M 7.0 - Haiti region

2010-01-12 21:53:10 (UTC)18.443°N 72.571°W13.0 km depth

https://earthquake.usgs.gov/earthquakes/eventpage/usp000h60h/executive

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
import statistics
import seaborn as sns # for plot visualization
import keras
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout
import pandas_datareader.data as web
import datetime
from matplotlib import style

# ignore warnings
import warnings
warnings.filterwarnings('ignore')
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarnir
  import pandas.util.testing as tm
```

```
dataset = pd.read_csv('sample_data/haiti.csv')
dataset_error_index = dataset
dataset.tail(2)
```

```
---------------------------------------------------------------------------
FileNotFoundError                         Traceback (most recent call last)
<ipython-input-2-464b602ad3b7> in <module>()
```

```
dataset['new_date'] = dataset['date'].str.cat(dataset['time'], sep =" ")
dataset['new_date'] = pd.to_datetime(dataset['new_date'],format="%d-%b-%Y %H:%M:%S") #conv
dataset= dataset[['new_date','tec']]
dataset.head(2)
```

	new_date	tec
0	2009-11-15 00:00:00	8.450762
1	2009-11-15 02:00:00	8.756442

```
train_df = dataset.loc[(dataset["new_date"] <= "2010-01-04 00:00:00")]
test_df = dataset.loc[(dataset["new_date"] > "2010-01-03 00:00:00") & (dataset["new_date"]
train_df.head(2)
```

	new_date	tec
0	2009-11-15 00:00:00	8.450762
1	2009-11-15 02:00:00	8.756442

```
test_df.tail(2)
```

	new_date	tec
743	2010-01-15 22:00:00	11.093591
744	2010-01-16 00:00:00	7.434167

```
train_data = train_df.loc[:,'tec'].to_numpy()
print(train_data.shape) # 1258


# Apply normalization before feeding to LSTM using sklearn:
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
train_data = train_data.reshape(-1,1)

scaler.fit(train_data)
train_data = scaler.transform(train_data)
```

```
(601,)
```

```
'''Function to create a dataset to feed into an LSTM'''
def create_dataset(dataset, look_back):
    dataX, dataY = [], []
    for i in range(len(dataset)-look_back):
        a = dataset[i:(i + look_back), 0]
```

```
        dataX.append(a)
        dataY.append(dataset[i + look_back, 0])
    return np.array(dataX), np.array(dataY)


# Create the data to train our model on:
time_steps = 12
X_train, y_train = create_dataset(train_data, time_steps)

# reshape it [samples, time steps, features]
X_train = np.reshape(X_train, (X_train.shape[0], time_steps, 1))

print(X_train.shape)


# Visualizing our data with prints:
print('X_train:')
print(str(scaler.inverse_transform(X_train[0])))
print("\n")
print('y_train: ' + str(scaler.inverse_transform(y_train[0].reshape(-1,1)))+'\n')
```

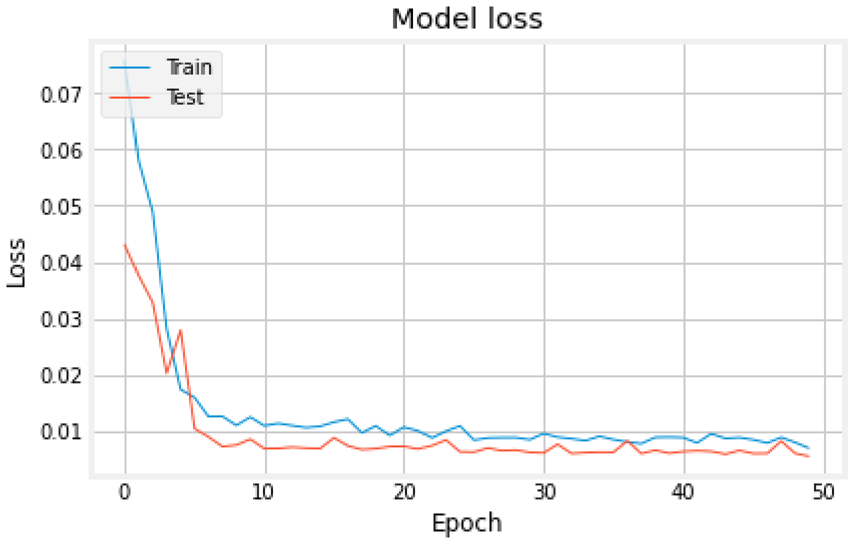
```
(589, 12, 1)
X_train:
[[ 8.4507625 ]
 [ 8.7564425 ]
 [ 7.8341825 ]
 [ 6.59306687]
 [ 6.27081562]
 [ 6.32279125]
 [10.23952875]
 [13.21316875]
 [14.07652   ]
 [16.09714438]
 [17.23024   ]
 [12.70906   ]]


y_train: [[7.90446687]]
```

```
# Build the model
model = keras.Sequential()

model.add(LSTM(units = 48, return_sequences = True, input_shape = (X_train.shape[1], 1)))
model.add(Dropout(0.2))

model.add(LSTM(units = 48))
model.add(Dropout(0.2))

# Output layer
model.add(Dense(units = 1))

# Compiling the model
model.compile(optimizer = 'adam', loss = 'mean_squared_error')

# Fitting the model to the Training set
```

```
history = model.fit(X_train, y_train, epochs = 50, batch_size = 12, validation_split=.30)
```

