938155
2016 -0.85148156 -0.04111765  0.249121130 -0.20542462  0.04439940 -0.02909082
2017 -1.09278956  0.07265004 -0.002637120 -0.05590738  0.03228217  0.01961823
2018 -0.89734222  0.04318461  0.005927420  0.07285193  0.01017979 -0.01341357
2019 -0.68186379 -0.01284894 -0.003288612  0.05373265 -0.01639547  0.01514242
2020 -0.31431142 -0.08656837 -0.089899793 -0.02334018 -0.09566778 -0.02707222
            Dim.7        Dim.8
2015 -0.024379949  0.031789942
2016  0.030987576  0.004670100
2017 -0.029932924 -0.008876569
2018 -0.011326270  0.010052450
2019  0.028983340 -0.003685415
2020 -0.005240498 -0.004424267
```

```
> head(row$cos2)
         Dim.1        Dim.2        Dim.3       Dim.4        Dim.5        Dim.6
2015 0.0165523 0.0135430499 3.709354e-01 0.122197255 0.4182343846 0.0534160673
2016 0.8685259 0.0020252974 7.434528e-02 0.050551874 0.0023614916 0.0010137809
2017 0.9910271 0.0043801010 5.771281e-06 0.002593885 0.0008648444 0.0003193979
2018 0.9905032 0.0022940222 4.321864e-05 0.006528627 0.0001274728 0.0002213239
2019 0.9905938 0.0003517507 2.304228e-05 0.006151442 0.0005727272 0.0004885299
2020 0.7913161 0.0600272112 6.473618e-02 0.004363531 0.0733096374 0.0058705296
            Dim.7        Dim.8
2015 0.0018966745 3.224829e-03
2016 0.0011502903 2.612670e-05
2017 0.0007435509 6.538870e-05
2018 0.0001578024 1.243036e-04
2019 0.0017897699 2.893831e-05
2020 0.0002199757 1.567878e-04
> head(row$contrib)
            Dim.1     Dim.2        Dim.3     Dim.4      Dim.5     Dim.6     Dim.7
2015  0.008756662 0.1171681  5.624252225  6.204998 36.5378575 31.762281  1.324691
2016  7.658563007 0.2920559 18.789022592 42.786013  3.4386985 10.047736 13.391020
2017 27.656132539 1.9989534  0.004615985  6.947950  3.9855391 10.018380 27.394181
2018 27.552273146 1.0435464  0.034455526 17.431044  0.5855475  6.919736  5.795044
2019 19.302013306 0.1120868  0.012868229 11.504930  1.8428839 10.699359 46.041118
2020  3.093725657 3.8378902  7.253792410  1.637457 47.3299441 25.796966  1.135398
         Dim.8
2015 18.238779
2016  2.462963
2017 19.508214
2018 36.965278
2019  6.028219
2020  6.553194
> fviz_ca_row(res.ca,repel = TRUE)


>

> fviz_ca_row(res.ca,repel = TRUE)
> fviz_ca_biplot(res.ca,repe=TRUE)
> fviz_ca_biplot(res.ca,map="rowprincipal",arrow=c(TRUE,TRUE),repel=TRUE)
```



INTERPRETATION:- From above plot we can see that Maharastra, Punjab, Karnataka, Haryana & UP have good number of Electronic Vehicles . But we need to spread awareness about EV in AP, Himachal Pradesh & Tamilnadu.

CONCLUSION

This study has discussed the application of time series study of TRADITIONAL & NON-TRADITIONAL FUELS.

According to data study it is observed that –

1)Highly used vehicle category is 2wheeler in which petrol is highly used. while, Diesel is mostly used in other vehicle categories.

2) Electric vehicle is Future of India. Their will be highly increased in Electric Vehicle.

3) As Diesel and Petrol are our traditional fuels it will not be easy for Electric vehicle to increased its count than these fuels.

4)According to clustering, Andhra Pradesh, Himachal Pradesh, Punjab and Haryana are the states in which awareness of Electric Vehicle should be increased.

The common reasons we have seen in all the states for least number of EV are the limited charging infrastructure (most cities/towns still do not have charging stations), recent EV battery-related explosions in various parts of the state, the high upfront cost compared to conventional vehicles, and doubts over the range (distance one can travel with a single charge) .

We can also say that if EV will use electricity from Coal then it will be not useful for zero carbon emission. Instead, if we shift to solar panels, windmills, Hydro-electric power, etc then it will be very helpful for our future.

LIMITATIONS

1)Due to Corona pandemic their was high decreased in number of all vehicles which has affected our forecasting.

2)Due to small amount of data of Electric Vehicles, its prediction was worthless.

THANK YOU