Time Series router traffic forecasting challenge

Problem statement

The problem is to forecast the router traffic given its historical data. This is a time series problem as you know. The dataset consists of router traffic data from 1/10/2018 to 2/11/2018 for 5 router/network devices. Our task is to build a model which identifies the patterns of 5 of those network devices and to forecast traffic seperately for the next 2 or 3 days.

This problem was a part of my internship interview at CanGo Networks pvt ltd, Chennai.

Overview of dataset

Dataset was given by CanGo Networks pvt ltd. It consists of KPI, ne_date, ne_id, ne_hour, metric and the value. Here value is our predictor variable. There are 5 network devices in the data for which we will have to forecast their value for the next 2 or 3 days. Dataset has 3600 odd records and 6 features

image.png

Techniques I tried

I started with AR and Arima since we had hourly predictions for a month. But unfortunately, both of these models were not able to capture the dynamics in the data. Hence I posed this as a regression problem, I created some more features and did regression using XGBoost regressor and the results were good!

Evaluation Criteria

I used MSE and MAE as metrics for this problem since we are regresing the data

Resources

I used kaggle, google and some stackexchanges to get help from as usual

Author

Karthikeyan MG

The reason I choose this problem is the data I'm working are from real physical network devices and not some curated data which is clean and neat. And solving this problem has a business impact.

[1.0] Imports

In [221]:
```
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from collections import Counter
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.tsa.ar_model import AR
from statsmodels.tsa.arima_model import ARIMA
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
import matplotlib.pyplot as plt
import xgboost as xgb
```

In [9]:
```
df = pd.read_csv('Call_Setup_Success_Rate_1month_hourly.csv')
```

In [10]:
```
df.shape
```

Out[10]: (3960, 1)

In [11]:
```
df.head()
```

Out[11]:

	kpi$unit$kpi_idne_datene_hourne_idvalue
0	Call Setup Success Rate3561851598725308$201...
1	Call Setup Success Rate3561851598725308$201...
2	Call Setup Success Rate3561851598725308$201...
3	Call Setup Success Rate3561851598725308$201...
4	Call Setup Success Rate3561851598725308$201...

[1.1] Data organizer function

Eventhough there are many other simpler methods to organize this data. I tried solving this programatically

In [12]:
```
def data_corrector(df):

    new_df = pd.DataFrame(columns=[i for i in np.squeeze(df.columns.str.split(
pat='$'))])
    for i in range(len(df)):
        row_data = list(df.iloc[i].str.split(pat="$"))
        squeezed_row = np.squeeze(row_data)
        new_df = new_df.append(pd.Series(squeezed_row, index=[i for i in np.sq
ueeze(df.columns.str.split(pat='$'))]), ignore_index=True)
    return new_df
```

In [13]:
```
new_df = data_corrector(df)
```

In [14]:
```
new_df.head()
```

Out[14]:

	kpi	unit	kpi_id	ne_date	ne_hour	ne_id	value
0	Call Setup Success Rate	%	3561851598725308	2018-10-01	0	MEXTLAMSS1	90.3200
1	Call Setup Success Rate	%	3561851598725308	2018-10-01	0	MEXTIJMSS1	94.9000
2	Call Setup Success Rate	%	3561851598725308	2018-10-01	0	MEXMTYMSS1	90.3400
3	Call Setup Success Rate	%	3561851598725308	2018-10-01	0	MEXMTYMSS2	92.8500
4	Call Setup Success Rate	%	3561851598725308	2018-10-01	0	MEXGDLMSS1	90.1700

In [22]:
```
new_df.to_csv('new_df.csv', index=False)
```

[1.2] Change dates to timestamp

In [15]:
```
def date_converter(date):
    return pd.datetime.strptime(date, '%Y-%m-%d')
```

In [16]:
```
new_df = pd.read_csv('new_df.csv', parse_dates=[3], date_parser=date_converter
, index_col=[3])
```

In [17]:
```
new_df.head()
```

Out[17]:

	kpi	unit	kpi_id	ne_hour	ne_id	value
ne_date						
2018-10-01	Call Setup Success Rate	%	3561851598725308	0	MEXTLAMSS1	90.32
2018-10-01	Call Setup Success Rate	%	3561851598725308	0	MEXTIJMSS1	94.90
2018-10-01	Call Setup Success Rate	%	3561851598725308	0	MEXMTYMSS1	90.34
2018-10-01	Call Setup Success Rate	%	3561851598725308	0	MEXMTYMSS2	92.85
2018-10-01	Call Setup Success Rate	%	3561851598725308	0	MEXGDLMSS1	90.17

In [18]:
```
new_df.shape
```

Out[18]: (3960, 6)

In [24]:
```
new_df.to_csv('new_df.csv', index=False)
```

[1.3] Simple data cleaning

[1.3.1] Checking for duplicates

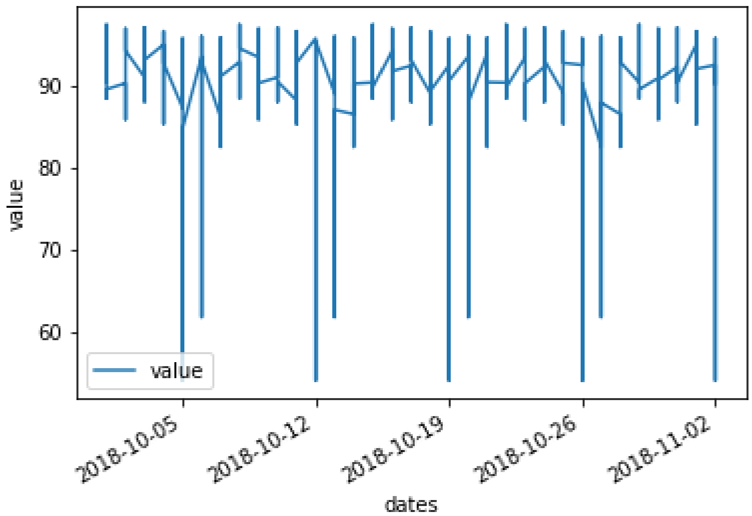
In [25]:
```
sum(new_df.duplicated())
```

Out[25]: 0

We will first explore the entire dataset once and after this we will split datapoints based on network devices and will perform a in-depth analysis and prediction on data of each of the network device

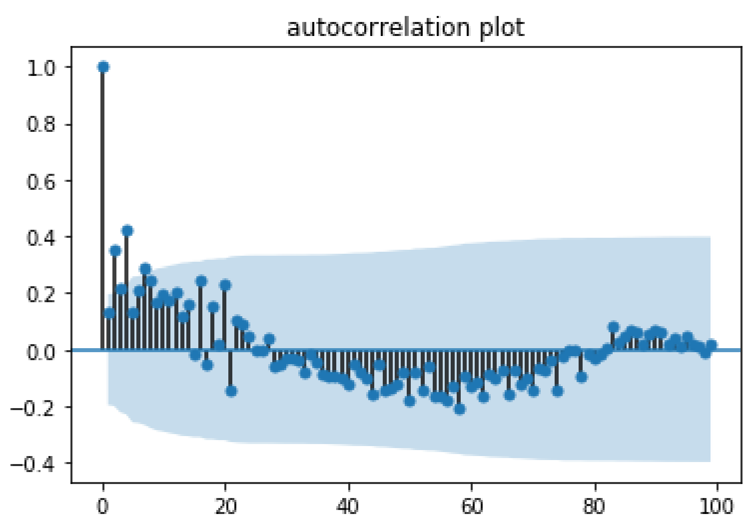
In [31]:
```
ax = new_df.plot(y='value')
ax.set_ylabel('value')
ax.set_xlabel('dates')
```

Out[31]: Text(0.5,0,'dates')



There is no clear trend in the graph, the time series graph of the data and we observe the data is stationary i.e the mean, variance and covariance are equal throughout different time steps. Still we will check using statistical methods to prove it.

In [27]:
```
plot_acf(new_df['value'][:100], title='autocorrelation plot');
```



But the autocorrelation plot shows a little bit of non stationarity in the data

[1.4] Getting data for each and every network device

In [28]:
```
split_df = new_df.groupby(by='ne_id')
split_df.describe()
```

Out[28]:

	kpi_id					
	count	mean	std	min	25%	50%
ne_id						
MEXGDLMSS1	792.0	3.561852e+15	18.011374	3.561852e+15	3.561852e+15	3.561852e+
MEXMTYMSS1	792.0	3.561852e+15	18.011374	3.561852e+15	3.561852e+15	3.561852e+
MEXMTYMSS2	792.0	3.561852e+15	18.011374	3.561852e+15	3.561852e+15	3.561852e+
MEXTIJMSS1	792.0	3.561852e+15	18.011374	3.561852e+15	3.561852e+15	3.561852e+
MEXTLAMSS1	792.0	3.561852e+15	18.011374	3.561852e+15	3.561852e+15	3.561852e+

5 rows × 24 columns

There are not a lot of major outliers in the data and the quantiles seem to fine which is a good sign

In [36]:
```
np.unique(new_df['ne_id'])
```

Out[36]:
```
array(['MEXGDLMSS1', 'MEXMTYMSS1', 'MEXMTYMSS2', 'MEXTIJMSS1',
       'MEXTLAMSS1'], dtype=object)
```

We will segeregate data based on network device id such we can forecast each of our network devices seperately

In [30]:
```
MEXGDLMSS1_df = new_df[new_df['ne_id'] == 'MEXGDLMSS1']
MEXMTYMSS1_df = new_df[new_df['ne_id'] == 'MEXMTYMSS1']
MEXMTYMSS2_df = new_df[new_df['ne_id'] == 'MEXMTYMSS2']
MEXTIJMSS1_df = new_df[new_df['ne_id'] == 'MEXTIJMSS1']
MEXTLAMSS1_df = new_df[new_df['ne_id'] == 'MEXTLAMSS1']
```

[1.5] Lets export all the induvidual datasets

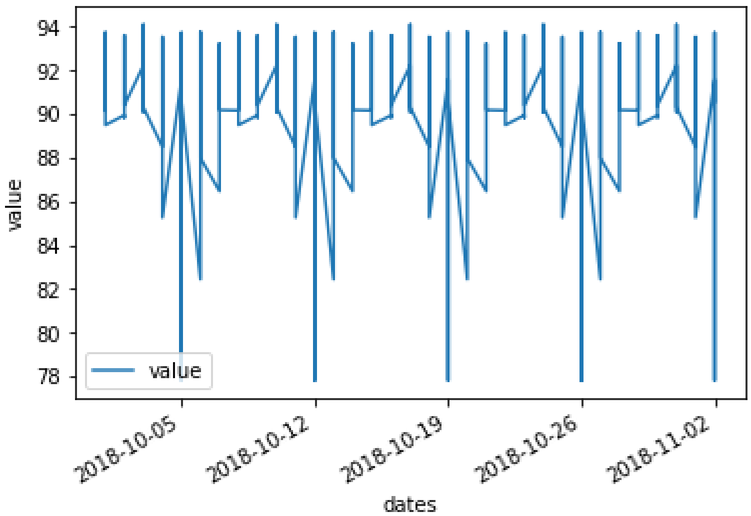
In [ ]:
```
MEXGDLMSS1_df.to_csv('MEXGDLMSS1_df.csv', index=False)
MEXMTYMSS1_df.to_csv('MEXMTYMSS1_df.csv', index=False)
MEXMTYMSS2_df.to_csv('MEXMTYMSS2_df.csv', index=False)
MEXTIJMSS1_df.to_csv('MEXTIJMSS1_df.csv', index=False)
MEXTLAMSS1_df.to_csv('MEXTLAMSS1_df.csv', index=False)
```

