Time Series Analysis for Energy Data | Spring 2023

Kelsey Husted

```
#Load/install required package here
#install.packages("openxlsx")
library(readxl)
library(openxlsx)
library(lubridate)
library(ggplot2)
library(forecast)
library(tseries)
library(Kendall)
library(tidyverse)
```

Part 1: Import data

The data comes from the US Energy Information and Administration and corresponds to the December 2022 Monthly Energy Review. Will focus only on the column "Total Renewable Energy Production".

```
#Importing data set - using xlsx package
df <- read.xlsx("./Data/Table_10.1_Renewable_Energy_Production_and_Consumption_by_Source.xlsx", startRow
df$Month <- convertToDate(df$Month)

df <- df[-c(1), ] #remove the row with the units

#Selecting for Renewable Energy Production column
energy_data <- df %>%
  select(Month, Total.Renewable.Energy.Production)
#transform renewable energy data column from character to numeric
energy_data$Total.Renewable.Energy.Production = as.numeric(energy_data$Total.Renewable.Energy.Productio
```

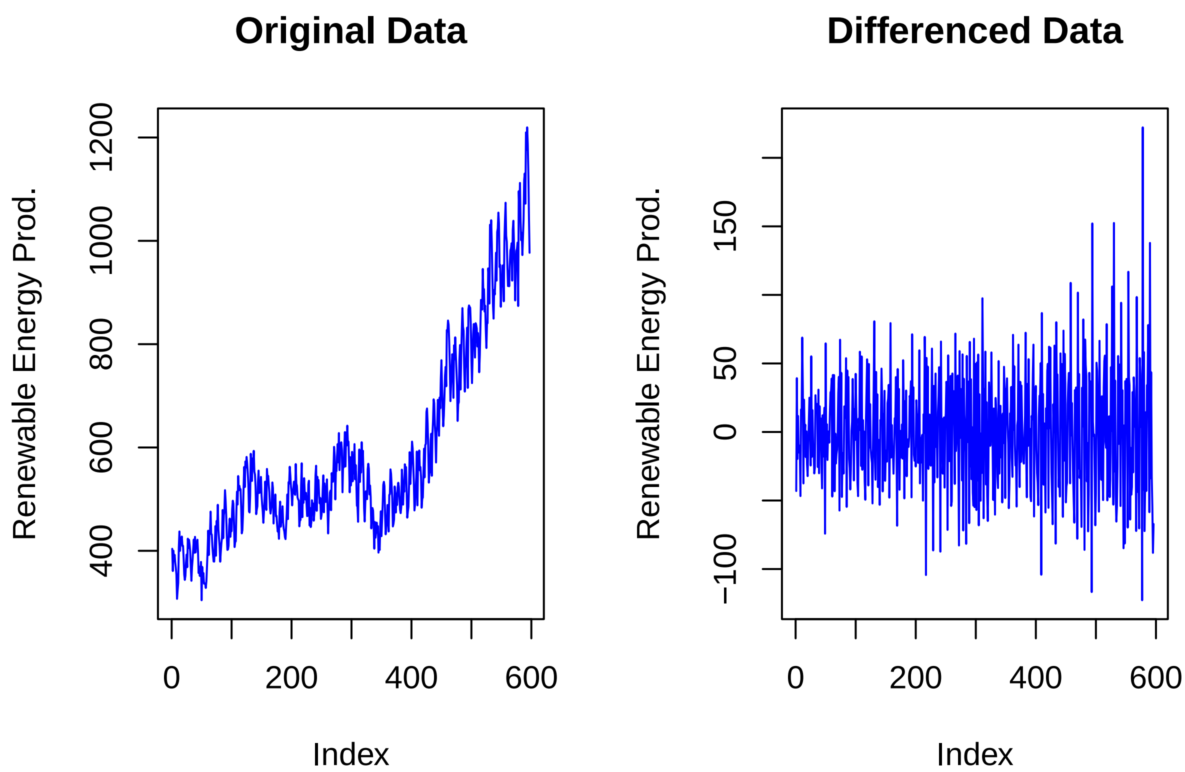
Part 2: Stochastic Trend and Stationary Tests

Differencing the Data

Note: The trend was removed after differencing the time series as displayed in the plots below.

```
#differencing
diff <- diff(energy_data[,2], lag = 1, differences = 1)

par(mfrow = c(1,2))
plot(energy_data[,2], type="l", col = "blue", ylab = "Renewable Energy Prod.", main = "Original Data")
plot(diff, type = "l", col="blue", ylab = "Renewable Energy Prod.", main = "Differenced Data")
```



Part 3: Compare Differenced and Detrended Series

Comparing the differenced series with the detrended series I calculated in the previous section.

