Predicting Average Monthly Electricity Price of Residential Sector in the United States

Capstone project-2 for Data Science Career Track bootcamp
Benhur Tedros

Summary

Today in our world, there are many electric power industries, which cover the generation, transmission, distribution and sale of electric power to the general public and industry. As world's population, commerce and transportations are expected to grow, the demand for electric power will increase and so does the revenues from the electricity sales. Electricity retailing is the end product of the processes of electric power industry. This industry makes a lot of revenues from electric sales to residential, commercial, and industrial, transportation sectors and others. The other sector refers to activities such as Public Street and highway lighting. The U.S. Energy Information Administration (EIA) collects sales of this electricity and associated revenue, each month, from a statistically chosen sample of electric utilities in the United States. As the change in the electricity price affects people's life, prediction of future electricity price is helpful in visualizing the overall rates for grid electricity and finding out alternative options.

The analysis of the electricity price can help the electric power industry and the government in designing new electricity coverage, improving the existing ones and helping their customers better. State based further prediction would also provide important asset for the pertinent sectors.

Objective of this project

The goal of this capstone project is to predict the rates of electricity price for U.S residential houses.

Data

The dataset for this project was published by U.S. Energy Information Administration and was downloaded from their website. The dataset is comprised of year, month, year_month, data status, Revenue in thousand dollars, Sales in megawatt hours, and price in cents/kwh for residential sector. The data includes the years from January 1990 to August 2017 and can be downloaded from:

https://www.eia.gov/electricity/data/eia861m/index.html

Methods/Approach

I will treat this project as a time series analysis related problem. The following libraries were used for data loading, wrangling, cleaning, data visualization, developing test harness, data analysis, model evaluation etc.

- Pandas
- Numpy
- Matplotlib
- Scikit-learn
- SciPy
- Statsmodels

A. Data Loading and Wrangling

The dataset is stored in MS Excel spreadsheet in CSV format, which was easily loaded into pandas dataframes. It contains 332 observations with 7 data fields with no missing/null values. The data fields include information on year, month, year_month, Data Status, Revenue_dollar, Sales_Mwatt and Price_Centkwh. The year_month were converted to date-time format. For this project's purpose, a subset of year_month and Price_Centkwh were created, and an exploratory data analysis was carried out.

B. Exploratory Data Analysis

Exploratory data analysis for this dataset is useful in determining the trend of the target variable across the given time. The electricity price was plotted against time [1990-2017] to display the overall trend and variance in seasonality (fig.1). It is also good to visualize the fluctuation of the electricity price of each month across the given years (fig.2). The distribution pattern of the dataset was explored using density and Q-Q plots to figure out if the dataset needs some transformation.

