Final Demand Forecast

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Load and clean data

The file loaded is the telecommunication companies´s subscribers by ten years, for each service provided by this companies. The service offering are: Internet residential and business, Video on demand and VoIP.

```
## Loading required package: lattice

## Loading required package: ggplot2

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

## Loading required package: timeDate

## This is forecast 7.1
```

Data Preparation

```
year<-years$Year
start<-year[1]
hi<-dim(years)[1]
end<-year[hi]
year1<-year[round(hi*0.70)]

seth<-8   ##Set predictions quantity
f1<-end+1 #Q forecast
f2<-end+5 #Q forecast

time<-1:hi
```

1.Demand Models for Internet Residential Subscribers

1.1 Predicting with Growth curves InRes

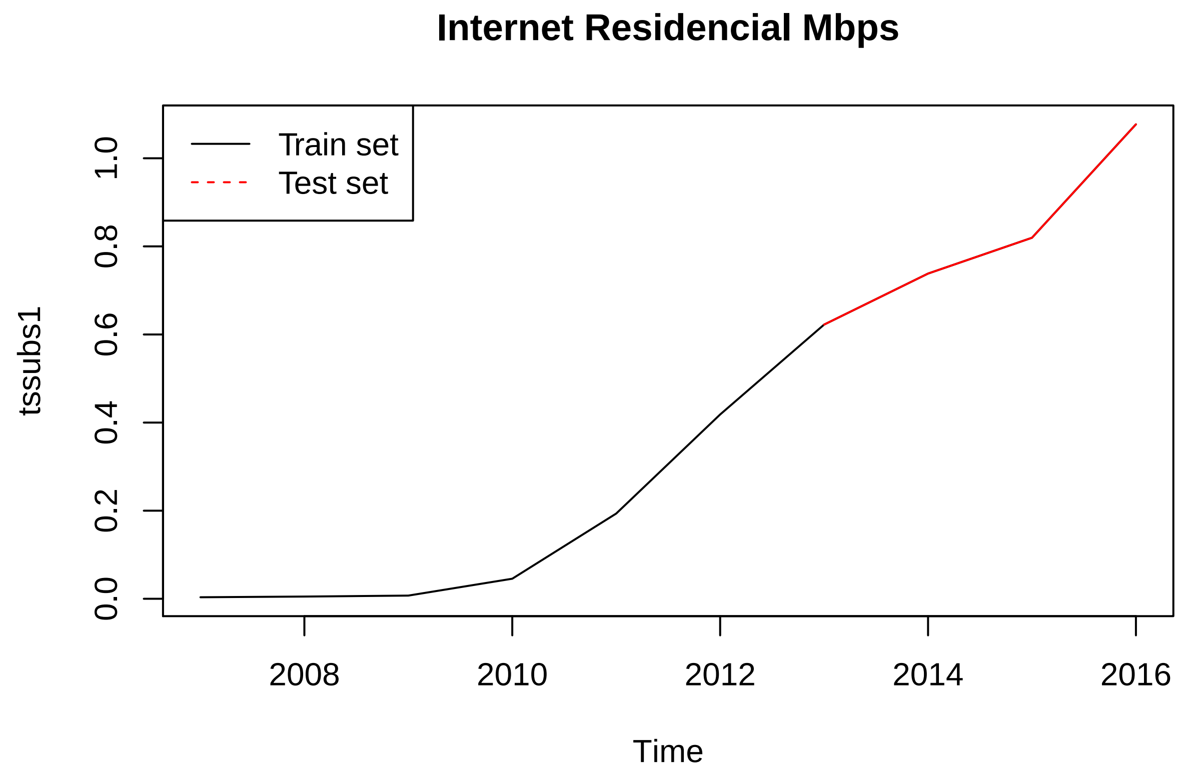
Simple random sampling of time series is probably not the best way to resample times series data. Hyndman and Athanasopoulos (2013)) discuss rolling forecasting origin techniques that move the training and test sets in time.

```
#Operator1
tssubs1<-ts(oper1$Internet_Res1,start=start,end=end) #Time serie
tsset1<-tssubs1
tstrain1<-window(tsset1,start=start,end=year1)      #Training and Testing data
tstest1<-window(tsset1,start=year1,end=end)

#Operator2
tssubs2<-ts(oper2$Internet_Res2,start=start,end=end) #Time serie
tsset2<-tssubs2/1
tstrain2<-window(tsset2,start=start,end=year1)        #Training and Testing data
tstest2<-window(tsset2,start=year1,end=end)

#Operator3
tssubs3<-ts(oper3$Internet_Res3,start=start,end=end) #Time serie
tsset3<-tssubs3/1
tstrain3<-window(tsset3,start=start,end=year1)        #Training and Testing data
tstest3<-window(tsset3,start=year1,end=end)

plot(tssubs1,main="Internet Residencial Mbps")
lines(tstest1,col="red")
legend("topleft",legend = c("Train set","Test set"), col=c("black","red"), lty = 1:2)
```



Linear Model

```
#Operator 1
fitlm1<-tslm(tstrain1~trend)       #Model
predlm1<-forecast(fitlm1, h=seth)  #Prediction
#Operator 2
fitlm2<-tslm(tstrain2~trend)       #Model
predlm2<-forecast(fitlm2, h=seth)  #Prediction
#Operator 3
fitlm3<-tslm(tstrain3~trend)       #Model
predlm3<-forecast(fitlm3, h=seth)  #Prediction
```

Parabolic Model

```
#Operator 1
fitpar1=lm(tsset1 ~ time + I(time^2))  #Model
predpar1<-predict(fitpar1)             #Prediction
forepar1<-forecast(predpar1,h=seth-3)  #Forecast
#Operator 2
fitpar2=lm(tsset2 ~ time + I(time^2))  #Model
predpar2<-predict(fitpar2)             #Prediction
forepar2<-forecast(predpar2,h=seth-3)  #Forecast
```

```r
#Operator 3
fitpar3=lm(tsset3 ~ time + I(time^2))  #Model
predpar3<-predict(fitpar3)              #Prediction
forepar3<-forecast(predpar3,h=seth-3)  #Forecast
```

Exponential Model

```r
#Operator 1
Yexp1=lm(log(tsset1) ~ time)          #Transform
parmexp1<-as.list(Yexp1$coeff)
betae1<- exp(parmexp1$"(Intercept)")  #growth range (a)
ke1<- parmexp1$time                   #growth rate (b)
fitexp1<-betae1*exp(ke1*time)         #Model
predexp1<-forecast(fitexp1,h=seth-3)

#Operator 2
Yexp2=lm(log(tsset2) ~ time)          #Transform
parmexp2<-as.list(Yexp2$coeff)
betae2<- exp(parmexp2$"(Intercept)")  #growth range (a)
ke2<- parmexp2$time                   #growth rate (b)
fitexp2<-betae2*exp(ke2*time)         #Model
predexp2<-forecast(fitexp2,h=seth-3)

#Operator 3
Yexp3=lm(log(tsset3) ~ time)          #Transform
parmexp3<-as.list(Yexp3$coeff)
betae3<- exp(parmexp3$"(Intercept)")  #growth range (a)
ke3<- parmexp3$time                   #growth rate (b)
fitexp3<-betae3*exp(ke3*time)         #Model
predexp3<-forecast(fitexp3,h=seth-3)
```

The predictions with growth curves are:

```r
#Operator 1
set1a<-data.frame(predlm1)  #Linear predictions
lma<-data.frame(Fore_Lin1=set1a$Point.Forecast[4:8])
data_predlm1<-data.frame(Lin1=c(fitlm1$fitted.values,set1a$Point.Forecast[1:3]))
#Operator 2
set1b<-data.frame(predlm2)  #Linear predictions
lmb<-data.frame(Fore_Lin2=set1b$Point.Forecast[4:8])
data_predlm2<-data.frame(Lin2=c(fitlm2$fitted.values,set1b$Point.Forecast[1:3]))
#Operator 3
set1c<-data.frame(predlm3)  #Linear predictions
lmc<-data.frame(Fore_Lin3=set1c$Point.Forecast[4:8])
data_predlm3<-data.frame(Lin3=c(fitlm3$fitted.values,set1c$Point.Forecast[1:3]))


#Operator 1
data_predpar1<-data.frame(Par1=predpar1) #Parabolic predictions
set2a<-data.frame(forepar1)
```

```
para<-data.frame(Fore_Par1=set2a$Point.Forecast)
#Operator 2
data_predpar2<-data.frame(Par2=predpar2) #Parabolic predictions
set2b<-data.frame(forepar2)
parb<-data.frame(Fore_Par2=set2b$Point.Forecast)
#Operator 3
data_predpar3<-data.frame(Par3=predpar3) #Parabolic predictions
set2c<-data.frame(forepar3)
parc<-data.frame(Fore_Par3=set2c$Point.Forecast)


#Operator 1
set3a<-data.frame(predexp1)  #Exponential predictions
expa<-data.frame(Fore_Exp1=set3a$Point.Forecast)
data_predexp1<-data.frame(Exp1=fitexp1)
#Operator 2
set3b<-data.frame(predexp2)  #Exponential predictions
expb<-data.frame(Fore_Exp2=set3b$Point.Forecast)
data_predexp2<-data.frame(Exp2=fitexp2)
#Operator 1
set3c<-data.frame(predexp3)  #Exponential predictions
expc<-data.frame(Fore_Exp3=set3c$Point.Forecast)
data_predexp3<-data.frame(Exp3=fitexp3)
```

Sets of predictions and forecasting for 5 years are:

```
data_pred1a<-data.frame(data_predlm1,data_predpar1,data_predexp1)  #Operator 1
data_pred2a<-data.frame(data_predlm2,data_predpar2,data_predexp2)  #Operator 2
data_pred3a<-data.frame(data_predlm3,data_predpar3,data_predexp3)  #Operator 3

fore1a<-data.frame(Year=f1:f2,lma,para,expa)   #Operator 1
fore1b<-data.frame(lmb,parb,expb)              #Operator 2
fore1c<-data.frame(lmc,parc,expc)              #Operator 3
```