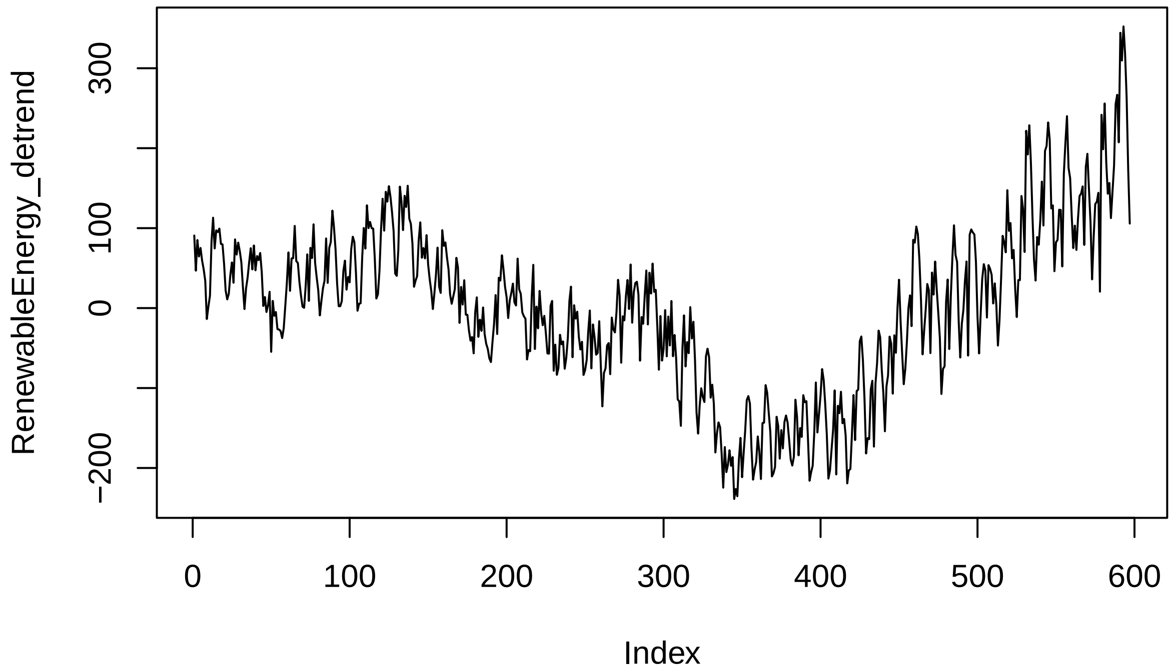
```r
num.obs <- nrow(energy_data)
observ <- 1:num.obs

#run linear model
linear_renewable<- lm(energy_data[,2] ~ observ)
summary(linear_renewable)
```

```
##
## Call:
## lm(formula = energy_data[, 2] ~ observ)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -238.75  -61.85    8.59   64.48  352.27
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 312.2475     8.4902   36.78   <2e-16 ***
## observ        0.9362     0.0246   38.05   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 103.6 on 595 degrees of freedom
## Multiple R-squared:  0.7088, Adjusted R-squared:  0.7083
## F-statistic:  1448 on 1 and 595 DF,  p-value: < 2.2e-16
```

