Neural Network (Gas Turbines)

predicting turbine energy yield (TEY) using ambient variables as features.

The dataset contains 36733 instances of 11 sensor measures aggregated over one hour (by means of average or sum) from a gas turbine.
The Dataset includes gas turbine parameters (such as Turbine Inlet Temperature and Compressor Discharge pressure) in addition to the ambient variables.

The explanations of sensor measurements and their brief statistics are given below.

Variable (Abbr.) Unit Min Max Mean
Ambient temperature (AT) C â€“6.23 37.10 17.71
Ambient pressure (AP) mbar 985.85 1036.56 1013.07
Ambient humidity (AH) (%) 24.08 100.20 77.87
Air filter difference pressure (AFDP) mbar 2.09 7.61 3.93
Gas turbine exhaust pressure (GTEP) mbar 17.70 40.72 25.56
Turbine inlet temperature (TIT) C 1000.85 1100.89 1081.43
Turbine after temperature (TAT) C 511.04 550.61 546.16
Compressor discharge pressure (CDP) mbar 9.85 15.16 12.06
Turbine energy yield (TEY) MWH 100.02 179.50 133.51
Carbon monoxide (CO) mg/m3 0.00 44.10 2.37
Nitrogen oxides (NOx) mg/m3 25.90 119.91 65.29

1. import Libs

In [36]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
import keras
from sklearn.model_selection import GridSearchCV, KFold
from keras.models import Sequential
from keras.layers import Dense, Activation,Layer,Lambda
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import cross_val_score
from sklearn.decomposition import PCA
from mlxtend.plotting import plot_decision_regions
from keras.models import Sequential
from keras.callbacks import History
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
import tensorflow as tf
from keras.wrappers.scikit_learn import KerasRegressor
from tensorflow.keras.optimizers import Adam
from keras.layers import Dropout
tf.config.experimental.list_physical_devices('GPU')
history = History()
import warnings
warnings.filterwarnings('ignore')
```

2. Import Data

In [4]:

```
gas_tubine = pd.read_csv('gas_turbines.csv')
gas_tubine
```

Out[4]:

	AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY	CDP	CO	NOX
0	6.8594	1007.9	96.799	3.5000	19.663	1059.2	550.00	114.70	10.605	3.1547	82.722
1	6.7850	1008.4	97.118	3.4998	19.728	1059.3	550.00	114.72	10.598	3.2363	82.776
2	6.8977	1008.8	95.939	3.4824	19.779	1059.4	549.87	114.71	10.601	3.2012	82.468
3	7.0569	1009.2	95.249	3.4805	19.792	1059.6	549.99	114.72	10.606	3.1923	82.670
4	7.3978	1009.7	95.150	3.4976	19.765	1059.7	549.98	114.72	10.612	3.2484	82.311
...	...	...	...	...	...	...	...	...	...	...	...
15034	9.0301	1005.6	98.460	3.5421	19.164	1049.7	546.21	111.61	10.400	4.5186	79.559
15035	7.8879	1005.9	99.093	3.5059	19.414	1046.3	543.22	111.78	10.433	4.8470	79.917
15036	7.2647	1006.3	99.496	3.4770	19.530	1037.7	537.32	110.19	10.483	7.9632	90.912
15037	7.0060	1006.8	99.008	3.4486	19.377	1043.2	541.24	110.74	10.533	6.2494	93.227
15038	6.9279	1007.2	97.533	3.4275	19.306	1049.9	545.85	111.58	10.583	4.9816	92.498

15039 rows × 11 columns

3. EDA

In [5]:

```
gas_tubine.isna().sum()
```

Out[5]:

```
AT      0
AP      0
AH      0
AFDP    0
GTEP    0
TIT     0
TAT     0
TEY     0
CDP     0
CO      0
NOX     0
dtype: int64
```

In [6]:

```
gas_tubine.dtypes
```

Out[6]:

```
AT      float64
AP      float64
AH      float64
AFDP    float64
GTEP    float64
TIT     float64
TAT     float64
TEY     float64
CDP     float64
CO      float64
NOX     float64
dtype: object
```

In [7]:

```
gas_tubine.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	I
AT	15039.0	17.764381	7.574323	0.522300	11.408000	18.1860	23.8625	34.9
AP	15039.0	1013.199240	6.410760	985.850000	1008.900000	1012.8000	1016.9000	1034.2
AH	15039.0	79.124174	13.793439	30.344000	69.750000	82.2660	90.0435	100.2
AFDP	15039.0	4.200294	0.760197	2.087400	3.723900	4.1862	4.5509	7.6
GTEP	15039.0	25.419061	4.173916	17.878000	23.294000	25.0820	27.1840	37.4
TIT	15039.0	1083.798770	16.527806	1000.800000	1079.600000	1088.7000	1096.0000	1100.8
TAT	15039.0	545.396183	7.866803	512.450000	542.170000	549.8900	550.0600	550.6
TEY	15039.0	134.188464	15.829717	100.170000	127.985000	133.7800	140.8950	174.6
CDP	15039.0	12.102353	1.103196	9.904400	11.622000	12.0250	12.5780	15.0
CO	15039.0	1.972499	2.222206	0.000388	0.858055	1.3902	2.1604	44.1
NOX	15039.0	68.190934	10.470586	27.765000	61.303500	66.6010	73.9355	119.8

In [9]:

```
# check for duplicate data
duplicate = gas_tubine.duplicated()
print(duplicate.sum())
gas_tubine[duplicate]
```

```
0
```

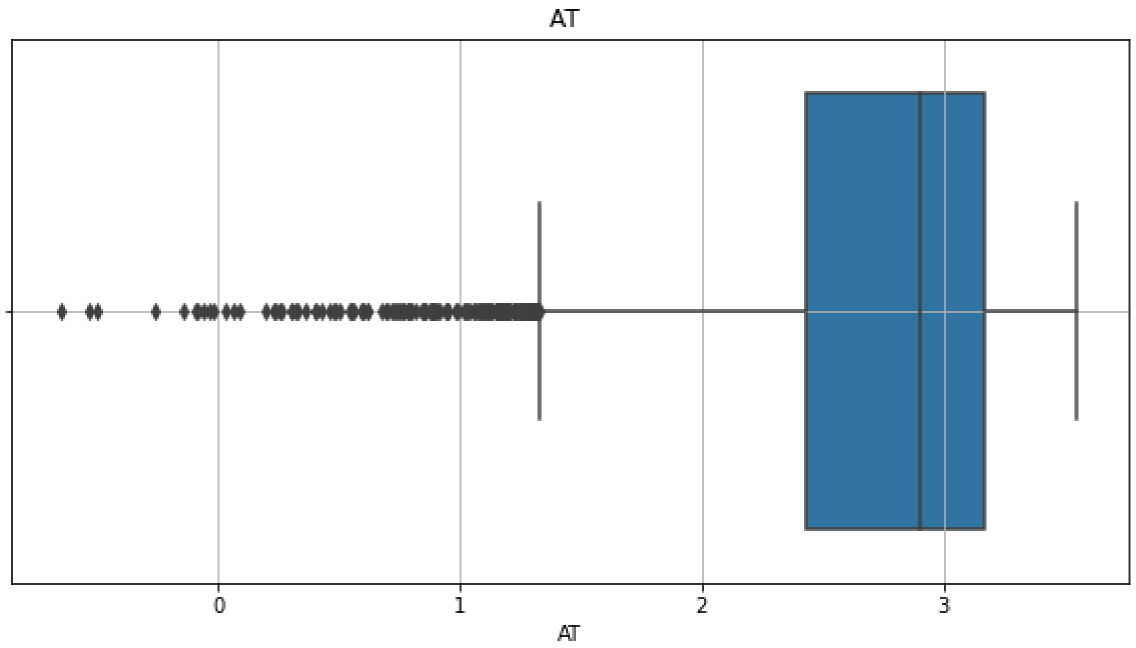
Out[9]:

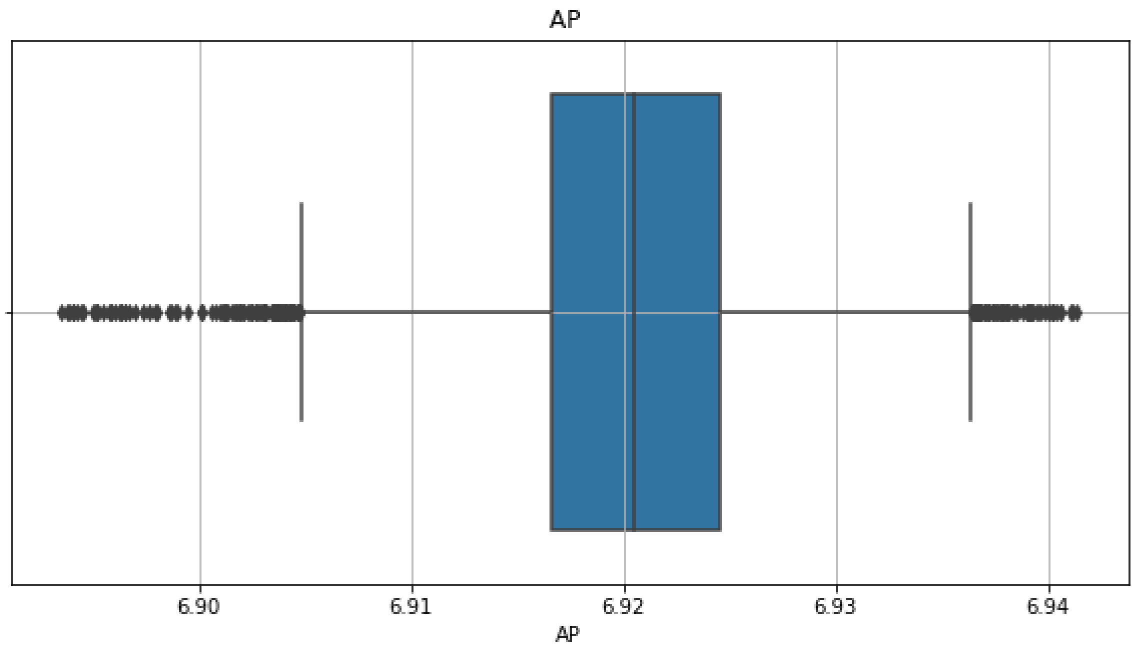
AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY	CDP	CO	NOX