```
Epoch 1/50
35/35 [==============================] - 1s 33ms/step - loss: 0.0759 - val_loss: 0
Epoch 2/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0580 - val_loss: 0
Epoch 3/50
35/35 [==============================] - 0s 12ms/step - loss: 0.0489 - val_loss: 0
Epoch 4/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0281 - val_loss: 0
Epoch 5/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0174 - val_loss: 0
Epoch 6/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0159 - val_loss: 0
Epoch 7/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0125 - val_loss: 0
Epoch 8/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0126 - val_loss: 0
Epoch 9/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0110 - val_loss: 0
Epoch 10/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0124 - val_loss: 0
Epoch 11/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0109 - val_loss: 0
Epoch 12/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0113 - val_loss: 0
Epoch 13/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0109 - val_loss: 0
Epoch 14/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0106 - val_loss: 0
Epoch 15/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0108 - val_loss: 0
Epoch 16/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0115 - val_loss: 0
Epoch 17/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0121 - val_loss: 0
Epoch 18/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0096 - val_loss: 0
Epoch 19/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0109 - val_loss: 0
Epoch 20/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0092 - val_loss: 0
Epoch 21/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0106 - val_loss: 0
Epoch 22/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0100 - val_loss: 0
Epoch 23/50
35/35 [==============================] - 0s 12ms/step - loss: 0.0087 - val_loss: 0
Epoch 24/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0099 - val_loss: 0
Epoch 25/50
35/35 [==============================] - 0s 12ms/step - loss: 0.0109 - val_loss: 0
Epoch 26/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0083 - val_loss: 0
Epoch 27/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0087 - val_loss: 0
Epoch 28/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0088 - val_loss: 0
Epoch 29/50
35/35 [==============================] - 0s 11ms/step - loss: 0.0088 - val_loss: 0
```

```
# Plot training & validation loss values
ax = plt.gca()
ax.set_facecolor('white')
plt.plot(history.history['loss'], linewidth=1.0)
plt.plot(history.history['val_loss'], linewidth=1.0)
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```

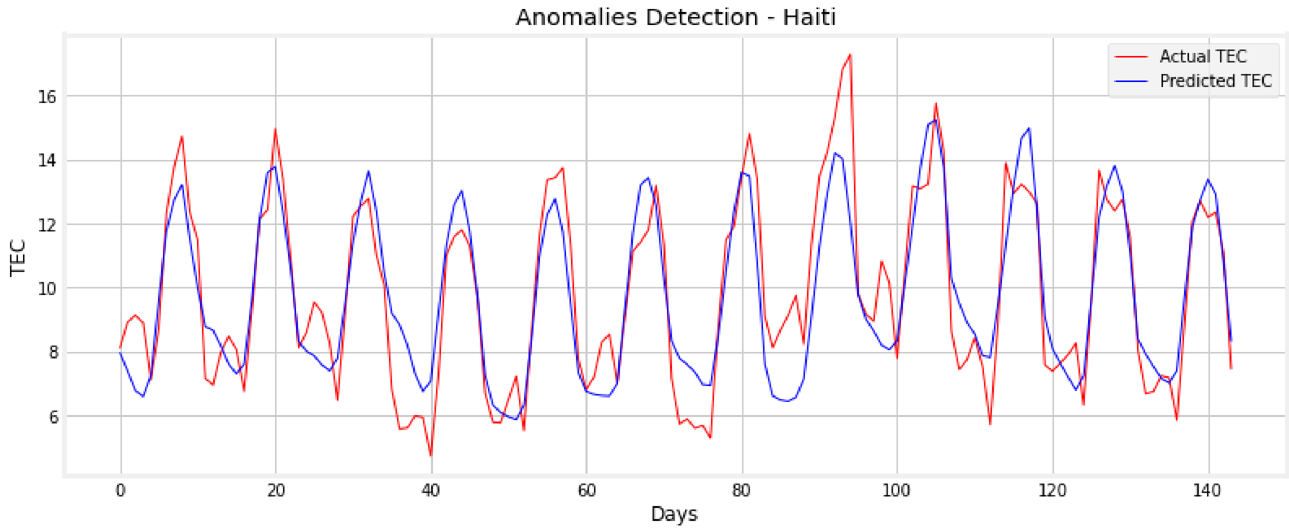



```
results = model.evaluate(X_train, y_train)
print("test loss", results)
```

```
19/19 [==============================] - 0s 4ms/step - loss: 0.0056
test loss 0.005569768138229847
```

```
test_data = test_df['tec'].values
test_data = test_data.reshape(-1,1)
test_data = scaler.transform(test_data)

# Create the data to test our model on:
time_steps = 12
X_test, y_test = create_dataset(test_data, time_steps)
# store the original vals for plotting the predictions
y_test = y_test.reshape(-1,1)
org_y = scaler.inverse_transform(y_test)

# reshape it [samples, time steps, features]
X_test = np.reshape(X_test, (X_test.shape[0], time_steps, 1))

# Predict the prices with the model
predicted_y = model.predict(X_test)
predicted_y = scaler.inverse_transform(predicted_y)


# plot the results
plt.figure(figsize=(12,5))
```

```
plt.figure(figsize=(12,5))
ax = plt.gca()
ax.set_facecolor('white')
plt.plot(org_y, color = 'red', label = 'Actual TEC', linewidth=1.0)
plt.plot(predicted_y, color = 'blue', label = 'Predicted TEC', linewidth=1.0)
#plt.axvline(x=10, color='black', linestyle='-', linewidth=1.0)
#plt.axvline(x="2010-04-10 00:00:00", color='black', linestyle='-', linewidth=1.0)
#plt.axvline(x="2010-01-12 22:00:00", color='black', linestyle='-', linewidth=1.0)
plt.title('Anomalies Detection - Haiti')
plt.xlabel('Days')
plt.ylabel('TEC')
plt.legend()
plt.show()
```




```
error_data = org_y - predicted_y
```

```
len(error_data)
```

    144

```
dataset_error_index['date'] = pd.to_datetime(dataset_error_index['date'],format="%d-%b-%Y"
error_dataset = dataset_error_index.loc[(dataset_error_index["date"] > "2010-01-03") & (da
#error_dataset = error_dataset[:-1]
error_dataset['error'] = error_data
error_dataset['predicted'] = predicted_y
#len(error_dataset)
error_dataset.head(2)
```