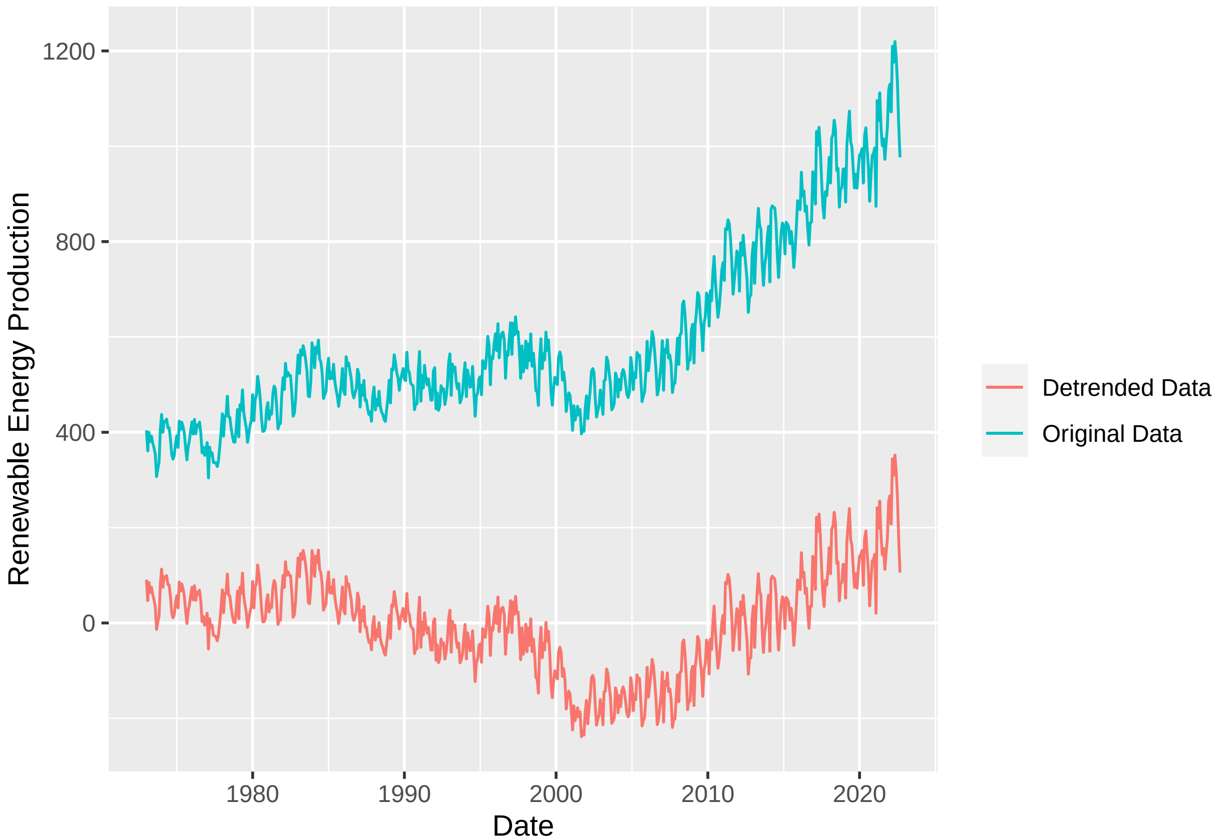
```r
#save regression coefficients
beta0_renewable=as.numeric(linear_renewable$coefficients[1])  #first coefficient is the intercept term
beta1_renewable=as.numeric(linear_renewable$coefficients[2])

#Detrend data by using the regression coefficients saved above
RenewableEnergy_detrend <- energy_data[,2]-(beta0_renewable+beta1_renewable*observ)
plot(RenewableEnergy_detrend, type = "l")
```




```r
#Plot original data versus detrended data
ggplot(energy_data, aes(x = Month, y = energy_data[,2], colour = "Original Data", col="blue")) +
  geom_line() +
  ylab(paste0("Detrended Renewable Energy")) +
  geom_line(aes(y=RenewableEnergy_detrend, colour = "Detrended Data"))+
  labs(x = "Date", y = "Renewable Energy Production", color = ' ')
```

```
## Warning: Duplicated aesthetics after name standardisation: colour
```



Part 4: Create New Dataframe

Creating a new data frame with 4 columns: month, original series, detrended by regression series and differenced series. Make sure you properly name all columns.

```
#Remove first row (i.e., January 1973) because differenced series will have less rows
energy_data<- energy_data[-c(1), ]
Detrend <- RenewableEnergy_detrend[2:597]

#Create data frame - remember to not include January 1973
date <- energy_data[,1]
RenewableEnergyProduction <- energy_data[,2]
energy_df <- data.frame(date ,RenewableEnergyProduction, Detrend, diff)
```