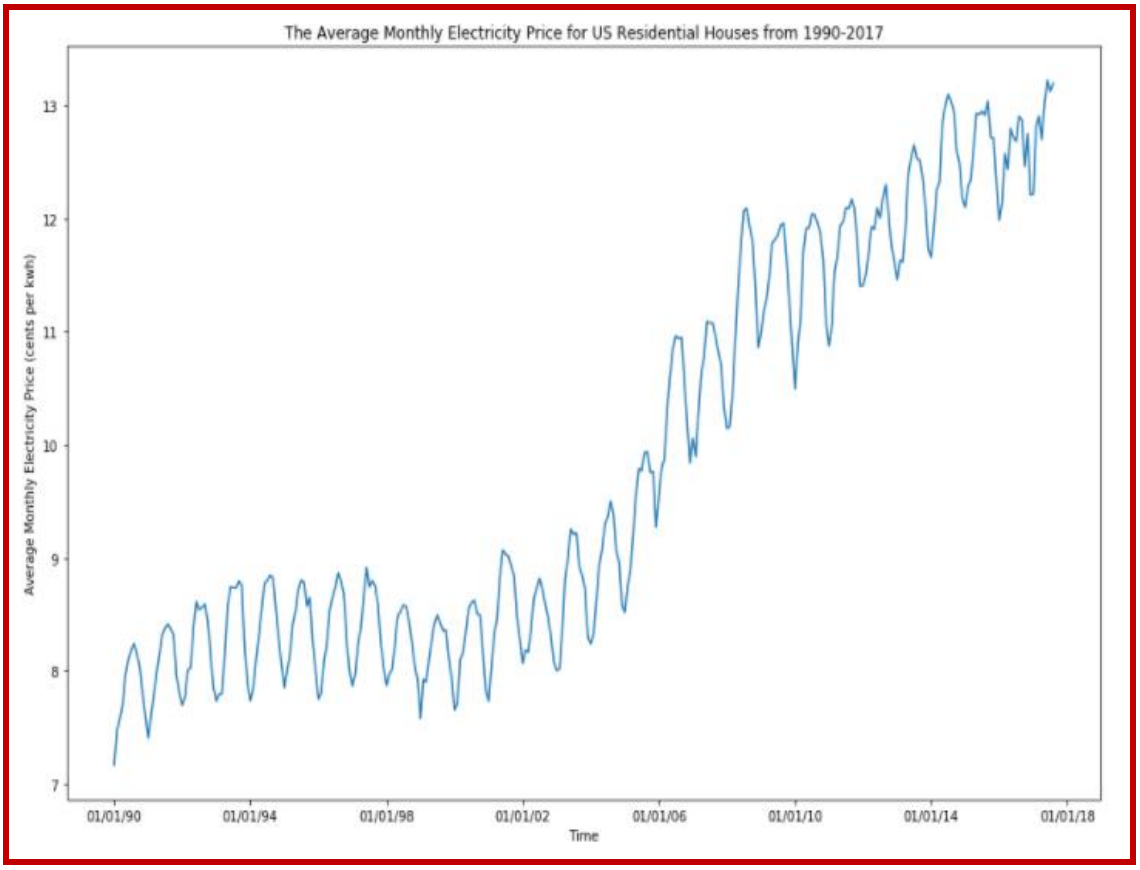


Fig.1 The average electricity price plotted against time

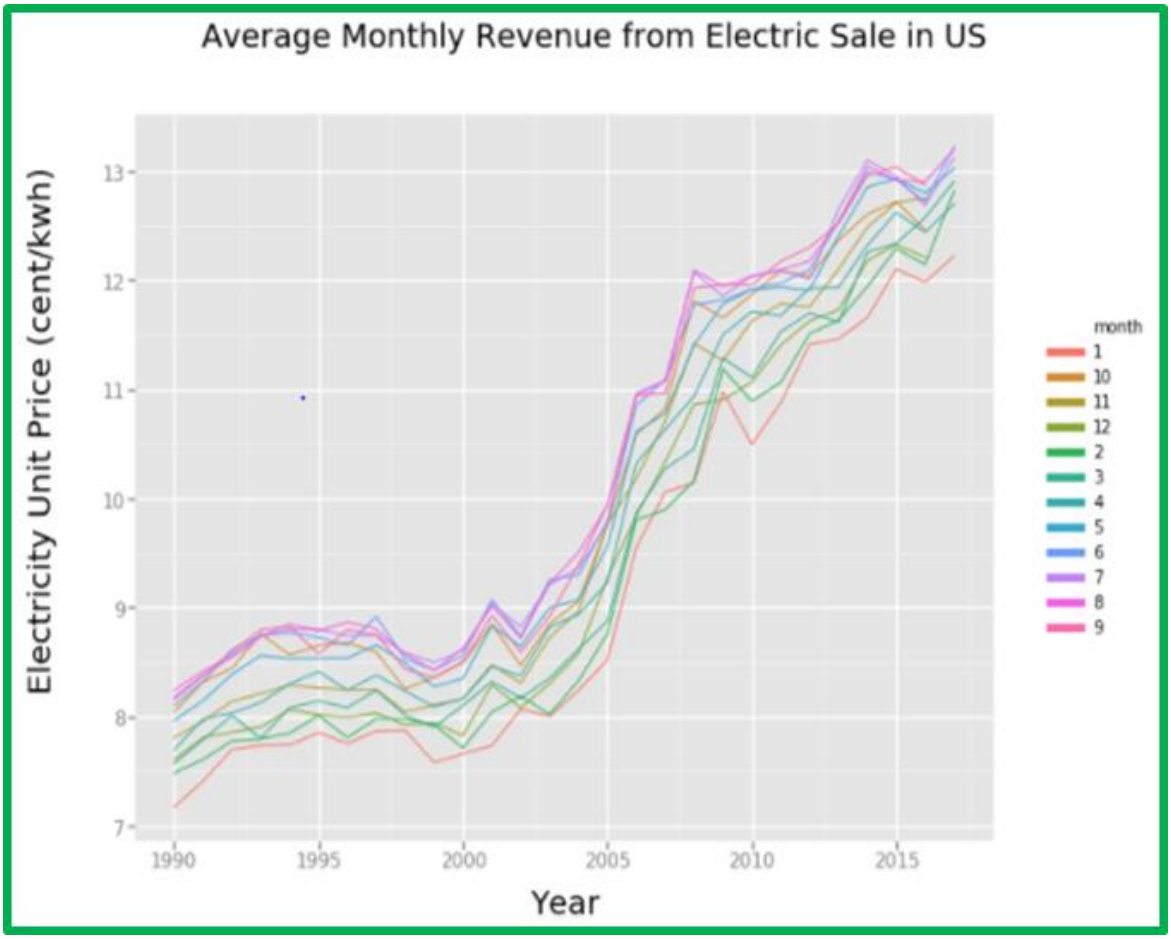


Fig.2 The average monthly electricity price between 1990-2017 across each month

C. Stationarity, Trend and Seasonality in the dataset

When we visualize our time series dataset, it is recommended to look out for few things. The main areas that should be observed are the seasonality, trend and noise in the dataset. Are we seeing any clear periodic pattern in the data; does the data show a consistent trend either upward or downward; is the data have any outlier points which are not consistent with the rest of the data. The rolling statistics and Dickey-Fuller test was carried out to check for the stationarity. As the time series dataset was found to be non-stationary, it was deseasonalized by differencing the electricity values. Once the differenced values were proved to be stationary, the model fitting and prediction was done.

Model Fitting

Time Series algorithms, ARIMA models, was utilized for this project. The predictors depend on the parameters (p, d, q) of the ARIMA model. It is necessary to figure out the values of p and q, for the AR and MA models [ARIMA models] respectively. This was done by plotting ACF and PACF functions. The d value refers to the number of nonseasonal difference. In this case, d was appeared to be zero as the test statistics shows that there is no need for further differencing. Before conducting model fitting, the dataset was split into training [01/1990-06/2003], testing [07/2003-12/2016] and validating [01/2017-08/2017] dataset. The ARIMA models were trained, and a one-step prediction was made. Then, the actual value from the test dataset was added to the training dataset before carrying out the next iteration to test the models. The model with smaller RMSE was chosen to be tested on validating dataset.

Results

ARIMA models were utilized to achieve the objective of this project. With the identified values of p, d and q parameters, the models were trained, tested and evaluated on the given dataset. The p, d and q values were appeared to be 1,0 and 1 respectively. The RMSE of each model was calculated to identify the best one. The AR, MR and ARIMA resulted to a RMSE of 0.3540, 0.3364 and 0.3519 respectively. The MR model was selected to be applied on the validating dataset. Moreover, it is good to review the residual error of the forecast, as its distribution should ideally be gaussian with a zero mean. The residual error from the MR model forecast (considered as bias) was calculated and added to the predicted values for model optimization/correction. The model fit with the calculated bias value was applied to the validating dataset. The result shows a better prediction with the predicted values falling very close to the observed ones. Based on this forecast on the validating dataset, the final RMSE is predicted to be 0.1653 cents per kwh in a month, which was better than that of training/testing dataset (fig.3).

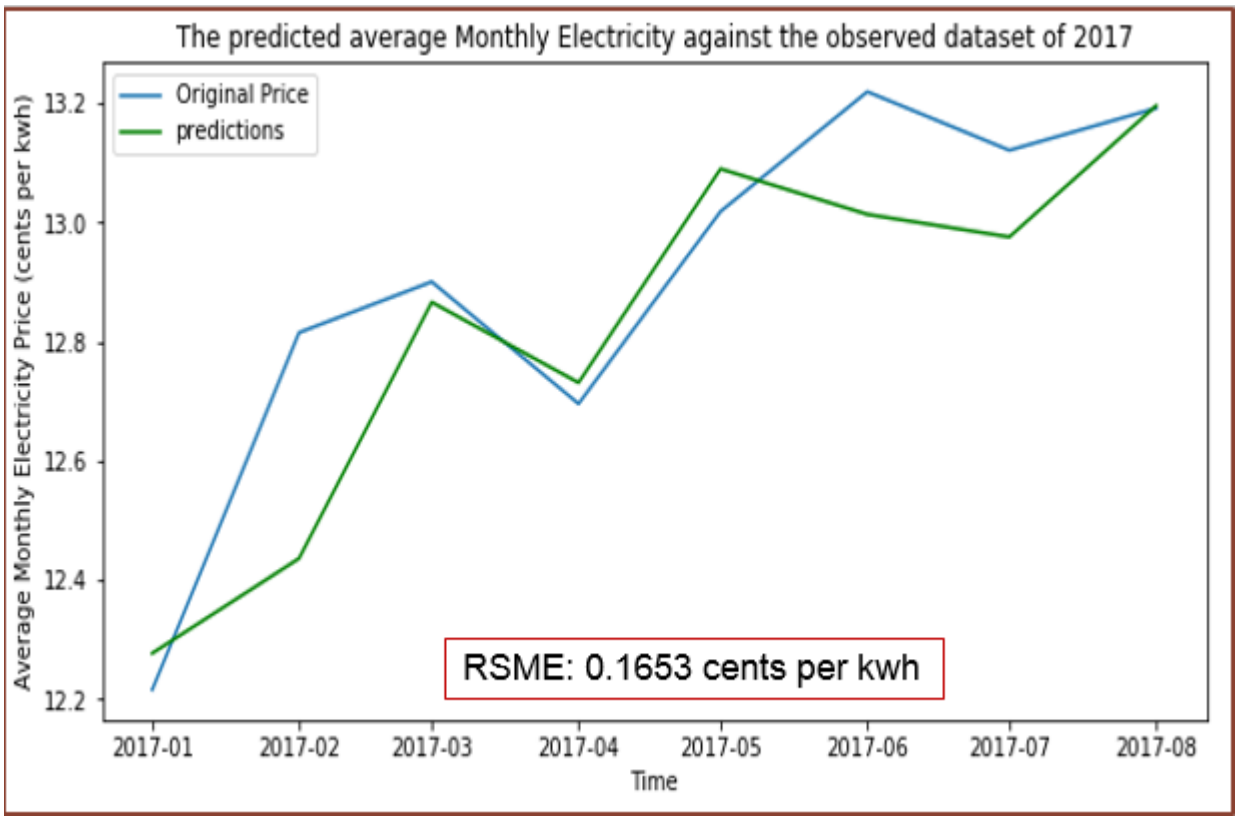


Fig.3 Correlation plot between the predicted and observed electricity price values of the validating dataset

Limitations

The electricity sources might have been different within one state through the given time [1990-2017]. The data does not show whether the given state was using the same type of electricity source throughout that period. Moreover, were there any natural causes/external factors which made the price lower or higher within states? Further, it is good to know how the data was collected and if the same method of data collection was utilized throughout the states.