1.2 Predicting with Logistic and Gompertz Model InRes

Logistic Model

Using the **growthmodels** package, with the *logistic* function to get the logistic curve **Usage** logistic(t, alpha, beta, k) **Arguments** t time,x size, alpha upper asymptote, beta growth range, k growth rate

```
#Operator 1
alpha1<-tssubs1[hi] +0.5          #upper asymptote (M)
Y1<-log(alpha1/tssubs1-1)         #Transform
Reglm1<-tslm(Y1~trend)            #Lineal Regression
parmlm1<-as.list(Reglm1$coeff)

beta1<- exp(parmlm1$"(Intercept)")  #growth range (a)
k1<- -parmlm1$trend                 #growth rate (b)
fitlog1 <- logistic(1:10, alpha1, beta1, k1)
```

```r
predlog1<-forecast(fitlog1,h=seth)

#Operator 2
alpha2<-tssubs2[hi] +0.5           #upper asymptote (M)
Y2<-log(alpha2/tssubs2-1)          #Transform
Reglm2<-tslm(Y2~trend)             #Lineal Regression
parmlm2<-as.list(Reglm2$coeff)

beta2<- exp(parmlm2$"(Intercept)")  #growth range (a)
k2<- -parmlm2$trend                 #growth rate (b)
fitlog2 <- logistic(1:10, alpha2, beta2, k2)
predlog2<-forecast(fitlog2,h=seth)

#Operator 3
alpha3<-tssubs3[hi] +0.5           #upper asymptote (M)
Y3<-log(alpha3/tssubs3-1)          #Transform
Reglm3<-tslm(Y3~trend)             #Lineal Regression
parmlm3<-as.list(Reglm3$coeff)

beta3<- exp(parmlm3$"(Intercept)")  #growth range (a)
k3<- -parmlm3$trend                 #growth rate (b)
fitlog3 <- logistic(1:10, alpha3, beta3, k3)
predlog3<-forecast(fitlog3,h=seth)
```

The predictions using logistic model are:

```r
set4a<-data.frame(predlog1)
alog<-set4a$Point.Forecast   #Operator 1 predictions
set4b<-data.frame(predlog2)
blog<-set4b$Point.Forecast   #Operator 2 predictions
set4c<-data.frame(predlog3)
clog<-set4c$Point.Forecast   #Operator 3 predictions

data_predlog1<-data.frame(Log1=fitlog1)
data_predlog2<-data.frame(Log2=fitlog2)
data_predlog3<-data.frame(Log3=fitlog3)
```

Gompertz Model

Using the **growthmodels** package, Computes the Gompertz growth model **Usage** gompertz(t, alpha, beta, k) **Arguments** t time x size alpha upper asymptote beta growth displacement k growth rate

```r
#Operator 1
alphag1<-tssubs1[hi] +5                #upper asymptote (M)
Y1g<-log(log(alphag1/tssubs1))         #Transform
Reglmg1<-tslm(Y1g~trend)               #Lineal Regression
parmglm1<-as.list(Reglmg1$coeff)

betag1<- exp(parmglm1$"(Intercept)")  #growth range (a)
kg1<- -parmglm1$trend                 #growth rate (b)
fitgom1 <- gompertz(1:10, alphag1, betag1, kg1)
predgom1<-forecast(fitgom1,h=seth)
```

```r
#Operator 2
alphag2<-tssubs2[hi] +5                 #upper asymptote (M)
Y2g<-log(log(alphag2/tssubs2))          #Transform
Reglmg2<-tslm(Y2g~trend)                #Lineal Regression
parmglm2<-as.list(Reglmg2$coeff)

betag2<- exp(parmglm2$"(Intercept)")  #growth range (a)
kg2<- -parmglm2$trend                 #growth rate (b)
fitgom2 <- gompertz(1:10, alphag2, betag2, kg2)
predgom2<-forecast(fitgom2,h=seth)

#Operator 3
alphag3<-tssubs3[hi] +5                 #upper asymptote (M)
Y3g<-log(log(alphag3/tssubs3))          #Transform
Reglmg3<-tslm(Y3g~trend)                #Lineal Regression
parmglm3<-as.list(Reglmg3$coeff)

betag3<- exp(parmglm3$"(Intercept)")  #growth range (a)
kg3<- -parmglm3$trend                 #growth rate (b)
fitgom3 <- gompertz(1:10, alphag3, betag3, kg3)
predgom3<-forecast(fitgom3,h=seth)
```

The predictions using gompertz model are:

```r
set5a<-data.frame(predgom1)
agom<-set5a$Point.Forecast   #Operator 1 predictions
set5b<-data.frame(predgom2)
bgom<-set5b$Point.Forecast   #Operator 2 predictions
set5c<-data.frame(predgom3)
cgom<-set5c$Point.Forecast   #Operator 3 predictions

data_predgom1<-data.frame(Gom1=fitgom1)
data_predgom2<-data.frame(Gom2=fitgom2)
data_predgom3<-data.frame(Gom3=fitgom3)
```

Forecasting for 5 years

```r
fore2a<-data.frame(Fore_Log1=alog[1:5],Fore_Gom1=agom[1:5])
fore2b<-data.frame(Fore_Log2=blog[1:5],Fore_Gom1=bgom[1:5])
fore2c<-data.frame(Fore_Log3=clog[1:5],Fore_Gom1=cgom[1:5])
```

1.3 Performance Models for Internet Residential

Using the forecast package, the performance models are: **(ME)**:Mean Error **(RMSE)**:Root Mean Square Error #**(MAE)**: Mean Absolute Error **(MPE)**: Mean Porcentual Error **(MAPE)**: Mean Absolute Porcentual Error

```r
#Modelo Lineal
acc_d1<-accuracy(predlm1) #Operator 1
```

```
acc_d2<-accuracy(predlm2) #Operator 2
acc_d3<-accuracy(predlm3) #Operator 3

#Modelo Parabólico
acc_e1<-accuracy(predpar1,tsset1)  #Operator 1
acc_e2<-accuracy(predpar2,tsset2)  #Operator 2
acc_e3<-accuracy(predpar3,tsset3)  #Operator 3

#Modelo Exponencial
acc_f1<-accuracy(predexp1)  #Operator 1
acc_f2<-accuracy(predexp2)  #Operator 2
acc_f3<-accuracy(predexp3)  #Operator 3

#Modelo Logístico
acc_g1<-accuracy(predlog1) #Operator 1
acc_g2<-accuracy(predlog2) #Operator 2
acc_g3<-accuracy(predlog3) #Operator 3

#Modelo Gompertz
acc_h1<-accuracy(predgom1) #Operator 1
acc_h2<-accuracy(predgom2) #Operator 2
acc_h3<-accuracy(predgom3) #Operator 3
```

The performance sets are:

```
Models<-c("Linear","Parabolic","Exponential","Logistic","Gompertz")

#Opereator 1
accd1<-acc_d1[1,1:5]  #Linear
acce1<-acc_e1[1,1:5]  #Parabolic
accf1<-acc_f1[1,1:5]  #Exponential
accg1<-acc_g1[1,1:5]  #Logistic
acch1<-acc_h1[1,1:5]  #Gompertz
acc_all1b<-round(rbind(accd1,acce1,accf1,accg1,acch1),2)
performIRes1<-data.frame(Models,acc_all1b)

#Operator 2
accd2<-acc_d2[1,1:5]
acce2<-acc_e2[1,1:5]
accf2<-acc_f2[1,1:5]
accg2<-acc_g2[1,1:5]
acch2<-acc_h2[1,1:5]
acc_all2b<-round(rbind(accd2,acce1,accf1,accg1,acch1),2)
performIRes2<-data.frame(Models,acc_all2b)

#Operator 3
accd3<-acc_d3[1,1:5]
acce3<-acc_e3[1,1:5]
accf3<-acc_f3[1,1:5]
accg3<-acc_g3[1,1:5]
acch3<-acc_h3[1,1:5]
acc_all3b<-round(rbind(accd3,acce1,accf1,accg1,acch1),2)
performIRes3<-data.frame(Models,acc_all3b)
```

Predictions Reports

Internet Residential Predictions by service provider

```
predIRes1<-data.frame(data_pred1a,data_predlog1,data_predgom1) #Operator 1
predIRes2<-data.frame(data_pred2a,data_predlog2,data_predgom2) #Operator 2
predIRes3<-data.frame(data_pred3a,data_predlog3,data_predgom3) #Operator 3
```

Forecast Reports

Forecasting for 5 Years Internet Residential

```
foreIRes1<-data.frame(fore1a,fore2a)  #Operator 1
foreIRes2<-data.frame(fore1b,fore2b)  #Operator 2
foreIRes3<-data.frame(fore1c,fore2c)  #Operator 3
```

2.Demand Models for Internet Bussines Subscribers

Preparation Data

```
#Operator1
tssubs1<-ts(oper1$Internet_Bus1,start=start,end=end) #Time serie
tsset1<-tssubs1
tstrain1<-window(tsset1,start=start,end=year1)        #Training and Testing data
tstest1<-window(tsset1,start=year1,end=end)

#Operator2
tssubs2<-ts(oper2$Internet_Bus2,start=start,end=end) #Time serie
tsset2<-tssubs2/1
tstrain2<-window(tsset2,start=start,end=year1)        #Training and Testing data
tstest2<-window(tsset2,start=year1,end=end)

#Operator3
tssubs3<-ts(oper3$Internet_Bus3,start=start,end=end) #Time serie
tsset3<-tssubs3/1
tstrain3<-window(tsset3,start=start,end=year1)        #Training and Testing data
tstest3<-window(tsset3,start=year1,end=end)
```

2.1 Predicting with Growth curves InBus

Linear Model

```
#Operator 1
fitlm1<-tslm(tstrain1~trend)       #Model
predlm1<-forecast(fitlm1, h=seth)  #Prediction
#Operator 2
```

```r
fitlm2<-tslm(tstrain2~trend)       #Model
predlm2<-forecast(fitlm2, h=seth)  #Prediction
#Operator 3
fitlm3<-tslm(tstrain3~trend)       #Model
predlm3<-forecast(fitlm3, h=seth)  #Prediction
```

Parabolic Model

```r
#Operator 1
fitpar1=lm(tsset1 ~ time + I(time^2))  #Model
predpar1<-predict(fitpar1)             #Prediction
forepar1<-forecast(predpar1,h=seth-3)  #Forecast
#Operator 2
fitpar2=lm(tsset2 ~ time + I(time^2))  #Model
predpar2<-predict(fitpar2)             #Prediction
forepar2<-forecast(predpar2,h=seth-3)  #Forecast
#Operator 3
fitpar3=lm(tsset3 ~ time + I(time^2))  #Model
predpar3<-predict(fitpar3)             #Prediction
forepar3<-forecast(predpar3,h=seth-3)  #Forecast
```