[1.6] Working with data

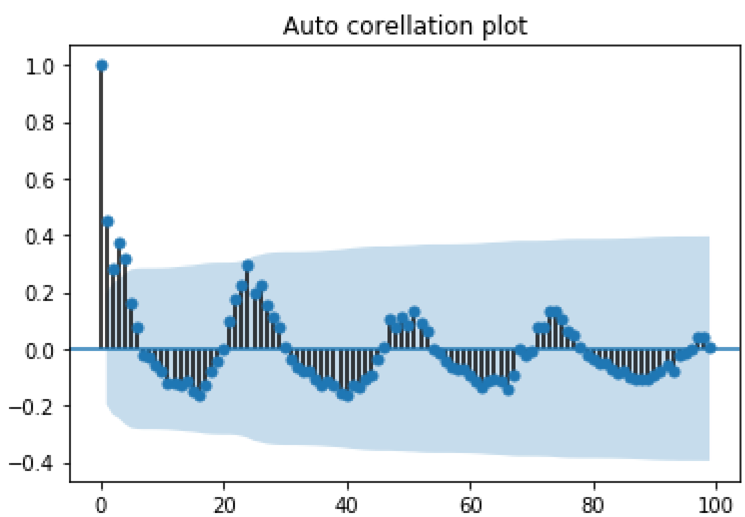
[1.6.1]Network device MEXGDLMSS1

In [32]:
```
ax = MEXGDLMSS1_df.plot(y='value')
ax.set_ylabel('value')
ax.set_xlabel('dates')
```

Out[32]: Text(0.5,0,'dates')



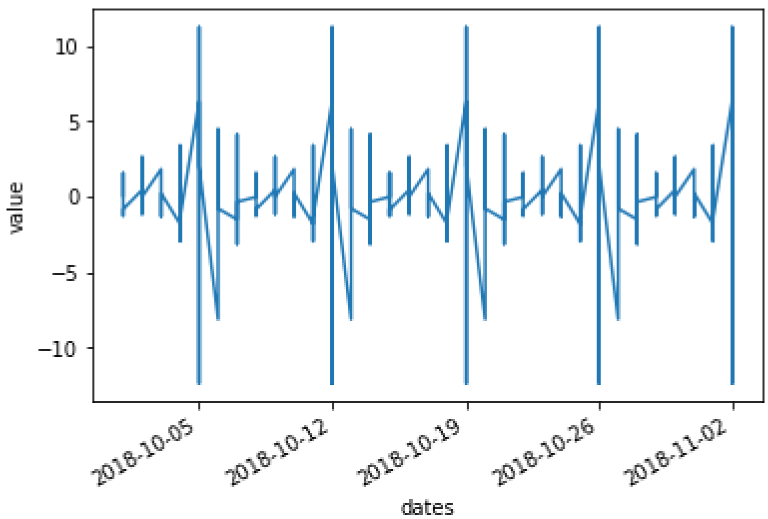
In [55]:
```
plot_acf(MEXGDLMSS1_df['value'][:100], title='Auto corellation plot');
```



So its almost stationary i.e mean, variance and covariance at different time intervals are almost equal and hence we can apply time series forecasting models such as ARMA, ARIMA etc etc

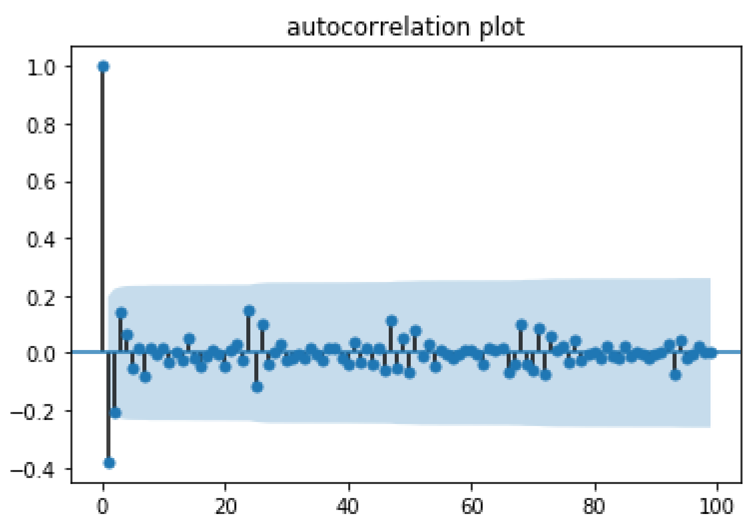
In [36]:
```
MEXGDLMSS1_df_diff = MEXGDLMSS1_df['value'].diff(periods=1)
ax = MEXGDLMSS1_df_diff.plot(y='value')
ax.set_xlabel('dates')
ax.set_ylabel('value')
```

Out[36]: Text(0,0.5,'value')



In [37]:
```
MEXGDLMSS1_df_diff = pd.DataFrame(MEXGDLMSS1_df_diff, columns=['date', 'value'
])
MEXGDLMSS1_df_diff.drop(columns=['date'], axis=1, inplace=True)
```

In [38]:
```
plot_acf(MEXGDLMSS1_df_diff[1:][:100], title='autocorrelation plot');
```

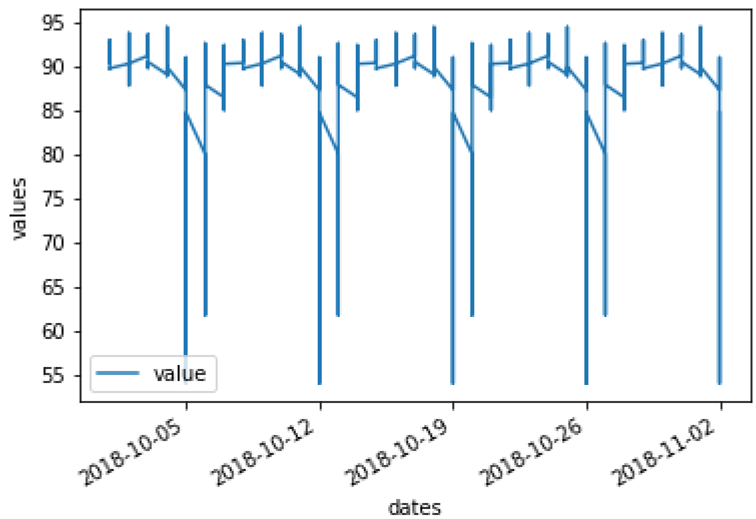


This signal is more close to being stationary and this is what we want. Now we will figure out whether rest of the network devices have similar behaviour

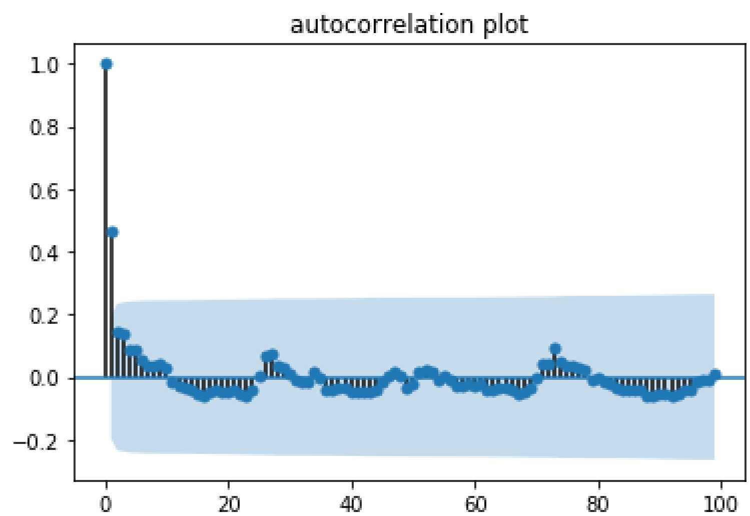
[1.7] MEXMTYMSS1_df network device

In [40]:
```
ax = MEXMTYMSS1_df.plot(y='value'[:100])
ax.set_xlabel('dates')
ax.set_ylabel('values')
```

Out[40]: `Text(0,0.5,'values')`



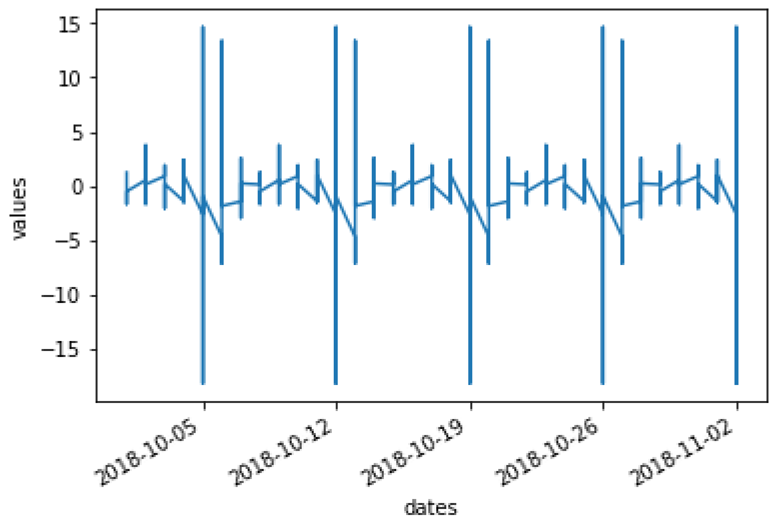
In [42]:
```
plot_acf(MEXMTYMSS1_df['value'][:100], title='autocorrelation plot');
```



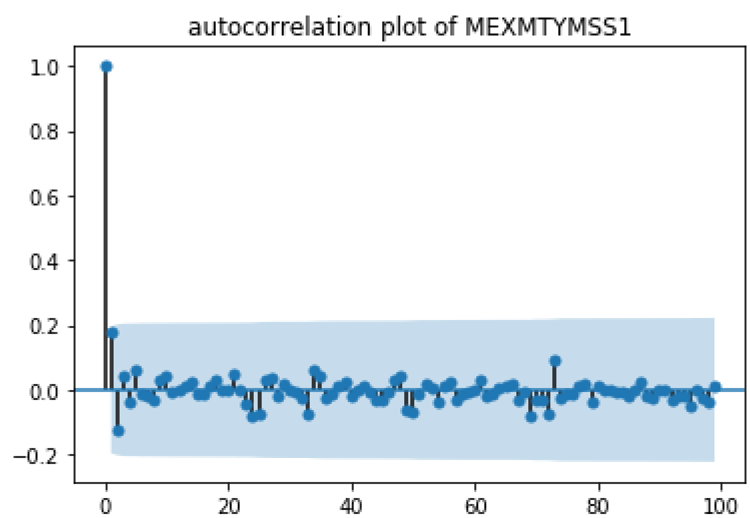
This is also close to being stationary

In [43]:
```
MEXMTYMSS1_df_diff = MEXMTYMSS1_df['value'].diff(periods=1)
ax = MEXMTYMSS1_df_diff.plot(y='value')
ax.set_xlabel('dates')
ax.set_ylabel('values')
```

Out[43]: Text(0,0.5,'values')



In [45]:
```
plot_acf(MEXMTYMSS1_df_diff[1:][:100], title='autocorrelation plot of MEXMTYMS
S1');
```

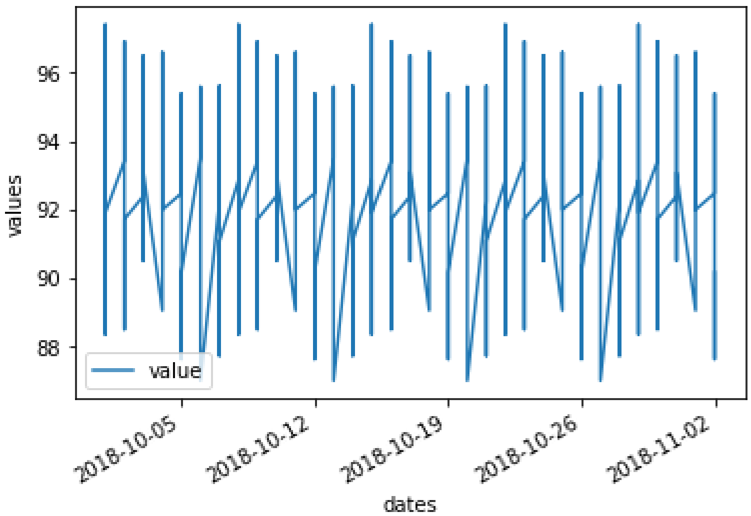


This one looks so close to being perfectly stationary which is good

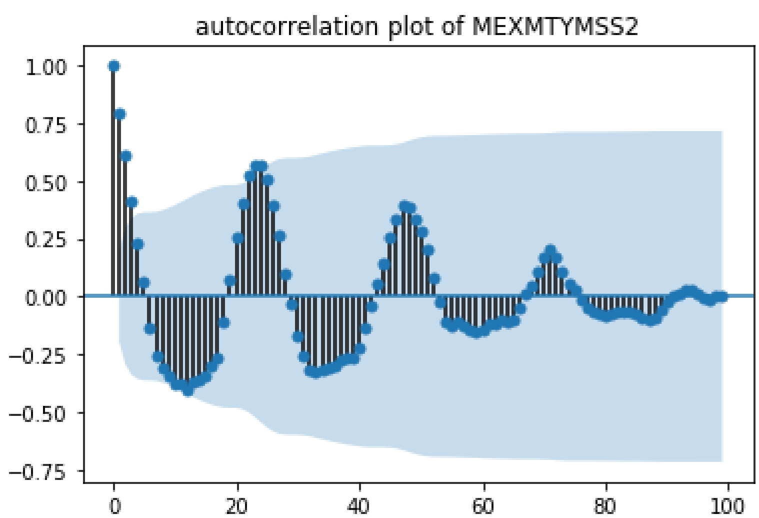
MEXMTYMSS2_df network device

In [46]:
```
ax = MEXMTYMSS2_df.plot(y='value'[:100])
ax.set_xlabel('dates')
ax.set_ylabel('values')
```