Further Research

This capstone project tried to predict the average monthly of electricity prices for US residential houses. This research can be broadened by carrying out the prediction for each state independently. From the bi-modal distribution plot, it can be observed that there are two groups of states which bear similar distribution in the electricity prices. As the electric source [natural gas, hydropower, petroleum, coal, solar/wind...etc] differs from state to state, so does the electricity price. Similar research can also be done for commercial, transportation, industrial and other sectors.

Client Recommendations

As the model showed a strong correlation to the dataset, some recommendations can be taken from the carried-out analysis.

- Our client may use the model to forecast the average monthly residential electricity price within the state with an error of 0.1653 cents per kwh.
- It would be helpful if State based prediction has been carried out, as the above analysis is country-based.
- The above analysis assumed that each state had used the same tool and approach to collect their data. It also did not weigh the electric sources' difference from one State to another State. Therefore, the percentage of each electricity source utilized by a state should be weigh and added in the analysis.

Code

In [53]:
```
# Importing the required libraries

%matplotlib inline
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import scipy as sp
import os
from matplotlib import dates
from pandas import TimeGrouper
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error
from math import sqrt
from scipy import stats
import pylab
from ggplot import *
```

In [54]:
```
# Setting up the path directory
os.chdir('F:\\BENHUR FOLDER\\Data Science Career Track\\Capstone_Project_2\\Dataset')
os.getcwd()
```

In [55]:
```
sale_price = pd.read_csv('sales_revenue_monthly.csv')
sale_price.head()
```

Out[55]:

	year	month	year_month	Data Status	Revenue_dollar	Sales_Mwatt	Price_Centkwh
0	1990	1	1/1990	Final	6841300	95420231	7.169654
1	1990	2	2/1990	Final	5571807	74498370	7.479099
2	1990	3	3/1990	Final	5442934	71901767	7.569959
3	1990	4	4/1990	Final	5015134	65190618	7.693030
4	1990	5	5/1990	Final	5006417	62881008	7.961731

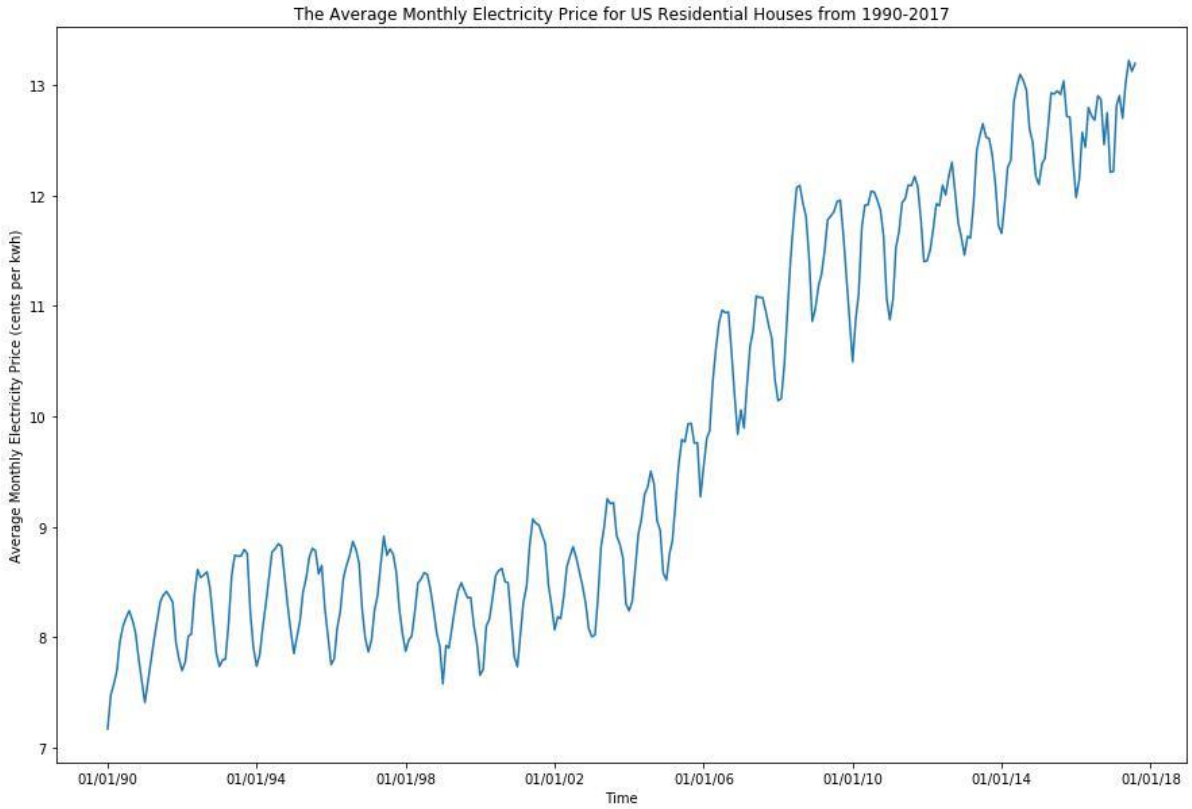
In [56]:
```
# converting to datetime format
sale_price['year_month'] = pd.to_datetime(sale_price['year_month'])
sale_price.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 332 entries, 0 to 331
Data columns (total 7 columns):
year            332 non-null int64
month           332 non-null int64
year_month      332 non-null datetime64[ns]
Data Status     332 non-null object
Revenue_dollar  332 non-null int64
Sales_Mwatt     332 non-null int64
Price_Centkwh   332 non-null float64
```

```
dtypes: datetime64[ns](1), float64(1), int64(4), object(1)
memory usage: 18.2+ KB
```

Exploratory Data Analysis

In [57]:
```
# Let us create dataframe with the time and the revenue dollar
data_price = pd.DataFrame(sale_price,columns = ['year_month','Price_Centkwh'])
data_price['year_month'] = pd.to_datetime(data_price['year_month'],format='%Y%m%d', errors='coerce')


# plotting the dataset

fig,ax = plt.subplots(figsize=(15,10))

# Changing the x-axis formatting by creating an object of formatter

date_format = '%d/%m/%y'
formatter_date = dates.DateFormatter(date_format)
ax.xaxis.set_major_formatter(formatter_date)

ax.plot(data_price['year_month'], data_price['Price_Centkwh'])
ax.set_xlabel('Time')
ax.set_ylabel('Average Monthly Electricity Price (cents per kwh)')
ax.set_title('The Average Monthly Electricity Price for US Residential Houses from 1990-2017')
```



The trend pattern may suggest that there was a seasonality to the electricity price for each year. The use of log transform would be important to deal with the increasing trend in the seasonality.