Exponential Model

```r
#Operator 1
Yexp1=lm(log(tsset1) ~ time,na.action=)          #Transform
parmexp1<-as.list(Yexp1$coeff)
betae1<- exp(parmexp1$"(Intercept)")  #growth range (a)
ke1<- parmexp1$time                   #growth rate (b)
fitexp1<-betae1*exp(ke1*time)         #Model
predexp1<-forecast(fitexp1,h=seth-3)

#Operator 2
Yexp2=lm(log(tsset2) ~ time)          #Transform
parmexp2<-as.list(Yexp2$coeff)
betae2<- exp(parmexp2$"(Intercept)")  #growth range (a)
ke2<- parmexp2$time                   #growth rate (b)
fitexp2<-betae2*exp(ke2*time)         #Model
predexp2<-forecast(fitexp2,h=seth-3)

#Operator 3
Yexp3=lm(log(tsset3) ~ time)          #Transform
parmexp3<-as.list(Yexp3$coeff)
betae3<- exp(parmexp3$"(Intercept)")  #growth range (a)
ke3<- parmexp3$time                   #growth rate (b)
fitexp3<-betae3*exp(ke3*time)         #Model
predexp3<-forecast(fitexp3,h=seth-3)
```

The predictions with growth curves are:

```r
#Operator 1
set1a<-data.frame(predlm1)  #Linear predictions
lma<-data.frame(Fore_Lin1=set1a$Point.Forecast[4:8])
data_predlm1<-data.frame(Lin1=c(fitlm1$fitted.values,set1a$Point.Forecast[1:3]))
#Operator 2
set1b<-data.frame(predlm2)  #Linear predictions
lmb<-data.frame(Fore_Lin2=set1b$Point.Forecast[4:8])
data_predlm2<-data.frame(Lin2=c(fitlm2$fitted.values,set1b$Point.Forecast[1:3]))
#Operator 3
set1c<-data.frame(predlm3)  #Linear predictions
lmc<-data.frame(Fore_Lin3=set1c$Point.Forecast[4:8])
data_predlm3<-data.frame(Lin3=c(fitlm3$fitted.values,set1c$Point.Forecast[1:3]))


#Operator 1
data_predpar1<-data.frame(Par1=predpar1) #Parabolic predictions
set2a<-data.frame(forepar1)
para<-data.frame(Fore_Par1=set2a$Point.Forecast)
#Operator 2
data_predpar2<-data.frame(Par2=predpar2) #Parabolic predictions
set2b<-data.frame(forepar2)
parb<-data.frame(Fore_Par2=set2b$Point.Forecast)
#Operator 3
data_predpar3<-data.frame(Par3=predpar3) #Parabolic predictions
set2c<-data.frame(forepar3)
parc<-data.frame(Fore_Par3=set2c$Point.Forecast)


#Operator 1
set3a<-data.frame(predexp1)  #Exponential predictions
expa<-data.frame(Fore_Exp1=set3a$Point.Forecast)
data_predexp1<-data.frame(Exp1=fitexp1)
#Operator 2
set3b<-data.frame(predexp2)  #Exponential predictions
expb<-data.frame(Fore_Exp2=set3b$Point.Forecast)
data_predexp2<-data.frame(Exp2=fitexp2)
#Operator 1
set3c<-data.frame(predexp3)  #Exponential predictions
expc<-data.frame(Fore_Exp3=set3c$Point.Forecast)
data_predexp3<-data.frame(Exp3=fitexp3)


##Sets of predictions
data_pred1b<-data.frame(data_predlm1,data_predpar1,data_predexp1)  #Operator 1
data_pred2b<-data.frame(data_predlm2,data_predpar2,data_predexp2)  #Operator 2
data_pred3b<-data.frame(data_predlm3,data_predpar3,data_predexp3)  #Operator 3

##Forecasting for 5 Years
fore3a<-data.frame(Year=f1:f2,lma,para,expa)   #Operator 1
fore3b<-data.frame(lmb,parb,expb)              #Operator 2
fore3c<-data.frame(lmc,parc,expc)              #Operator 3
```

2.2.Predicting with Logistic and Gompertz Model InBus

Logistic Model

```
#Operator 1
alpha1<-tssubs1[hi] +0.5            #upper asymptote (M)
Y1<-log(alpha1/tssubs1-1)           #Transform
Reglm1<-tslm(Y1~trend)              #Lineal Regression
parmlm1<-as.list(Reglm1$coeff)

beta1<- exp(parmlm1$"(Intercept)")  #growth range (a)
k1<- -parmlm1$trend                 #growth rate (b)
fitlog1 <- logistic(1:10, alpha1, beta1, k1)
predlog1<-forecast(fitlog1,h=seth)

#Operator 2
alpha2<-tssubs2[hi] +0.5            #upper asymptote (M)
Y2<-log(alpha2/tssubs2-1)           #Transform
Reglm2<-tslm(Y2~trend)              #Lineal Regression
parmlm2<-as.list(Reglm2$coeff)

beta2<- exp(parmlm2$"(Intercept)")  #growth range (a)
k2<- -parmlm2$trend                 #growth rate (b)
fitlog2 <- logistic(1:10, alpha2, beta2, k2)
predlog2<-forecast(fitlog2,h=seth)

#Operator 3
alpha3<-tssubs3[hi] +0.5            #upper asymptote (M)
Y3<-log(alpha3/tssubs3-1)           #Transform
Reglm3<-tslm(Y3~trend)              #Lineal Regression
parmlm3<-as.list(Reglm3$coeff)

beta3<- exp(parmlm3$"(Intercept)")  #growth range (a)
k3<- -parmlm3$trend                 #growth rate (b)
fitlog3 <- logistic(1:10, alpha3, beta3, k3)
predlog3<-forecast(fitlog3,h=seth)
```

The predictions using logistic model are:

```
set4a<-data.frame(predlog1)
alog<-set4a$Point.Forecast   #Operator 1 predictions
set4b<-data.frame(predlog2)
blog<-set4b$Point.Forecast   #Operator 2 predictions
set4c<-data.frame(predlog3)
clog<-set4c$Point.Forecast   #Operator 3 predictions

data_predlog1<-data.frame(Log1=fitlog1)
data_predlog2<-data.frame(Log2=fitlog2)
data_predlog3<-data.frame(Log3=fitlog3)
```

Gompertz Model

```
#Operator 1
alphag1<-tssubs1[hi] +5                 #upper asymptote (M)
Y1g<-log(log(alphag1/tssubs1))          #Transform
Reglmg1<-tslm(Y1g~trend)                #Lineal Regression
parmglm1<-as.list(Reglmg1$coeff)

betag1<- exp(parmglm1$"(Intercept)")  #growth range (a)
kg1<- -parmglm1$trend                 #growth rate (b)
fitgom1 <- gompertz(1:10, alphag1, betag1, kg1)
predgom1<-forecast(fitgom1,h=seth)

#Operator 2
alphag2<-tssubs2[hi] +5                 #upper asymptote (M)
Y2g<-log(log(alphag2/tssubs2))          #Transform
Reglmg2<-tslm(Y2g~trend)                #Lineal Regression
parmglm2<-as.list(Reglmg2$coeff)

betag2<- exp(parmglm2$"(Intercept)")  #growth range (a)
kg2<- -parmglm2$trend                 #growth rate (b)
fitgom2 <- gompertz(1:10, alphag2, betag2, kg2)
predgom2<-forecast(fitgom2,h=seth)

#Operator 3
alphag3<-tssubs3[hi] +5                 #upper asymptote (M)
Y3g<-log(log(alphag3/tssubs3))          #Transform
Reglmg3<-tslm(Y3g~trend)                #Lineal Regression
parmglm3<-as.list(Reglmg3$coeff)

betag3<- exp(parmglm3$"(Intercept)")  #growth range (a)
kg3<- -parmglm3$trend                 #growth rate (b)
fitgom3 <- gompertz(1:10, alphag3, betag3, kg3)
predgom3<-forecast(fitgom3,h=seth)
```

The predictions using gompertz model are:

```
set5a<-data.frame(predgom1)
agom<-set5a$Point.Forecast   #Operator 1 predictions
set5b<-data.frame(predgom2)
bgom<-set5b$Point.Forecast   #Operator 2 predictions
set5c<-data.frame(predgom3)
cgom<-set5c$Point.Forecast   #Operator 3 predictions

data_predgom1<-data.frame(Gom1=fitgom1)
data_predgom2<-data.frame(Gom2=fitgom2)
data_predgom3<-data.frame(Gom3=fitgom3)
```

Forecasting for 5 years

```
fore4a<-data.frame(Fore_Log1=alog[1:5],Fore_Gom1=agom[1:5])
fore4b<-data.frame(Fore_Log2=blog[1:5],Fore_Gom1=bgom[1:5])
fore4c<-data.frame(Fore_Log3=clog[1:5],Fore_Gom1=cgom[1:5])
```

2.3.Performance Models for Internet Bussines

Using the forecast package, the performance models are: **(ME)**:Mean Error **(RMSE)**:Root Mean Square Error **(MAE)**: Mean Absolute Error **(MPE)**: Mean Porcentual Error **(MAPE)**: Mean Absolute Porcentual Error

```
#Modelo Lineal
acc_d1<-accuracy(predlm1) #Operator 1
acc_d2<-accuracy(predlm2) #Operator 2
acc_d3<-accuracy(predlm3) #Operator 3

#Modelo Parabólico
acc_e1<-accuracy(predpar1,tsset1)  #Operator 1
acc_e2<-accuracy(predpar2,tsset2)  #Operator 2
acc_e3<-accuracy(predpar3,tsset3)  #Operator 3

#Modelo Exponencial
acc_f1<-accuracy(predexp1)  #Operator 1
acc_f2<-accuracy(predexp2)  #Operator 2
acc_f3<-accuracy(predexp3)  #Operator 3

#Modelo Logístico
acc_g1<-accuracy(predlog1) #Operator 1
acc_g2<-accuracy(predlog2) #Operator 2
acc_g3<-accuracy(predlog3) #Operator 3

#Modelo Gompertz
acc_h1<-accuracy(predgom1) #Operator 1
acc_h2<-accuracy(predgom2) #Operator 2
acc_h3<-accuracy(predgom3) #Operator 3

#The performance sets are:
Models<-c("Linear","Parabolic","Exponential","Logistic","Gompertz")

#Opereator 1
accd1<-acc_d1[1,1:5]  #Linear
acce1<-acc_e1[1,1:5]  #Parabolic
accf1<-acc_f1[1,1:5]  #Exponential
accg1<-acc_g1[1,1:5]  #Logistic
acch1<-acc_h1[1,1:5]  #Gompertz
acc_all1b<-round(rbind(accd1,acce1,accf1,accg1,acch1),2)
performIBus1<-data.frame(Models,acc_all1b)

#Operator 2
accd2<-acc_d2[1,1:5]
acce2<-acc_e2[1,1:5]
accf2<-acc_f2[1,1:5]
accg2<-acc_g2[1,1:5]
```

```
acch2<-acc_h2[1,1:5]
acc_all2b<-round(rbind(accd2,acce2,accf2,accg2,acch2),2)
performIBus2<-data.frame(Models,acc_all2b)

#Operator 3
accd3<-acc_d3[1,1:5]
acce3<-acc_e3[1,1:5]
accf3<-acc_f3[1,1:5]
accg3<-acc_g3[1,1:5]
acch3<-acc_h3[1,1:5]
acc_all3b<-round(rbind(accd3,acce3,accf3,accg3,acch3),2)
performIBus3<-data.frame(Models,acc_all3b)
```