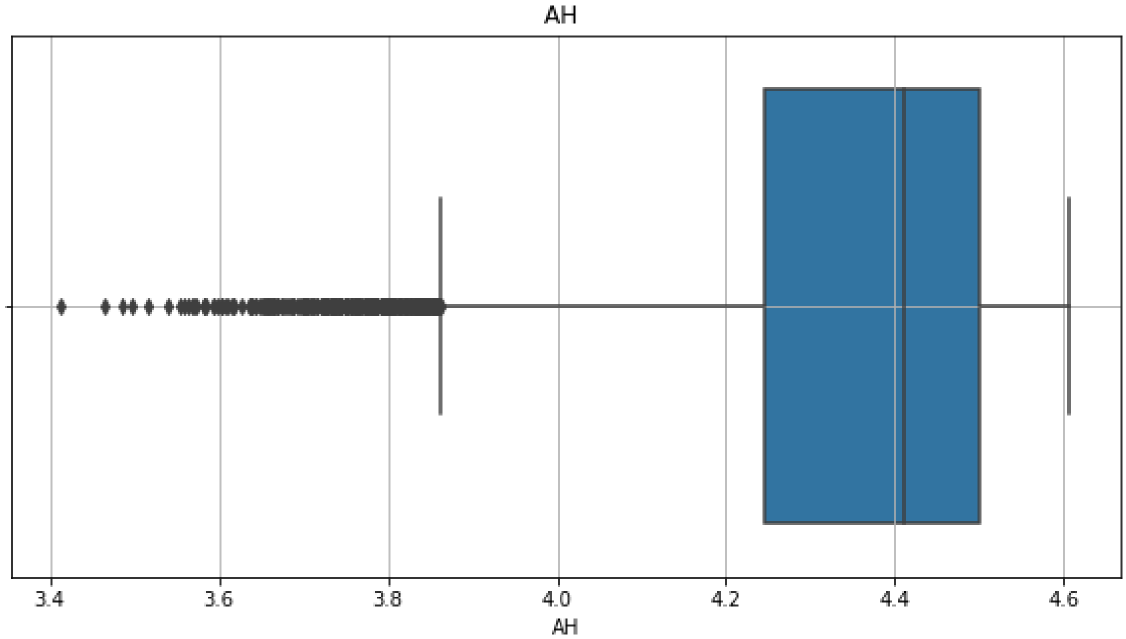
Checking Outlires

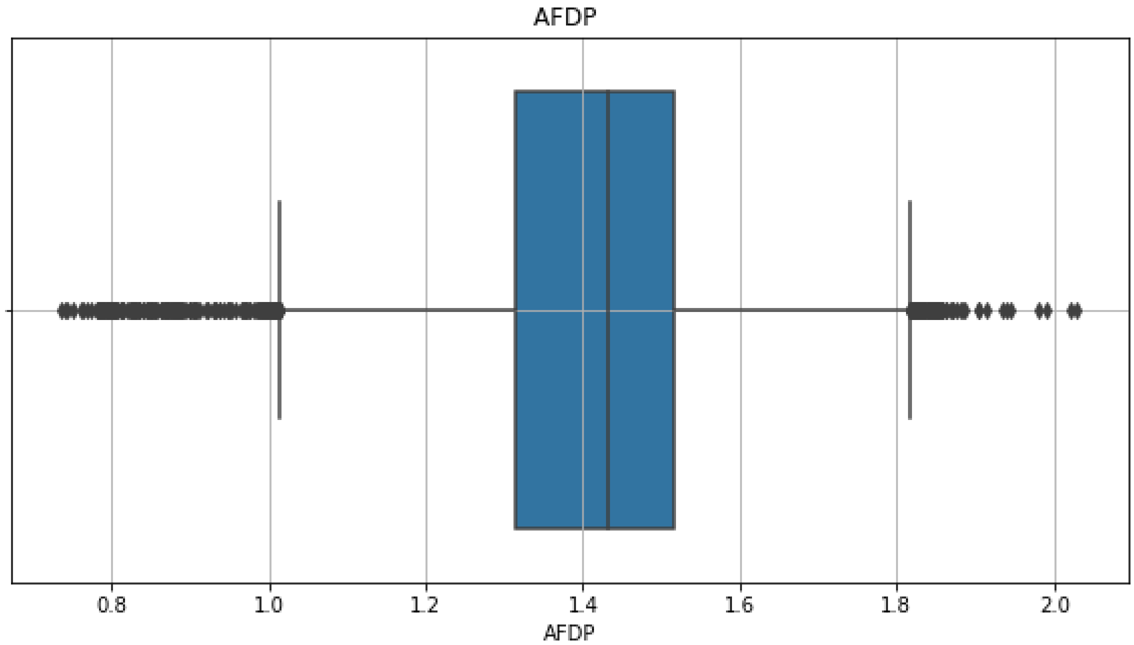
In [10]:

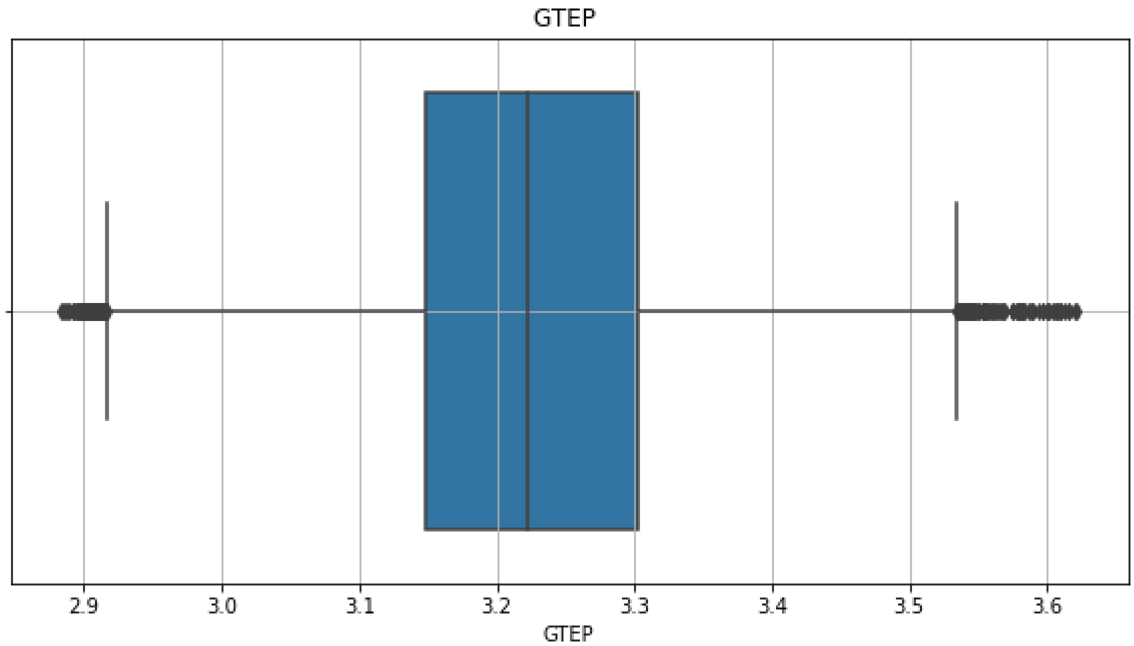
```
for i in gas_tubine.columns:
        plt.figure(figsize=(10,5))
        sns.boxplot(np.log(gas_tubine[i]))
        plt.title(i+ ' ')
        plt.grid()
        plt.show()
```