Out[46]: Text(0,0.5,'values')



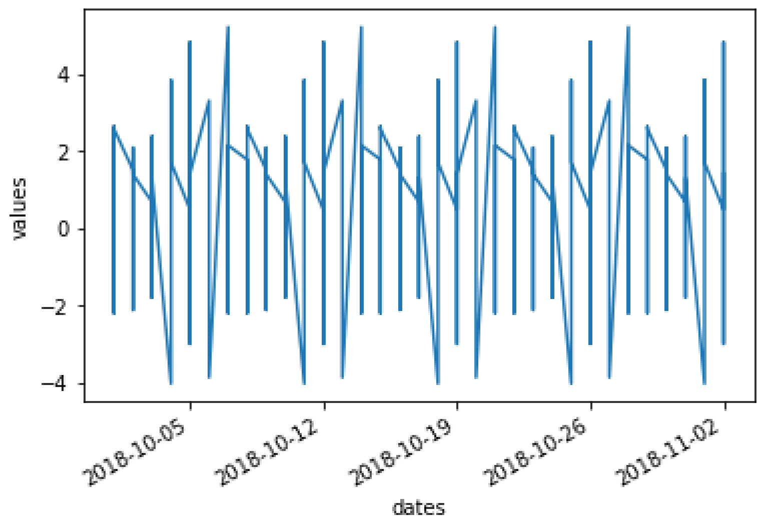
In [48]:
```
plot_acf(MEXMTYMSS2_df['value'][:100], title='autocorrelation plot of MEXMTYMS
S2');
```



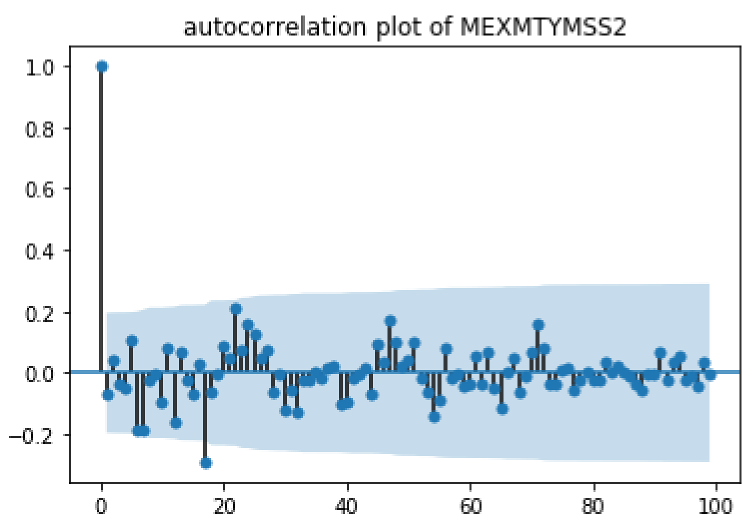
This is not anywhere close to being stationary. So the only way here is to use to autocorrelation stuff

In [50]:
```
MEXMTYMSS2_df_diff = MEXMTYMSS2_df['value'].diff(periods=1)
ax = MEXMTYMSS2_df_diff.plot(y='value')
ax.set_xlabel('dates')
ax.set_ylabel('values')
```

Out[50]: Text(0,0.5,'values')



In [51]:
```
plot_acf(MEXMTYMSS2_df_diff[1:][:100], title='autocorrelation plot of MEXMTYMS
S2');
```

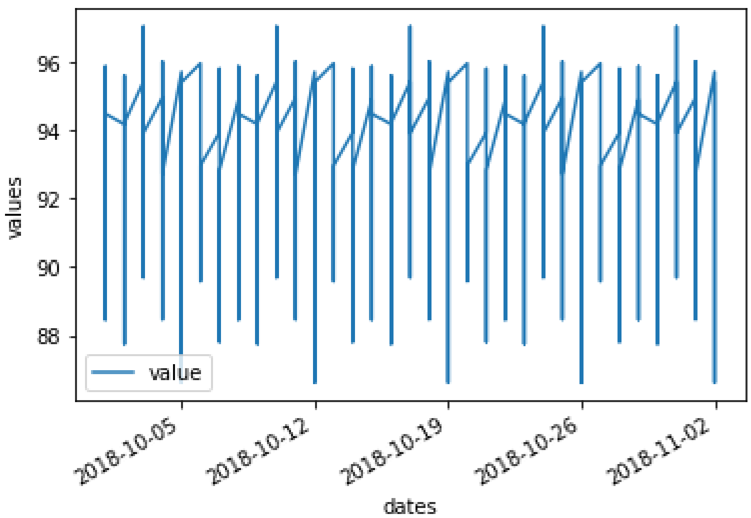


Again looks so close to being perfectly stationary

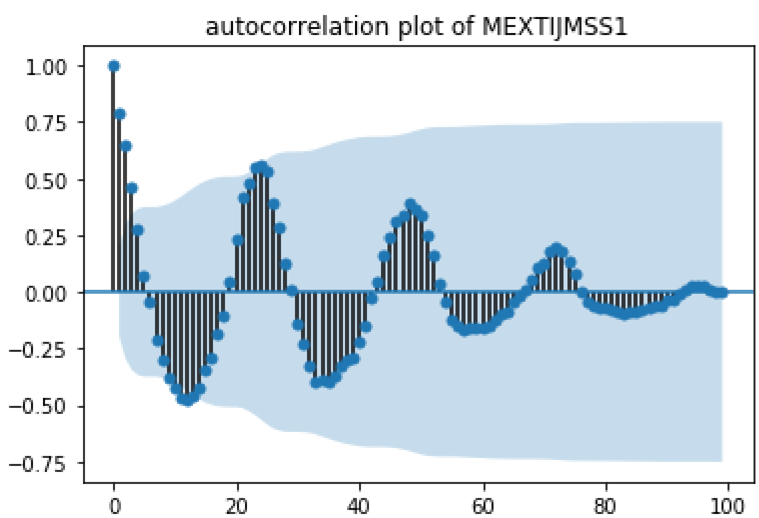
MEXTIJMSS1_df network device

In [52]:
```
ax = MEXTIJMSS1_df.plot(y='value'[:100])
ax.set_xlabel('dates')
ax.set_ylabel('values')
```

Out[52]: Text(0,0.5,'values')

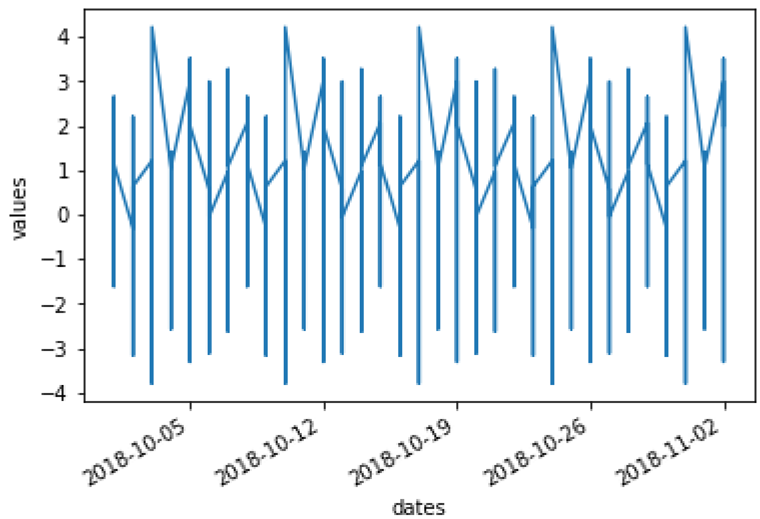


In [56]:
```
plot_acf(MEXTIJMSS1_df['value'][:100], title='autocorrelation plot of MEXTIJMS
S1');
```

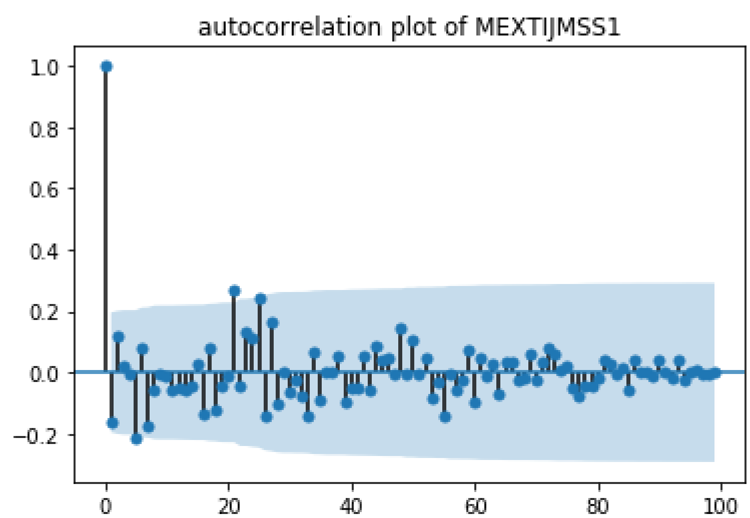


In [57]:
```
MEXTIJMSS1_df_dff = MEXTIJMSS1_df['value'].diff(periods=1)
ax=MEXTIJMSS1_df_dff.plot(y='value')
ax.set_xlabel('dates')
ax.set_ylabel('values')
```

Out[57]: Text(0,0.5,'values')



In [59]:
```
plot_acf(MEXTIJMSS1_df_dff[1:][:100], title='autocorrelation plot of MEXTIJMSS
1');
```

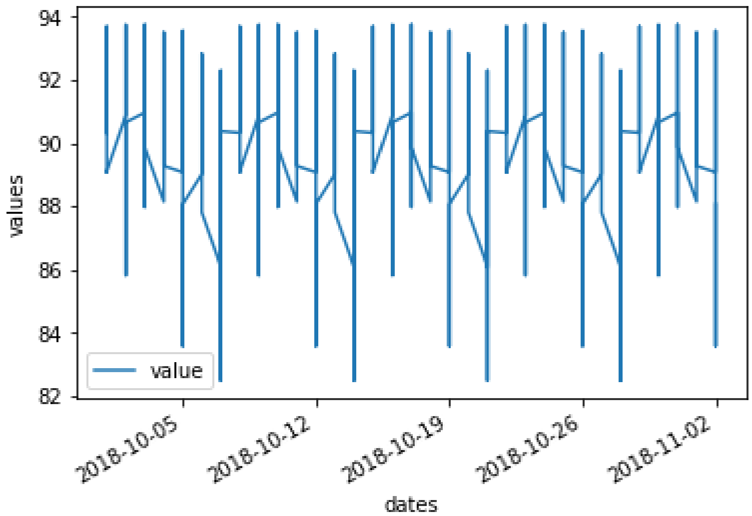


Close to being perfectly stationary

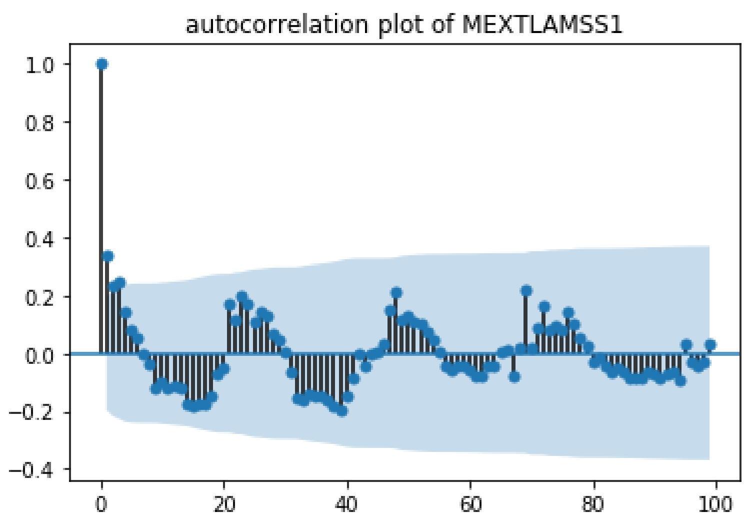
MEXTLAMSS1_df network device

In [60]:
```
ax=MEXTLAMSS1_df.plot(y='value'[:100])
ax.set_xlabel('dates')
ax.set_ylabel('values')
```