Predictions Report

Internet Bussines Predictions by service provider

```
predIBus1<-data.frame(data_pred1b,data_predlog1,data_predgom1) #Operator 1
predIBus2<-data.frame(data_pred2b,data_predlog2,data_predgom2) #Operator 2
predIBus3<-data.frame(data_pred3b,data_predlog3,data_predgom3) #Operator 3
```

Forecast Reports

Forecasting for 5 Years Internet Bussines

```
foreIBus1<-data.frame(fore3a,fore4a)  #Operator 1
foreIBus2<-data.frame(fore3b,fore4b)  #Operator 2
foreIBus3<-data.frame(fore3c,fore4c)  #Operator 3
```

3.Demand Models for VoD Subscribers

Subset data

```
dataVoD1<-data.frame(Year=year,Subs=oper1$VoD1)  #Operator 1
tssubs1<-ts(oper1$VoD1,start=start,end=end) #Time serie
dataVoD2<-data.frame(Year=year,Subs=oper2$VoD2)  #Operator 2
tssubs2<-ts(oper2$VoD2,start=start,end=end) #Time serie
dataVoD3<-data.frame(Year=year,Subs=oper3$VoD3)  #Operator 3
tssubs3<-ts(oper3$VoD3,start=start,end=end) #Time serie
```

3.1.Predicting with Logistic and Gompertz Model VoD

Logistic Model

```r
#Operator 1
alpha1<-tssubs1[hi] +0.5           #upper asymptote (M)
Y1<-log(alpha1/tssubs1-1)*1          #Transform
Reglm1<-tslm(Y1~trend)             #Lineal Regression  #ERROR
parmlm1<-as.list(Reglm1$coeff)

beta1<- exp(parmlm1$"(Intercept)")  #growth range (a)
k1<- -parmlm1$trend                 #growth rate (b)
fitlog1 <- logistic(1:10, alpha1, beta1, k1)
predlog1<-forecast(fitlog1,h=seth)

#Operator 2
alpha2<-tssubs2[hi] +0.5           #upper asymptote (M)
Y2<-log(alpha2/tssubs2-1)          #Transform
Reglm2<-tslm(Y2~trend)             #Lineal Regression
parmlm2<-as.list(Reglm2$coeff)

beta2<- exp(parmlm2$"(Intercept)")  #growth range (a)
k2<- -parmlm2$trend                 #growth rate (b)
fitlog2 <- logistic(1:10, alpha2, beta2, k2)
predlog2<-forecast(fitlog2,h=seth)

#Operator 3
alpha3<-tssubs3[hi] +0.5           #upper asymptote (M)
Y3<-log(alpha3/tssubs3-1)          #Transform
Reglm3<-tslm(Y3~trend)             #Lineal Regression
parmlm3<-as.list(Reglm3$coeff)

beta3<- exp(parmlm3$"(Intercept)")  #growth range (a)
k3<- -parmlm3$trend                 #growth rate (b)
fitlog3 <- logistic(1:10, alpha3, beta3, k3)
predlog3<-forecast(fitlog3,h=seth)
```

The predictions using logistic model are:

```r
set4a<-data.frame(predlog1)
alog<-set4a$Point.Forecast   #Operator 1 predictions
set4b<-data.frame(predlog2)
blog<-set4b$Point.Forecast   #Operator 2 predictions
set4c<-data.frame(predlog3)
clog<-set4c$Point.Forecast   #Operator 3 predictions

data_predlog1<-data.frame(Log1=fitlog1)
data_predlog2<-data.frame(Log2=fitlog2)
data_predlog3<-data.frame(Log3=fitlog3)
```

Gompertz Model

Using the **growthmodels** package, Computes the Gompertz growth model **Usage** gompertz(t, alpha, beta, k) **Arguments** t time x size alpha upper asymptote beta growth displacement k growth rate

```r
#Operator 1
alphag1<-tssubs1[hi] +5                   #upper asymptote (M)
Y1g<-log(log(alphag1/tssubs1))            #Transform
Reglmg1<-tslm(Y1g~trend)                  #Lineal Regression
parmglm1<-as.list(Reglmg1$coeff)

betag1<- exp(parmglm1$"(Intercept)")  #growth range (a)
kg1<- -parmglm1$trend                 #growth rate (b)
fitgom1 <- gompertz(1:10, alphag1, betag1, kg1)
predgom1<-forecast(fitgom1,h=seth)

#Operator 2
alphag2<-tssubs2[hi] +5                   #upper asymptote (M)
Y2g<-log(log(alphag2/tssubs2))            #Transform
Reglmg2<-tslm(Y2g~trend)                  #Lineal Regression
parmglm2<-as.list(Reglmg2$coeff)

betag2<- exp(parmglm2$"(Intercept)")  #growth range (a)
kg2<- -parmglm2$trend                 #growth rate (b)
fitgom2 <- gompertz(1:10, alphag2, betag2, kg2)
predgom2<-forecast(fitgom2,h=seth)

#Operator 3
alphag3<-tssubs3[hi] +5                   #upper asymptote (M)
Y3g<-log(log(alphag3/tssubs3))            #Transform
Reglmg3<-tslm(Y3g~trend)                  #Lineal Regression
parmglm3<-as.list(Reglmg3$coeff)

betag3<- exp(parmglm3$"(Intercept)")  #growth range (a)
kg3<- -parmglm3$trend                 #growth rate (b)
fitgom3 <- gompertz(1:10, alphag3, betag3, kg3)
predgom3<-forecast(fitgom3,h=seth)
```

The predictions using gompertz model are:

```r
set5a<-data.frame(predgom1)
agom<-set5a$Point.Forecast   #Operator 1 predictions
set5b<-data.frame(predgom2)
bgom<-set5b$Point.Forecast   #Operator 2 predictions
set5c<-data.frame(predgom3)
cgom<-set5c$Point.Forecast   #Operator 3 predictions

data_predgom1<-data.frame(Gom1=fitgom1)
data_predgom2<-data.frame(Gom2=fitgom2)
data_predgom3<-data.frame(Gom3=fitgom3)
```

Parabolic Model

```r
#Operator 1
fitpar1=lm(tssubs1 ~ time + I(time^2))  #Model
predpar1<-predict(fitpar1)             #Prediction
```

```
forepar1<-forecast(predpar1,h=seth-3)  #Forecast
#Operator 2
fitpar2=lm(tssubs2 ~ time + I(time^2))  #Model
predpar2<-predict(fitpar2)             #Prediction
forepar2<-forecast(predpar2,h=seth-3)  #Forecast
#Operator 3
fitpar3=lm(tssubs3 ~ time + I(time^2))  #Model
predpar3<-predict(fitpar3)             #Prediction
forepar3<-forecast(predpar3,h=seth-3)  #Forecast

#Operator 1
data_predpar1<-data.frame(Par1=predpar1) #Parabolic predictions
set2a<-data.frame(forepar1)
para<-data.frame(Fore_Par1=set2a$Point.Forecast)
#Operator 2
data_predpar2<-data.frame(Par2=predpar2) #Parabolic predictions
set2b<-data.frame(forepar2)
parb<-data.frame(Fore_Par2=set2b$Point.Forecast)
#Operator 3
data_predpar3<-data.frame(Par3=predpar3) #Parabolic predictions
set2c<-data.frame(forepar3)
parc<-data.frame(Fore_Par3=set2c$Point.Forecast)
```

Forecasting for 5 years

```
fore5a<-data.frame(Fore_Log1=alog[1:5],Fore_Gom1=agom[1:5],Fore_Par1=forepar1)
fore5b<-data.frame(Fore_Log2=blog[1:5],Fore_Gom2=bgom[1:5],Fore_Par2=forepar2)
fore5c<-data.frame(Fore_Log3=clog[1:5],Fore_Gom3=cgom[1:5],Fore_Par3=forepar3)
```

3.2.Predicting with Fisher Pry

Model applied When substitution is driven by superior technology. The new product or service presents some technological advantage over the old one.

```
#Operator 1
L1<-tssubs1[hi]+5                      #upper asymptote (L)
transf1<-log((L1-tssubs1)/tssubs1)    #transform

fitpry1<-tslm(transf1~trend)         #model
set5a<-fitpry1$fitted.values
predpry1<-L1/(1+exp(set5a))          #Prediction
forepry1<-forecast(predpry1,h=seth) #Forecast

#Operator 2
L2<-tssubs2[hi]+5                      #upper asymptote (L)
transf2<-log((L2-tssubs2)/tssubs2)    #transform

fitpry2<-tslm(transf2~trend)         #model
set5b<-fitpry2$fitted.values
predpry2<-L2/(1+exp(set5b))          #Prediction
```

```
forepry2<-forecast(predpry2,h=seth) #Forecast

#Operator 3
L3<-tssubs3[hi]+5                      #upper asymptote (L)
transf3<-log((L3-tssubs3)/tssubs3)    #transform

fitpry3<-tslm(transf3~trend)        #model
set5c<-fitpry3$fitted.values
predpry3<-L3/(1+exp(set5c))         #Prediction
forepry3<-forecast(predpry3,h=seth) #Forecast
```