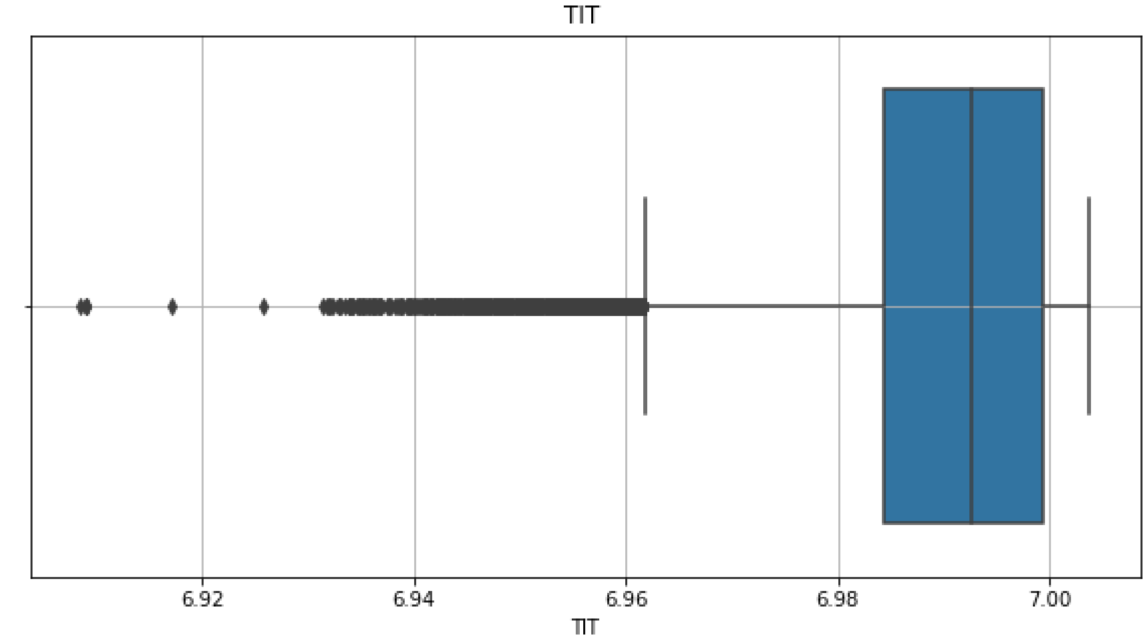


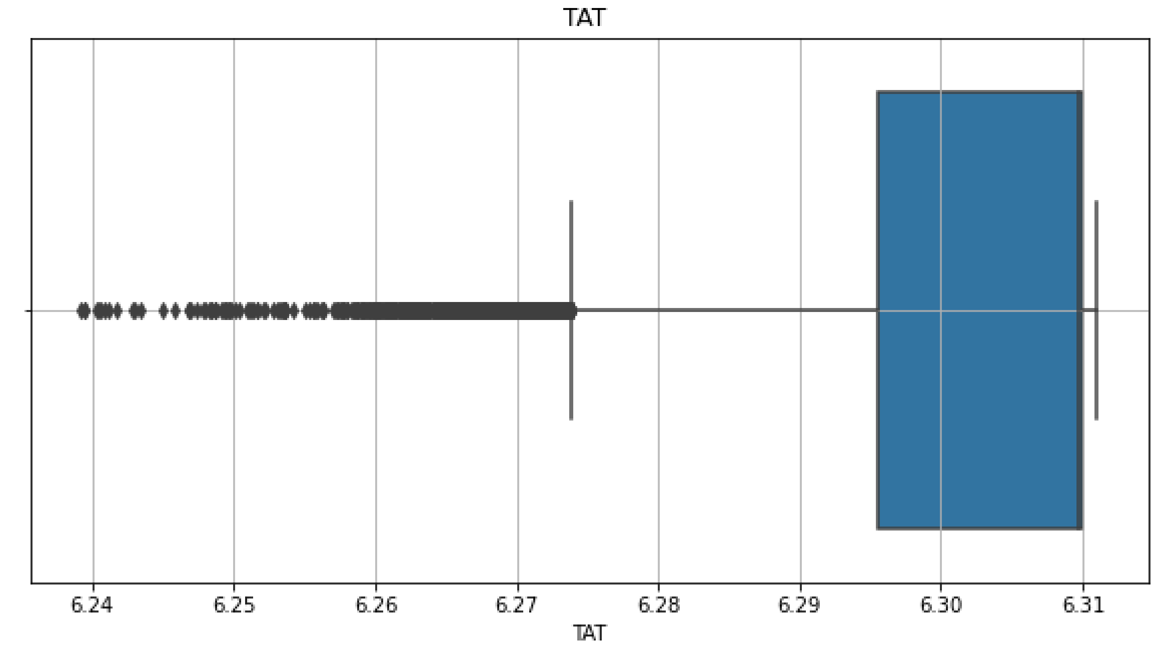


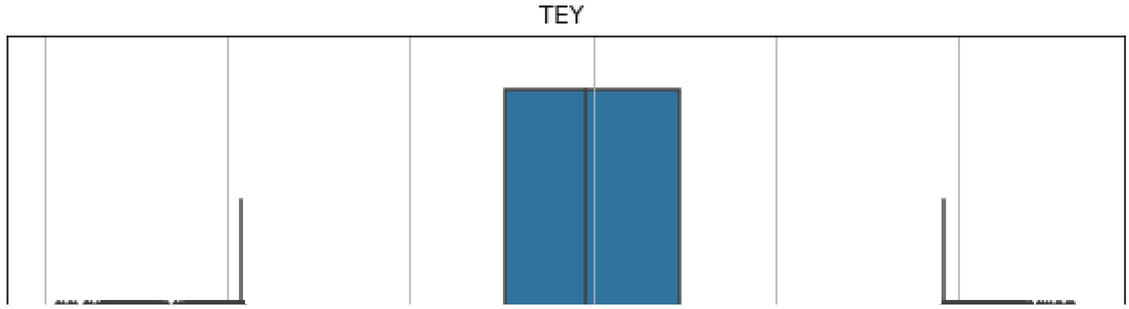

AH
3.4
3.6
3.8
4.0
4.2
4.4
4.6
AH

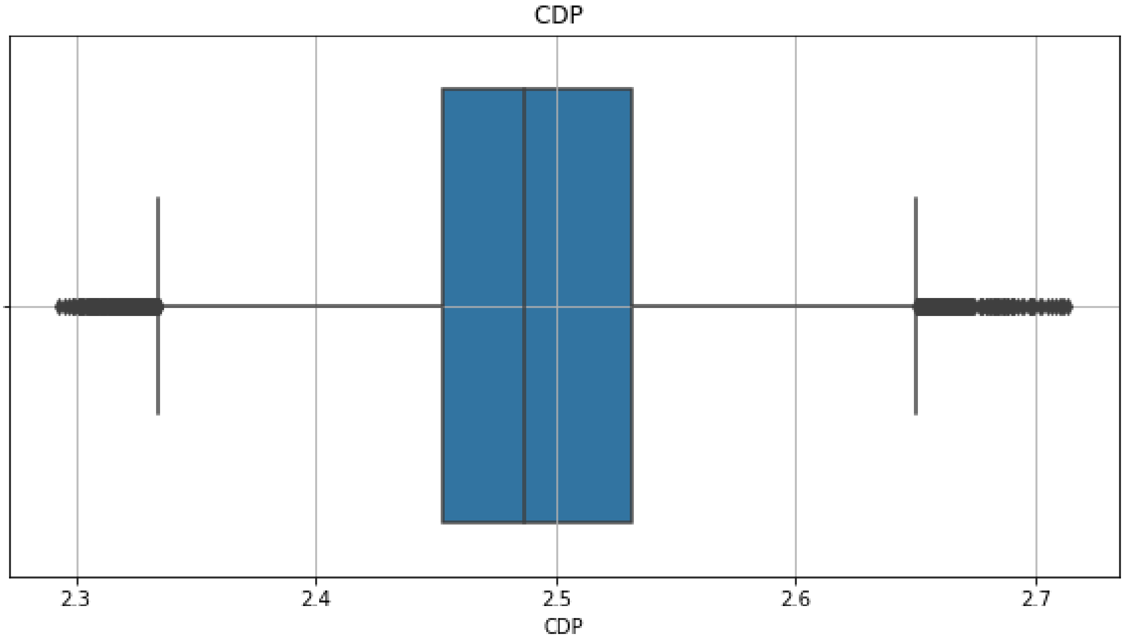

AFDP
0.8
1.0
1.2
1.4
1.6
1.8
2.0
AFDP

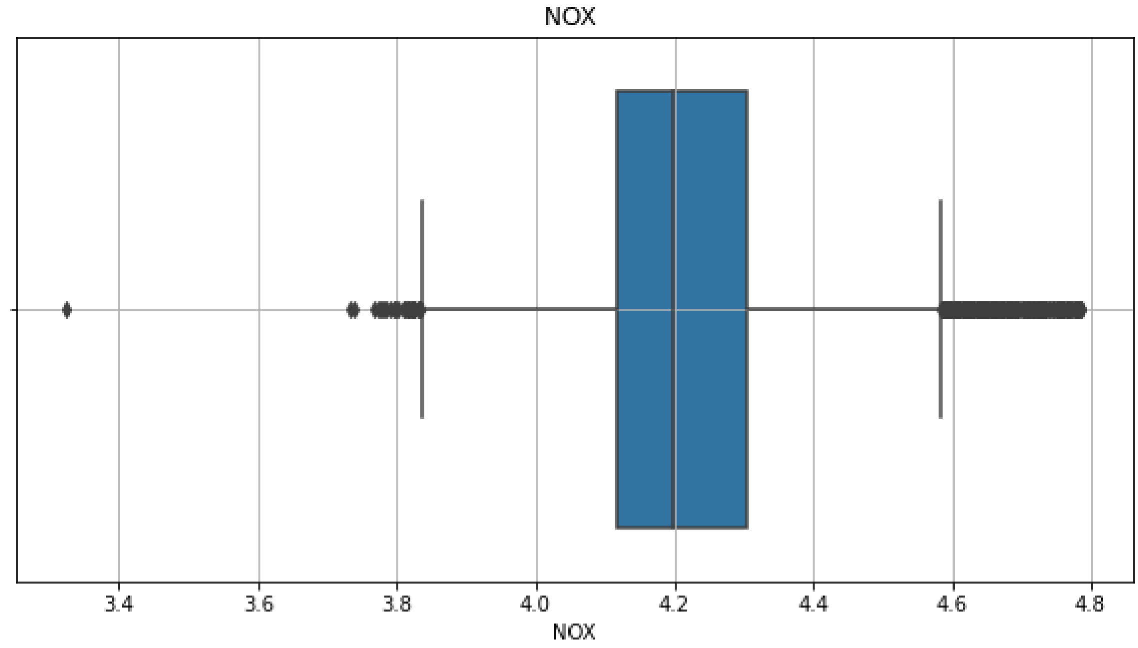

GTEP
2.9
3.0
3.1
3.2
3.3
3.4
3.5
3.6
GTEP


TIT
6.92
6.94
6.96
6.98
7.00
TIT


TAT
6.24
6.25
6.26
6.27
6.28
6.29
6.30
6.31
TAT


TEY

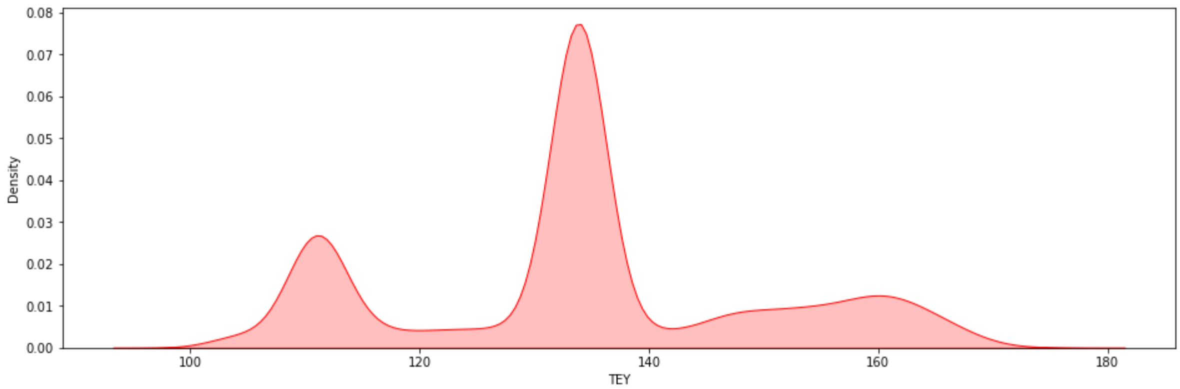

CDP
2.3
2.4
2.5
2.6
2.7
CDP



In [11]:

```
plt.figure(figsize=(16,5))
print("Skewness =",gas_tubine['TEY'].skew())
print("Kurtosis =",gas_tubine['TEY'].kurtosis())