Out[60]: Text(0,0.5,'values')



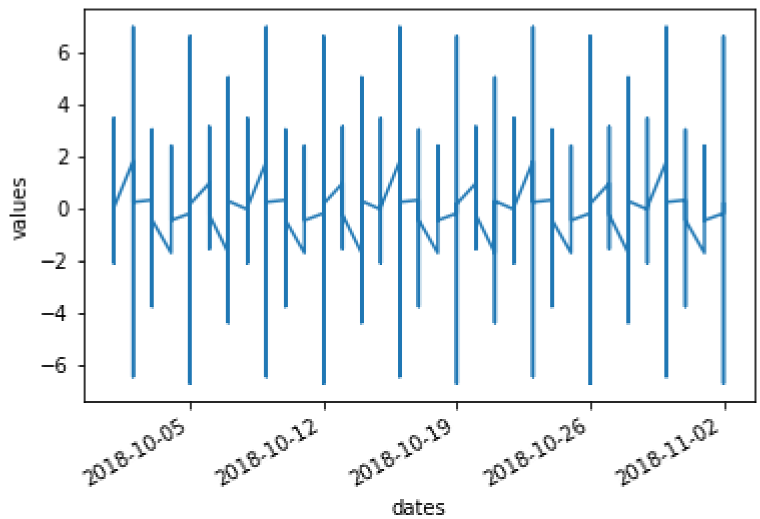
In [61]:
```
plot_acf(MEXTLAMSS1_df['value'][:100], title='autocorrelation plot of MEXTLAMS
S1');
```



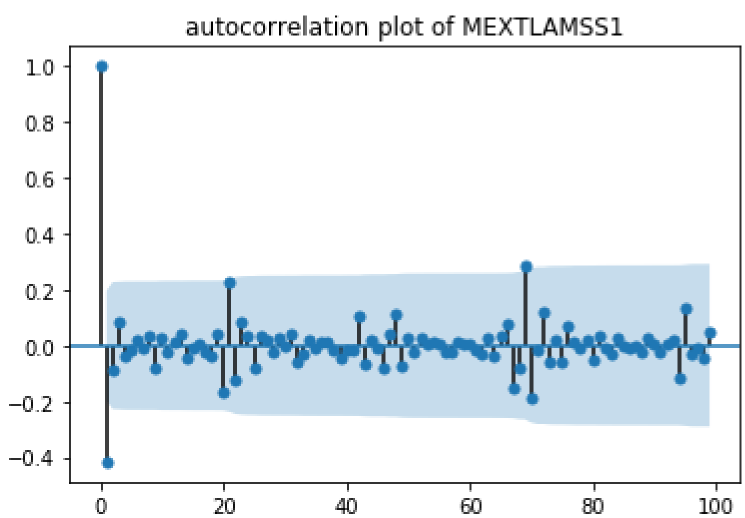
This is also close to being stationary

In [62]:
```
MEXTLAMSS1_df_dff = MEXTLAMSS1_df['value'].diff(periods=1)
ax=MEXTLAMSS1_df_dff.plot(y='value')
ax.set_xlabel('dates')
ax.set_ylabel('values')
```

Out[62]: Text(0,0.5,'values')



In [64]:
```
plot_acf(MEXTLAMSS1_df_dff[1:][:100], title='autocorrelation plot of MEXTLAMSS
1');
```



This is perfectly stationary

[1.7] Modelling

Network device = MEXGDLMSS1

Here we are doing time based splitting. i.e we put the oldest 80% data as train and the newest 20% as test as the model is going to predict for future and hence need to be fed with newest data which will closely model the future data

[1.7.1] Train test split

In [31]:
```
MEXGDLMSS1_x_train = MEXGDLMSS1_df[0:int(np.round(0.8*MEXGDLMSS1_df.shape[0
]))]
MEXGDLMSS1_x_test = MEXGDLMSS1_df[int(np.round(0.8*MEXGDLMSS1_df.shape[0])):]
```

In [32]:
```
print(str(MEXGDLMSS1_x_train.shape) + ' is the size of train data')
print(str(MEXGDLMSS1_x_test.shape) + ' is the size of test data')
```

```
(634, 6) is the size of train data
(158, 6) is the size of test data
```

In [48]:
```
MEXGDLMSS1_x_train = MEXGDLMSS1_x_train.drop(columns=['kpi', 'unit', 'kpi_id',
'ne_hour', 'ne_id'])
```

[1.8] Simple AR Model

In [51]:
```
model_ar = AR(MEXGDLMSS1_x_train)
model_ar_fit = model_ar.fit()
```

```
C:\Users\karth\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:
225: ValueWarning: A date index has been provided, but it has no associated f
requency information and so will be ignored when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)
```

In [52]:
```
MEXGDLMSS1_pred = (model_ar_fit.predict(start=634, end=791))
```

```
C:\Users\karth\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:
531: ValueWarning: No supported index is available. Prediction results will b
e given with an integer index beginning at `start`.
  ValueWarning)
```

In [53]:
```
MEXGDLMSS1_pred.values[:10]
```

Out[53]:
```
array([91.85479013, 92.26073341, 91.7485111 , 91.17972818, 90.77289361,
       91.08951199, 92.18544221, 91.84174396, 91.83301036, 89.77164584])
```

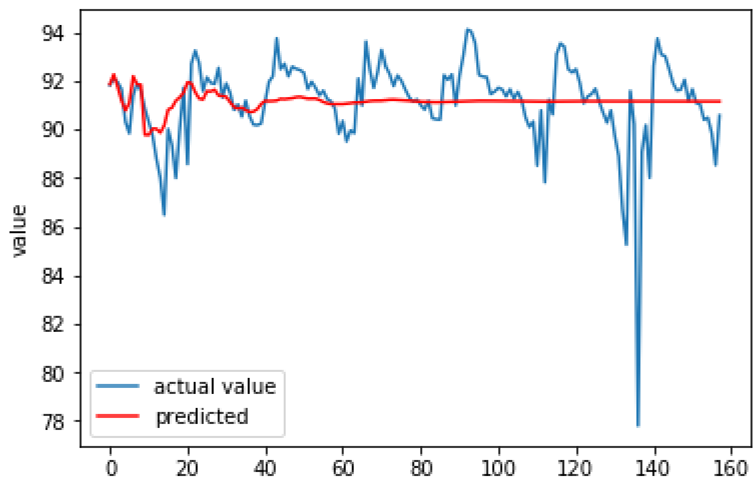
In [54]:
```
MEXGDLMSS1_x_test = MEXGDLMSS1_x_test.drop(columns=['kpi', 'unit', 'kpi_id',
'ne_hour', 'ne_id'])
```

[1.8.1] Plots comparing actual and predicted

In [55]:
```
actual = np.array(MEXGDLMSS1_x_test['value'])
predicted = MEXGDLMSS1_pred.values
```

In [59]:
```
plt.plot(actual, label='actual value')
plt.plot(predicted, color='red', label='predicted')
plt.ylabel('value')
plt.legend()
```

Out[59]: <matplotlib.legend.Legend at 0x1f872cde860>



The above graph shows the AR model clearly did not understand our data well. We will try various other models next

[1.9] ARIMA Model

In [60]:
```
#The three values are for AR model, Integrated order and moving average values

model_arima = ARIMA(MEXGDLMSS1_x_train, order=(3,1,6))
model_arima_fit = model_arima.fit(start_ar_lags=13)
print('the aic score is ', model_arima_fit.aic)
```

```
C:\Users\karth\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:
225: ValueWarning: A date index has been provided, but it has no associated f
requency information and so will be ignored when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)
C:\Users\karth\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:
225: ValueWarning: A date index has been provided, but it has no associated f
requency information and so will be ignored when e.g. forecasting.
  ' ignored when e.g. forecasting.', ValueWarning)

the aic score is  2412.0236755722703
```

In [61]:
```
MEXGDLMSS1_pred = (model_arima_fit.forecast(steps=158))
```

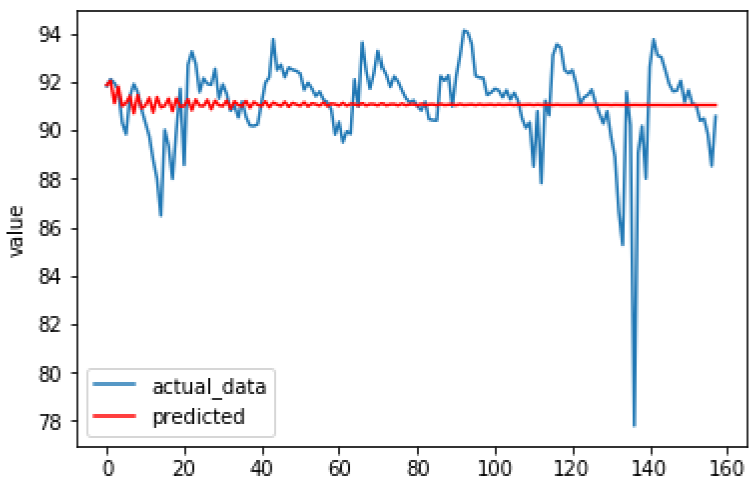
In [62]:
```
predicted = MEXGDLMSS1_pred[0]
```

Plots comparing actual and predicted

In [63]:
```
actual = np.array(MEXGDLMSS1_x_test['value'])
# predicted = MEXGDLMSS1_pred.values
```

In [66]:
```
plt.plot(actual, label='actual_data')
plt.plot(predicted, color='red', label='predicted')
plt.legend()
plt.ylabel('value')
```

Out[66]: Text(0,0.5,'value')



OK, Even ARIMA was not able to capture the dynamics in the data. Now lets start exploring Machine learning models

[1.10] Another Simple test for stationarity just to be sure

In [200]:
```
np.mean(MEXGDLMSS1_df['value'].values)
```

Out[200]: 91.16626262626262

In [201]:
```
np.mean(MEXGDLMSS1_x_train['value'].values)
```

Out[201]: 91.16900630914826

In [202]:
```
np.mean(MEXGDLMSS1_x_test['value'].values)
```

Out[202]: 91.15525316455697

In [203]:
```
from statistics import variance
```

In [204]:
```
variance(MEXGDLMSS1_x_train['value'].values)
```

Out[204]: 3.8055186002760877

In [205]:
```
variance(MEXGDLMSS1_x_test['value'].values)
```

Out[205]: 3.2076454769007507

[1.11] Machine learning approach

In [68]:
```
df = pd.read_csv('new_df.csv')
```

[1.11.1] XGBoost

[1.11.1.1] Lets create features for our data

In [131]:
```
def date_converter(date):
    return pd.datetime.strptime(date, '%Y-%m-%d')
```

In [132]:
```
new_df = pd.read_csv('new_df.csv', parse_dates=[3], date_parser=date_converter
, index_col=[3])
```