3.3. Bass Model

m Total number of potential buyers of the new product **p** The coefficient of innovation **q** The coefficient of imitation

```
#Operator1
setbas1<-subset(dataVoD1,Subs>=0.11)
setbas2<-subset(dataVoD1,Subs<0.11)
demand1<-tssubs1[(tssubs1)>=0.11]
time<-1:length(demand1)
Tdelt <- time     #Accuracy, size predictions

Bass.nls <- nls(demand1 ~ M * (((P + Q)^2/P) * exp(-(P + Q) * time))/(1 + (Q/P)
                                                                *exp(-(P + Q) * time))^2, start =
Bcoef <- coef(Bass.nls) # get coefficient operator 1
m <- Bcoef[1]
p <- Bcoef[2]
q <- Bcoef[3]
ngete <- exp(-(p + q) * Tdelt)  #Setting the starting values for M to the Subs

fitbas1 <- m * ((p + q)^2/p) * ngete/(1 + (q/p) * ngete)^2   #Model
setbas3<-data.frame(Year=setbas1$Year,Subs=fitbas1)            #Prediction
x<-nrow(setbas2)
cero<-data.frame(Year=setbas2$Year,Subs=c(1:x*0))
predbas1<-rbind(cero,setbas3)
forebas1<-forecast(predbas1$Subs,h=seth)                      #Forecast


#Operator2
setbas1<-subset(dataVoD2,Subs>=0.101)
setbas2<-subset(dataVoD2,Subs<0.101)
demand2<-tssubs2[(tssubs2)>=0.101]
time<-1:length(demand2)
Tdelt <- time     #Accuracy, size predictions

Bass.nls <- nls(demand2 ~ M * (((P + Q)^2/P)*exp(-(P + Q) * time))/
                   (1 + (Q/P)*exp(-(P + Q) * time))^2, start = list(M = 60630, P = 0.03, Q = 0.38))
Bcoef <- coef(Bass.nls) # get coefficient operator 1
m <- Bcoef[1]
p <- Bcoef[2]
q <- Bcoef[3]
```

```
ngete <- exp(-(p + q) * Tdelt)  #Setting the starting values for M to the Subs

fitbas2 <- m * ((p + q)^2/p) * ngete/(1 + (q/p) * ngete)^2   #Model
setbas3<-data.frame(Year=setbas1$Year,Subs=fitbas2)          #Prediction
x<-nrow(setbas2)
cero<-data.frame(Year=setbas2$Year,Subs=c(1:x*0))
predbas2<-rbind(cero,setbas3)
forebas2<-forecast(predbas2$Subs,h=seth)                     #Forecast

#Operator3
setbas1<-subset(dataVoD3,Subs>=0.101)
setbas2<-subset(dataVoD3,Subs<0.101)
demand3<-tssubs3[(tssubs3)>=0.101]
time<-1:length(demand3)
Tdelt <- time     #Accuracy, size predictions

Bass.nls <- nls(demand3 ~ M * (((P + Q)^2/P) * exp(-(P + Q) * time))/(1 + (Q/P)
                                                                    *exp(-(P + Q) * time))^2, start =
Bcoef <- coef(Bass.nls) # get coefficient operator 1
m <- Bcoef[1]
p <- Bcoef[2]
q <- Bcoef[3]
ngete <- exp(-(p + q) * Tdelt)  #Setting the starting values for M to the Subs

fitbas3 <- m * ((p + q)^2/p) * ngete/(1 + (q/p) * ngete)^2   #Model
setbas3<-data.frame(Year=setbas1$Year,Subs=fitbas3)             #Prediction
x<-nrow(setbas2)
cero<-data.frame(Year=setbas2$Year,Subs=c(1:x*0))
predbas3<-rbind(cero,setbas3)
forebas3<-forecast(predbas3$Subs,h=seth)                     #Forecast
```

The predictions using Bass and Fisher Pry model are:

```
set6a<-data.frame(forepry1)
apry<-set6a$Point.Forecast   #Operator 1 predictions
set6b<-data.frame(forepry2)
bpry<-set6b$Point.Forecast   #Operator 2 predictions
set6c<-data.frame(forepry3)
cpry<-set6c$Point.Forecast   #Operator 3 predictions

set7a<-data.frame(forebas1)
abas<-set7a$Point.Forecast   #Operator 1 predictions
set7b<-data.frame(forebas2)
bbas<-set7b$Point.Forecast   #Operator 2 predictions
set7c<-data.frame(forebas3)
cbas<-set7c$Point.Forecast   #Operator 3 predictions

data_pred1c<-data.frame(Pry1=predpry1,Bass1=predbas1$Subs)
data_pred2c<-data.frame(Pry2=predpry2,Bass2=predbas2$Subs)
data_pred3c<-data.frame(Pry3=predpry3,Bass3=predbas3$Subs)
```

Forecasting for 5 years

```
fore6a<-data.frame(Fore_Pry1=apry[1:5],Fore_Bas1=abas[1:5])
fore6b<-data.frame(Fore_Pry2=bpry[1:5],Fore_Bas2=bbas[1:5])
fore6c<-data.frame(Fore_Pry3=cpry[1:5],Fore_Bas3=cbas[1:5])
```

3.4.Performance Models for VoD

Using the forecast package, the performance models are: **(ME)**:Mean Error **(RMSE)**:Root Mean Square Error **(MAE)**: Mean Absolute Error *(MPE)**: Mean Porcentual Error** (MAPE)**: Mean Absolute Porcentual Error

```
#Modelo Parabólico
acc_e1<-accuracy(predpar1,tssubs1)  #Operator 1
acc_e2<-accuracy(predpar2,tssubs2)  #Operator 2
acc_e3<-accuracy(predpar3,tssubs3)  #Operator 3

#Modelo Logístico
acc_g1<-accuracy(predlog1) #Operator 1
acc_g2<-accuracy(predlog2) #Operator 2
acc_g3<-accuracy(predlog3) #Operator 3

#Modelo Gompertz
acc_h1<-accuracy(predgom1) #Operator 1
acc_h2<-accuracy(predgom2) #Operator 2
acc_h3<-accuracy(predgom3) #Operator 3

#Modelo Fisher-Pry
acc_i1<-accuracy(predpry1,tssubs1) #Operator 1
acc_i2<-accuracy(predpry2,tssubs2) #Operator 2
acc_i3<-accuracy(predpry3,tssubs3) #Operator 3

#Modelo Bass
acc_j1<-accuracy(predbas1$Subs,dataVoD1$Subs)   #Duda Operator 1
acc_j2<-accuracy(predbas2$Subs,dataVoD2$Subs)   #Duda Operator 2
acc_j3<-accuracy(predbas3$Subs,dataVoD3$Subs)   #Duda Operator 3
```

The performance sets are:

```
Models<-c("Parabolic","Logistic","Gompertz","Fisher-Pry","Bass")

#Opereator 1
acce1<-acc_e1[1,1:5]  #Parabolic
accg1<-acc_g1[1,1:5]  #Logistic
acch1<-acc_h1[1,1:5]  #Gompertz
acci1<-acc_i1[1,1:5]  #Fisher-Pry
accj1<-acc_j1[1,1:5]  #Bass
acc_all1b<-round(rbind(acce1,accg1,acch1,acci1,accj1),2)
performVoD1<-data.frame(Models,acc_all1b)

#Operator 2
```

```r
acce2<-acc_e1[1,1:5]  #Parabolic
accg2<-acc_g2[1,1:5]
acch2<-acc_h2[1,1:5]
acci2<-acc_i2[1,1:5]
accj2<-acc_j2[1,1:5]
acc_all2b<-round(rbind(acce2,accg2,acch2,acci2,accj2),2)
performVoD2<-data.frame(Models,acc_all2b)

#Operator 3
acce3<-acc_e1[1,1:5]  #Parabolic
accg3<-acc_g3[1,1:5]
acch3<-acc_h3[1,1:5]
acci3<-acc_i3[1,1:5]
accj3<-acc_j3[1,1:5]
acc_all3b<-round(rbind(acce3,accg3,acch3,acci3,accj3),2)
performVoD3<-data.frame(Models,acc_all3b)
```

Predictions Reports

```r
#Internet Residential Predictions by service provider
predVoD1<-data.frame(data_predlog1,data_predgom1,data_predpar1,data_pred1c) #Operator 1
predVoD2<-data.frame(data_predlog2,data_predgom2,data_predpar2,data_pred2c) #Operator 2
predVoD3<-data.frame(data_predlog3,data_predgom3,data_predpar3,data_pred3c) #Operator 3
```

Forecast Reports

Forecasting for 5 Years Video on Demand

```r
foreVoD1<-data.frame(fore5a,fore6a)  #Operator 1
foreVoD2<-data.frame(fore5b,fore6b)  #Operator 2
foreVoD3<-data.frame(fore5c,fore6c)  #Operator 3
```

4.Demand Models for VoIP Subscribers

Subset data

```r
dataVoIP1<-data.frame(Year=year,Subs=oper1$VoIP1)  #Operator 1
tssubs1<-ts(oper1$VoIP1,start=start,end=end) #Time serie
dataVoIP2<-data.frame(Year=year,Subs=oper2$VoIP2)  #Operator 2
tssubs2<-ts(oper2$VoIP2,start=start,end=end) #Time serie
dataVoIP3<-data.frame(Year=year,Subs=oper3$VoIP3)  #Operator 3
tssubs3<-ts(oper3$VoIP3,start=start,end=end) #Time serie
```

4.1.Predicting with Logistic and Gompertz Model VoIP

Logistic Model

```
#Operator 1
alpha1<-tssubs1[hi] +0.5           #upper asymptote (M)
Y1<-log(alpha1/tssubs1-1)          #Transform
Reglm1<-tslm(Y1~trend)             #Lineal Regression
parmlm1<-as.list(Reglm1$coeff)

beta1<- exp(parmlm1$"(Intercept)")  #growth range (a)
k1<- -parmlm1$trend                 #growth rate (b)
fitlog1 <- logistic(1:10, alpha1, beta1, k1)
predlog1<-forecast(fitlog1,h=seth)

#Operator 2
alpha2<-tssubs2[hi] +0.5           #upper asymptote (M)
Y2<-log(alpha2/tssubs2-1)          #Transform
Reglm2<-tslm(Y2~trend)             #Lineal Regression
parmlm2<-as.list(Reglm2$coeff)

beta2<- exp(parmlm2$"(Intercept)")  #growth range (a)
k2<- -parmlm2$trend                 #growth rate (b)
fitlog2 <- logistic(1:10, alpha2, beta2, k2)
predlog2<-forecast(fitlog2,h=seth)

#Operator 3
alpha3<-tssubs3[hi] +0.5           #upper asymptote (M)
Y3<-log(alpha3/tssubs3-1)          #Transform
Reglm3<-tslm(Y3~trend)             #Lineal Regression
parmlm3<-as.list(Reglm3$coeff)

beta3<- exp(parmlm3$"(Intercept)")  #growth range (a)
k3<- -parmlm3$trend                 #growth rate (b)
fitlog3 <- logistic(1:10, alpha3, beta3, k3)
predlog3<-forecast(fitlog3,h=seth)

#The predictions using logistic model are:
set4a<-data.frame(predlog1)
alog<-set4a$Point.Forecast   #Operator 1 predictions
set4b<-data.frame(predlog2)
blog<-set4b$Point.Forecast   #Operator 2 predictions
set4c<-data.frame(predlog3)
clog<-set4c$Point.Forecast   #Operator 3 predictions

data_predlog1<-data.frame(Log1=fitlog1)
data_predlog2<-data.frame(Log2=fitlog2)
data_predlog3<-data.frame(Log3=fitlog3)
```