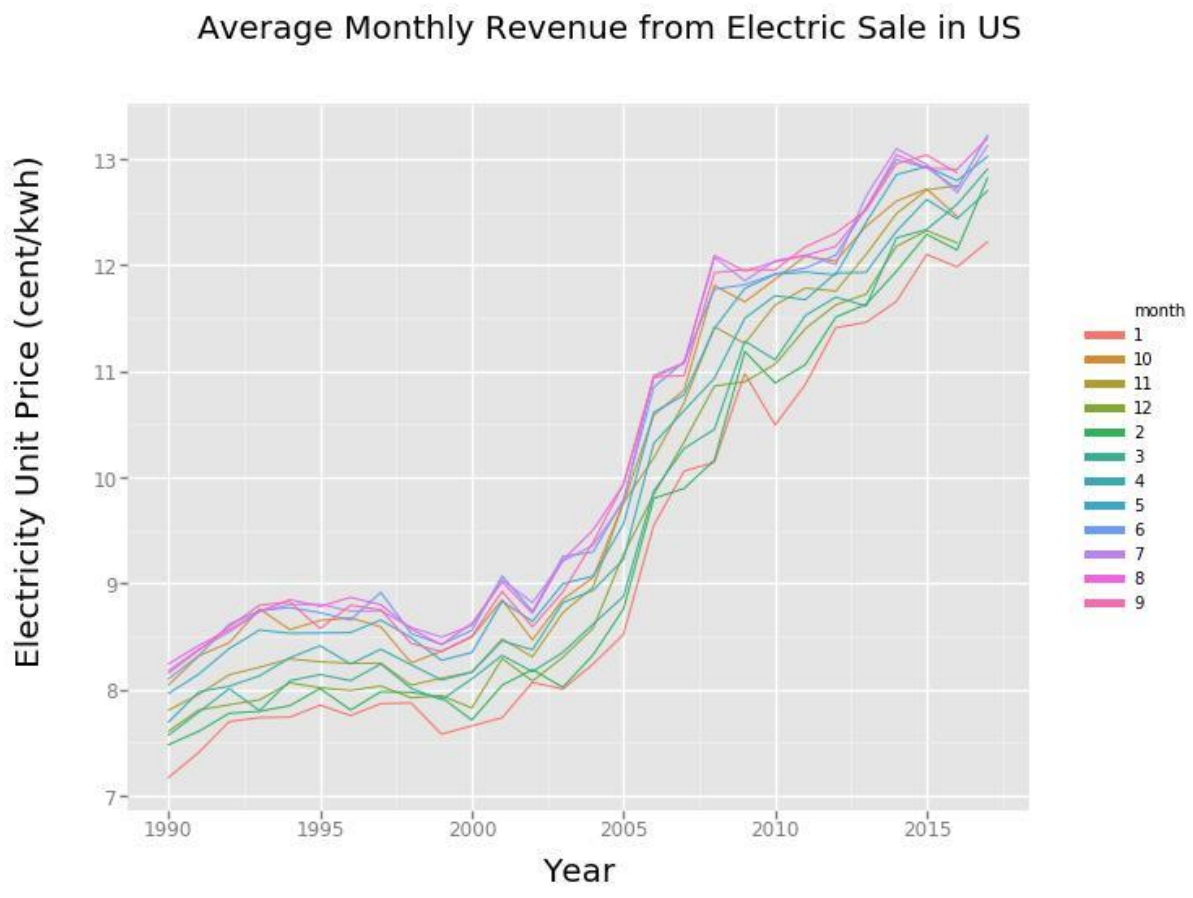
Let us review the summary statistics of the price of electricity per kwh. This will help us to have a quick overview of the data we are working on.

In [58]:
```
# Summary statistics of the electricity price
price_stat = data_price.groupby('year_month')['Price_Centkwh'].agg('mean')
price_stat.describe()
```

Out[58]:
```
count    332.000000
mean       9.833654
std        1.792077
min        7.169654
25%        8.300719
50%        8.916086
75%       11.712423
max       13.219444
Name: Price_Centkwh, dtype: float64
```

The dataset has 332 number of observations with the mean value of 9.834 cents/kwh with standard deviation of 1.79. The average min and max values were 7.17 and 13.22 cents/kwh respectively.

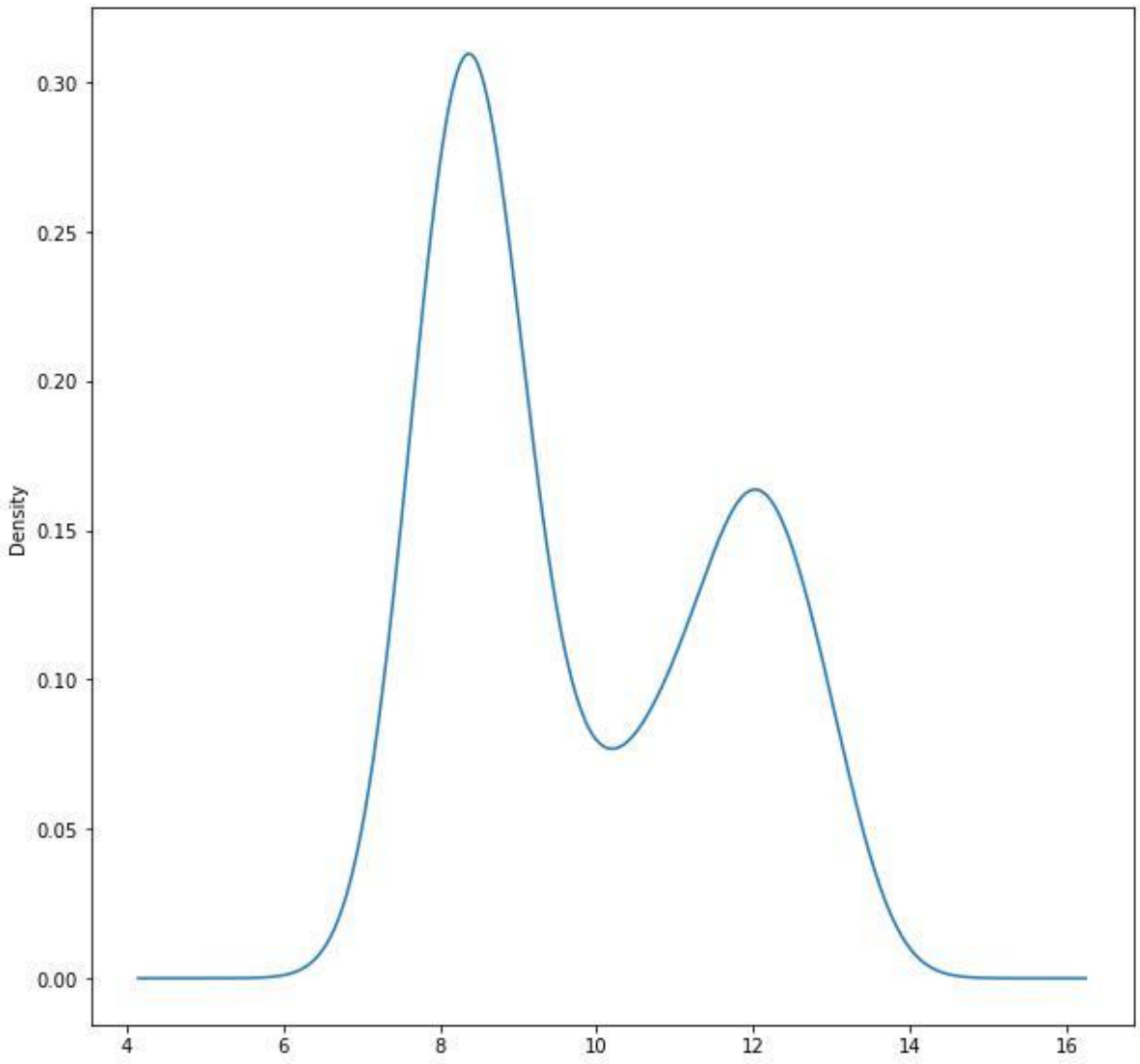
In [59]:
```
# converting month into series nature for the plotting purposes
sale_price['month'] = sale_price['month'].astype('str')
sale_price_sort = sale_price.sort_values(by='month')

# plotting the monthly revenue across the years
b =ggplot(sale_price_sort,aes('year','Price_Centkwh',color='month')) + ggtitle(element_text(text='Average
M onthly Revenue from Electric Sale in US', size=20)) + \
   xlab(element_text(size=20, text='Year',hjust = -0.025)) + ylab(element_text(size=20, text='Electricity
 Unit Price (cent/kwh)',vjust = 0.30)) + \
   geom_line(colour = 'month')

b
```