In [133]:
```
##credits: www.kaggle.coms

def create_features(df, label=None):
    """
    Creates time series features from datetime index
    """
    df['date'] = df.index
    df['hour'] = df['date'].dt.hour
    df['dayofweek'] = df['date'].dt.dayofweek
    df['quarter'] = df['date'].dt.quarter
    df['month'] = df['date'].dt.month
    df['year'] = df['date'].dt.year
    df['dayofyear'] = df['date'].dt.dayofyear
    df['dayofmonth'] = df['date'].dt.day
    df['weekofyear'] = df['date'].dt.weekofyear

    X = df[['hour','dayofweek','quarter','month','year',
           'dayofyear','dayofmonth','weekofyear']]
    if label:
        y = df[label]
        return X, y
    return X
```

In [135]:
```
xgboost_data = create_features(new_df, label='value')[0]
xgboost_labels = create_features(new_df, label='value')[1]

#hour data from the create_features functions seems to be incorrect. Therefor
e, we are adding in the original hour values
xgboost_data['hour'] = new_df['ne_hour'].values
xgboost_data['ne_id'] = new_df['ne_id']
xgboost_labels = pd.DataFrame(xgboost_labels, columns=['value'])
```

In [321]:
```
xgboost_data.to_csv('xgboost_data.csv', index=False)
xgboost_labels.to_csv('xgboost_labels.csv', index=False)
```

In [145]:
```
xgboost_data['labels'] = xgboost_labels
```

[1.11.2] We will split data based on the network device. There are 5 devices and hence we will have 5 datasets

In [147]:
```
xgboost_MEXGDLMSS1_df = xgboost_data[xgboost_data['ne_id'] == 'MEXGDLMSS1']
xgboost_MEXMTYMSS1_df = xgboost_data[xgboost_data['ne_id'] == 'MEXMTYMSS1']
xgboost_MEXMTYMSS2_df = xgboost_data[xgboost_data['ne_id'] == 'MEXMTYMSS2']
xgboost_MEXTIJMSS1_df = xgboost_data[xgboost_data['ne_id'] == 'MEXTIJMSS1']
xgboost_MEXTLAMSS1_df = xgboost_data[xgboost_data['ne_id'] == 'MEXTLAMSS1']
```

[1.11.3] Lets export all the induvidual datasets

In [349]:
```
xgboost_MEXGDLMSS1_df.to_csv('xgboost_MEXGDLMSS1_df.csv', index=False)
xgboost_MEXMTYMSS1_df.to_csv('xgboost_MEXMTYMSS1_df.csv', index=False)
xgboost_MEXMTYMSS2_df.to_csv('xgboost_MEXMTYMSS2_df.csv', index=False)
xgboost_MEXTIJMSS1_df.to_csv('xgboost_MEXTIJMSS1_df.csv', index=False)
xgboost_MEXTLAMSS1_df.to_csv('xgboost_MEXTLAMSS1_df.csv', index=False)
```

[1.11.4] Lets start modelling

For each network device's data we are splitting data as train and test. Since the data is already present in ascending date wise, We will take first 80% data as train and last 20% data as split

In [200]:
```
xgboost_MEXGDLMSS1_train = xgboost_MEXGDLMSS1_df[0:int(np.round(0.8*xgboost_ME
XGDLMSS1_df.shape[0]))]
xgboost_MEXGDLMSS1_test = xgboost_MEXGDLMSS1_df[int(np.round(0.8*xgboost_MEXGD
LMSS1_df.shape[0])):]

train_labels = xgboost_MEXGDLMSS1_train['labels']
test_labels = xgboost_MEXGDLMSS1_test['labels']

xgboost_MEXGDLMSS1_train = xgboost_MEXGDLMSS1_train.drop(columns=['ne_id', 'la
bels'])
xgboost_MEXGDLMSS1_test = xgboost_MEXGDLMSS1_test.drop(columns=['ne_id', 'labe
ls'])
```

[1.11.4] Run the model

In [214]:
```
reg = xgb.XGBRegressor(n_estimators=50)

reg.fit(xgboost_MEXGDLMSS1_train, train_labels)
```

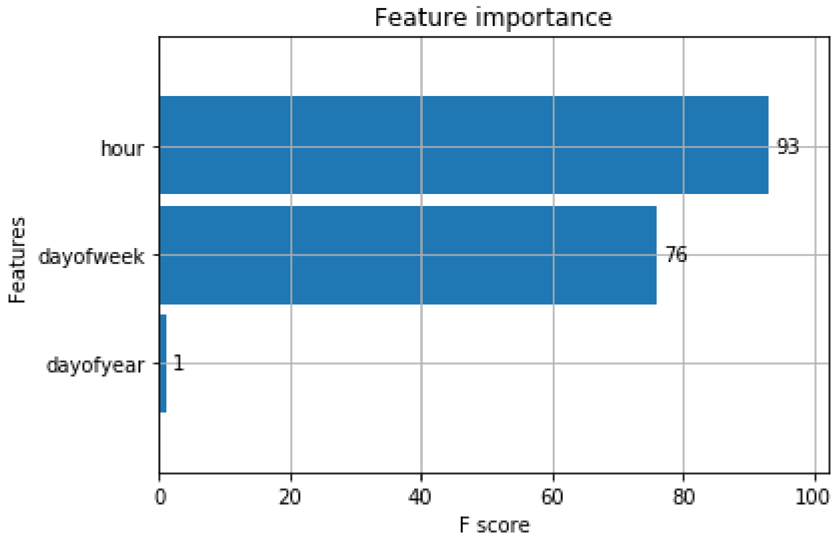
Out[214]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bytree=1, gamma=0, importance_type='gain',
             learning_rate=0.1, max_delta_step=0, max_depth=3,
             min_child_weight=1, missing=None, n_estimators=50, n_jobs=1,
             nthread=None, objective='reg:linear', random_state=0, reg_alpha=
0,
             reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
             subsample=1)
```

[1.11.5] Feature importance plots

These plots are very helpful as they convey which features are very important for prediction. From the below plot we understand that hour and dayofweek features have high FScore which means that hour and dayofweek are the most important value when the algorithm forecasts the predictor value

In [210]:
```
xgb.plot_importance(reg, height=0.9)
```

Out[210]: <matplotlib.axes._subplots.AxesSubplot at 0x1b0e9a67240>



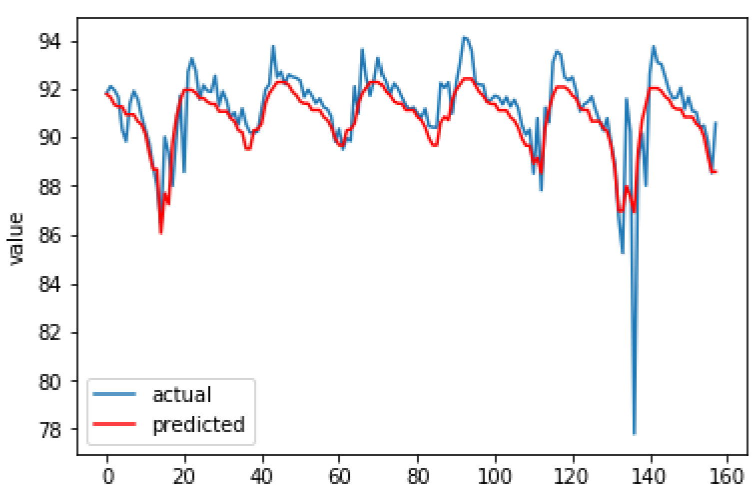
[1.11.6] prediction

In [211]:
```
pred = reg.predict(xgboost_MEXGDLMSS1_test)
```

[1.11.7] plots

In [212]:
```
plt.plot(test_labels.values, label='actual')
plt.plot(pred, color='red', label='predicted')
plt.ylabel('value')
plt.legend()
```

Out[212]: <matplotlib.legend.Legend at 0x1b0efad5588>



[1.11.8] metrics

In [219]:
```
print(mean_squared_error(test_labels.values, pred), ' is our mean squared erro
r')
```

```
1.3950209035836778  is our mean squared error
```

In [222]:
```
print(mean_absolute_error(test_labels.values, pred), ' is our mean absolute er
ror')
```

```
0.7408648585066012  is our mean absolute error
```

[1.12] Forecasting for unseen unknown data

[1.12.1] Here the last day in our test data is 02/11/2018 and so we will predict from 03/11/2018

Creates dates

In [223]:
```
import datetime
dt = datetime.datetime(2018, 11, 3)
end = datetime.datetime(2018, 11, 6, 23, 59, 59)
step = datetime.timedelta(seconds=3600)

result = []

while dt < end:
    result.append(dt.strftime('%Y-%m-%d'))
    dt += step
```

In [224]:
```
forecast_df = pd.DataFrame(data=[date_converter(i) for i in result], columns=[
'ne_date'])
```

In [225]:
```
#sanity check
Counter(forecast_df['ne_date'])
```

Out[225]:
```
Counter({Timestamp('2018-11-03 00:00:00'): 24,
         Timestamp('2018-11-04 00:00:00'): 24,
         Timestamp('2018-11-05 00:00:00'): 24,
         Timestamp('2018-11-06 00:00:00'): 24})
```

In [226]:
```
forecast_df = forecast_df.set_index(['ne_date'])
```

In [227]:
```
def date_converter(date):
    return pd.datetime.strptime(date, '%Y-%m-%d')
```

In [228]:
```
def new_create_features(df, label=None):
    """
    Creates time series features from datetime index
    """
    df['date'] = df.index
    df['hour'] = df['date'].dt.hour
    df['dayofweek'] = df['date'].dt.dayofweek
    df['quarter'] = df['date'].dt.quarter
    df['month'] = df['date'].dt.month
    df['year'] = df['date'].dt.year
    df['dayofyear'] = df['date'].dt.dayofyear
    df['dayofmonth'] = df['date'].dt.day
    df['weekofyear'] = df['date'].dt.weekofyear

    X = df[['hour','dayofweek','quarter','month','year',
           'dayofyear','dayofmonth','weekofyear']]
    if label:
        y = df[label]
        return X, y
    return X
```

In [229]:
```
forecast_df = new_create_features(forecast_df, label=None)
forecast_df['hour'] = (xgboost_MEXGDLMSS1_df['hour'].values[:96])
```

In [230]:
```
forecast_df.head()
```

Out[230]:

	hour	dayofweek	quarter	month	year	dayofyear	dayofmonth	weekofyear
ne_date								
2018-11-03	0	5	4	11	2018	307	3	44
2018-11-03	1	5	4	11	2018	307	3	44
2018-11-03	2	5	4	11	2018	307	3	44
2018-11-03	3	5	4	11	2018	307	3	44
2018-11-03	4	5	4	11	2018	307	3	44

So lets now predict for the next 3 days 3/11/2018 to 6/11/2018

In [231]:
```
pred = reg.predict(forecast_df)
```

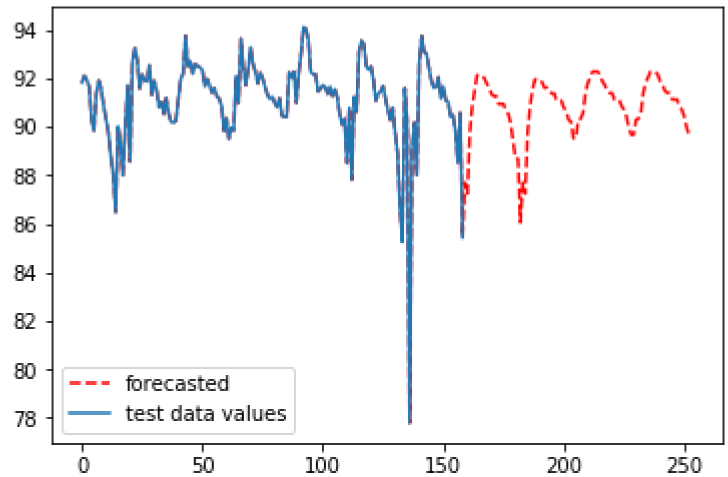
In [232]:
```
test_values = list(test_labels.values)
forecasted_values = list(pred)