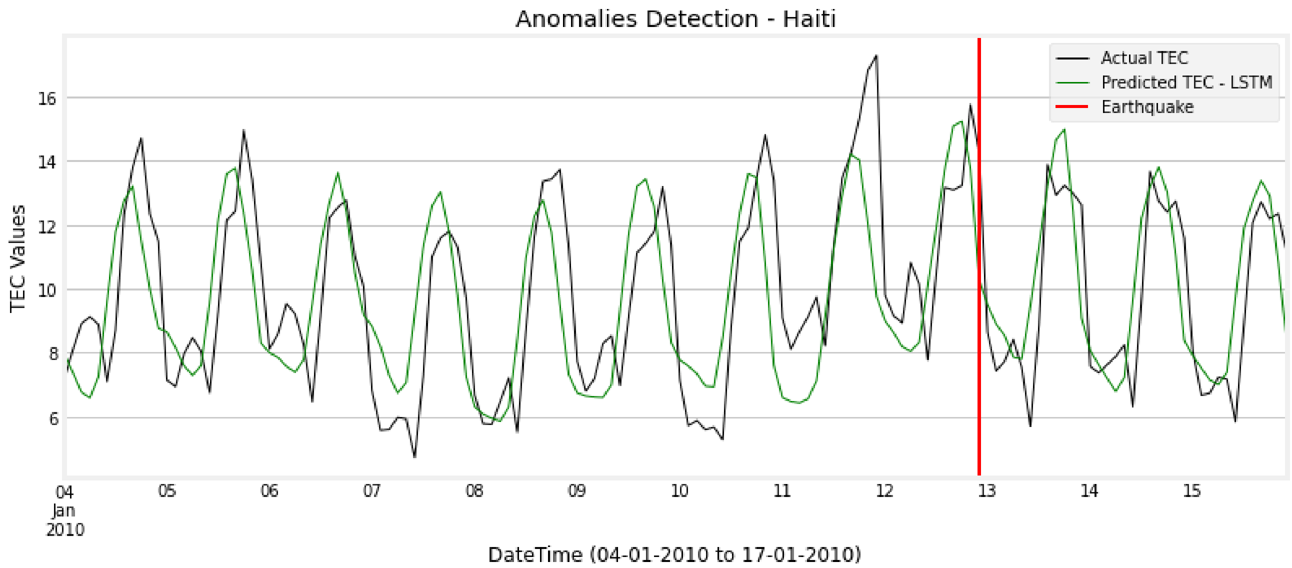
	date	time	tec	new_date	error	predicted
600	2010-01-04	00:00:00	7.163351	2010-01-04 00:00:00	0.121420	7.970560
601	2010-01-04	02:00:00	8.091980	2010-01-04 02:00:00	1.524103	7.387272

```
error_dataset['date'] = error_dataset['date'].dt.strftime('%Y-%m-%d')
```

```
error_dataset = error_dataset.set_index(['new_date'])
error_dataset.head(2)
```

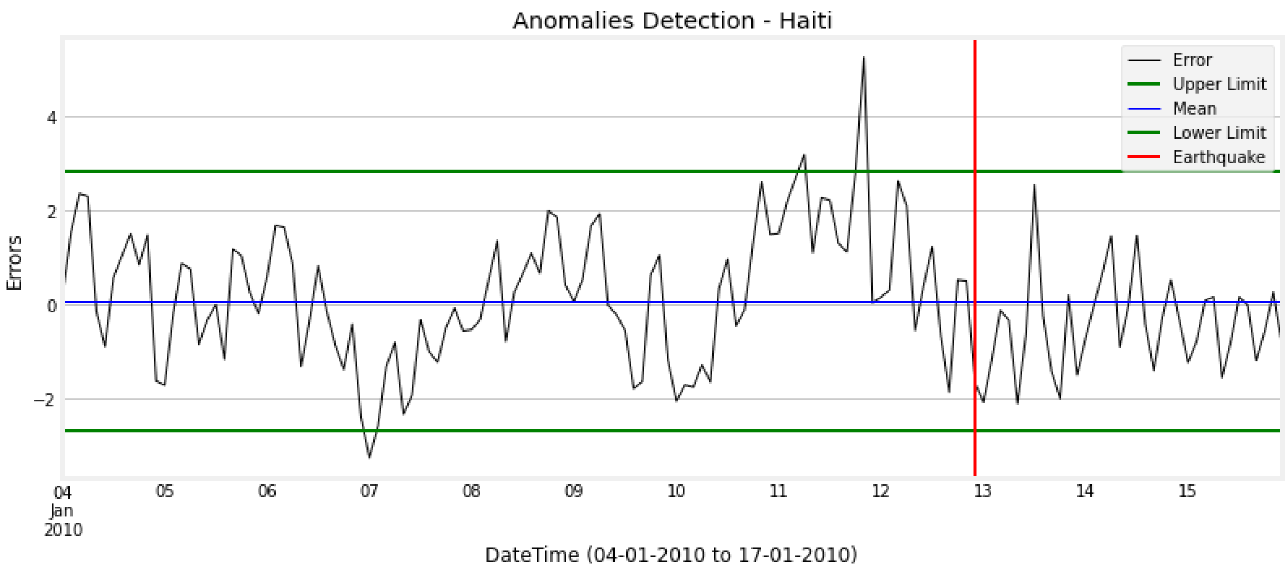
new_date	date	time	tec	error	predicted
2010-01-04 00:00:00	2010-01-04	00:00:00	7.163351	0.121420	7.970560
2010-01-04 02:00:00	2010-01-04	02:00:00	8.091980	1.524103	7.387272

```
plt.figure(figsize=(12,5))
ax = plt.gca()
ax.set_facecolor('white')
error_dataset["tec"].plot(subplots=True, color='black', linewidth=1.0, label = "Actual TEC
error_dataset["predicted"].plot(subplots=True, color='green', linewidth=1.0, label = "Pred
plt.axvline(x="2010-01-12 22:00:00", color='red', linestyle='-', linewidth=2.0, label = "E
#plt.axvline(x="2015-04-10 00:00:00", color='black', linestyle='-', linewidth=1.0)
#plt.axvline(x="2015-04-21 00:00:00", color='black', linestyle='-', linewidth=1.0)
plt.title('Anomalies Detection - Haiti')
plt.xlabel('DateTime (04-01-2010 to 17-01-2010)')
plt.ylabel('TEC Values')
plt.legend()
plt.show()
```




```
plt.figure(figsize=(12,5))
ax = plt.gca()
ax.set_facecolor('white')
error_dataset["error"].plot(subplots=True, color='black', linewidth=1.0, label = "Error")
plt.axhline(y=np.mean(error_dataset['error']) + (2*np.std(error_dataset['error'])), color=
plt.axhline(y=np.mean(error_dataset['error']), color='blue', linestyle='-', linewidth=1.0,
plt.axhline(y=np.mean(error_dataset['error']) + (-2*np.std(error_dataset['error'])), color
plt.axvline(x="2010-01-12 22:00:00", color='red', linestyle='-', linewidth=2.0, label = "E
#plt.axvline(x="2015-04-10 00:00:00", color='black', linestyle='-', linewidth=1.0)
```

```
#plt.axvline(x="2015-04-21 00:00:00", color='black', linestyle='-', linewidth=1.0)
plt.title('Anomalies Detection - Haiti')
plt.xlabel('DateTime (04-01-2010 to 17-01-2010)')
plt.ylabel('Errors')
plt.legend()
plt.show()
```