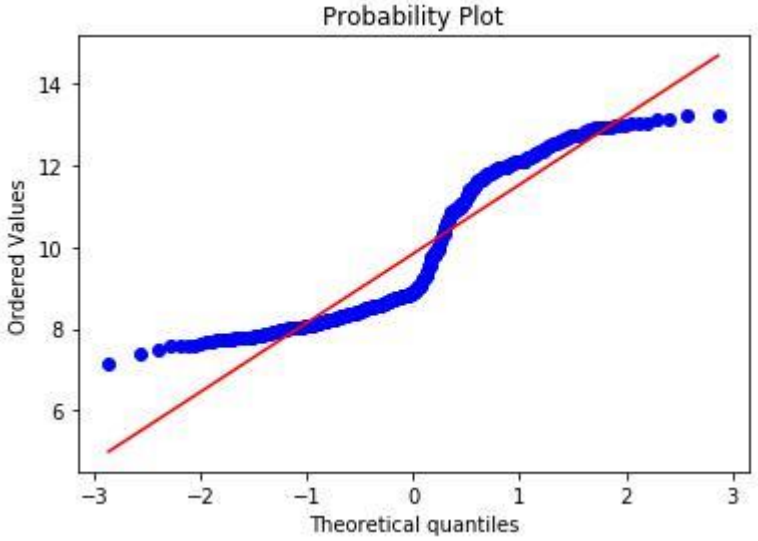
The above figure shows the trend of the average revenue electricity price of each month across the years 1990-2017. The monthly revenue from electric sale increased with time. The trend from 1990 to 2005 was appeared to be gradual, but it showed a sharp increase towards 2009. The trend continued to increase gradually until mid of 2012 where it displayed a sharp increase. However, it decreased again around 2015. Beyond mid-2015, it looked the trend to increase again. Though, there was some monthly price fluctuations (small increase or decrease) throughout the years, the average electricity price was appeared to display a general increasing trend. Further, the price was higher in the months of July and August followed by January, June and September. April was the one with low electricity prices. The weather conditions could be one of the factors that happen to manipulate the difference in the monthly prices, however further research should be done to have a conclusion.

It is also helpful to explore the distribution pattern of the dataset using density plot. This may help us when setting up statistical hypothesis tests for checking the normality of the dataset observations.

In [60]:
```
# Density plot for the monthly sale revenue
price_density = pd.Series(data_price['Price_Centkwh'])
fig, ax = plt.subplots(figsize=(10,10))
price_density.plot(kind='kde')
```



In [77]:
```
# QQ-plot to test the normal distribution
stats.probplot(data_price['Price_Centkwh'], dist="norm", fit=True, plot=pylab)
pylab.show()
```

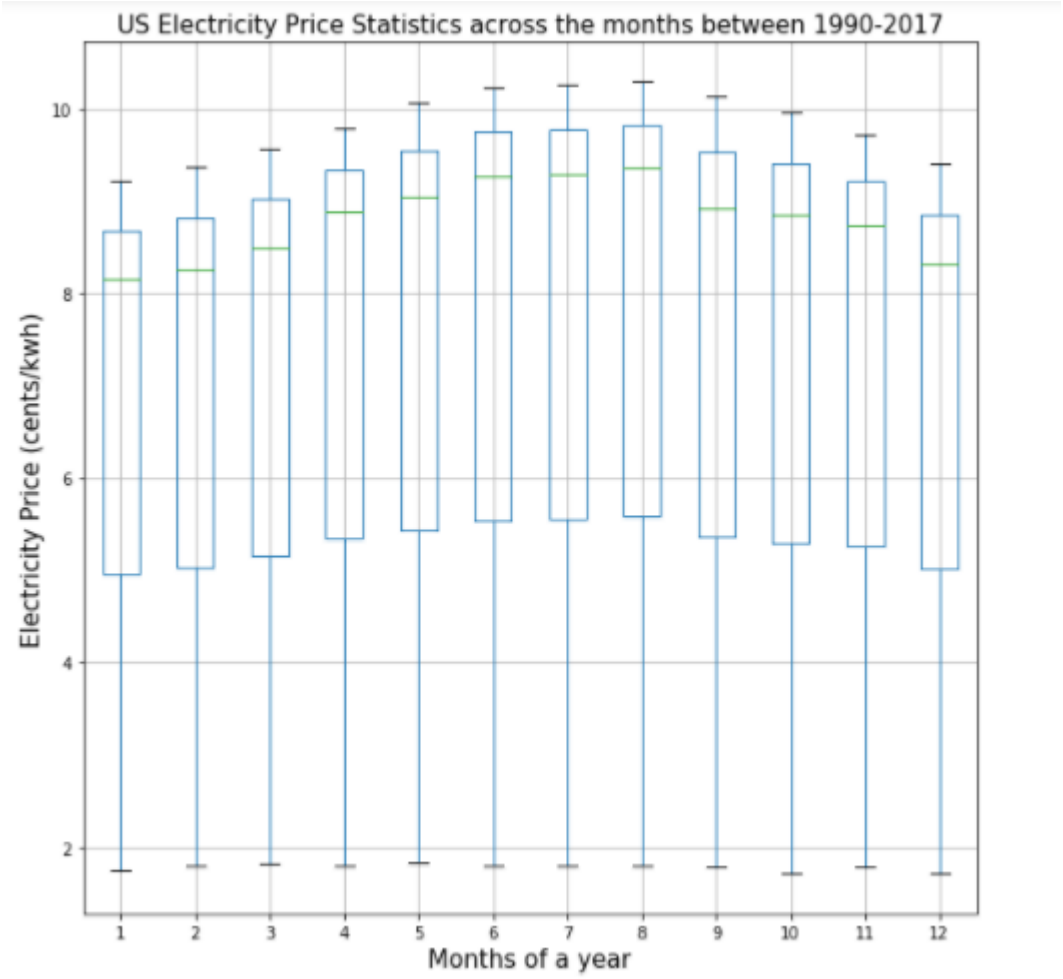


The plot appeared to show a bimodal distribution. This may suggest to explore and use some power transforms before proceeding to model fitting. However,the transformation by log, square root or reciprocal for bimodal distributed dataset might not be effective.

In [62]:
```
# distribution of the average electricity prices across months with a year
price_bx = pd.DataFrame(sale_price.groupby('month')['Price_Centkwh'].agg(['mean','median','std']))
price_bx.index = price_bx.index.astype('int')
price_bx.sort_index(inplace=True)


# Transpose the index to
columns price_bp = price_bx.T

# ploting the the data
fig, ax = plt.subplots(figsize=(10,10))
price_bp.boxplot()

ax.set_xlabel('Months of a year',fontsize =15)
ax.set_ylabel('Electricity Price (cents/kwh)',fontsize =15)
ax.set_title('US Electricity Price Statistics across the months between 1990-2017',fontsize =15)

price_bx.head()
```

Out[62]:

	mean	median	std
month			
1	9.206425	8.152348	1.755209
2	9.375988	8.255709	1.798704
3	9.567864	8.482098	1.814061
4	9.789529	8.875615	1.796706
5	10.064005	9.030773	1.827817