print(len(test_values))
print(len(forecasted_values))
```

```
158
96
```

In [233]:
```
test_and_forecasted = test_values + forecasted_values
```

In [508]:
```
fig, ax = plt.subplots()
ax.plot(test_and_forecasted, 'r--',label='forecasted')
ax.plot(test_and_forecasted[0:159], label='test data values', )
plt.legend()
```

Out[508]: <matplotlib.legend.Legend at 0x152b838aac8>



Results

As we see the above results, We understand our model is performing better than the previously seen models without any hyperparameter tuning. Hence if we tune the model well, this should perform very well.

Now we will do the same for all the other network devices

Now for the next network device - MEXMTYMSS1

In [235]:
```
xgboost_MEXMTYMSS1_train = xgboost_MEXMTYMSS1_df[0:int(np.round(0.8*xgboost_ME
XMTYMSS1_df.shape[0]))]
xgboost_MEXMTYMSS1_test = xgboost_MEXMTYMSS1_df[int(np.round(0.8*xgboost_MEXMT
YMSS1_df.shape[0])):]
train_labels = xgboost_MEXMTYMSS1_train['labels']
test_labels = xgboost_MEXMTYMSS1_test['labels']
xgboost_MEXMTYMSS1_train = xgboost_MEXMTYMSS1_train.drop(columns=['ne_id', 'la
bels'])
xgboost_MEXMTYMSS1_test = xgboost_MEXMTYMSS1_test.drop(columns=['ne_id', 'labe
ls'])
```

checking shapes

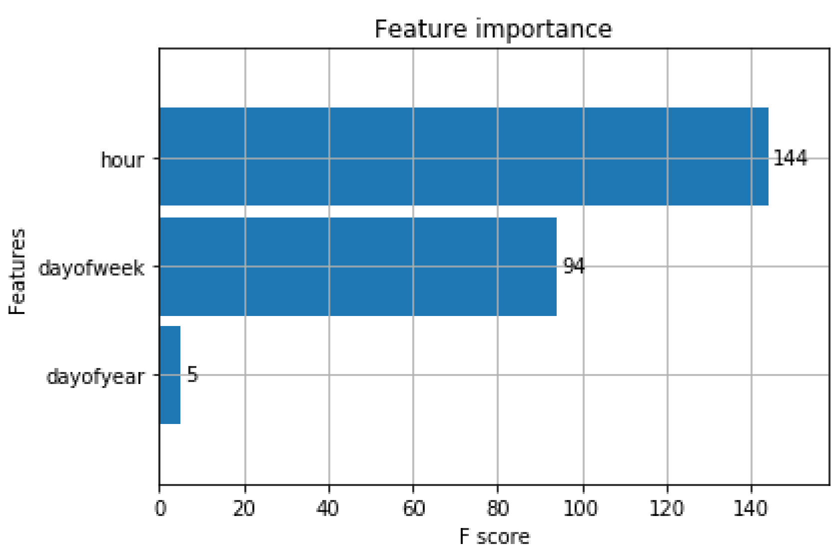
In [236]:
```
reg = xgb.XGBRegressor(n_estimators=50)
reg.fit(xgboost_MEXMTYMSS1_train, train_labels)
```

Out[236]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bytree=1, gamma=0, importance_type='gain',
             learning_rate=0.1, max_delta_step=0, max_depth=3,
             min_child_weight=1, missing=None, n_estimators=50, n_jobs=1,
             nthread=None, objective='reg:linear', random_state=0, reg_alpha=
0,
             reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
             subsample=1)
```

These plots are very helpful as they convey which features are very important for prediction. From the below plot we understand that hour and dayofweek features have high FScore which means that hour and dayofweek are the most important value when the algorithm forecasts the predictor value

In [238]:
```
xgb.plot_importance(reg, height=0.9)
```

Out[238]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1b0e9966f98>
```



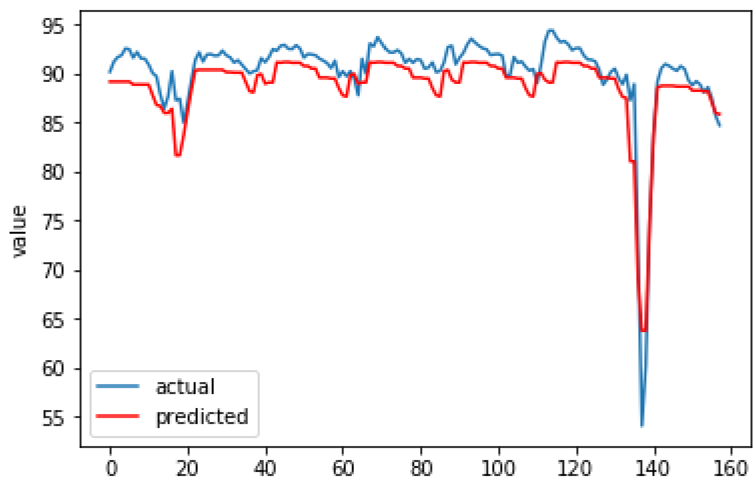
prediction

In [239]:
```
pred = reg.predict(xgboost_MEXMTYMSS1_test)
```

plots on test data

In [240]:
```
plt.plot(test_labels.values, label='actual')
plt.plot(pred, color='red', label='predicted')
plt.ylabel('value')
plt.legend()
```

Out[240]: <matplotlib.legend.Legend at 0x1b0efc18e10>



metrics

In [243]:
```
print(mean_squared_error(test_labels.values, pred), ' is our mean squared erro
r')
```

```
5.078298504704865  is our mean squared error
```

In [244]:
```
print(mean_absolute_error(test_labels.values, pred),  ' is our mean absolute e
rror')
```

```
1.8163311960727353  is our mean absolute error
```

So lets now predict for the next 3 days 3/11/2018 to 6/11/2018

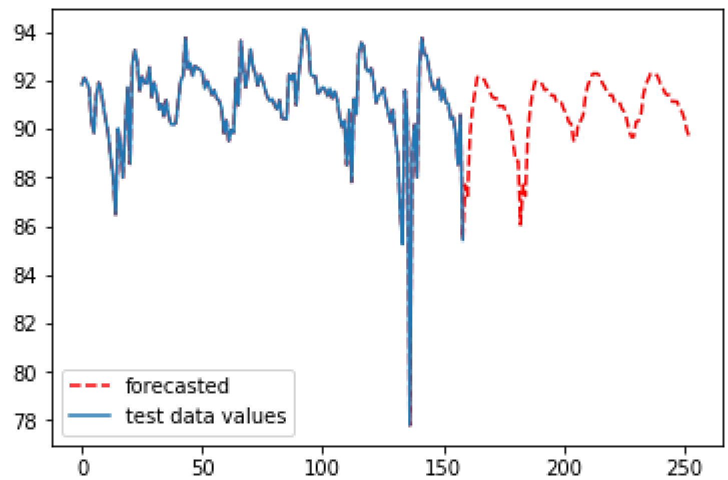
In [245]:
```
pred = reg.predict(forecast_df)
```

In [247]:
```
test_values = list(test_labels.values)
forecasted_values = list(pred)
```

In [533]:
```
test_and_forecasted = test_values + forecasted_values
```

In [248]:
```
fig, ax = plt.subplots()
ax.plot(test_and_forecasted, 'r--',label='forecasted')
ax.plot(test_and_forecasted[0:159], label='test data values', )
plt.legend()
```

Out[248]: <matplotlib.legend.Legend at 0x1b0efc95320>



Now for the next network device - MEXMTYMSS2

modelling

In [249]:
```
xgboost_MEXMTYMSS2_train = xgboost_MEXMTYMSS2_df[0:int(np.round(0.8*xgboost_ME
XMTYMSS2_df.shape[0]))]
xgboost_MEXMTYMSS2_test = xgboost_MEXMTYMSS2_df[int(np.round(0.8*xgboost_MEXMT
YMSS2_df.shape[0])):]
train_labels = xgboost_MEXMTYMSS2_train['labels']
test_labels = xgboost_MEXMTYMSS2_test['labels']
xgboost_MEXMTYMSS2_train = xgboost_MEXMTYMSS2_train.drop(columns=['labels', 'n
e_id'])
xgboost_MEXMTYMSS2_test = xgboost_MEXMTYMSS2_test.drop(columns=['labels', 'ne_
id'])
```

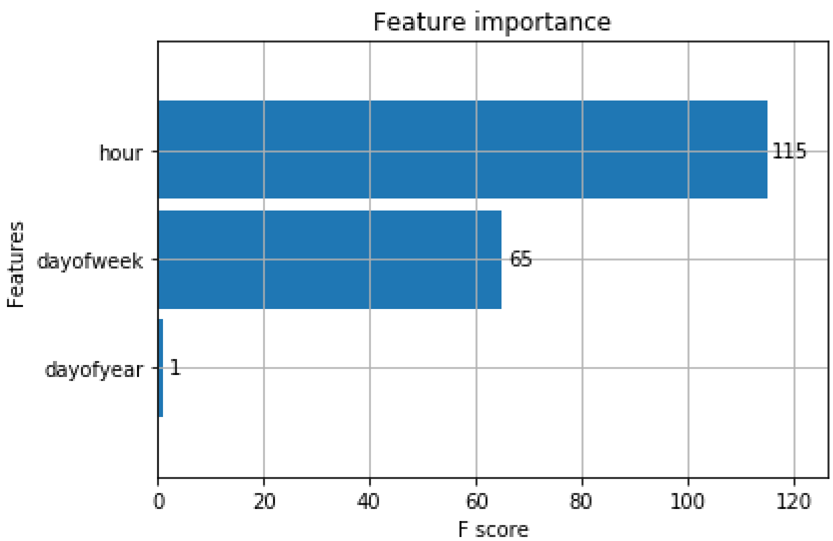
In [250]:
```
reg = xgb.XGBRegressor(n_estimators=50)
reg.fit(xgboost_MEXMTYMSS2_train, train_labels)
```

Out[250]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bytree=1, gamma=0, importance_type='gain',
             learning_rate=0.1, max_delta_step=0, max_depth=3,
             min_child_weight=1, missing=None, n_estimators=50, n_jobs=1,
             nthread=None, objective='reg:linear', random_state=0, reg_alpha=
0,
             reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
             subsample=1)
```

These plots are very helpful as they convey which features are very important for prediction. From the below plot we understand that hour and dayofweek features have high FScore which means that hour and dayofweek are the most important value when the algorithm forecasts the predictor value

In [252]:
```
xgb.plot_importance(reg, height=0.9)
```

Out[252]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1b0efcd19b0>
```



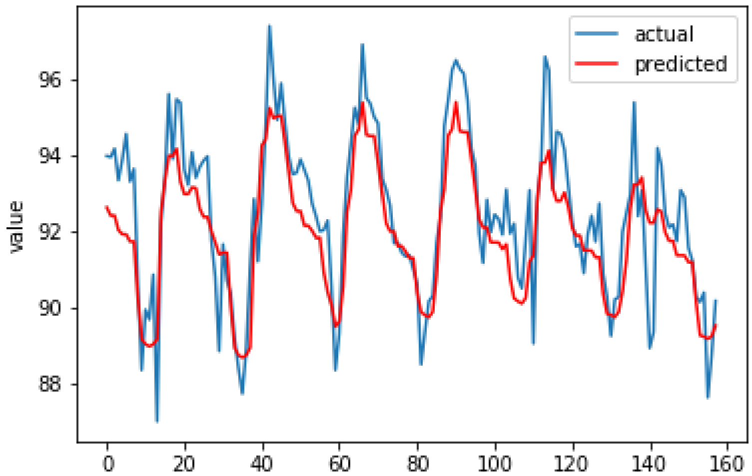
prediction

In [253]:
```
pred = reg.predict(xgboost_MEXMTYMSS2_test)
```

plots on test data

In [254]:
```
plt.plot(test_labels.values, label='actual')
plt.plot(pred, color='red', label='predicted')
plt.ylabel('value')
plt.legend()
```

Out[254]: <matplotlib.legend.Legend at 0x1b0efd62a58>



metrics

In [256]:
```
print(mean_squared_error(test_labels.values, pred), ' is our mean squared erro
r')
```

```
1.3493126710692576  is our mean squared error
```

In [257]:
```
print(mean_absolute_error(test_labels.values, pred), ' is our mean absolute er
ror')
```