Gompertz Model VoIP

```
#Operator 1
alphag1<-tssubs1[hi] +5                 #upper asymptote (M)
Y1g<-log(log(alphag1/tssubs1))          #Transform
Reglmg1<-tslm(Y1g~trend)                #Lineal Regression
parmglm1<-as.list(Reglmg1$coeff)

betag1<- exp(parmglm1$"(Intercept)")  #growth range (a)
kg1<- -parmglm1$trend                 #growth rate (b)
fitgom1 <- gompertz(1:10, alphag1, betag1, kg1)
predgom1<-forecast(fitgom1,h=seth)

#Operator 2
alphag2<-tssubs2[hi] +5                 #upper asymptote (M)
Y2g<-log(log(alphag2/tssubs2))          #Transform
Reglmg2<-tslm(Y2g~trend)                #Lineal Regression
parmglm2<-as.list(Reglmg2$coeff)

betag2<- exp(parmglm2$"(Intercept)")  #growth range (a)
kg2<- -parmglm2$trend                 #growth rate (b)
fitgom2 <- gompertz(1:10, alphag2, betag2, kg2)
predgom2<-forecast(fitgom2,h=seth)

#Operator 3
alphag3<-tssubs3[hi] +5                 #upper asymptote (M)
Y3g<-log(log(alphag3/tssubs3))          #Transform
Reglmg3<-tslm(Y3g~trend)                #Lineal Regression
parmglm3<-as.list(Reglmg3$coeff)

betag3<- exp(parmglm3$"(Intercept)")  #growth range (a)
kg3<- -parmglm3$trend                 #growth rate (b)
fitgom3 <- gompertz(1:10, alphag3, betag3, kg3)
predgom3<-forecast(fitgom3,h=seth)
```

The predictions using gompertz model are:

```
set5a<-data.frame(predgom1)
agom<-set5a$Point.Forecast   #Operator 1 predictions
set5b<-data.frame(predgom2)
bgom<-set5b$Point.Forecast   #Operator 2 predictions
set5c<-data.frame(predgom3)
cgom<-set5c$Point.Forecast   #Operator 3 predictions

data_predgom1<-data.frame(Gom1=fitgom1)
data_predgom2<-data.frame(Gom2=fitgom2)
data_predgom3<-data.frame(Gom3=fitgom3)
```

4.2 Parabolic Model VoIP

```
time<-1:hi
#Operator 1
fitpar1=lm(tssubs1 ~ time + I(time^2))  #Model
predpar1<-predict(fitpar1)             #Prediction
forepar1<-forecast(predpar1,h=seth-3)  #Forecast
#Operator 2
fitpar2=lm(tssubs2 ~ time + I(time^2))  #Model
predpar2<-predict(fitpar2)             #Prediction
forepar2<-forecast(predpar2,h=seth-3)  #Forecast
#Operator 3
fitpar3=lm(tssubs3 ~ time + I(time^2))  #Model
predpar3<-predict(fitpar3)             #Prediction
forepar3<-forecast(predpar3,h=seth-3)  #Forecast

#Operator 1
data_predpar1<-data.frame(Par1=predpar1) #Parabolic predictions
set2a<-data.frame(forepar1)
para<-data.frame(Fore_Par1=set2a$Point.Forecast)
#Operator 2
data_predpar2<-data.frame(Par2=predpar2) #Parabolic predictions
set2b<-data.frame(forepar2)
parb<-data.frame(Fore_Par2=set2b$Point.Forecast)
#Operator 3
data_predpar3<-data.frame(Par3=predpar3) #Parabolic predictions
set2c<-data.frame(forepar3)
parc<-data.frame(Fore_Par3=set2c$Point.Forecast)
```

Forecasting for 5 years VoIP

```
fore7a<-data.frame(Fore_Log1=alog[1:5],Fore_Gom1=agom[1:5],Fore_Par1=forepar1)
fore7b<-data.frame(Fore_Log2=blog[1:5],Fore_Gom2=bgom[1:5],Fore_Par1=forepar1)
fore7c<-data.frame(Fore_Log3=clog[1:5],Fore_Gom3=cgom[1:5],Fore_Par1=forepar1)
```

4.3 Predicting with Fisher Pry

Model applied When substitution is driven by superior technology. The new product or service presents some technological advantage over the old one.

```
#Operator 1
L1<-tssubs1[hi]+5                    #upper asymptote (L)
transf1<-log((L1-tssubs1)/tssubs1)   #transform

fitpry1<-tslm(transf1~trend)        #model
set5a<-fitpry1$fitted.values
predpry1<-L1/(1+exp(set5a))         #Prediction
forepry1<-forecast(predpry1,h=seth) #Forecast

#Operator 2
L2<-tssubs2[hi]+5                    #upper asymptote (L)
transf2<-log((L2-tssubs2)/tssubs2)   #transform
```

```
fitpry2<-tslm(transf2~trend)        #model
set5b<-fitpry2$fitted.values
predpry2<-L2/(1+exp(set5b))         #Prediction
forepry2<-forecast(predpry2,h=seth) #Forecast

#Operator 3
L3<-tssubs3[hi]+5                    #upper asymptote (L)
transf3<-log((L3-tssubs3)/tssubs3)   #transform

fitpry3<-tslm(transf3~trend)        #model
set5c<-fitpry3$fitted.values
predpry3<-L3/(1+exp(set5c))         #Prediction
forepry3<-forecast(predpry3,h=seth) #Forecast
```

4.4 Bass Model

m Total number of potential buyers of the new product **p** The coefficient of innovation **q** The coefficient of imitation

```
#Operator1
setbas1<-subset(dataVoIP1,Subs>=0.11)
setbas2<-subset(dataVoIP1,Subs<0.11)
demand1<-tssubs1#[(tssubs1)>=0.11]
time<-1:length(demand1)
Tdelt <- time     #Accuracy, size predictions

Bass.nls <- nls(demand1 ~ M * (((P + Q)^2/P) * exp(-(P + Q) * time))/(1 + (Q/P)
                                                                *exp(-(P + Q) * time))^2, start =
Bcoef <- coef(Bass.nls) # get coefficient operator 1
m <- Bcoef[1]
p <- Bcoef[2]
q <- Bcoef[3]
ngete <- exp(-(p + q) * Tdelt)  #Setting the starting values for M to the Subs

fitbas1 <- m * ((p + q)^2/p) * ngete/(1 + (q/p) * ngete)^2   #Model
setbas3<-data.frame(Year=setbas2$Year,Subs=fitbas1)          #Prediction
#x<-nrow(setbas2)
#cero<-data.frame(Year=setbas2$Year,Subs=c(1:x*0))
#predbas1<-rbind(cero,setbas3)
predbas1<-setbas3
forebas1<-forecast(predbas1$Subs,h=seth)                     #Forecast

#Operator2
setbas1<-subset(dataVoIP2,Subs>=0.11)
setbas2<-subset(dataVoIP2,Subs<0.11)
demand2<-tssubs2[(tssubs2)>=0.11]
time<-1:length(demand2)
Tdelt <- time     #Accuracy, size predictions

Bass.nls <- nls(demand2 ~ M * (((P + Q)^2/P) * exp(-(P + Q) * time))/(1 + (Q/P)
                                                                *exp(-(P + Q) * time))^2, start =
Bcoef <- coef(Bass.nls) # get coefficient operator 1
```

```
m <- Bcoef[1]
p <- Bcoef[2]
q <- Bcoef[3]
ngete <- exp(-(p + q) * Tdelt)  #Setting the starting values for M to the Subs

fitbas2 <- m * ((p + q)^2/p) * ngete/(1 + (q/p) * ngete)^2   #Model
setbas3<-data.frame(Year=setbas1$Year,Subs=fitbas2)             #Prediction
x<-nrow(setbas2)
cero<-data.frame(Year=setbas2$Year,Subs=c(1:x*0))
predbas2<-rbind(cero,setbas3)
forebas2<-forecast(predbas2$Subs,h=seth)                     #Forecast

#Operator3
setbas1<-subset(dataVoIP3,Subs>=0.11)
setbas2<-subset(dataVoIP3,Subs<0.11)
demand3<-tssubs3[(tssubs3)>=0.11]
time<-1:length(demand3)
Tdelt <- time     #Accuracy, size predictions

Bass.nls <- nls(demand3 ~ M * (((P + Q)^2/P) * exp(-(P + Q) * time))/(1 + (Q/P)
                                                                  *exp(-(P + Q) * time))^2, start =
Bcoef <- coef(Bass.nls) # get coefficient operator 1
m <- Bcoef[1]
p <- Bcoef[2]
q <- Bcoef[3]
ngete <- exp(-(p + q) * Tdelt)  #Setting the starting values for M to the Subs

fitbas3 <- m * ((p + q)^2/p) * ngete/(1 + (q/p) * ngete)^2   #Model
setbas3<-data.frame(Year=setbas1$Year,Subs=fitbas3)             #Prediction
x<-nrow(setbas2)
cero<-data.frame(Year=setbas2$Year,Subs=c(1:x*0))
predbas3<-rbind(cero,setbas3)
forebas3<-forecast(predbas3$Subs,h=seth)                     #Forecast
```

The predictions using Bass and Fisher Pry model are:

```
set6a<-data.frame(forepry1)
apry<-set6a$Point.Forecast   #Operator 1 predictions
set6b<-data.frame(forepry2)
bpry<-set6b$Point.Forecast   #Operator 2 predictions
set6c<-data.frame(forepry3)
cpry<-set6c$Point.Forecast   #Operator 3 predictions

set7a<-data.frame(forebas1)
abas<-set7a$Point.Forecast   #Operator 1 predictions
set7b<-data.frame(forebas2)
bbas<-set7b$Point.Forecast   #Operator 2 predictions
set7c<-data.frame(forebas3)
cbas<-set7c$Point.Forecast   #Operator 3 predictions

data_pred1c<-data.frame(Pry1=predpry1,Bass1=predbas1$Subs)
data_pred2c<-data.frame(Pry2=predpry2,Bass2=predbas2$Subs)
data_pred3c<-data.frame(Pry3=predpry3,Bass3=predbas3$Subs)
```