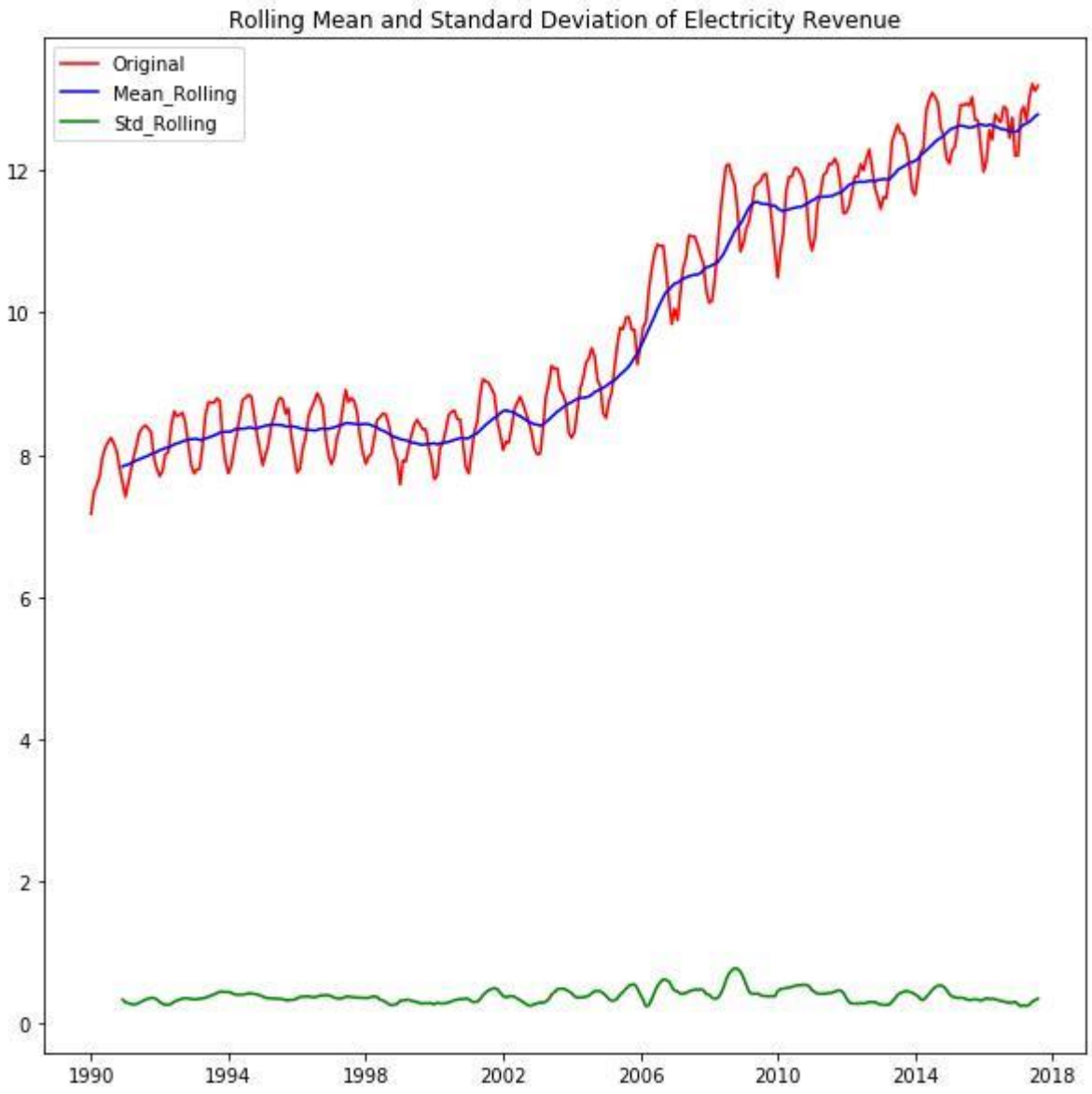
Checking the Stationarity, Trend and Seasonality in the dataset

Based on the above plots, it is clear evident that there is an overall increasing trend with some monthly/seasonal variations. Let us do formal analysis on the stationarity of the dataset

In [63]:
```
# Setting the dataframe index
data_price_final = data_price.set_index('year_month')

# Let us check the stationarity using rolling statistics

rollmean_price = pd.rolling_mean(data_price_final, window = 12)
rollstd_price = pd.rolling_std(data_price_final, window = 12)

# Plotting the statistics results
fig,ax = plt.subplots(figsize=(10,10))

ax.plot(data_price_final, color='red',label='Original')
ax.plot(rollmean_price, color='blue',label='Mean_Rolling')
ax.plot(rollstd_price, color='green',label='Std_Rolling')

plt.legend(loc='best')
plt.title('Rolling Mean and Standard Deviation of Electricity Revenue')
```


```
C:\Users\benbahtin\Anaconda3\lib\site-packages\ipykernel_launcher.py:6: FutureWarning:
pd.rolling_mea n is deprecated for DataFrame and will be removed in a future version, replace with
    DataFrame.rolling(window=12,center=False).mean()
```

```
C:\Users\benbahtin\Anaconda3\lib\site-packages\ipykernel_launcher.py:7: FutureWarning: pd.rolling_std
i s deprecated for DataFrame and will be removed in a future version, replace with
        DataFrame.rolling(window=12,center=False).std()
  import sys
```



The plot shows that the mean of this time series data does not look constant and stationary, though the standard deviation variation looks small.

In [64]:
```
# Applying to Dickey-Fuller test results to check stationarity
stat_test = adfuller(data_price_final['Price_Centkwh'], autolag = 'BIC')
Output = pd.Series(stat_test[0:4], index = ['Test Statistic','p-value','number of Lags use','Number of observati
ons used'])
print(Output)
print('Critical value at:')

for key,value in stat_test[4].items():
    print (key,value)
```

```
Test Statistic                  0.482779
p-value                         0.984340
number of Lags use             12.000000
Number of observations used    319.000000
dtype: float64
Critical value at:
1% -3.45101677515
5% -2.87064334231
10% -2.57162017443
```

As it can be observed in the statistics summary, the test statistics is greater than the critical value at 1% or 5% and the p-value is appeared to be greater than 0.05 threshold. These results imply that it is much less likely to reject the null hypothesis and the time series is non-stationary.

Model Fitting

Separating validation dataset

The electricity price values from the last 8 months were kept for validating purposes.

In [65]:
```
# Splitting validation dataset
# data_price= data_price.set_index('year_month')
split = len(data_price)-8
data, validate_set = data_price[0:split],data_price[split:]
print('data = %d, validate_set = %d' % (len(data),len(validate_set)))

# Copying the validating dataset for later use
validate_index = validate_set.copy()
validate_index = validate_index.set_index('year_month')
```

```
data = 324, validate_set = 8
```

Deseasonlized the time series

To get rid off the effect of seasonality variation in the dataset, we have to take the difference of the electricity price values for equivalent months throughout the given years.

In [66]:
```
# Differencing the electricity price values
def ts_difference(df,inter=1):
    diff = list()
    for d in range(inter,len(df)):
        x = float(df.values[d] - df.values[d-inter])
        diff.append(x)
    return pd.Series(diff)

data111 = data_price.set_index('year_month')

numMonth = 12
stat_data = ts_difference(data111,numMonth)
stat_data.index = data111.index[numMonth:]


# The above process can also be done easily by utilizing the shift() function:
ans = (data111-data111.shift(12)).dropna(axis=0, how='any')
```

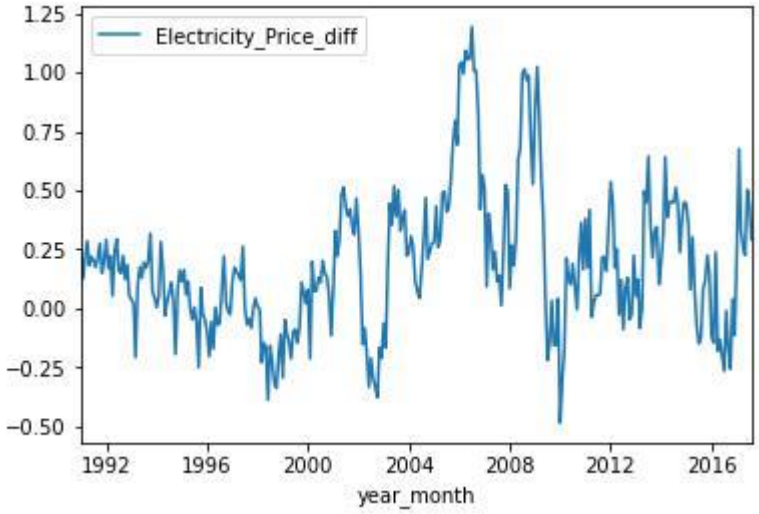
We have now a seasonality differenced dataset, and the next step is to make sure this new evaluated dataset is stationary.