sns.kdeplot(gas_tubine['TEY'],shade=True,color='r')
# plt.xticks([i for i in range(0,1200,50)])
plt.show()
```

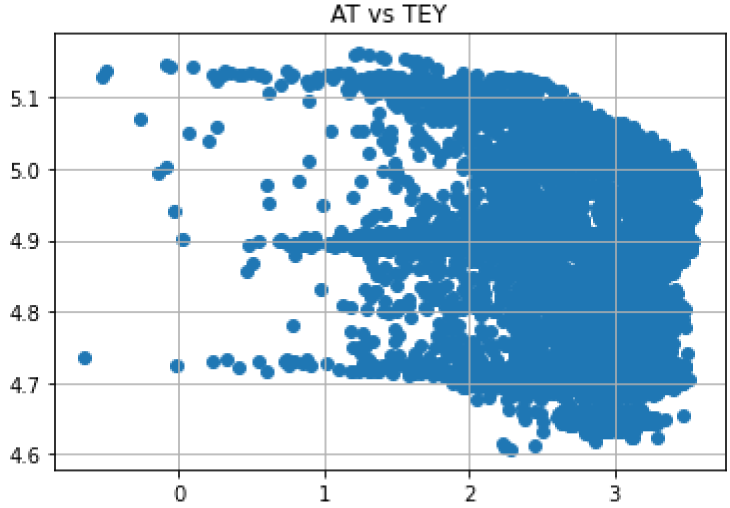
```
Skewness = 0.14596270190452942
Kurtosis = -0.4870582497451621
```

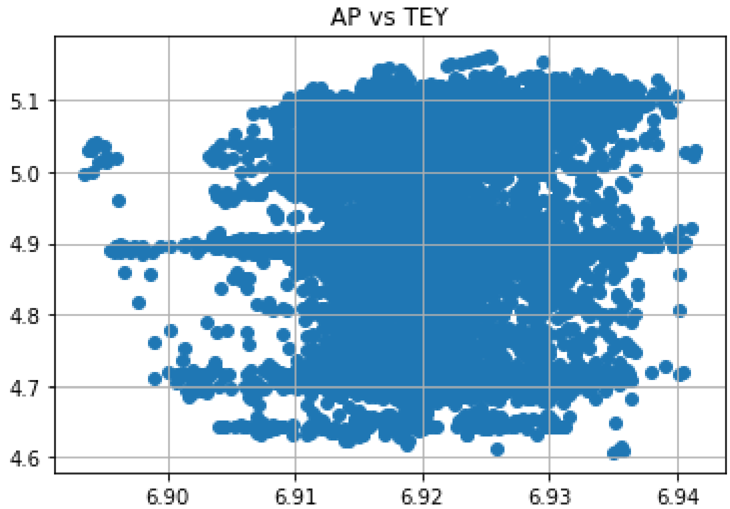


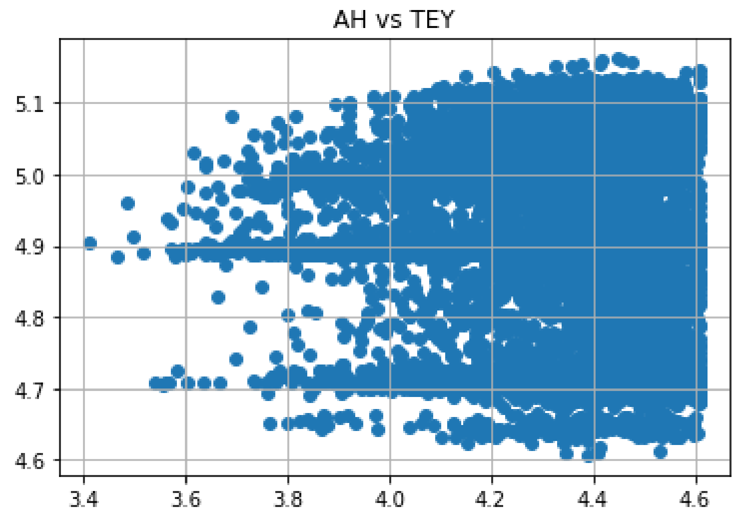
The Data is highly skewed and has Negative kurtosis value

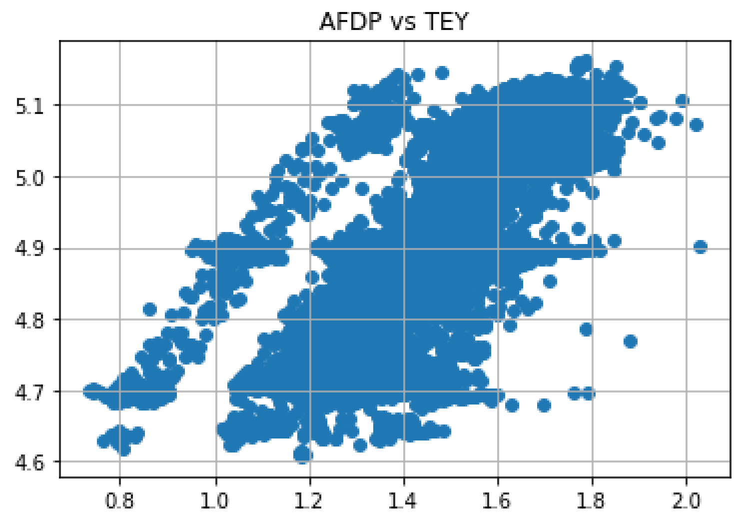
In [12]:

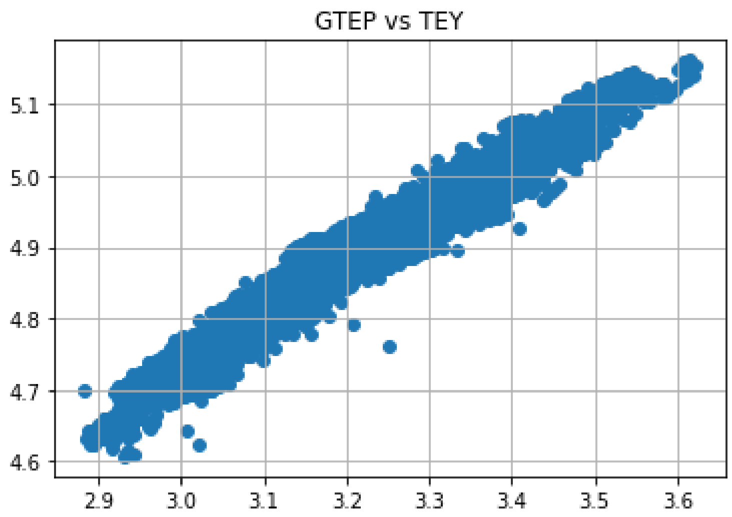
```
for i in gas_tubine.columns:
    if i!="TEY":
        plt.scatter(np.log(gas_tubine[i]), np.log(gas_tubine['TEY']))
        plt.title(i+ ' vs TEY')
        plt.grid()
        plt.show()
```