ARIMA

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
import statistics
import seaborn as sns # for plot visualization
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.tsa.stattools import adfuller, acf, pacf
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

```
ARIMA_dataset = pd.read_csv('sample_data/train.csv')
ARIMA_dataset.head(2)
```

	date	time	tec
0	15-Nov-09	00:00:00	8.450762
1	15-Nov-09	02:00:00	8.756442

```
ARIMA_dataset['new_date'] = ARIMA_dataset['date'].str.cat(ARIMA_dataset['time'], sep =" ")
ARIMA_dataset['new_date'] = pd.to_datetime(ARIMA_dataset['new_date'],format="%d-%b-%y %H:%
ARIMA_dataset= ARIMA_dataset[['new_date','tec']]
```

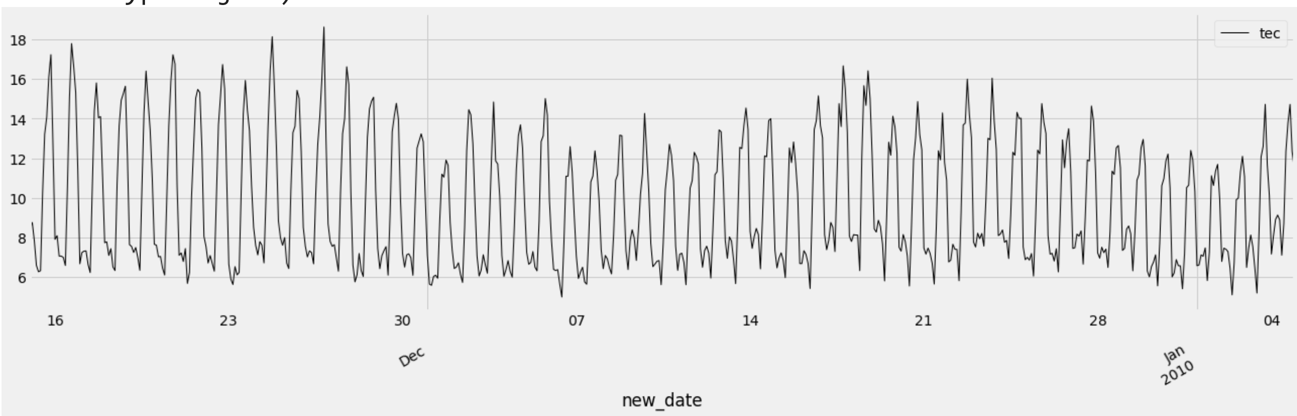
```
ARIMA_indexedDataset = ARIMA_dataset.set_index(['new_date'])
ARIMA_indexedDataset.head(2)
```

	tec
new_date	
2009-11-15 00:00:00	8.450762
2009-11-15 02:00:00	8.756442

```
ARIMA_indexedDataset.index = pd.to_datetime(ARIMA_indexedDataset.index)
```

```
ARIMA_indexedDataset.plot(subplots=True, figsize=(20,6),color='black', linewidth=1.0)
```

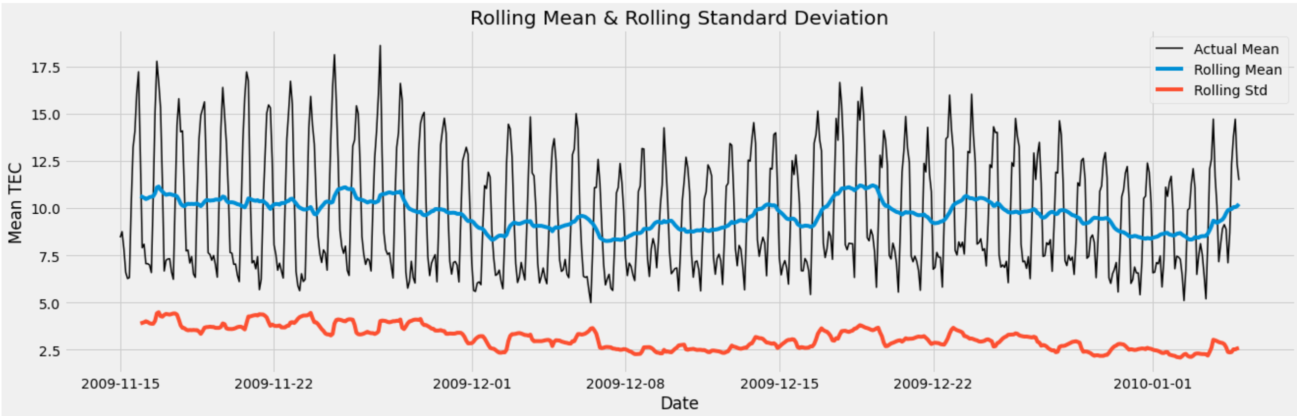
```
array([<matplotlib.axes._subplots.AxesSubplot object at 0x7faa167ad908>],
      dtype=object)
```




```
# check rolling mean and rolling standard deviation
def plot_rolling_mean_std(ts):
    rolling_mean = ts.rolling(12).mean()
    rolling_std = ts.rolling(12).std()
    plt.figure(figsize=(20,6))

    plt.plot(ts, label='Actual Mean',color='black',linewidth=1.5)
    plt.plot(rolling_mean, label='Rolling Mean')
    plt.plot(rolling_std, label = 'Rolling Std')
    plt.xlabel("Date")
    plt.ylabel("Mean TEC")
    plt.title('Rolling Mean & Rolling Standard Deviation')
    plt.legend()
    plt.show()
```

```
# Augmented Dickey-Fuller test
def test_stationarity(timeseries):
    timeseries.dropna(inplace=True)
    #Perform Dickey-Fuller test:
    print('Results of Dickey Fuller Test:')
```