In [67]:
```
# Inverting the seasonality differenced values
def diff_invert(histData,y_pred,inter=1):
    return y_pred + histData[-inter]
```

In [68]:
```
# Check stationarity
stat_test = adfuller(stat_data, autolag = 'AIC')
Output = pd.Series(stat_test[0:4], index = ['Test Statistic','p-value','number of Lags use','Number of observati
ons used'])
print(Output)
print('Critical value at:')

for key,value in stat_test[4].items():
    print (key,value)

# Converting into date format
x = (pd.DataFrame(stat_data,columns=['Electricity_Price_diff'])).reset_index()
x['year_month'] = (pd.to_datetime(x['year_month'])).apply(lambda x: x.date())
elec = x.set_index('year_month')

# Plotting the seasonal differenced electricity price
elec['Electricity_Price_diff'] = elec['Electricity_Price_diff'].astype('float')
elec.plot()
```

```
Test Statistic                -2.902593
p-value                       0.045047
number of Lags use           15.000000
Number of observations used  304.000000
dtype: float64
Critical value at:
1% -3.45204531783
5% -2.87109480556
```

10% -2.57186092149

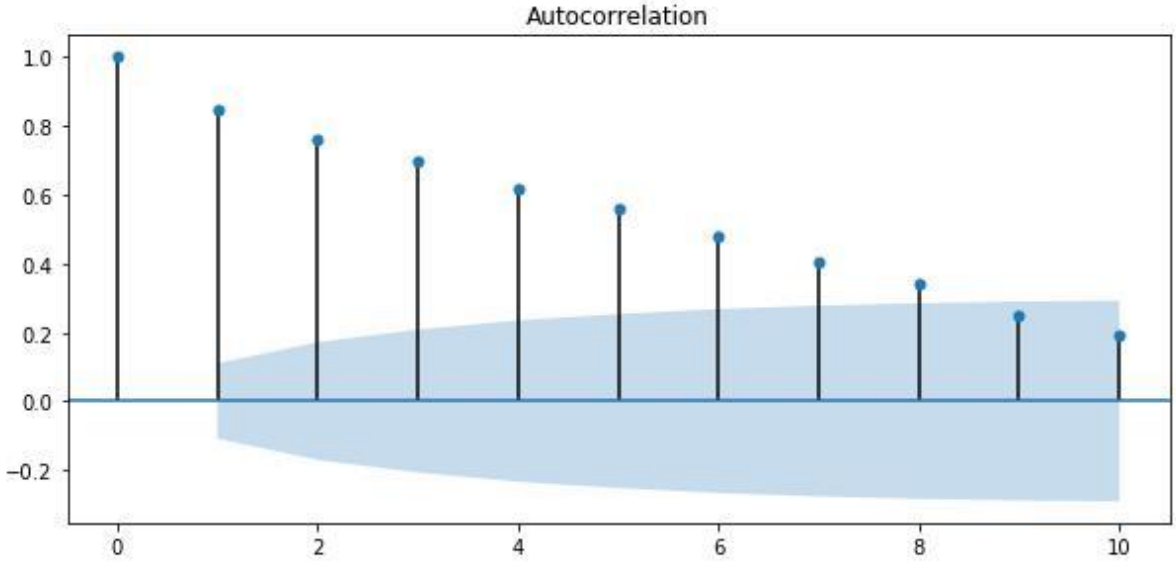


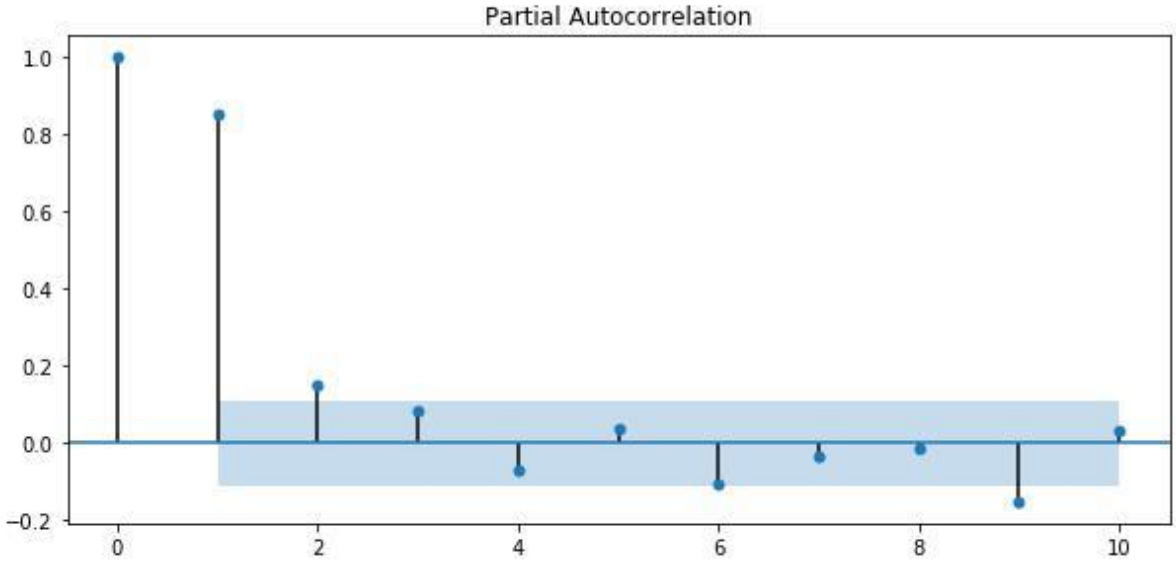
The above result shows that the test statistic value of -2.903 is lower than the crtical value at 5% of -2.8712. Also, the p-value of 0.045 shows a lower value than the threshold of 0.05. This explains that we can reject the null hypothesis with a significance level at 5%. The time series is now stationary and does not have time-dependent structure. The plot also displays no seasonality or trend variations.

ARIMA Models

These models have three parameters (p,d,q), which are needed to be configured. It is necessary to figure out the parameters, p and q, for the AR and MA models respectively. This can be done by plotting ACF and PACF functions. The d value refers to the number of nonseasonal difference. In this case, d is appeared to be zerovas the test statistics shows that there is no need for further differencing.

In [69]:
```
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf

plt.figure(figsize=(10,10))
plt.subplot(211)
plot_acf(stat_data, ax=plt.gca(),lags=10)
plt.subplot(212)
plot_pacf(stat_data, ax=plt.gca(),lags=10)
plt.show()
```


Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0
2
4
6
8
10


Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0
2
4
6
8
10

The plot crosses the upper confidence interval for the first time at lag value of 1 for the ACF plot, and this value refers to q value. For the second PACF plot, the cross was appeared at a value of 1, which is p-value. Therefore, (1,0,0), (0,0,1) and (1,0,1) orders should be used for AR, MR and ARIMA models respectively.

Training and Testing dataset

Before building the models, it is necessary to split the dataset (data) into training and testing dataset for model fitting and evaluation purposes.