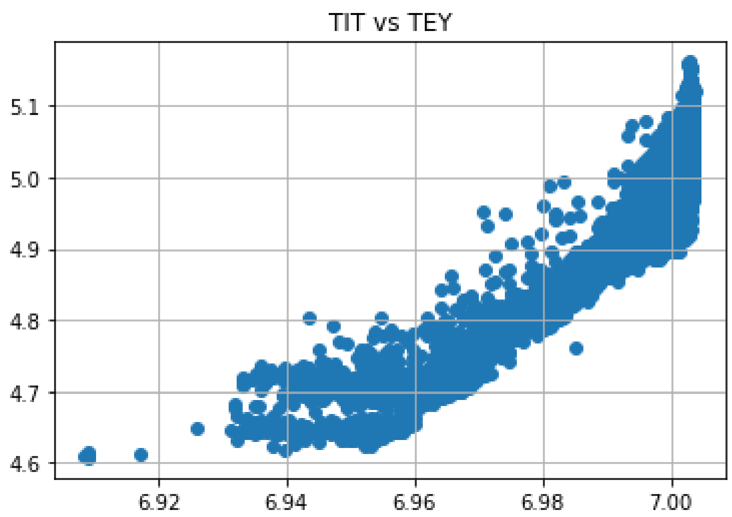


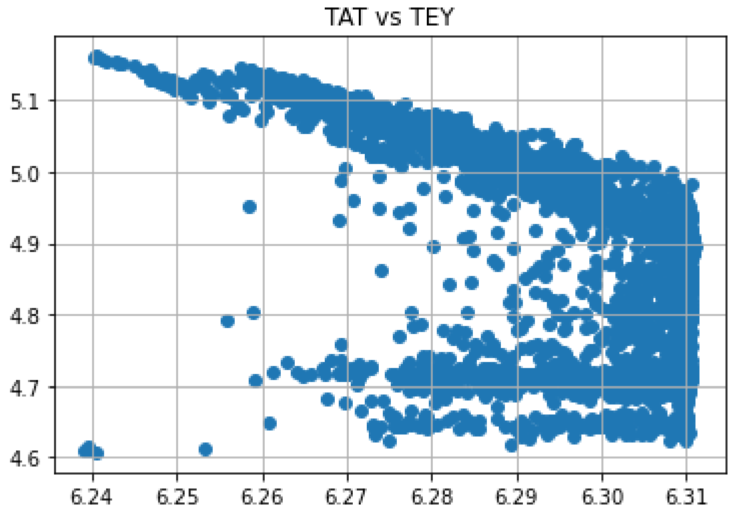


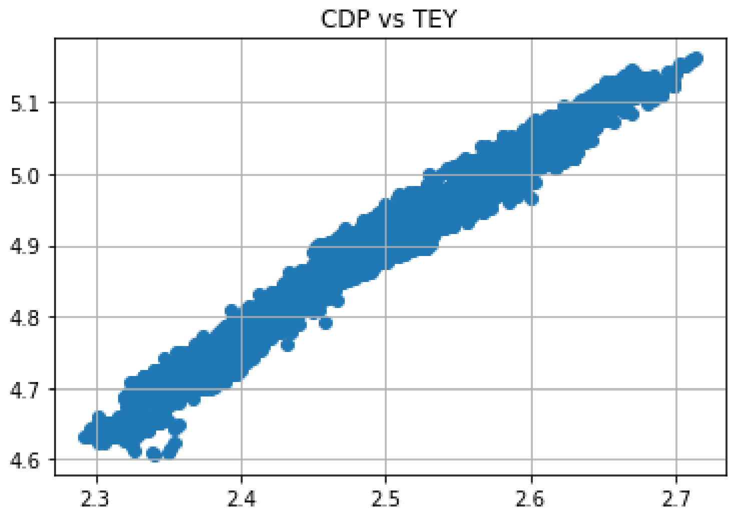

AH vs TEY
5.1
5.0
4.9
4.8
4.7
4.6
3.4
3.6
3.8
4.0
4.2
4.4
4.6

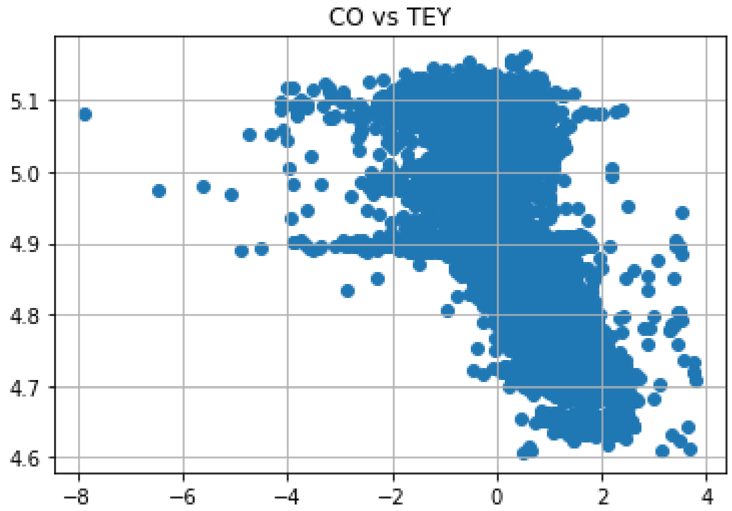

AFDP vs TEY
5.1
5.0
4.9
4.8
4.7
4.6
0.8
1.0
1.2
1.4
1.6
1.8
2.0

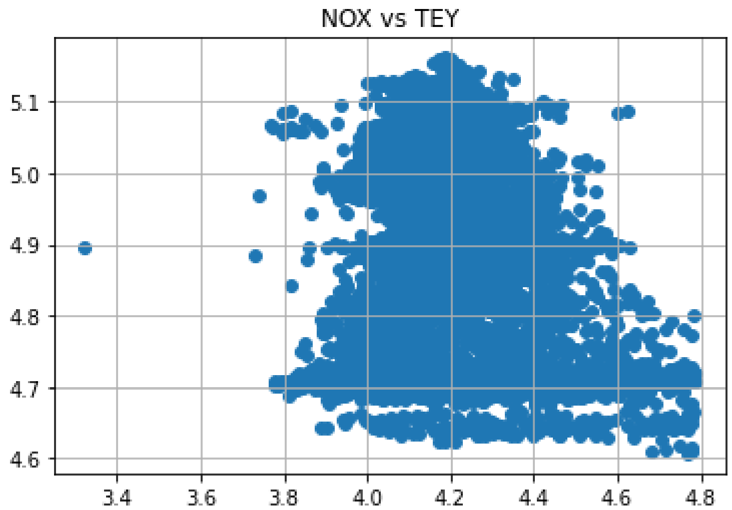

GTEP vs TEY
5.1
5.0
4.9
4.8
4.7
4.6
2.9
3.0
3.1
3.2
3.3
3.4
3.5
3.6


TIT vs TEY
5.1
5.0
4.9
4.8
4.7
4.6
6.92
6.94
6.96
6.98
7.00


TAT vs TEY
5.1
5.0
4.9
4.8
4.7
4.6
6.24
6.25
6.26
6.27
6.28
6.29
6.30
6.31


CDP vs TEY
5.1
5.0
4.9
4.8
4.7
4.6
2.3
2.4
2.5
2.6
2.7



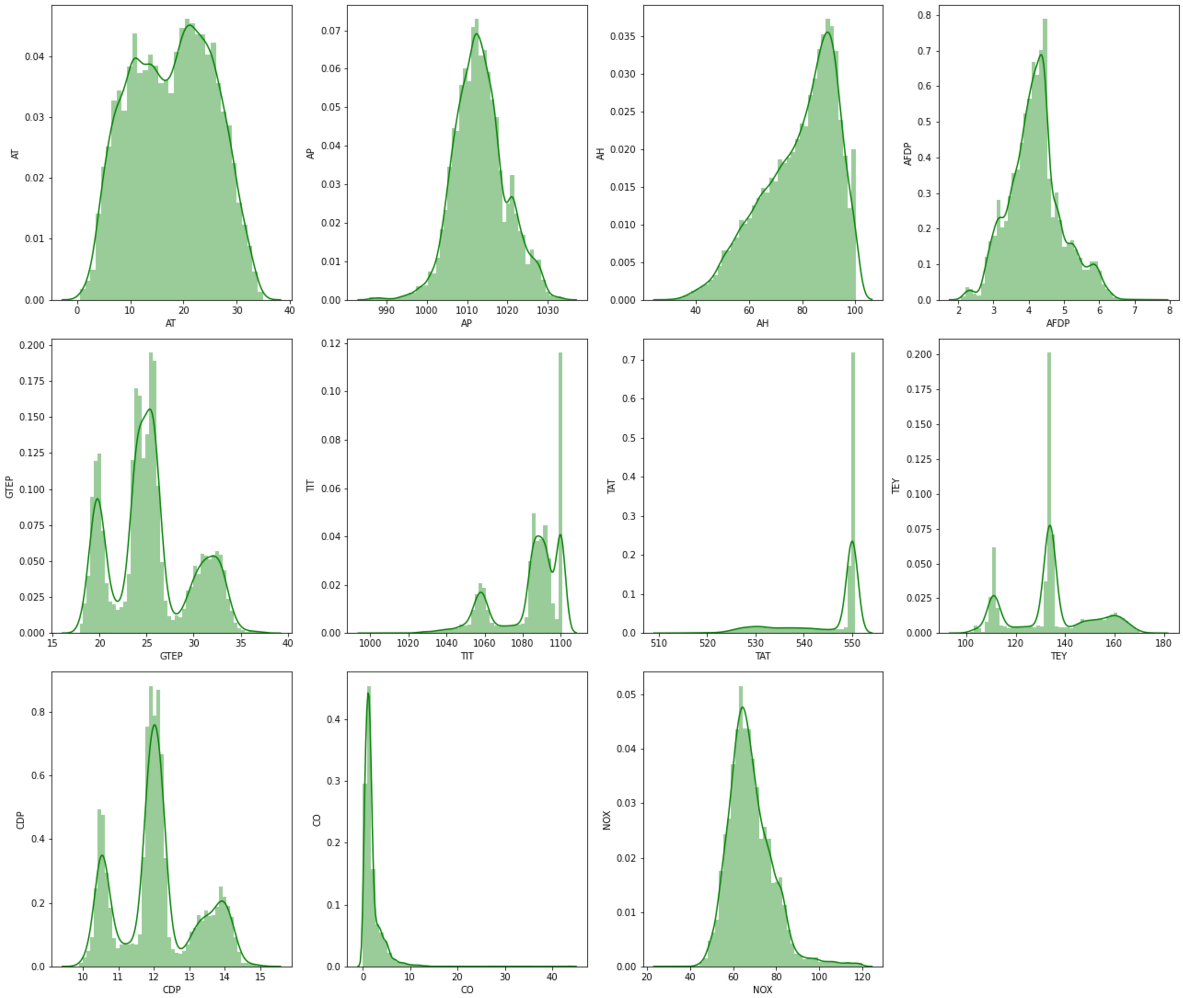


In [13]:

```
num_columns = gas_tubine.select_dtypes(exclude='object')
```

In [14]:

```
plt.figure(figsize=(18,40))
for i,col in enumerate(num_columns,1):
    plt.subplot(8,4,i)
    sns.distplot(gas_tubine[col],color='g')
    plt.ylabel(col)
plt.tight_layout()
plt.show()
```



In [15]:

```
pd.DataFrame(data=[num_columns.skew(),num_columns.kurtosis()],index=['skewness','kurtosis']