Part 5: Create ggplot

Using ggplot() creating a line plot that shows the three series together.

```
#Use ggplot
ggplot(energy_df, aes(x = date, y = RenewableEnergyProduction, colour = "Original Data", col="blue")) +
  geom_line() +
  geom_line(aes(y=Detrend, colour = "Detrended Data", col = "green")) +
  geom_line(aes(y=diff, colour = "Differenced Data", col = "red")) +
  labs(x = "Date", y = "Renewable Energy Production", color = ' ')
```

```
## Warning: Duplicated aesthetics after name standardisation: colour
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```

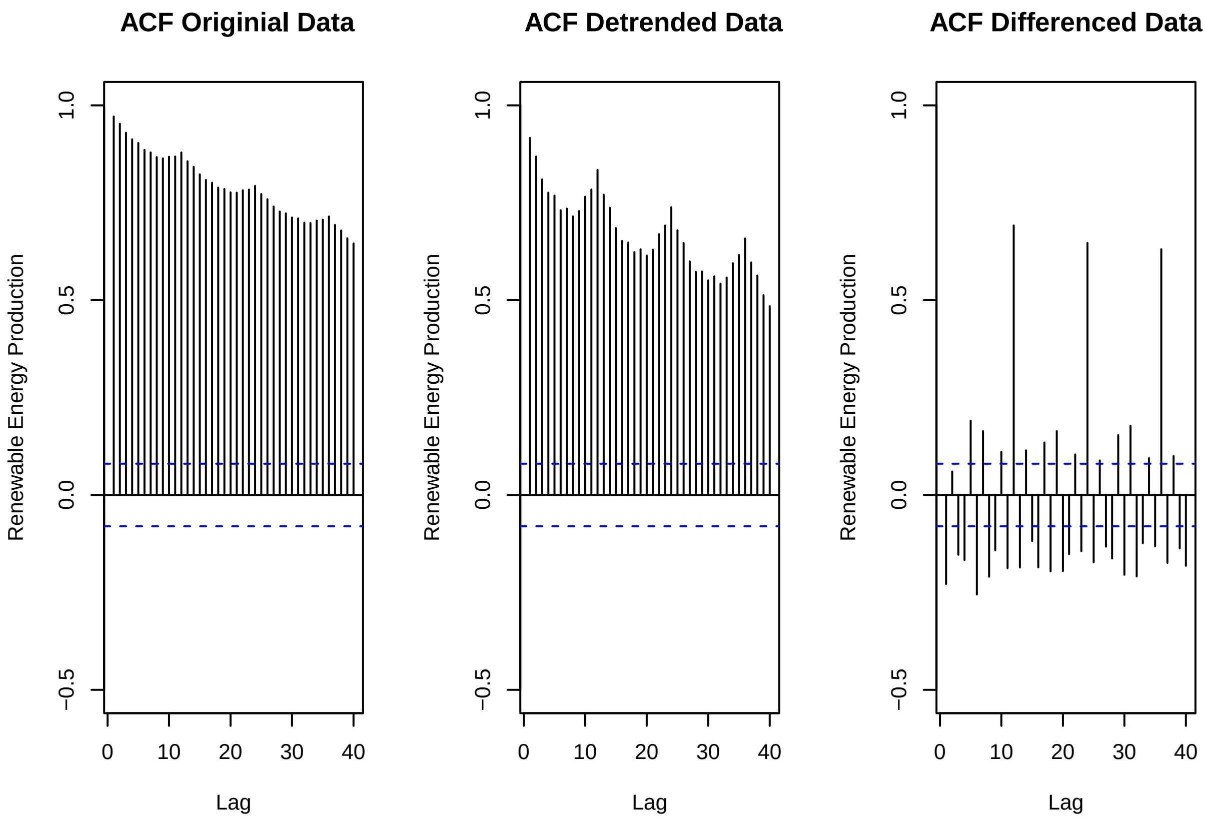
Part 6: Plot ACF (Autocorrelation function)

Plotting the ACF for the three series and comparing the plots.

> Plot interpretations: According to the ACF plots displayed below, differencing the original data seems to be a more efficient approach to removing the trend. Small lags that are small and positive and diminish over time are typically associated with a trend which is not seen in the differenced ACF plot compared to the other plots.