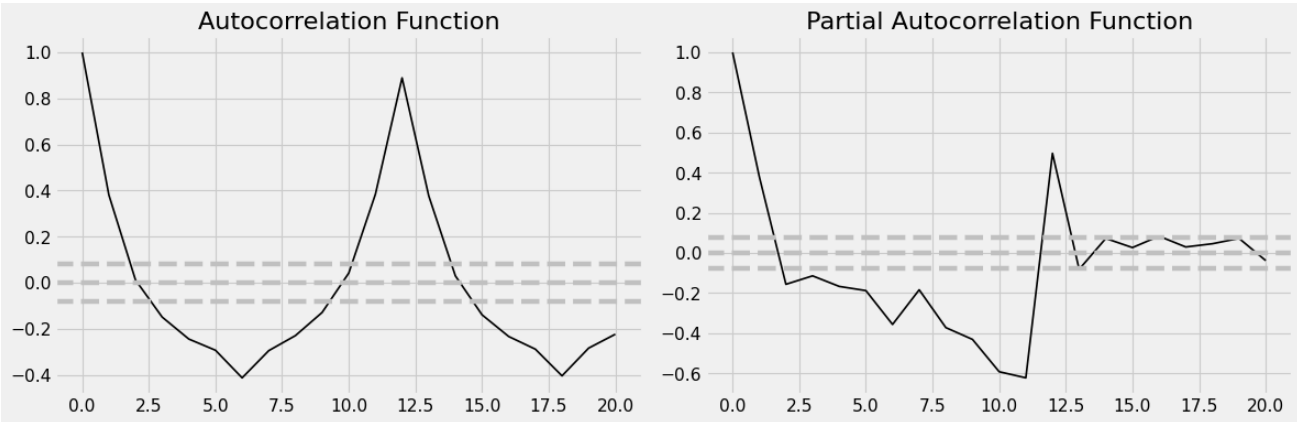
```
    print('Results of Dickey Fuller Test:')
    dftest = adfuller(timeseries['tec'], autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Used','Numb
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print(dfoutput)


ARIMA_train_df = ARIMA_indexedDataset


# check stationary: mean, variance(std)and adfuller test
plot_rolling_mean_std(ARIMA_train_df.tec)
test_stationarity(ARIMA_train_df)
```




```
Results of Dickey Fuller Test:
Test Statistic                  -3.863629
p-value                          0.002319
#Lags Used                      19.000000
Number of Observations Used    592.000000
Critical Value (1%)             -3.441444
Critical Value (5%)             -2.866435
Critical Value (10%)            -2.569377
dtype: float64
```

```
acf_lag = acf(ARIMA_train_df.diff().dropna().values, nlags=20)
pacf_lag = pacf(ARIMA_train_df.diff().dropna().values, nlags=20, method='ols')

plt.figure(figsize=(15,5))

plt.subplot(121)
plt.plot(acf_lag, linewidth=1.5,color='black')
plt.axhline(y=0,linestyle='--',color='silver')
plt.axhline(y=-1.96/np.sqrt(len(ARIMA_train_df.diff().values)),linestyle='--',color='silve
plt.axhline(y=1.96/np.sqrt(len(ARIMA_train_df.diff().values)),linestyle='--',color='silver
plt.title("Autocorrelation Function")

plt.subplot(122)
plt.plot(pacf_lag, linewidth=1.5,color='black')
plt.axhline(y=0,linestyle='--',color='silver')
plt.axhline(y=-1.96/np.sqrt(len(ARIMA_train_df.diff().values)),linestyle='--',color='silve
```

```
plt.axhline(y=1.96/np.sqrt(len(ARIMA_train_df.diff().values)),linestyle='--',color='silver
plt.title("Partial Autocorrelation Function")
plt.tight_layout()
```