```

Out[15]:

	AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY
skewness	-0.030710	0.107601	-0.681224	0.315150	0.370987	-1.133744	-1.485524	0.145963
kurtosis	-0.987597	0.424070	-0.282476	0.281642	-0.618358	0.375232	0.847637	-0.487058

Finding Correlation

In [16]:

```
corr = pd.DataFrame(data = gas_tubine.corr().iloc[:,7], index=gas_tubine.columns)
```

In [17]:

```
corr = corr.sort_values(by = 'TEY',ascending=False)
corr
```

Out[17]:

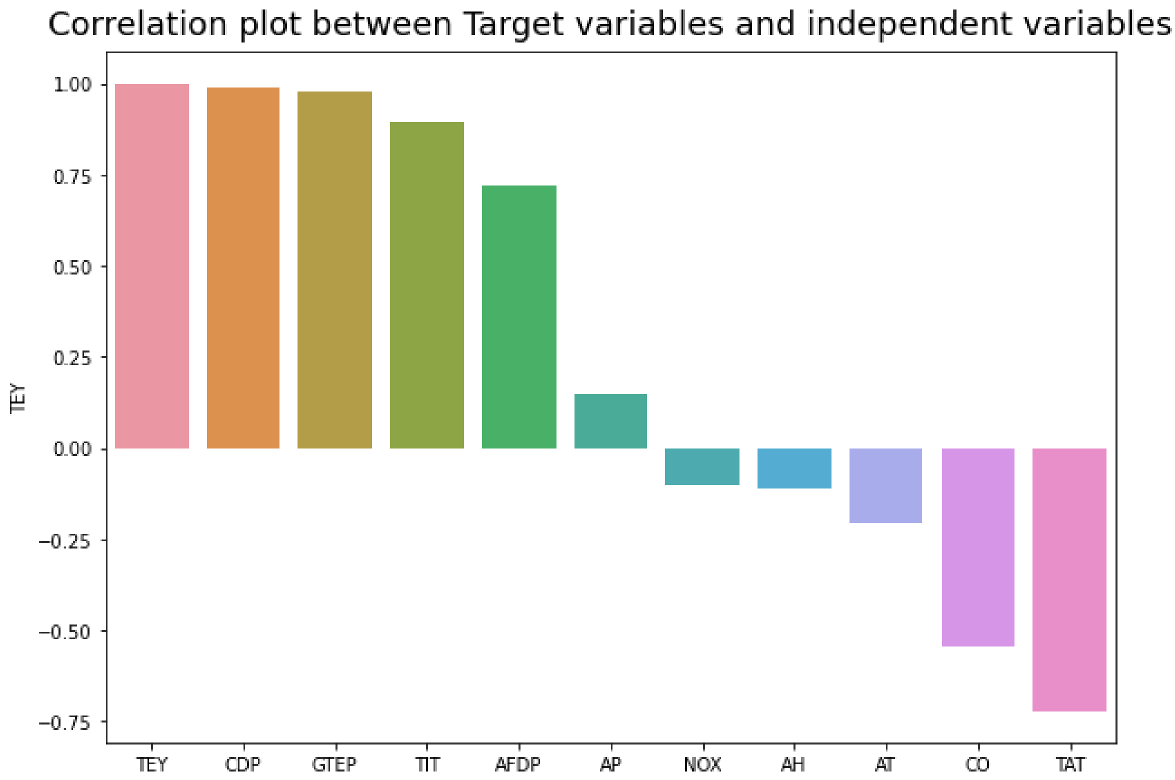
	TEY
TEY	1.000000
CDP	0.988473
GTEP	0.977042
TIT	0.891587
AFDP	0.717995
AP	0.146939
NOX	-0.102631
AH	-0.110272
AT	-0.207495
CO	-0.541751
TAT	-0.720356

In [18]:

```
plt.figure(figsize=(10,7))
plt.title("Correlation plot between Target variables and independent variables", y=1.01, fo
sns.barplot(x = corr.index, y = corr.TEY)
```

Out[18]:

```
<AxesSubplot:title={'center':'Correlation plot between Target variables and
independent variables'}, ylabel='TEY'>
```