Forecasting for 5 years

```
fore8a<-data.frame(Fore_Pry1=apry[1:5],Fore_Bas1=abas[1:5])
fore8b<-data.frame(Fore_Pry2=bpry[1:5],Fore_Bas2=bbas[1:5])
fore8c<-data.frame(Fore_Pry3=cpry[1:5],Fore_Bas3=cbas[1:5])
```

4.5 Performance Models for VoIP

Using the forecast package, the performance models are: **(ME)**:Mean Error **(RMSE)**:Root Mean Square Error **(MAE)**: Mean Absolute Error **(MPE)**: Mean Porcentual Error **(MAPE)**: Mean Absolute Porcentual Error

```
#Modelo Parabólico
acc_e1<-accuracy(predpar1,tssubs1)  #Operator 1
acc_e2<-accuracy(predpar2,tssubs2)  #Operator 2
acc_e3<-accuracy(predpar3,tssubs3)  #Operator 3

#Modelo Logístico
acc_g1<-accuracy(predlog1) #Operator 1
acc_g2<-accuracy(predlog2) #Operator 2
acc_g3<-accuracy(predlog3) #Operator 3

#Modelo Gompertz
acc_h1<-accuracy(predgom1) #Operator 1
acc_h2<-accuracy(predgom2) #Operator 2
acc_h3<-accuracy(predgom3) #Operator 3

#Modelo Fisher-Pry
acc_i1<-accuracy(predpry1,tssubs1) #Operator 1
acc_i2<-accuracy(predpry2,tssubs2) #Operator 2
acc_i3<-accuracy(predpry3,tssubs3) #Operator 3

#Modelo Bass
acc_j1<-accuracy(predbas1$Subs,dataVoIP1$Subs)   #Duda Operator 1
acc_j2<-accuracy(predbas2$Subs,dataVoIP2$Subs)   #Duda Operator 2
acc_j3<-accuracy(predbas3$Subs,dataVoIP3$Subs)   #Duda Operator 3
```

The performance sets are:

```
Models<-c("Parabolic","Logistic","Gompertz","Fisher-Pry","Bass")

#Opereator 1
acce1<-acc_e1[1,1:5]  #Parabolic
accg1<-acc_g1[1,1:5]  #Logistic
acch1<-acc_h1[1,1:5]  #Gompertz
acci1<-acc_i1[1,1:5]  #Fisher-Pry
accj1<-acc_j1[1,1:5]  #Bass
acc_all1b<-round(rbind(acce1,accg1,acch1,acci1,accj1),2)
performVoIP1<-data.frame(Models,acc_all1b)

#Operator 2
```

```
acce2<-acc_e1[1,1:5]  #Parabolic
accg2<-acc_g2[1,1:5]
acch2<-acc_h2[1,1:5]
acci2<-acc_i2[1,1:5]
accj2<-acc_j2[1,1:5]
acc_all2b<-round(rbind(acce2,accg2,acch2,acci2,accj2),2)
performVoIP2<-data.frame(Models,acc_all2b)

#Operator 3
acce3<-acc_e1[1,1:5]  #Parabolic
accg3<-acc_g3[1,1:5]
acch3<-acc_h3[1,1:5]
acci3<-acc_i3[1,1:5]
accj3<-acc_j3[1,1:5]
acc_all3b<-round(rbind(acce3,accg3,acch3,acci3,accj3),2)
performVoIP3<-data.frame(Models,acc_all3b)
```

Predictions Reports

VoIP Predictions by service provider

```
predVoIP1<-data.frame(data_predlog1,data_predgom1,data_predpar1,data_pred1c) #Operator 1
predVoIP2<-data.frame(data_predlog2,data_predgom2,data_predpar2,data_pred2c) #Operator 2
predVoIP3<-data.frame(data_predlog3,data_predgom3,data_predpar3,data_pred3c) #Operator 3
```

Forecast Reports

Forecasting for 5 Years Video on Demand

```
foreVoIP1<-data.frame(fore7a,fore8a)  #Operator 1
foreVoIP2<-data.frame(fore7b,fore8b)  #Operator 2
foreVoIP3<-data.frame(fore7c,fore8c)  #Operator 3
```

5.Predictions, Forecast and Performance Reports

```
library(knitr)
```

Predictions Report

The data set for fit each model are:

```
predIRes<-round(data.frame(predIRes1,predIRes2,predIRes3),2)
predIBus<-round(data.frame(predIBus1,predIBus2,predIBus3),2)
predVoD<-round(data.frame(predVoD1,predVoD2,predVoD3),2)
predVoIP<-round(data.frame(predVoIP1,predVoIP2,predVoIP3),2)

kable(predIRes,format = "markdown",caption = "Internet Residential")
```

Lin1	Par1	Exp1	Log1	Gom1	Lin2	Par2	Exp2	Log2	Gom2	Lin3	Par3	Exp3	Log3	Gom3
-0.12	-0.05	0.00	0.00	0.00	21.49	21.47	21.66	18.86	20.69	2.08	2.32	3.28	2.01	1.96
-0.02	-0.01	0.01	0.01	0.01	22.52	22.50	22.56	21.25	22.18	3.91	3.91	4.10	3.27	3.48
0.08	0.05	0.02	0.02	0.02	23.55	23.54	23.49	23.38	23.58	5.75	5.62	5.13	5.10	5.44
0.19	0.14	0.04	0.04	0.06	24.59	24.58	24.46	25.20	24.86	7.59	7.44	6.42	7.51	7.69
0.29	0.24	0.07	0.09	0.13	25.62	25.63	25.48	26.68	26.05	9.42	9.37	8.02	10.30	10.06
0.39	0.37	0.15	0.20	0.25	26.65	26.68	26.53	27.86	27.13	11.26	11.41	10.03	13.10	12.37
0.49	0.52	0.31	0.40	0.43	27.68	27.74	27.63	28.78	28.11	13.09	13.57	12.55	15.53	14.53
0.60	0.69	0.65	0.70	0.67	28.71	28.81	28.78	29.47	28.99	14.93	15.84	15.69	17.38	16.45
0.70	0.88	1.33	1.02	0.97	29.75	29.88	29.97	29.99	29.78	16.76	18.22	19.62	18.65	18.11
0.80	1.10	2.73	1.28	1.32	30.78	30.96	31.21	30.37	30.50	18.60	20.71	24.53	19.47	19.51

```
kable(predIBus,format = "markdown",caption = "Internet Bussines")
```

Lin1	Par1	Exp1	Log1	Gom1	Lin2	Par2	Exp2	Log2	Gom2	Lin3	Par3	Exp3	Log3	Gom3
-0.04	-0.02	0.00	0.00	0.00	0.37	0.38	0.47	0.41	0.44	0.37	0.38	0.47	0.41	0.44
-0.01	0.00	0.00	0.00	0.00	0.54	0.54	0.55	0.53	0.55	0.54	0.54	0.55	0.53	0.55
0.03	0.02	0.01	0.01	0.01	0.70	0.70	0.65	0.67	0.67	0.70	0.70	0.65	0.67	0.67
0.06	0.05	0.01	0.01	0.02	0.86	0.86	0.77	0.83	0.81	0.86	0.86	0.77	0.83	0.81
0.10	0.08	0.02	0.03	0.04	1.02	1.02	0.91	1.00	0.97	1.02	1.02	0.91	1.00	0.97
0.13	0.12	0.05	0.06	0.08	1.18	1.18	1.07	1.18	1.13	1.18	1.18	1.07	1.18	1.13
0.16	0.17	0.10	0.12	0.13	1.34	1.34	1.27	1.36	1.31	1.34	1.34	1.27	1.36	1.31
0.20	0.23	0.22	0.22	0.22	1.50	1.50	1.50	1.53	1.50	1.50	1.50	1.50	1.53	1.50
0.23	0.29	0.44	0.37	0.34	1.66	1.67	1.77	1.68	1.70	1.66	1.67	1.77	1.68	1.70
0.27	0.37	0.91	0.54	0.49	1.82	1.83	2.08	1.81	1.90	1.82	1.83	2.08	1.81	1.90

```
kable(predVoD,format = "markdown",caption = "VoD")
```

Log1	Gom1	Par1	Pry1	Bass1	Log2	Gom2	Par2	Pry2	Bass2	Log3	Gom3	Par3	Pry3	Bass3
0.03	0.03	0.05	0.04	0.00	0.00	0.00	-0.02	0.00	0.00	0.00	0.00	-0.02	0.00	0.00
0.05	0.05	0.04	0.05	0.00	0.00	0.00	-0.05	0.00	0.00	0.00	0.00	-0.05	0.00	0.00
0.07	0.08	0.06	0.07	0.00	0.00	0.00	-0.03	0.00	0.00	0.00	0.00	-0.03	0.00	0.00
0.11	0.12	0.09	0.11	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.04	0.00	0.00
0.16	0.17	0.15	0.15	0.14	0.00	0.01	0.16	0.00	0.00	0.00	0.01	0.16	0.00	0.00
0.23	0.24	0.22	0.21	0.21	0.00	0.05	0.33	0.00	0.00	0.00	0.05	0.33	0.00	0.00
0.32	0.32	0.32	0.29	0.32	0.03	0.19	0.55	0.02	0.80	0.03	0.19	0.55	0.02	0.80
0.43	0.43	0.44	0.41	0.45	0.28	0.51	0.81	0.17	1.01	0.28	0.51	0.81	0.17	1.01
0.56	0.55	0.58	0.56	0.60	1.14	1.03	1.12	1.21	1.19	1.14	1.03	1.12	1.21	1.19
0.69	0.69	0.75	0.77	0.73	1.70	1.72	1.48	4.20	1.30	1.70	1.72	1.48	4.20	1.30

```
kable(predVoIP,format = "markdown",caption = "VoIP")
```

Log1	Gom1	Par1	Pry1	Bass1	Log2	Gom2	Par2	Pry2	Bass2	Log3	Gom3	Par3	Pry3	Bass3
0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.02	0.00	0.00	0.00	0.00	-0.02	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.05	0.00	0.00	0.00	0.00	-0.05	0.00	0.00
0.00	0.00	0.01	0.00	0.00	0.00	0.00	-0.03	0.00	0.00	0.00	0.00	-0.03	0.00	0.00
0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.04	0.00	0.00