In [70]:
```
# Training and testing dataset
data.year_month = data.year_month.values.astype('float32')
dataYear = data.set_index('year_month')
price_data = pd.Series(dataYear['Price_Centkwh'].values)
train_bound = int(len(price_data)* 0.50)
train,test = price_data[0:train_bound],price_data[train_bound:]
print('training dataset = %d, testing dataset = %d' % (len(train),len(test)))
```

```
training dataset = 162, testing dataset = 162

C:\Users\benbahtin\Anaconda3\lib\site-packages\pandas\core\generic.py:2999: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing -view-versus-copy
  self[name] = value
```

1) AR Model

In [71]:
```
# Creating the differencing function
def diff_data(df,inter=1):
    diffaa = list()
    for d in range(inter,len(df)):
        y = float(df[d] - df[d-inter])
        diffaa.append(y)
    return diffaa

# Inverting the differenced values
def diff_invert(histData,y_pred,inter=1):
    return y_pred + histData[-inter]

# Evaluating the candidate models Using walk-forward testing
hist_data = [h for h in train]
ss = pd.Series(hist_data)
pred= list()
for j in range(len(test)):
    numMonth = 12
    dd = diff_data(ss,numMonth)
    # Prediction
    model = ARIMA(dd,order = (1,0,0))
    fit_model = model.fit(trend='nc',disp=0) # no need to include the constant and print the convergence
infor mation
    y_pred = fit_model.forecast()[0]
    # inverting the forecasted data
    y_pred_invert = diff_invert(hist_data, y_pred,numMonth)
    pred.append(y_pred_invert)
```

```
    # original observed data
    observed = test.values[j]
    hist_data.append(observed)
#     print('Predicted =%0.4f, Observed=%0.4f' % (y_pred_invert,observed))
# Estimating the RMSE
rmse = np.sqrt(mean_squared_error(test,pred))
print('RMSE=%0.4f' % rmse)
```

RMSE=0.3540

2) MA Model

In [72]:
```
# Evaluating the candidate models Using walk-forward testing
hist_data2 = [h for h in train]
ss2 = pd.Series(hist_data2)
pred2= list()
for j in range(len(test)):
    dd2 = diff_data(ss2,numMonth)
    # Prediction
    model2 = ARIMA(dd2,order = (0,0,1))
    fit_model2 = model2.fit(trend='nc',disp=0) # no need to include the constant and print the convergence
inf ormation
    y_pred2 = fit_model2.forecast()[0]
    # inverting the forecasted data
    y_pred_invert2 = diff_invert(hist_data2, y_pred2,numMonth)
    pred2.append(y_pred_invert2)
    # original observed data
    observed2 = test.values[j]
    hist_data2.append(observed2)
#     print('Predicted =%0.4f, Observed=%0.4f' % (y_pred_invert2,observed2))

# Estimating the RMSE
rmse2 = np.sqrt(mean_squared_error(test,pred2))
print('RMSE=%0.4f' % rmse2)
```

RMSE=0.3364

3) ARIMA Model

In [73]:
```
# Evaluating the candidate models Using walk-forward testing
hist_data3 = [h for h in train]
ss3 = pd.Series(hist_data3)
pred3= list()
for j in range(len(test)):
    dd3 = diff_data(ss3,numMonth)
    # Prediction
    model3 = ARIMA(dd3,order = (1,0,1))
    fit_model3 = model3.fit(trend='nc',disp=0) # no need to include the constant and print the convergence
inf ormation
    y_pred3 = fit_model3.forecast()[0]
    # inverting the forecasted data
    y_pred_invert3 = diff_invert(hist_data3, y_pred3,numMonth)
    pred3.append(y_pred_invert3)
    # original observed data
    observed3 = test.values[j]
    hist_data3.append(observed3)
#     print('Predicted =%0.4f, Observed=%0.4f' % (y_pred_invert3,observed3))
```

```
# Estimating the RMSE
rmse3 = np.sqrt(mean_squared_error(test,pred3))
print('RMSE=%0.4f' % rmse3)
```

```
RMSE=0.3519
```

Residual Error Review

It is good to review the residual error of the forecast, as its distribution should ideally be gaussian with a zero mean.

In [74]:
```
res = [test.values[k]-pred2[k] for k in range(len(test))]
pd.DataFrame(res).describe()
```

Out[74]:

	0
count	162.000000
mean	0.042433
std	0.334714
min	-0.740121
25%	-0.177052
50%	-0.012971
75%	0.195673
max	0.939276

We can add the mean residual error in the model to correct the prediction. Let us add the value to the selected model (MR).

In [75]:
```
# Evaluating the candidate models Using walk-forward testing
hist_data4 = [h for h in train]
ss4 = pd.Series(hist_data4)
pred4= list()
for j in range(len(test)):
    dd4 = diff_data(ss4,numMonth)
    # Prediction
    model4 = ARIMA(dd4,order = (0,0,1))
    fit_model4 = model4.fit(trend='nc',disp=0) # no need to include the constant and print the convergence
inf ormation
    y_pred4 = fit_model4.forecast()[0]
    # inverting the forecasted data
    mean_residError = 0.042433
    y_pred_invert4 = mean_residError + diff_invert(hist_data4,
    y_pred4,numMonth) pred4.append(y_pred_invert4)
    # original observed data
    observed4 = test.values[j]
    hist_data4.append(observed4)
#     print('Predicted =%0.4f, Observed=%0.4f' % (y_pred_invert4,observed4))

# Estimating the RMSE
```

```
rmse4 = np.sqrt(mean_squared_error(test,pred4))
print('RMSE=%0.4f' % rmse4)
```

```
RMSE=0.3337
```

The RMSE shows that the AR, MR and ARIMA models, on average, have an error value of 0.3540, 0.3364 and 0.3519 respectively, from the observed values. All the models seemed to perform well, but we tend to select the MR model as its RMSE resulted in slightly lower value.

Model Validation

In the above section, we split the original dataset into two datasets (data and validate_set) for model validating purposes. The final year data was previously kept in validate_set and will be used to validate the final model. From the above analysis, the MR model performed better and is selected as our final model to be utilized on the validating dataset.

In [76]:
```
# Preparing the validating dataset
validate_set.year_month = validate_set.year_month.values.astype('float32')
validateYear = validate_set.set_index('year_month')
valPrice = pd.Series(validateYear['Price_Centkwh'].values)

# Preparing the data dataset [historical data except the final
year] data.year_month = data.year_month.values.astype('float32')
dataYear = data.set_index('year_month')
dataPrice = pd.Series(dataYear['Price_Centkwh'].values)

# Prediction in the validating dataset
histFinal = [y for y in dataPrice]
predictions = list()

for p in range(0, len(valPrice)):
    prefinal = float(fit_model4.forecast()[0])
    # inverting the forecasted data
    invert_pred = mean_residError + diff_invert(histFinal, prefinal,numMonth)
    predictions.append(invert_pred)
    #Observed data/validating dataset
    histFinal.append(valPrice[p])
    print('>Predicted=%.3f, Expected=%0.3f' % (invert_pred, valPrice[p]))

# Estimating the RMSE
final_rmse = np.sqrt(mean_squared_error(valPrice,predictions))
print('RMSE=%0.4f' % final_rmse)

# Replacing the index
valPrice.index = validate_index.index
predictions = pd.Series(predictions)
predictions.index = validate_index.index

# Ploting the predicted vs the observed
fig,ax =plt.subplots(figsize=(10,5))

plt.plot(valPrice, label='Original Price')
plt.plot(predictions,color='green', label='predictions')
plt.legend()

ax.set_xlabel('Time')
ax.set_ylabel('Average Monthly Electricity Price (cents per kwh)')
ax.set_title('The predicted average Monthly Electricity against the observed dataset of 2017')
```

C:\Users\benbahtin\Anaconda3\lib\site-packages\pandas\core\generic.py:2999: SettingWithCopyWarning:
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Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing -view-versus-copy
  self[name] = value

>Predicted=12.277, Expected=12.216
>Predicted=12.436, Expected=12.815
>Predicted=12.866, Expected=12.900
>Predicted=12.731, Expected=12.696
>Predicted=13.090, Expected=13.019
>Predicted=13.014, Expected=13.219
>Predicted=12.976, Expected=13.121
>Predicted=13.196, Expected=13.192
RMSE=0.1653