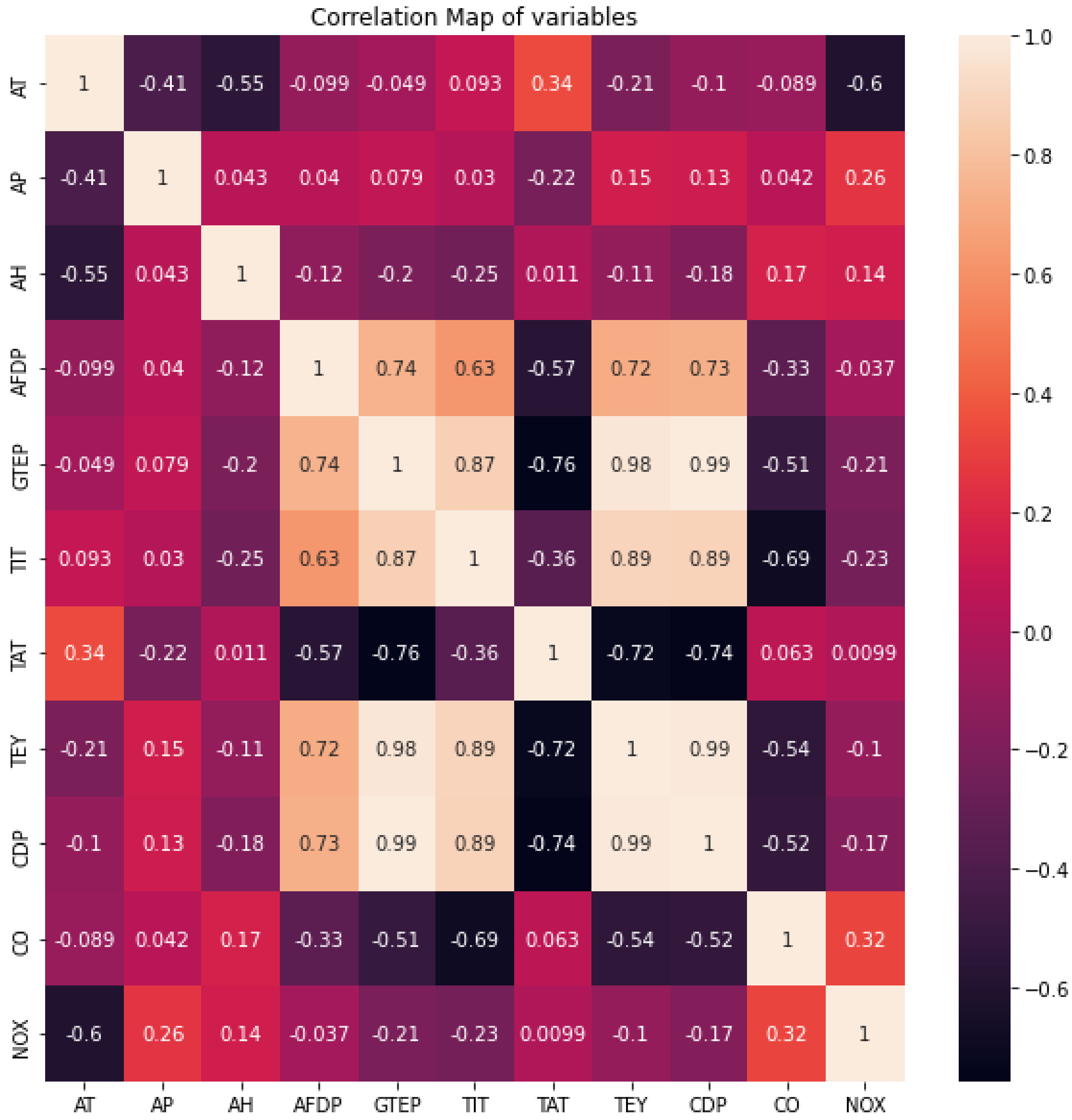


In [19]:

```
plt.figure(figsize=(10,10))
sns.heatmap(gas_tubine.corr(),annot=True)
plt.title("Correlation Map of variables")
```

Out[19]:

```
Text(0.5, 1.0, 'Correlation Map of variables')
```



4. Model Building

In [155]:

```
X = gas_tubine.loc[:,['AT', 'AP', 'AH', 'AFDP', 'GTEP', 'TIT', 'TAT', 'CDP', 'CO','NOX']]
y= gas_tubine.loc[:,['TEY']]
```

CROSS VALIDATION TECHNIQUE

In [157]:

```
scaler = StandardScaler()
X = scaler.fit_transform(X)
y = scaler.fit_transform(y)
```

In [158]:

```
def baseline_model():
    model = Sequential()
    model.add(Dense(10, input_dim=10, activation='tanh'))
    model.add(Dense(1))
    model.compile(loss='mean_squared_error', optimizer='adam')
    return model
```

In [160]:

```
from sklearn.model_selection import cross_val_score
```

In [161]:

```
estimator = KerasRegressor(build_fn=baseline_model, nb_epoch=50, batch_size=100, verbose=Fa
kfold = KFold(n_splits=10)
results = cross_val_score(estimator, X, y, cv=kfold)
print("Results: %.2f (%.2f) MSE" % (results.mean(), results.std()))
```

```
Results: -0.15 (0.14) MSE
```

In [162]:

```
estimator.fit(X, y)
prediction = estimator.predict(X)
prediction
```

Out[162]:

```
array([-1.0119994, -1.0098575, -1.0141087, ..., -1.1376699, -1.0127207,
       -0.9795867], dtype=float32)
```

Train-Test Split Model Validation Technique

In [163]:

```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3)
```

In [164]:

```
estimator.fit(X_train, y_train)
prediction = estimator.predict(X_test)
```

In [165]:

```
prediction
```

Out[165]:

```
array([ 0.00477274, -0.14861444, -0.7552343 , ...,  0.49390388,
       -0.84462726,  0.31057233], dtype=float32)
```

In [166]:

```
X = gas_tubine.drop(columns = ['TEY'], axis = 1)
y = gas_tubine.iloc[:,7]
```

In [167]:

```
from sklearn.preprocessing import scale
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.1, random_state = 4
X_train_scaled = scale(X_train)
X_test_scaled = scale(X_test)
X_test_scaled
```

Out[167]:

```
array([[ 0.82623246, -0.43954308, -0.25924569, ...,  0.10039242,
        -0.3796304 , -0.69217007],
       [ 0.35282087,  0.23279782,  0.80230139, ..., -1.18541222,
         0.39149515, -1.09475442],
       [ 0.32839008, -0.07135639,  0.25312287, ...,  0.01665304,
        -0.00296896, -0.31891741],
       ...,
       [-0.74071701,  0.37687087,  0.43427425, ...,  1.77157829,
        -1.00127821, -0.4818816 ],
       [-0.49965786, -0.39151873,  0.64680105, ..., -0.26517949,
        -0.48137538,  0.12808615],
       [ 0.13151427,  0.32884652,  0.98830762, ..., -1.40331469,
         0.13152215, -0.64456466]])
```

In [168]:

```
input_size = len(X.columns)
output_size = 1
hidden_layer_size = 50
```

In [169]:

```
model = tf.keras.Sequential([

                               tf.keras.layers.Dense(hidden_layer_size, input_dim = input_s
                               tf.keras.layers.Dense(hidden_layer_size, activation = 'relu'
                               tf.keras.layers.Dense(hidden_layer_size, activation = 'relu'
                               tf.keras.layers.Dense(hidden_layer_size, activation = 'relu'
                               tf.keras.layers.Dense(output_size)
                             ])
```

In [170]:

```
optimizer = tf.keras.optimizers.SGD(learning_rate = 0.03)
model.compile(optimizer = 'adam', loss = 'mean_squared_error', metrics = ['MeanSquaredError
```

In [171]:

```
num_epochs = 100
early_stopping = tf.keras.callbacks.EarlyStopping(patience = 2)
model.fit(X_train_scaled, y_train, callbacks = [early_stopping], validation_split = 0.1, ep
```

```
Epoch 1/100
381/381 - 2s - loss: 2788.8911 - mean_squared_error: 2788.8911 - val_loss: 2
01.8141 - val_mean_squared_error: 201.8141 - 2s/epoch - 5ms/step
Epoch 2/100
381/381 - 1s - loss: 98.9952 - mean_squared_error: 98.9952 - val_loss: 69.00
60 - val_mean_squared_error: 69.0060 - 1s/epoch - 3ms/step
Epoch 3/100
381/381 - 1s - loss: 40.2514 - mean_squared_error: 40.2514 - val_loss: 30.41
05 - val_mean_squared_error: 30.4105 - 959ms/epoch - 3ms/step
Epoch 4/100
381/381 - 1s - loss: 19.1062 - mean_squared_error: 19.1062 - val_loss: 14.95
36 - val_mean_squared_error: 14.9536 - 905ms/epoch - 2ms/step
Epoch 5/100
381/381 - 1s - loss: 10.1202 - mean_squared_error: 10.1202 - val_loss: 7.871
1 - val_mean_squared_error: 7.8711 - 1s/epoch - 3ms/step
Epoch 6/100
381/381 - 1s - loss: 5.8985 - mean_squared_error: 5.8985 - val_loss: 4.4836
- val_mean_squared_error: 4.4836 - 1s/epoch - 3ms/step
Epoch 7/100
381/381 - 1s - loss: 4.2205 - mean_squared_error: 4.2205 - val_loss: 4.1399
- val_mean_squared_error: 4.1399 - 1s/epoch - 3ms/step
Epoch 8/100
381/381 - 1s - loss: 2.9982 - mean_squared_error: 2.9982 - val_loss: 2.7782
- val_mean_squared_error: 2.7782 - 1s/epoch - 3ms/step
Epoch 9/100
381/381 - 1s - loss: 2.2930 - mean_squared_error: 2.2930 - val_loss: 2.4576
- val_mean_squared_error: 2.4576 - 1s/epoch - 3ms/step
Epoch 10/100
381/381 - 1s - loss: 1.9820 - mean_squared_error: 1.9820 - val_loss: 1.6915
- val_mean_squared_error: 1.6915 - 1s/epoch - 3ms/step
Epoch 11/100
381/381 - 1s - loss: 1.4866 - mean_squared_error: 1.4866 - val_loss: 1.5286
- val_mean_squared_error: 1.5286 - 1s/epoch - 3ms/step
Epoch 12/100
381/381 - 1s - loss: 1.2496 - mean_squared_error: 1.2496 - val_loss: 1.1525
- val_mean_squared_error: 1.1525 - 1s/epoch - 3ms/step
Epoch 13/100
381/381 - 1s - loss: 1.0668 - mean_squared_error: 1.0668 - val_loss: 0.9233
- val_mean_squared_error: 0.9233 - 1s/epoch - 3ms/step
Epoch 14/100
381/381 - 1s - loss: 0.9021 - mean_squared_error: 0.9021 - val_loss: 0.9749
- val_mean_squared_error: 0.9749 - 1s/epoch - 3ms/step
Epoch 15/100
381/381 - 1s - loss: 0.8902 - mean_squared_error: 0.8902 - val_loss: 0.9276
- val_mean_squared_error: 0.9276 - 1s/epoch - 3ms/step
```

Out[171]:

```
<keras.callbacks.History at 0x28bdc009b50>
```

In [172]:

```
test_loss, mean_squared_error = model.evaluate(X_test_scaled, y_test)
```

```
47/47 [==============================] - 0s 2ms/step - loss: 0.8426 - mean_s
quared_error: 0.8426
```

In [173]:

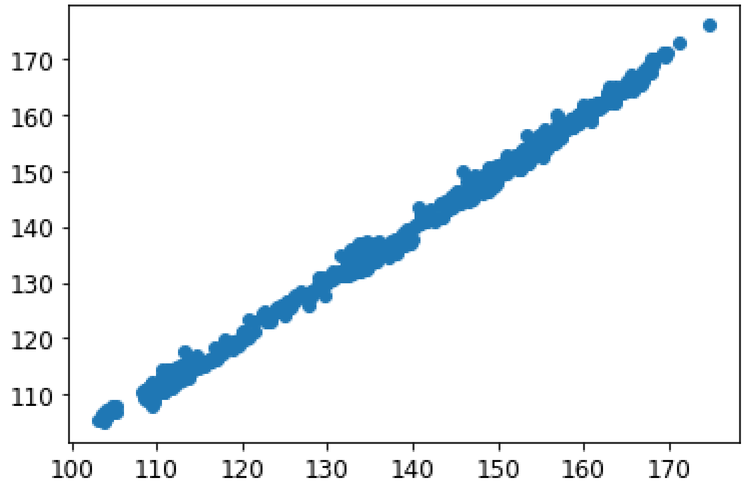
```
predictions = model.predict_on_batch(X_test_scaled)
```

In [174]:

```
plt.scatter(y_test, predictions)
```

Out[174]:

```
<matplotlib.collections.PathCollection at 0x28be9759df0>
```



In [183]:

```
predictions_df = pd.DataFrame()
predictions_df['Actual'] = y_test
predictions_df['Predicted'] = predictions
predictions_df['% Error'] = abs(predictions_df['Actual'] - predictions_df['Predicted'])/pre
predictions_df.reset_index(drop = True)
```

Out[183]:

	Actual	Predicted	% Error
0	134.46	134.483353	0.017368
1	111.88	112.919937	0.929511
2	133.72	134.674942	0.714136
3	133.79	133.407242	0.286089
4	110.77	111.853127	0.977816
...	...	...	...
1499	132.85	132.818970	0.023357
1500	125.07	124.232704	0.669462
1501	160.95	161.740555	0.491180
1502	133.12	133.048691	0.053568
1503	111.79	112.972961	1.058200

1504 rows × 3 columns

In [176]:

```
model.history.history.keys()
```

Out[176]:

```
dict_keys([])
```

In [177]:

```
hist= print(history.history.keys())
```

```
dict_keys(['loss', 'mean_squared_error', 'val_loss', 'val_mean_squared_erro
r', 'accuracy', 'val_accuracy'])
```

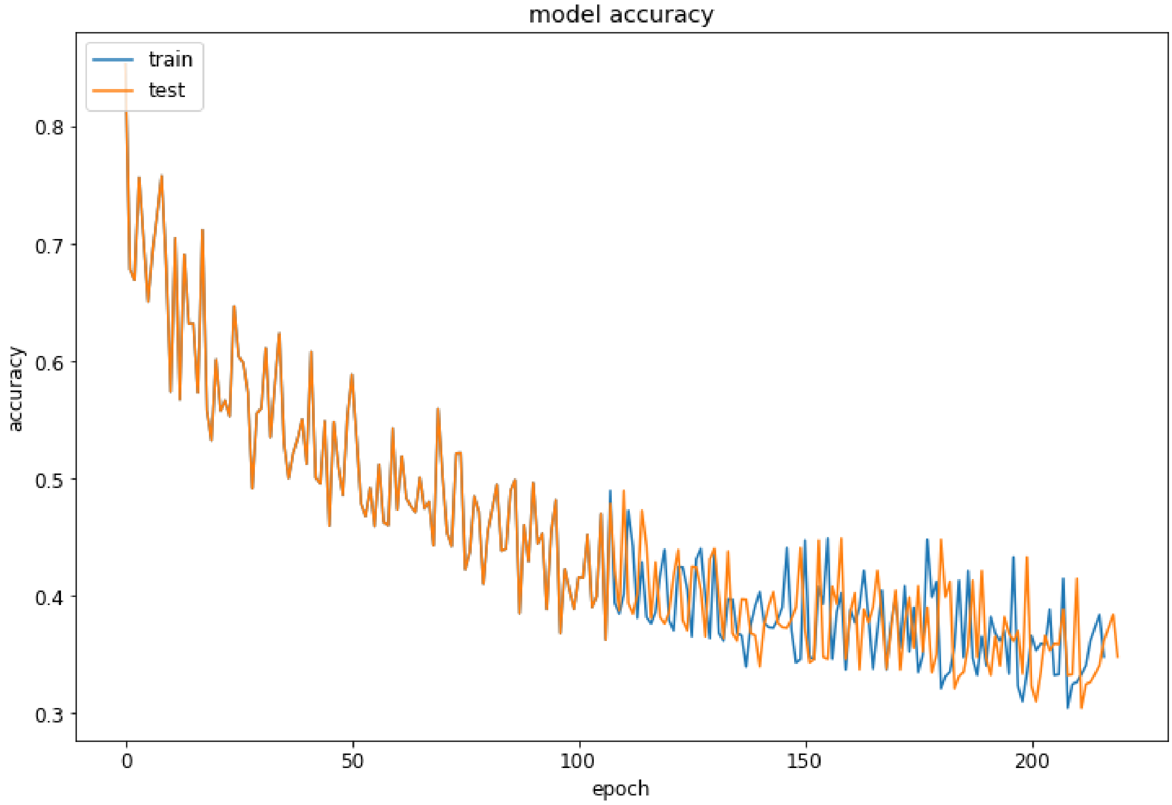
In [178]:

```
scores = model.evaluate(X_train_scaled, y_train)
print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

```
423/423 [==============================] - 1s 1ms/step - loss: 0.8062 - mean
_squared_error: 0.8062
mean_squared_error: 80.62%
```

In [179]:

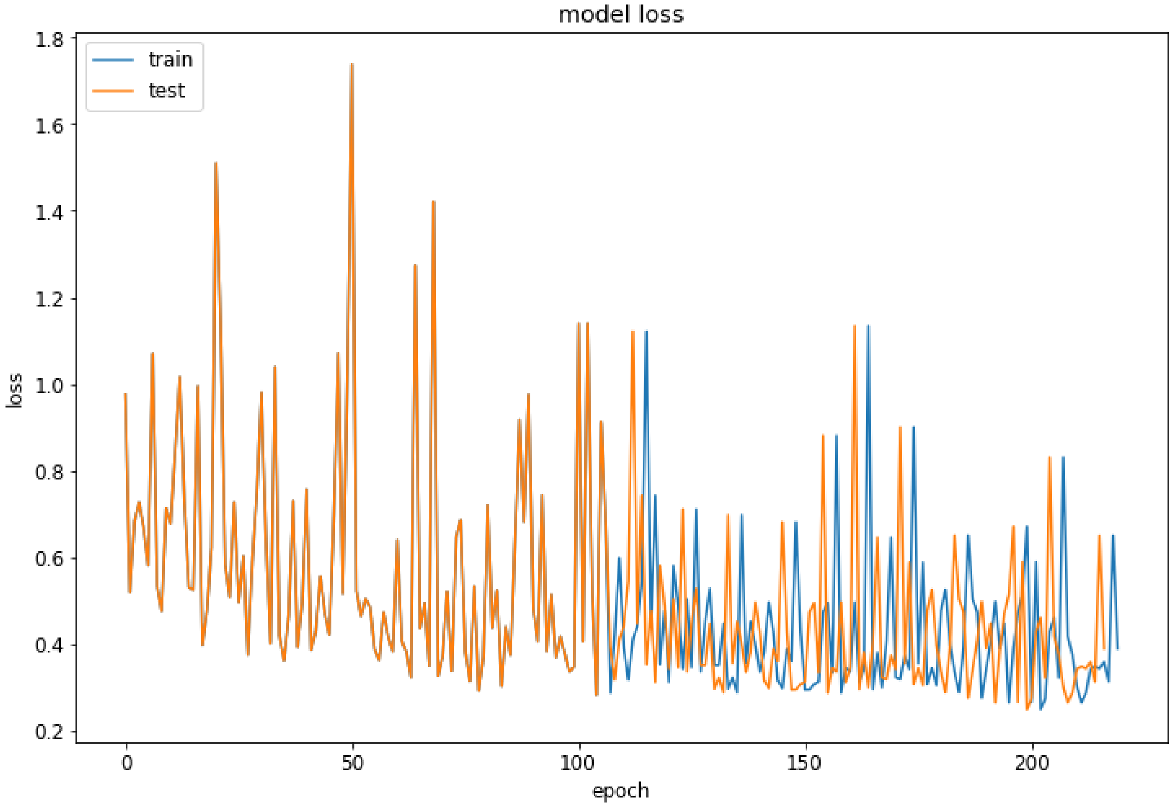
```
plt.figure(figsize=(12,8))
plt.rcParams['font.size'] = 12
plt.plot(history.history['mean_squared_error'])
plt.plot(history.history['loss'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



By using TensorFlow, Prediction of Turbine Energy Yield (TEY) we can see error is going to decrease it means we got better model.

In [181]:

```
plt.figure(figsize=(12,8))
plt.plot(history.history['val_loss'])
plt.plot(history.history['val_mean_squared_error'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



END

In [ ]:

```
```