```
0.9400626267058939  is our mean absolute error
```

So lets now predict for the next 3 days 3/11/2018 to 6/11/2018

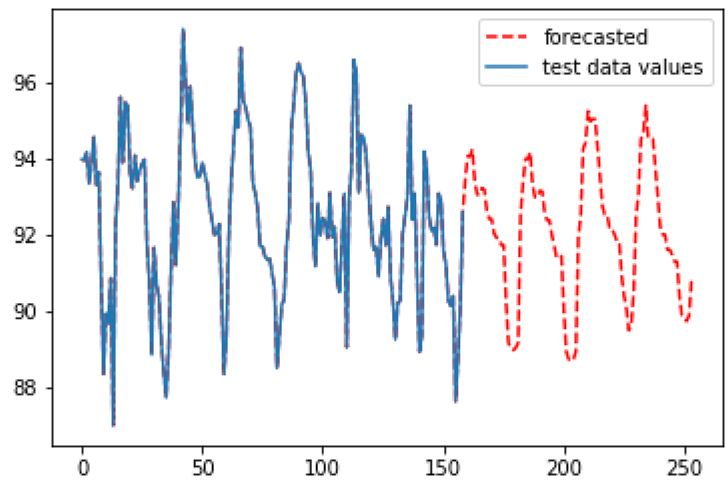
In [258]:
```
pred = reg.predict(forecast_df)
```

In [259]:
```
test_values = list(test_labels.values)
forecasted_values = list(pred)
```

In [260]:
```
test_and_forecasted = test_values + forecasted_values
```

In [261]:
```
fig, ax = plt.subplots()
ax.plot(test_and_forecasted, 'r--',label='forecasted')
ax.plot(test_and_forecasted[0:159], label='test data values', )
plt.legend()
```

Out[261]: <matplotlib.legend.Legend at 0x1b0efdcba58>



Now for the next network device - MEXTIJMSS1

modelling

In [262]:
```
xgboost_MEXTIJMSS1_train = xgboost_MEXTIJMSS1_df[0:int(np.round(0.8*xgboost_ME
XTIJMSS1_df.shape[0]))]
xgboost_MEXTIJMSS1_test = xgboost_MEXTIJMSS1_df[int(np.round(0.8*xgboost_MEXTI
JMSS1_df.shape[0])):]
train_labels = xgboost_MEXTIJMSS1_train['labels']
test_labels = xgboost_MEXTIJMSS1_test['labels']
xgboost_MEXTIJMSS1_train = xgboost_MEXTIJMSS1_train.drop(columns=['ne_id','lab
els'])
xgboost_MEXTIJMSS1_test = xgboost_MEXTIJMSS1_test.drop(columns=['ne_id','label
s'])
```

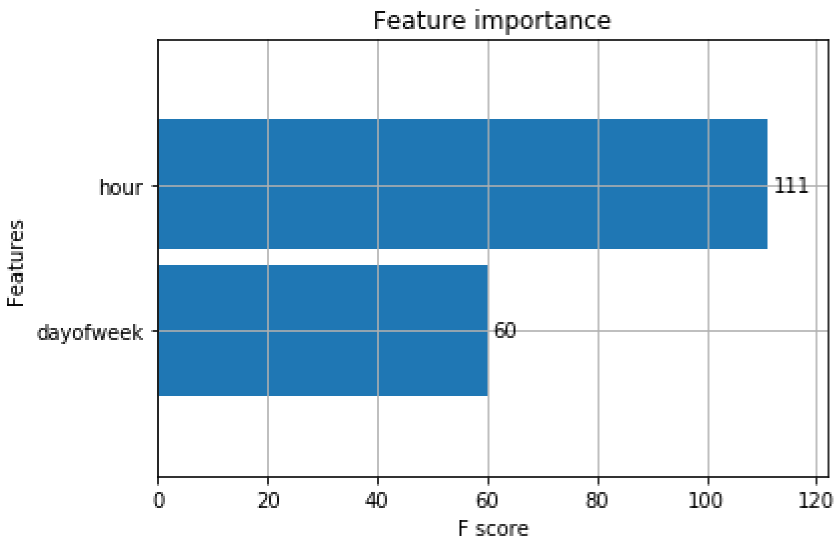
In [263]:
```
reg = xgb.XGBRegressor(n_estimators=50)
reg.fit(xgboost_MEXTIJMSS1_train, train_labels)
```

Out[263]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bytree=1, gamma=0, importance_type='gain',
             learning_rate=0.1, max_delta_step=0, max_depth=3,
             min_child_weight=1, missing=None, n_estimators=50, n_jobs=1,
             nthread=None, objective='reg:linear', random_state=0, reg_alpha=
0,
             reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
             subsample=1)
```

These plots are very helpful as they convey which features are very important for prediction. From the below plot we understand that hour and dayofweek features have high FScore which means that hour and dayofweek are the most important value when the algorithm forecasts the predictor value

In [264]:
```
xgb.plot_importance(reg, height=0.9)
```

Out[264]: <matplotlib.axes._subplots.AxesSubplot at 0x1b0efd17cc0>



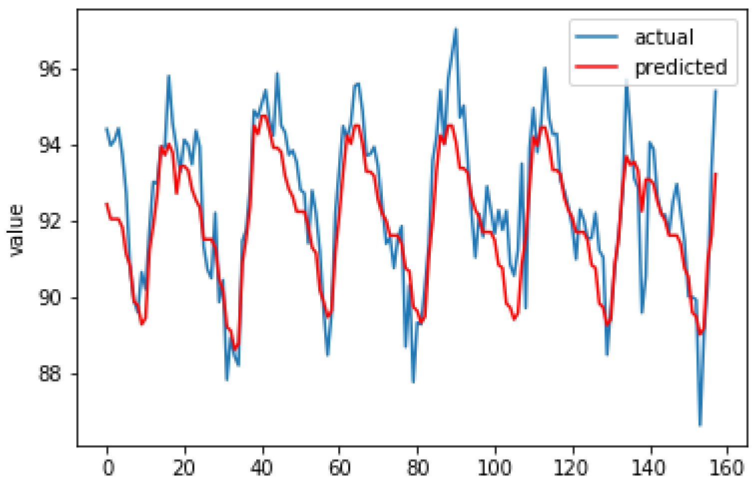
prediction

In [265]:
```
pred = reg.predict(xgboost_MEXTIJMSS1_test)
```

plots on test data

In [266]:
```
plt.plot(test_labels.values, label='actual')
plt.plot(pred, color='red', label='predicted')
plt.ylabel('value')
plt.legend()
```

Out[266]: <matplotlib.legend.Legend at 0x1b0f0e52e48>



metrics

In [267]:
```
print(mean_squared_error(test_labels.values, pred), ' is our mean squared erro
r')
```

```
1.192999459932552  is our mean squared error
```

In [268]:
```
print(mean_absolute_error(test_labels.values, pred), ' is mean absolute error'
)
```

```
0.8584582152547714  is mean absolute error
```

So lets now predict for the next 3 days 3/11/2018 to 6/11/2018

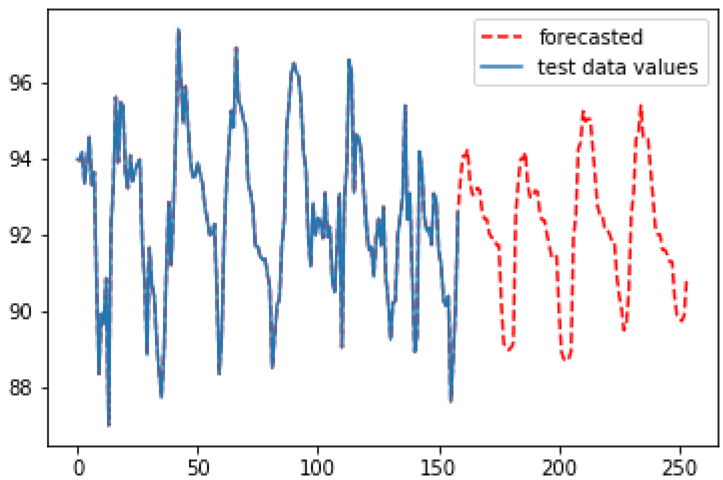
In [269]:
```
pred = reg.predict(forecast_df)
```

In [270]:
```
test_values = list(test_labels.values)
forecasted_values = list(pred)
```

In [578]:
```
test_and_forecasted = test_values + forecasted_values
```

In [271]:
```
fig, ax = plt.subplots()
ax.plot(test_and_forecasted, 'r--',label='forecasted')
ax.plot(test_and_forecasted[0:159], label='test data values', )
plt.legend()
```

Out[271]: <matplotlib.legend.Legend at 0x1b0f0ebcd68>



Now for the next network device

Now for the next network device - MEXTLAMSS1

modelling

In [272]:
```
xgboost_MEXTLAMSS1_train = xgboost_MEXTLAMSS1_df[0:int(np.round(0.8*xgboost_ME
XTLAMSS1_df.shape[0]))]
xgboost_MEXTLAMSS1_test = xgboost_MEXTLAMSS1_df[int(np.round(0.8*xgboost_MEXTL
AMSS1_df.shape[0])):]
train_labels = xgboost_MEXTLAMSS1_train['labels']
test_labels = xgboost_MEXTLAMSS1_test['labels']
xgboost_MEXTLAMSS1_train = xgboost_MEXTLAMSS1_train.drop(columns=['ne_id','lab
els'])
xgboost_MEXTLAMSS1_test = xgboost_MEXTLAMSS1_test.drop(columns=['ne_id','label
s'])
```

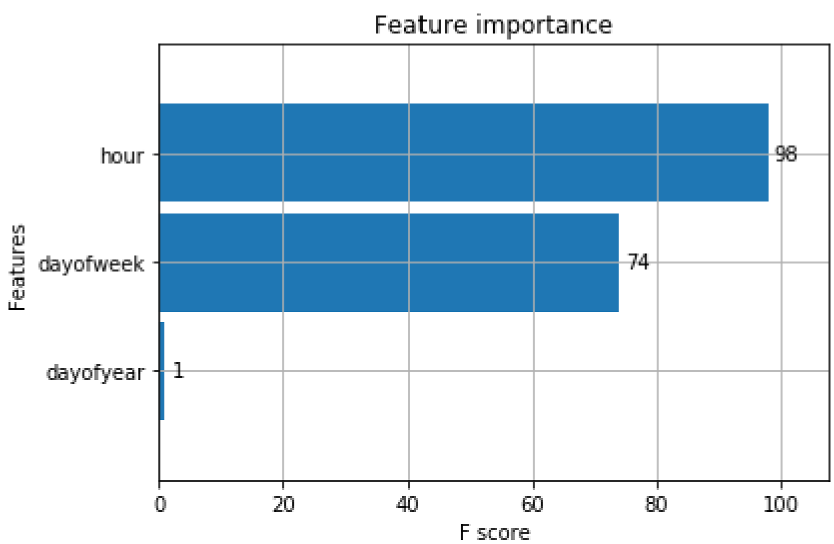
In [273]:
```
reg = xgb.XGBRegressor(n_estimators=50)
reg.fit(xgboost_MEXTLAMSS1_train, train_labels)
```

Out[273]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bytree=1, gamma=0, importance_type='gain',
             learning_rate=0.1, max_delta_step=0, max_depth=3,
             min_child_weight=1, missing=None, n_estimators=50, n_jobs=1,
             nthread=None, objective='reg:linear', random_state=0, reg_alpha=
0,
             reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
             subsample=1)
```

These plots are very helpful as they convey which features are very important for prediction. From the below plot we understand that hour and dayofweek features have high FScore which means that hour and dayofweek are the most important value when the algorithm forecasts the predictor value

In [274]:
```
xgb.plot_importance(reg, height=0.9)
```

Out[274]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1b0f0ef42e8>
```