Log1	Gom1	Par1	Pry1	Bass1	Log2	Gom2	Par2	Pry2	Bass2	Log3	Gom3	Par3	Pry3	Bass3
0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.16	0.00	0.00	0.00	0.01	0.16	0.00	0.00
0.00	0.00	0.02	0.00	0.02	0.00	0.05	0.33	0.00	0.00	0.00	0.05	0.33	0.00	0.00
0.01	0.01	0.02	0.01	0.02	0.03	0.19	0.55	0.02	0.80	0.03	0.19	0.55	0.02	0.80
0.02	0.02	0.02	0.02	0.02	0.28	0.51	0.81	0.17	1.01	0.28	0.51	0.81	0.17	1.01
0.06	0.03	0.02	0.06	0.02	1.14	1.03	1.12	1.21	1.19	1.14	1.03	1.12	1.21	1.19
0.13	0.05	0.02	0.16	0.01	1.70	1.72	1.48	4.20	1.30	1.70	1.72	1.48	4.20	1.30

```
#predictall<-data.frame(Res=predIRes,VoD=predVoD,VoIP=predVoIP,Bus=predIBus)
#write.csv2(predictall,"Predictions_Report.csv")
```

Forecast Report

The forecast by model are:

Year	Fore_Lin1	Fore_Par1	Fore_Exp1	Fore_Log1	Fore_Gom1
2017	0.9024694	1.226558	2.734026	1.277177	1.322436
2018	1.0049524	1.354703	2.734026	1.277177	1.322436
2019	1.1074355	1.482848	2.734026	1.277177	1.322436
2020	1.2099186	1.610993	2.734026	1.277177	1.322436
2021	1.3124016	1.739138	2.734026	1.277177	1.322436

Fore_Lin2	Fore_Par2	Fore_Exp2	Fore_Log2	Fore_Gom1
31.81071	32.04061	32.45574	30.72066	31.14785
32.84286	33.11939	33.69777	31.00922	31.74278
33.87500	34.19818	34.93980	31.25003	32.28654
34.90714	35.27697	36.18182	31.45099	32.78353
35.93929	36.35576	37.42385	31.61869	33.23778

Fore_Lin3	Fore_Par3	Fore_Exp3	Fore_Log3	Fore_Gom1
20.43571	23.20120	29.43338	20.29261	20.91747
22.27143	25.69332	34.34459	21.11257	22.31897
24.10714	28.18544	39.25580	21.93252	23.72047
25.94286	30.67756	44.16701	22.75247	25.12197
27.77857	33.16969	49.07822	23.57242	26.52347

Year	Fore_Lin1	Fore_Par1	Fore_Exp1	Fore_Log1	Fore_Gom1
2017	0.3008643	0.4316094	0.9070561	0.5368776	0.4895572
2018	0.3350286	0.4910805	0.9070561	0.5368776	0.4895572
2019	0.3691929	0.5451258	0.9070561	0.5368776	0.4895572
2020	0.4033571	0.5942402	0.9070561	0.5368776	0.4895572
2021	0.4375214	0.6388737	0.9070561	0.5368776	0.4895572

Fore_Lin2	Fore_Par2	Fore_Exp2	Fore_Log2	Fore_Gom1
1.982143	1.989767	2.401244	1.966764	2.106110
2.142857	2.149535	2.719286	2.122497	2.310125
2.303571	2.309303	3.037327	2.278230	2.514139
2.464286	2.469071	3.355369	2.433963	2.718153
2.625000	2.628839	3.673411	2.589695	2.922168

Fore_Lin3	Fore_Par3	Fore_Exp3	Fore_Log3	Fore_Gom1
1.982143	1.989767	2.401244	1.966764	2.106110
2.142857	2.149535	2.719286	2.122497	2.310125
2.303571	2.309303	3.037327	2.278230	2.514139
2.464286	2.469071	3.355369	2.433963	2.718153
2.625000	2.628839	3.673411	2.589695	2.922168

	Fore_Log1	Fore_Gom1	Fore_Par1.Point.Forecast	Fore_Par1.Lo.80	Fore_Par1.Hi.80	Fore_Par1.Lo.95	Fore
11	0.8074490	0.6880729	0.7456026	0.3546632	1.136542	0.1477125	
12	0.9186399	0.6880729	0.7456026	0.1700903	1.321115	-0.1345675	
13	1.0272105	0.6880729	0.7456026	0.0111310	1.480074	-0.3776748	
14	1.1332225	0.6880729	0.7456026	-0.1390059	1.630211	-0.6072894	
15	1.2367362	0.6880729	0.7456026	-0.2870144	1.778220	-0.8336487	

	Fore_Log2	Fore_Gom2	Fore_Par2.Point.Forecast	Fore_Par2.Lo.80	Fore_Par2.Hi.80	Fore_Par2.Lo.95	Fore
11	1.696964	0.000351	1.4836	1.2295645	1.737636	1.0950862	
12	1.696964	0.000351	1.4836	1.1243575	1.842843	0.9341860	
13	1.696964	0.000351	1.4836	1.0436269	1.923573	0.8107192	
14	1.696964	0.000351	1.4836	0.9755671	1.991633	0.7066307	
15	1.696964	0.000351	1.4836	0.9156048	2.051595	0.6149262	

	Fore_Log3	Fore_Gom3	Fore_Par3.Point.Forecast	Fore_Par3.Lo.80	Fore_Par3.Hi.80	Fore_Par3.Lo.95	Fore
11	1.696964	0.000351	1.4836	1.2295645	1.737636	1.0950862	
12	1.696964	0.000351	1.4836	1.1243575	1.842843	0.9341860	
13	1.696964	0.000351	1.4836	1.0436269	1.923573	0.8107192	
14	1.696964	0.000351	1.4836	0.9755671	1.991633	0.7066307	
15	1.696964	0.000351	1.4836	0.9156048	2.051595	0.6149262	

	Fore_Log1	Fore_Gom1	Fore_Par1.Point.Forecast	Fore_Par1.Lo.80	Fore_Par1.Hi.80	Fore_Par1.Lo.95	Fore
11	0.1279918	0.0738528	0.0140132	0.0132462	0.0147803	0.0128401	
12	0.1279918	0.0949960	0.0129205	0.0106617	0.0151793	0.0094660	
13	0.1279918	0.1161391	0.0119139	0.0083750	0.0154527	0.0065017	
14	0.1279918	0.1372823	0.0109865	0.0061636	0.0158094	0.0036105	
15	0.1279918	0.1584255	0.0101321	0.0040010	0.0162633	0.0007553	

	Fore_Log2	Fore_Gom2	Fore_Par1.Point.Forecast	Fore_Par1.Lo.80	Fore_Par1.Hi.80	Fore_Par1.Lo.95	Fore
11	1.696964	0.000351	0.0140132	0.0132462	0.0147803	0.0128401	
12	1.696964	0.000351	0.0129205	0.0106617	0.0151793	0.0094660	
13	1.696964	0.000351	0.0119139	0.0083750	0.0154527	0.0065017	
14	1.696964	0.000351	0.0109865	0.0061636	0.0158094	0.0036105	
15	1.696964	0.000351	0.0101321	0.0040010	0.0162633	0.0007553	

	Fore_Log3	Fore_Gom3	Fore_Par1.Point.Forecast	Fore_Par1.Lo.80	Fore_Par1.Hi.80	Fore_Par1.Lo.95	Fore
11	1.696964	0.000351	0.0140132	0.0132462	0.0147803	0.0128401	
12	1.696964	0.000351	0.0129205	0.0106617	0.0151793	0.0094660	
13	1.696964	0.000351	0.0119139	0.0083750	0.0154527	0.0065017	
14	1.696964	0.000351	0.0109865	0.0061636	0.0158094	0.0036105	
15	1.696964	0.000351	0.0101321	0.0040010	0.0162633	0.0007553	

Performance Report

	Models	ME	RMSE	MAE	MPE	MAPE	ME.1	RMSE.1	MAE.1	MPE.1	MAPE.1	ME.2
accd1	Linear	0.00	0.10	0.09	389.34	787.25	0.00	0.36	0.31	-0.03	1.27	0.00
acce1	Parabolic	0.00	0.06	0.05	82.09	254.52	0.00	0.06	0.05	82.09	254.52	0.00
accf1	Exponential	0.27	0.51	0.27	50.12	50.12	0.27	0.51	0.27	50.12	50.12	0.27
accg1	Logistic	0.13	0.18	0.13	46.15	46.15	0.13	0.18	0.13	46.15	46.15	0.13
acch1	Gompertz	0.13	0.18	0.13	48.66	48.66	0.13	0.18	0.13	48.66	48.66	0.13

	Models	ME	RMSE	MAE	MPE	MAPE	ME.1	RMSE.1	MAE.1	MPE.1	MAPE.1	ME.2
accd1	Linear	0.00	0.03	0.03	373.19	773.93	0.00	0.04	0.04	-0.03	4.56	0.00
acce1	Parabolic	0.00	0.02	0.02	77.43	251.19	0.00	0.04	0.03	-0.10	3.50	0.00
accf1	Exponential	0.09	0.17	0.09	50.03	50.03	0.02	0.03	0.02	1.80	1.93	0.02
accg1	Logistic	0.05	0.08	0.05	47.15	47.15	0.00	0.02	0.02	-0.45	1.80	0.00
acch1	Gompertz	0.05	0.07	0.05	48.40	48.40	0.01	0.01	0.01	0.96	0.96	0.01

	Models	ME	RMSE	MAE	MPE	MAPE	ME.1	RMSE.1	MAE.1	MPE.1	MAPE.1	ME.2	R
acce1	Parabolic	0.00	0.04	0.03	-0.43	11.51	0.00	0.04	0.03	-0.43	11.51	0.00	
accg1	Logistic	0.02	0.03	0.02	7.48	9.51	0.17	0.33	0.17	81.98	81.98	0.17	
acch1	Gompertz	0.07	0.08	0.07	27.93	27.93	0.35	0.66	0.35	93.96	93.96	0.35	
acci1	Fisher-Pry	0.00	0.04	0.03	-1.05	10.69	-0.12	0.98	0.46	-3382.14	3466.14	-0.12	
accj1	Bass	0.02	0.05	0.05	39.40	46.41	0.01	0.03	0.01	60.00	60.21	0.01	

	Models	ME	RMSE	MAE	MPE	MAPE	ME.1	RMSE.1	MAE.1	MPE.1	MAPE.1	M
acce1	Parabolic	0.00	0.00	0.00	22161.44	55282.03	0.00	0.00	0.00	22161.44	55282.03	0
accg1	Logistic	0.01	0.03	0.01	61.56	61.56	0.17	0.33	0.17	81.98	81.98	0
acch1	Gompertz	0.00	0.00	0.00	25.72	25.80	0.35	0.66	0.35	93.96	93.96	0
acci1	Fisher-Pry	-0.01	0.05	0.02	-789.25	873.86	-0.12	0.98	0.46	-3382.14	3466.14	-0
accj1	Bass	0.00	0.00	0.00	-38430.40	38441.36	0.01	0.03	0.01	60.00	60.21	0