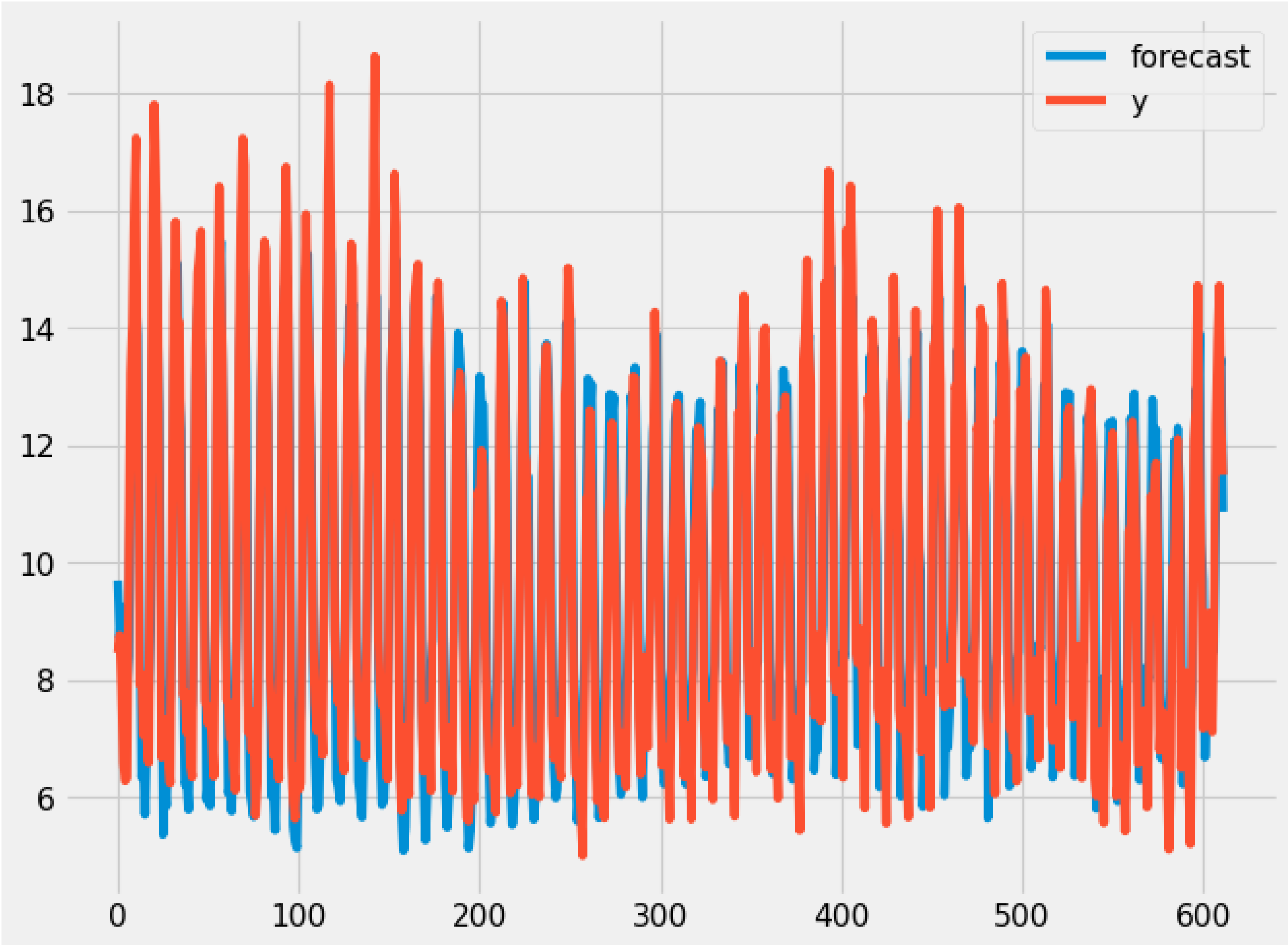



```
model = ARIMA(ARIMA_train_df.values, order=(3,0,3))
model_fit = model.fit(disp=0)
print(model_fit.summary())
```

```
                              ARMA Model Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  612
Model:                     ARMA(3, 3)   Log Likelihood               -1021.590
Method:                       css-mle   S.D. of innovations              1.276
Date:                Sun, 16 Aug 2020   AIC                           2059.180
Time:                        09:31:19   BIC                           2094.514
Sample:                             0   HQIC                          2072.923

==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          9.6812      0.088    110.460      0.000       9.509       9.853
ar.L1.y        1.8841      0.001   1486.255      0.000       1.882       1.887
ar.L2.y       -1.2628      0.002   -618.702      0.000      -1.267      -1.259
ar.L3.y        0.1518      0.001    129.013      0.000       0.150       0.154
ma.L1.y       -1.2247      0.035    -34.704      0.000      -1.294      -1.156
ma.L2.y        0.1257      0.060      2.081      0.038       0.007       0.244
ma.L3.y        0.4849      0.035     13.829      0.000       0.416       0.554
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            0.8663           -0.4998j            1.0001           -0.0833
AR.2            0.8663           +0.4998j            1.0001            0.0833
AR.3            6.5856           -0.0000j            6.5856           -0.0000
MA.1            0.8792           -0.4991j            1.0110           -0.0822
MA.2            0.8792           +0.4991j            1.0110            0.0822
MA.3           -2.0176           -0.0000j            2.0176           -0.5000
-----------------------------------------------------------------------------
```

```
# Actual vs Fitted
```

```
# Actual vs Fitted
model_fit.plot_predict(dynamic=False)
plt.show()
```




```
#train_df2 = train_df.iloc[1:]
ARIMA_train_error_data = ARIMA_train_df.tec - model_fit.predict()
ARIMA_train_error_data.head()
```

```
new_date
2009-11-15 00:00:00   -1.230407
2009-11-15 02:00:00    0.038416
2009-11-15 04:00:00   -1.399146
2009-11-15 06:00:00   -1.612622
2009-11-15 08:00:00   -1.343016
Name: tec, dtype: float64
```

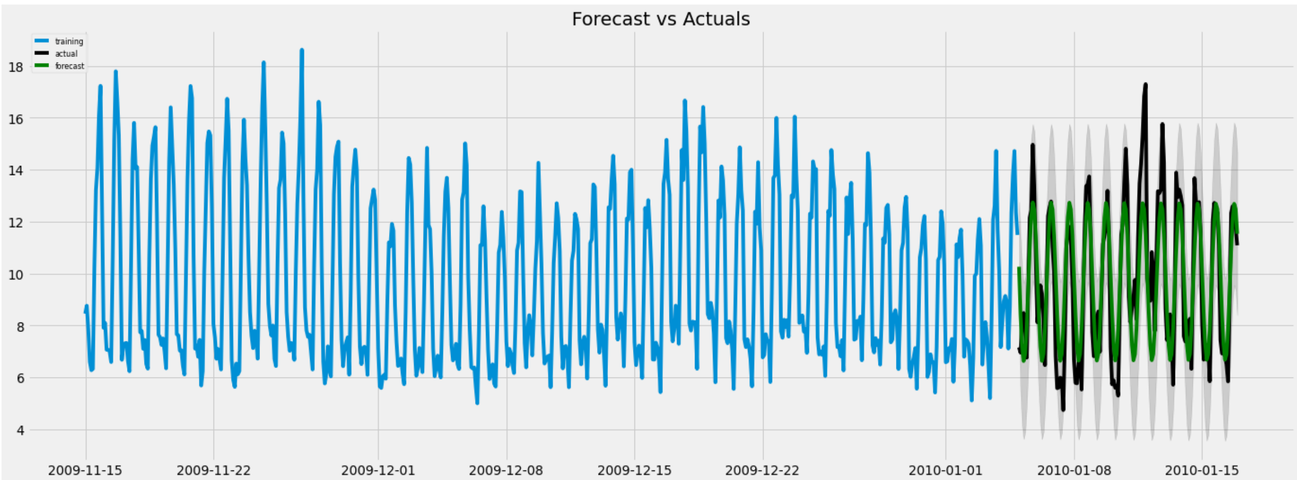
```
ARIMA_test_dataset = pd.read_csv('sample_data/test.csv')
ARIMA_test_dataset['new_date'] = ARIMA_test_dataset['date'].str.cat(ARIMA_test_dataset['ti
ARIMA_test_dataset['new_date'] = pd.to_datetime(ARIMA_test_dataset['new_date'],format="%d-
ARIMA_test_dataset= ARIMA_test_dataset[['new_date','tec']]
ARIMA_test_indexedDataset = ARIMA_test_dataset.set_index(['new_date'])
ARIMA_test_indexedDataset.head(2)
```