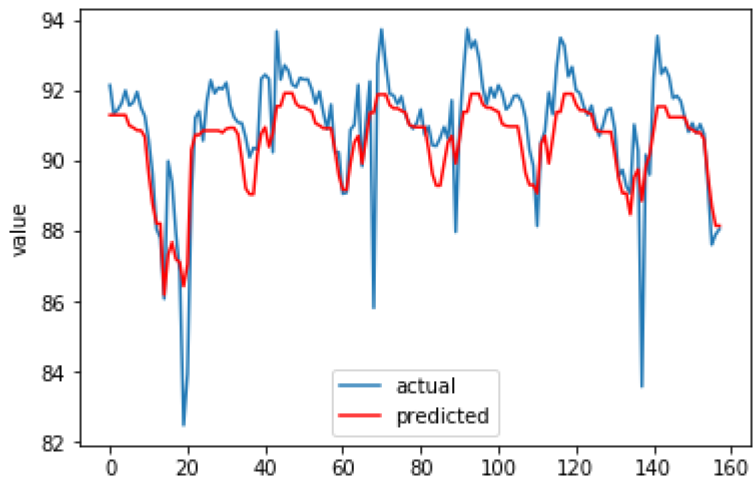
prediction

In [275]:
```
pred = reg.predict(xgboost_MEXTLAMSS1_test)
```

plots on test data

In [276]:
```
plt.plot(test_labels.values, label='actual')
plt.plot(pred, color='red', label='predicted')
plt.ylabel('value')
plt.legend()
```

Out[276]: <matplotlib.legend.Legend at 0x1b0f0f7f630>



metrics

In [277]:
```
print(mean_squared_error(test_labels.values, pred), ' is our mean squared erro
r')
```

```
1.344164337904645  is our mean squared error
```

In [278]:
```
print(mean_absolute_error(test_labels.values, pred), ' is our mean absolute er
ror')
```

```
0.823427440788172  is our mean absolute error
```

So lets now predict for the next 3 days 3/11/2018 to 6/11/2018

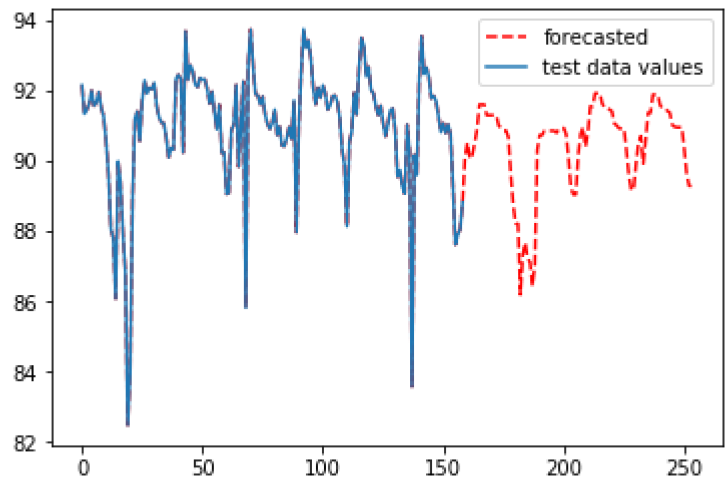
In [279]:
```
pred = reg.predict(forecast_df)
```

In [280]:
```
test_values = list(test_labels.values)
forecasted_values = list(pred)
```

In [281]:
```
test_and_forecasted = test_values + forecasted_values
```

In [282]:
```
fig, ax = plt.subplots()
ax.plot(test_and_forecasted, 'r--',label='forecasted')
ax.plot(test_and_forecasted[0:159], label='test data values', )
plt.legend()
```

Out[282]: <matplotlib.legend.Legend at 0x1b0f0fee080>



Now for the next network device - MEXTLAMSS1

modelling

In [283]:
```
xgboost_MEXTLAMSS1_train = xgboost_MEXTLAMSS1_df[0:int(np.round(0.8*xgboost_ME
XTLAMSS1_df.shape[0]))]
xgboost_MEXTLAMSS1_test = xgboost_MEXTLAMSS1_df[int(np.round(0.8*xgboost_MEXTL
AMSS1_df.shape[0])):]
train_labels = xgboost_MEXTLAMSS1_train['labels']
test_labels = xgboost_MEXTLAMSS1_test['labels']
xgboost_MEXTLAMSS1_train = xgboost_MEXTLAMSS1_train.drop(columns=['ne_id','lab
els'])
xgboost_MEXTLAMSS1_test = xgboost_MEXTLAMSS1_test.drop(columns=['ne_id','label
s'])
```

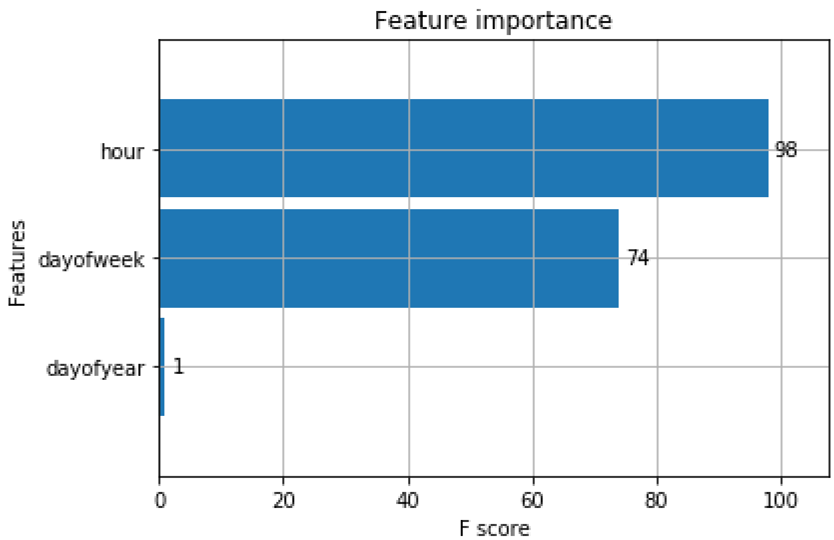
In [284]:
```
reg = xgb.XGBRegressor(n_estimators=50)
reg.fit(xgboost_MEXTLAMSS1_train, train_labels)
```

Out[284]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bytree=1, gamma=0, importance_type='gain',
             learning_rate=0.1, max_delta_step=0, max_depth=3,
             min_child_weight=1, missing=None, n_estimators=50, n_jobs=1,
             nthread=None, objective='reg:linear', random_state=0, reg_alpha=
0,
             reg_lambda=1, scale_pos_weight=1, seed=None, silent=True,
             subsample=1)
```

These plots are very helpful as they convey which features are very important for prediction. From the below plot we understand that hour and dayofweek features have high FScore which means that hour and dayofweek are the most important value when the algorithm forecasts the predictor value

In [285]:
```
xgb.plot_importance(reg, height=0.9)
```

Out[285]: <matplotlib.axes._subplots.AxesSubplot at 0x1b0f101def0>



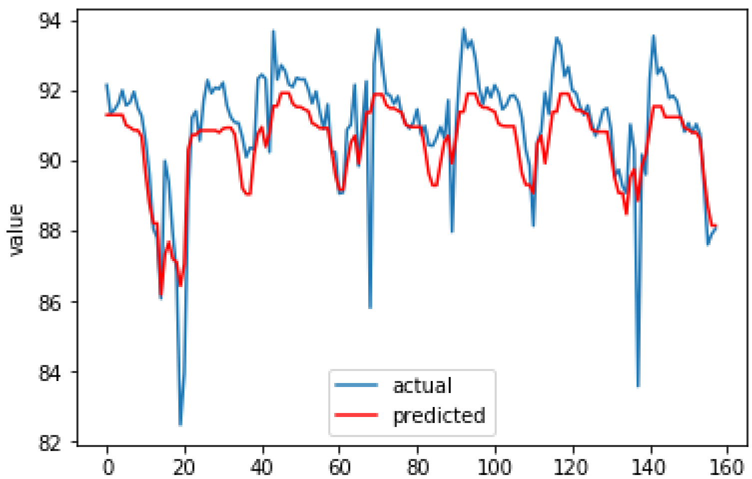
prediction

In [286]:
```
pred = reg.predict(xgboost_MEXTLAMSS1_test)
```

plots

In [287]:
```
plt.plot(test_labels.values, label='actual')
plt.plot(pred, color='red', label='predicted')
plt.ylabel('value')
plt.legend()
```

Out[287]: <matplotlib.legend.Legend at 0x1b0f10a7be0>



metrics

In [288]:
```
print(mean_squared_error(test_labels.values, pred), ' is our mean squared erro
r')
```

```
1.344164337904645  is our mean squared error
```

In [289]:
```
print(mean_absolute_error(test_labels.values, pred), ' is our mean absolute er
ror')
```

```
0.823427440788172  is our mean absolute error
```

So lets now predict for the next 3 days 3/11/2018 to 6/11/2018

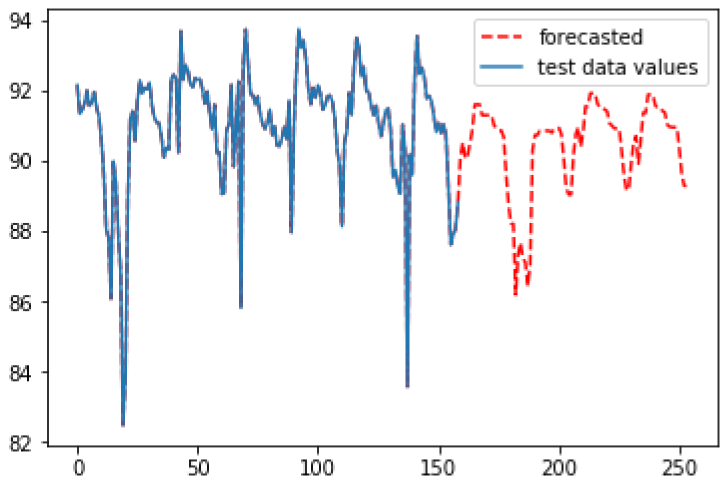
In [290]:
```
pred = reg.predict(forecast_df)
```

In [292]:
```
test_values = list(test_labels.values)
forecasted_values = list(pred)
```

In [293]:
```
test_and_forecasted = test_values + forecasted_values
```

In [294]:
```
fig, ax = plt.subplots()
ax.plot(test_and_forecasted, 'r--',label='forecasted')
ax.plot(test_and_forecasted[0:159], label='test data values', )
plt.legend()
```

Out[294]: <matplotlib.legend.Legend at 0x1b0f111db38>



Therefore, we have forecasted the value feature for all the 5 network devices for the next 2-3 days with a good accuracy which can be further improved

Results and discussions

The above is the detailed report of all the methods/algorithms I used to solve the problem of forecasting the value column for the next two days. Since this is a time series data, my first approach was to use statistical models such as AR, ARIMA etc. After trying with both of them, I got to know that their results were bad by their prediction plots of the test data. Next I tried non linear models that use decision trees as based learners. Decision trees are a tree based algorithm which splits the tree based on the amount of entropy reduced or amount of information gained by a feature. Random forests regressor and XGBoost are advanced versions of Decision tree as they contain lot of decision trees(n_estimators is a hyperparameter and needs to be tuned). After starting to use non linear models, the predictions became good and hence we solved this problem using XGBoost regressor

Which metrics did I use?
Since what we are solving is a regression problem, I used mean absolute error and mean squared error as my error metric to express the results as other commonly used metrics such as accuracy, precision, recall are classification metrics and will not work with regression.

Why did I choose XGBoost regressor?
XGBoost regressor aka boosting is a form of Gradient boosted decision trees from sklearn. It generally performs better on all kind of problem equal to standard linear models if not better. It's very effective for this kind of time series prediction problem because every set of inputs are row sampled with replacement and column sampled without replacement. This method of feeding in input creates better generalization of model to our data and moreover our model is trained on difference between actual valuse and predicted values during training which is very similar to moving averages model but in a better manner. Decision trees are the base learners in XGBoost with shallow depth and so they start with high bias, low variance and end up having reduced bias,low variance. Considering all the above positive facts about the model, I chose XGBoost regressor to solve this problem

Forecast plots
All my forecast plots have been plotted along with history on the XGBoost predicition for each of the network device above as you may have noticed

Note:
The code I have written above can be further optimized and repetability can be removed for better performance. The plots I had use here are simple and can be improved to better suit our needs if needed in future

*****THE END*****