```
#Compare ACFs

par(mfrow=c(1,3))
Acf(energy_df[,2], lag.max = 40, ylim=c(-0.5,1), ylab="Renewable Energy Production", main=" ACF Originia
Acf(energy_df[,3], lag.max = 40, ylim=c(-0.5,1), ylab="Renewable Energy Production", main=" ACF Detrende
Acf(energy_df[,4], lag.max = 40, ylim=c(-0.5,1),ylab="Renewable Energy Production", main="ACF Differenc
```



Part 7: Seasonal Mann-Kendall & ADF Test

Computing the Seasonal Mann-Kendall and ADF Test for the original "Total Renewable Energy Production" series.

> Statistical Results Interpretation: A Seasonal Mann-Kendall Test is used to determine whether or not a trend exists in a time series data. Since the results of the Seasonal Mann-Kendall Test had a p-value less than 0.05, the null hypothesis is rejected which indicates a trend present in the data. The ADF test had a p-value almost equal to 1 which indicates a stoichastic trend and differencing (rather than using regression) removed the trend more efficiently as seen in the plots from Q4.

```
#Create a ts variable
ts_energy_data <- ts(df[,5], frequency = 12, start = c(1973,1))
#Mann-Kendall Test
SMKtest <- SeasonalMannKendall(ts_energy_data)
print(summary(SMKtest)) # p-value=<2.22e-16 so we reject the null hypothesis (i.e., no trend)
```

```
## Score =  10577 , Var(Score) = 169001
## denominator =  14553
## tau = 0.727, 2-sided pvalue =< 2.22e-16
## NULL
```

```
#ADF Test
print(adf.test(ts_energy_data,alternative = "stationary")) #p-value = 0.9056 so we accept the null hypo
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  ts_energy_data
## Dickey-Fuller = -1.2055, Lag order = 8, p-value = 0.9056
```

```
## alternative hypothesis: stationary
```

Part 8: Aggregate by Year

Aggregating the original "Total Renewable Energy Production" series by year.

```
#Create a year column
annual_energy_data <- energy_data %>%
  mutate(Year = lubridate::year(energy_data$Month))%>%
  select('Year', 'Total.Renewable.Energy.Production')

#Group by Yyar for annual data
annual_energy_data <- annual_energy_data %>%
  group_by(Year) %>%
  summarise(RenewableEnergy = mean(Total.Renewable.Energy.Production))
```

Part 9: Mann-Kendall, Spearman Correlation Rank Test, & ADF Test

Applying the Mann Kendal, Spearman correlation rank test and ADF.

```
#Create a ts variable
ts_annual_energy_data <- ts(annual_energy_data[,2], frequency = 1, start = c(1973))

#Mann-Kendall Test
MKtest <- MannKendall(ts_annual_energy_data)
print(summary(MKtest)) # p-value=<2.22e-16 so we reject the null hypothesis (i.e., no trend)
```

```
## Score =  913 , Var(Score) = 14291.67
## denominator =  1225
## tau = 0.745, 2-sided pvalue =< 2.22e-16
## NULL
```

```
#Spearman Correlation Test
cor.test(annual_energy_data$RenewableEnergy,annual_energy_data$Year, method = "spearman")
```

```
##
##  Spearman's rank correlation rho
##
## data:  annual_energy_data$RenewableEnergy and annual_energy_data$Year
## S = 2548, p-value < 2.2e-16
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##       rho
## 0.8776471
```

```
#ADF Test
print(adf.test(ts_annual_energy_data,alternative = "stationary"))  #p-value = 0.99 so we accept the nul
```

```
## Warning in adf.test(ts_annual_energy_data, alternative = "stationary"): p-value
## greater than printed p-value
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  ts_annual_energy_data
## Dickey-Fuller = 0.066004, Lag order = 3, p-value = 0.99
## alternative hypothesis: stationary
```