tec

```
ARIMA_test_df = ARIMA_test_indexedDataset
```

2010-01-05 00:00:00 7.150207

```
fc, se, conf = model_fit.forecast(len(ARIMA_test_df), alpha=0.05)  # 95% conf

# print(fc)
# Make as pandas series
ARIMA_fc_series = pd.Series(fc, index=ARIMA_test_df.index)
lower_series = pd.Series(conf[:, 0], index=ARIMA_test_df.index)
upper_series = pd.Series(conf[:, 1], index=ARIMA_test_df.index)

# # Plot
plt.figure(figsize=(22,8), dpi=70)
plt.plot(ARIMA_train_df, label='training')
plt.plot(ARIMA_test_df, label='actual',color='black')
plt.plot(ARIMA_fc_series, label='forecast', color='green')
#plt.axvline(x="2010-01-13 10:00:00", color='red', linestyle='-', linewidth=4, label='Day
plt.fill_between(lower_series.index, lower_series, upper_series,
                 color='k', alpha=.15)
plt.title('Forecast vs Actuals')
plt.legend(loc='upper left', fontsize=8)
plt.show()
# test_df.index
```

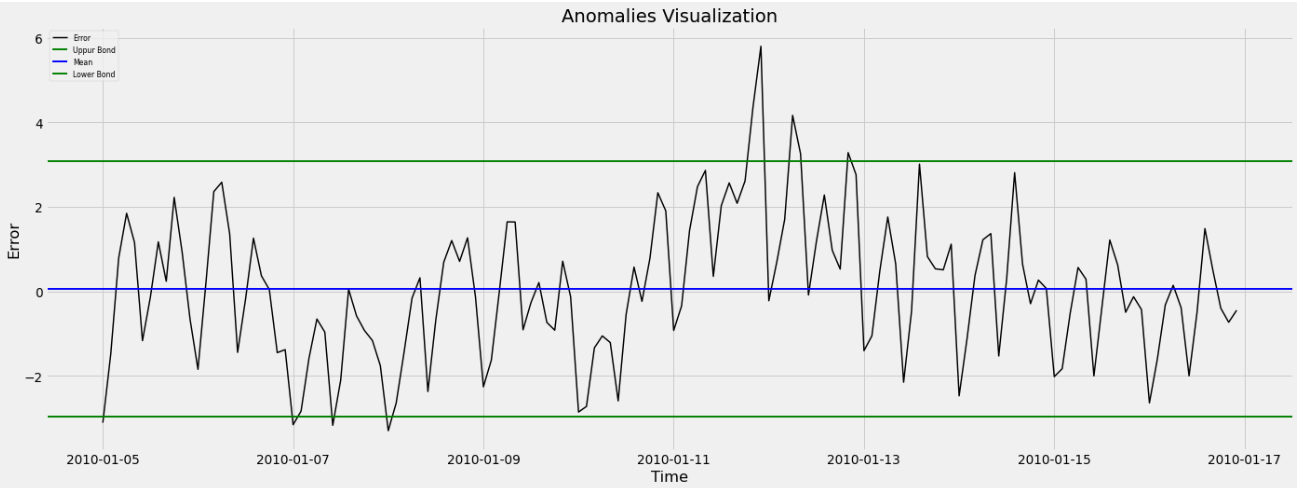



```
ARIMA_error_data = ARIMA_test_df.tec-ARIMA_fc_series
ARIMA_error_data.head(2)
```

```
new_date
2010-01-05 00:00:00   -3.107118
2010-01-05 02:00:00   -1.485185
dtype: float64
```

```
plt.figure(figsize=(22,8), dpi=70)
```

```
plt.figure(figsize=(22,8), dpi=70)
plt.plot(ARIMA_error_data, label='Error', color='black', linewidth=1.5)
plt.axhline(y=statistics.mean(ARIMA_error_data) + 1.8*statistics.stdev(ARIMA_error_data),
plt.axhline(y=statistics.mean(ARIMA_error_data), color='blue', linestyle='-', linewidth=2,
plt.axhline(y=statistics.mean(ARIMA_error_data) - (1.8*statistics.stdev(ARIMA_error_data))
#plt.axvline(x="2010-01-13 00:00:00", color='red', linestyle='-', linewidth=4, label='Day
plt.xlabel('Time')
plt.ylabel('Error')
plt.title('Anomalies Visualization')
plt.legend(loc='upper left', fontsize=8)
plt.show()
```

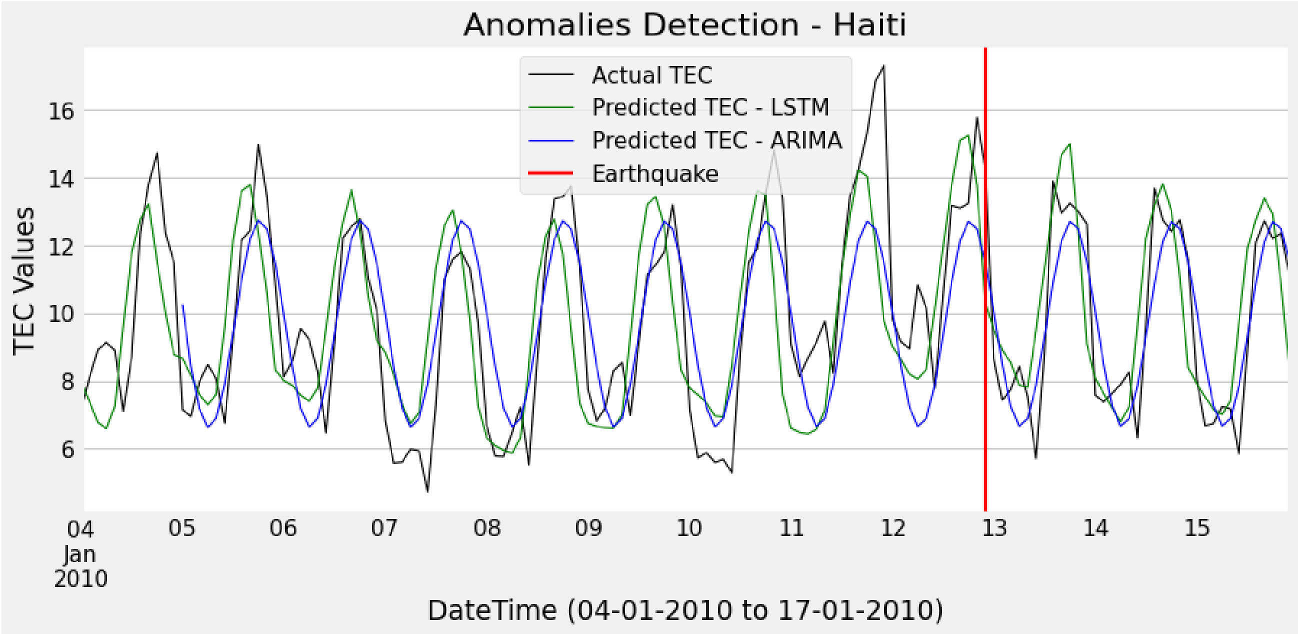



```
error_dataset['error_ARIMA'] = ARIMA_error_data
error_dataset['predicted_ARIMA'] = ARIMA_fc_series
error_dataset.tail(2)
```

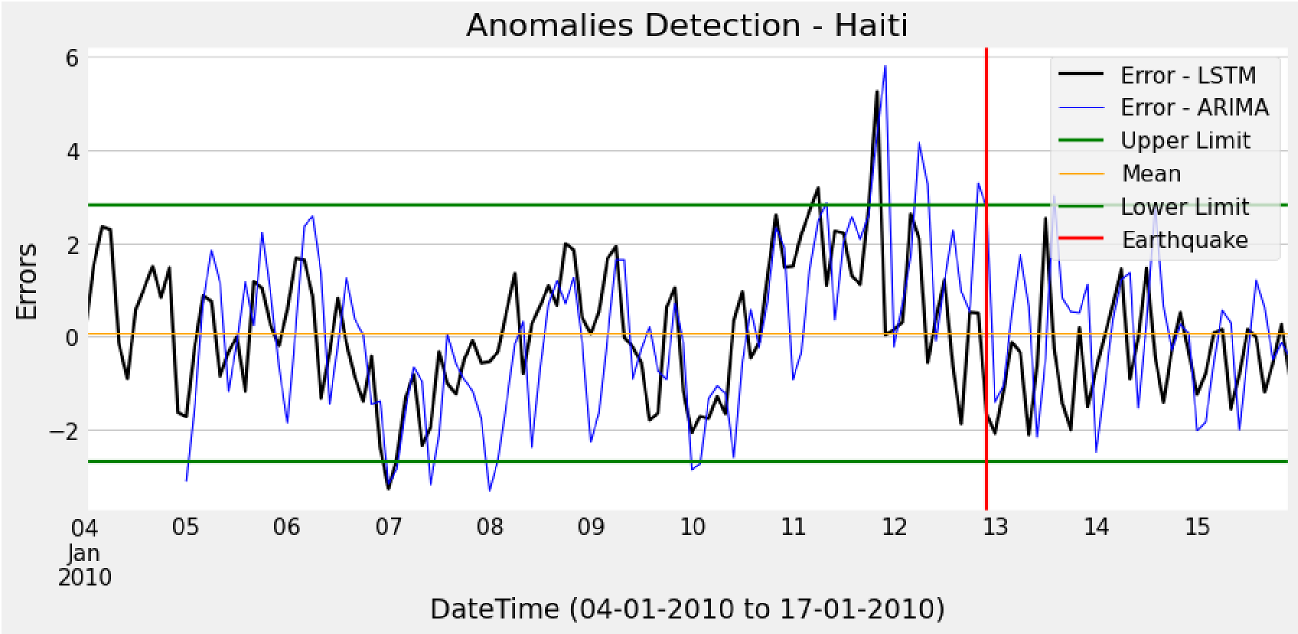
	date	time	tec	error	predicted	error_ARIMA	predicted_ARIM
new_date							
2010-01-15 20:00:00	2010-01-15	20:00:00	12.354816	0.266725	10.826866	-0.125481	12.48029

```
plt.figure(figsize=(12,5))
ax = plt.gca()
ax.set_facecolor('white')
error_dataset["tec"].plot(subplots=True, color='black', linewidth=1.0, label = "Actual TEC
error_dataset["predicted"].plot(subplots=True, color='green', linewidth=1.0, label = "Pred
error_dataset["predicted_ARIMA"].plot(subplots=True, color='blue', linewidth=1.0, label =
plt.axvline(x="2010-01-12 22:00:00", color='red', linestyle='-', linewidth=2.0, label = "E
#plt.axvline(x="2015-04-10 00:00:00", color='black', linestyle='-', linewidth=1.0)
#plt.axvline(x="2015-04-21 00:00:00", color='black', linestyle='-', linewidth=1.0)
plt.title('Anomalies Detection - Haiti')
plt.xlabel('DateTime (04-01-2010 to 17-01-2010)')
```

```
plt.ylabel('TEC Values')
plt.legend()
plt.show()
```




```
plt.figure(figsize=(12,5))
ax = plt.gca()
ax.set_facecolor('white')
error_dataset["error"].plot(subplots=True, color='black', linewidth=2.0, label = "Error -
error_dataset["error_ARIMA"].plot(subplots=True, color='blue', linewidth=1.0, label = "Err
plt.axhline(y=np.mean(error_dataset['error']) + (2*np.std(error_dataset['error'])), color=
plt.axhline(y=np.mean(error_dataset['error']), color='ORANGE', linestyle='-', linewidth=1.
plt.axhline(y=np.mean(error_dataset['error']) + (-2*np.std(error_dataset['error'])), color
plt.axvline(x="2010-01-12 22:00:00", color='red', linestyle='-', linewidth=2.0, label = "E
#plt.axvline(x="2015-04-10 00:00:00", color='black', linestyle='-', linewidth=1.0)
#plt.axvline(x="2015-04-21 00:00:00", color='black', linestyle='-', linewidth=1.0)
plt.title('Anomalies Detection - Haiti')
plt.xlabel('DateTime (04-01-2010 to 17-01-2010)')
plt.ylabel('Errors')
plt.legend()
plt.show()
```


Anomalies Detection - Haiti
Errors
6
4
2
0
−2
Error - LSTM
Error - ARIMA
Upper Limit
Mean
Lower Limit
Earthquake
04
Jan
2010
05
06
07
08
09
10
11
12
13
14
15
DateTime (04-01-2010 to 17-01-2010)