

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.

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

Attribute Information:

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   |

```
In [1]:  import warnings
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

sns.set_style('darkgrid')

import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import warnings
warnings.filterwarnings('ignore')
```

```
In [2]:  from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Dropout
from keras.utils import np_utils
from keras.constraints import maxnorm
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from keras.wrappers.scikit_learn import KerasRegressor, KerasClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import mutual_info_regression
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV, KFold, RandomizedSearchCV
```

```
In [3]:  gas_turbines = pd.read_csv("gas_turbines.csv")
gas_turbines.head()
```

Out[3]:

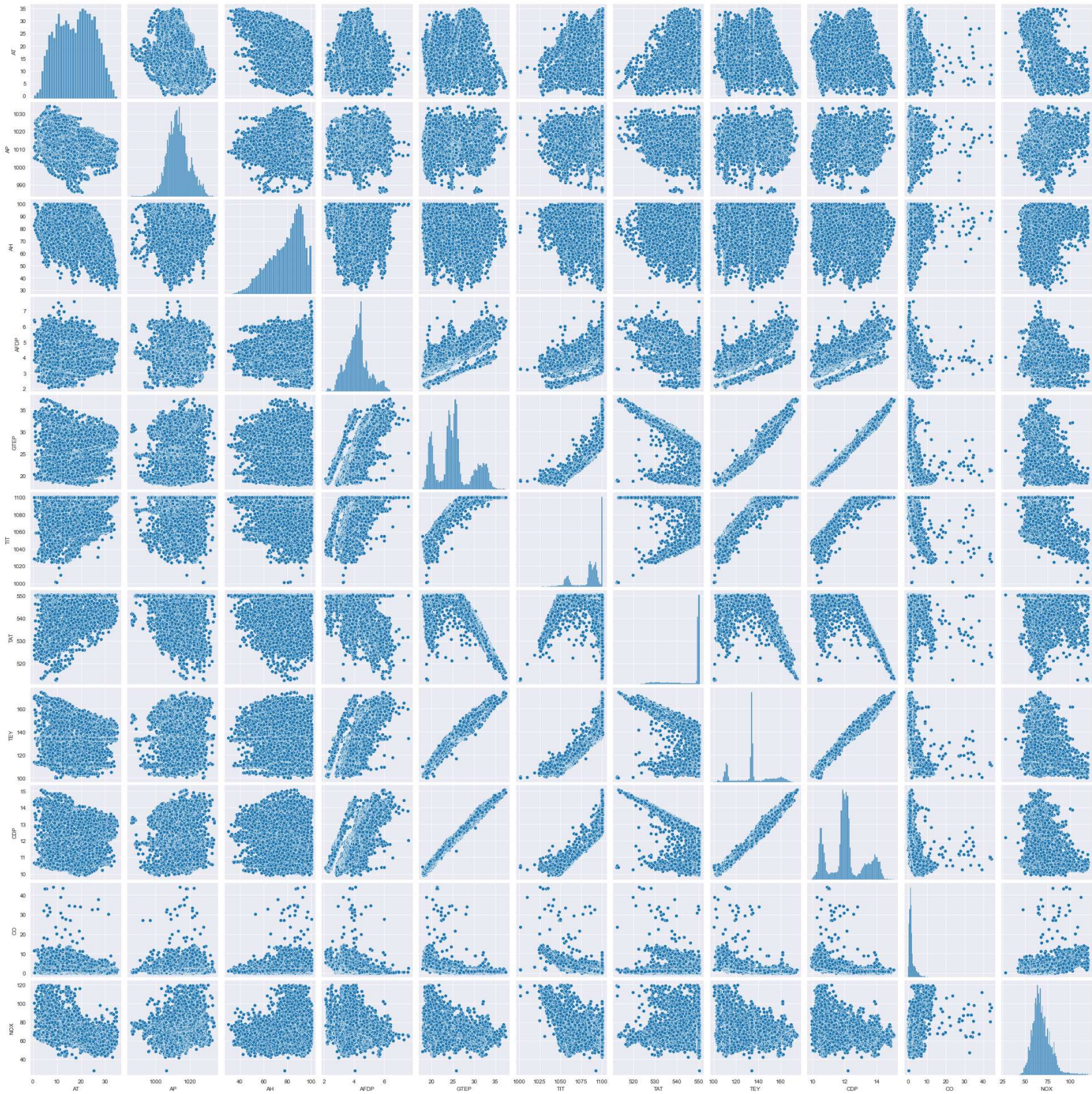
|   | AT     | AP     | AH     | AFDP   | GTEP   | TIT    | TAT    | TEY    | CDP    | CO     | NOX    |
|---|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| 0 | 6.8594 | 1007.9 | 96.799 | 3.5000 | 19.663 | 1059.2 | 550.00 | 114.70 | 10.605 | 3.1547 | 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 |



In [4]: `gas_turbines.info()`

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15039 entries, 0 to 15038
Data columns (total 11 columns):
#   Column  Non-Null Count  Dtype  
---  -
0    AT      15039 non-null    float64
1    AP      15039 non-null    float64
2    AH      15039 non-null    float64
3    AFDP    15039 non-null    float64
4    GTEP    15039 non-null    float64
5    TIT     15039 non-null    float64
6    TAT     15039 non-null    float64
7    TEY     15039 non-null    float64
8    CDP     15039 non-null    float64
9    CO      15039 non-null    float64
10   NOX     15039 non-null    float64
dtypes: float64(11)
memory usage: 1.3 MB
```

In [5]: `sns.set_style('darkgrid')`  
`sns.pairplot(gas_turbines)`  
  
`plt.show()`



In [6]: `"""color = ["g","y","r", "b","g","y","r", "b","g","y","r"]
for i,j in zip(gas_turbines.columns.values,color):
 f, axes = plt.subplots(figsize=(10,8))
 sns.regplot(x = 'TEY', y = i, data = gas_turbines,color = j, scatter_kws={'alpha':0.3})
 axes.set_xlabel('TEY', fontsize = 14)
 axes.set_ylabel(i, fontsize=14)
 plt.show()"""`

Out[6]: 'color = ["g","y","r", "b","g","y","r", "b","g","y","r"]\nfor i,j in zip(gas\_turbines.columns.values,color):\n f, axes = plt.subplots(figsize=(10,8))\n sns.regplot(x = \'TEY\', y = i, data = gas\_turbines,color = j, scatter\_kws={\'alpha\':0.3})\n axes.set\_xlabel(\'TEY\', fontsize = 14)\n axes.set\_ylabel(i, fontsize=14)\n plt.show()'



```
In [7]: ▶ import seaborn as sns
import matplotlib.pyplot as plt
#correlation matrix
corrmat = gas_turbines.corr()
f, ax = plt.subplots(figsize=(20, 10))
sns.heatmap(corrmat, vmax=.8, square=True, annot=True);
```



```
In [8]: ▶ y = gas_turbines[gas_turbines.columns[7]]
X = gas_turbines[['AT', 'AP', 'AH', 'AFDP', 'GTEP', 'TIT', 'TAT', 'CDP', 'CO', 'NOX']]
```

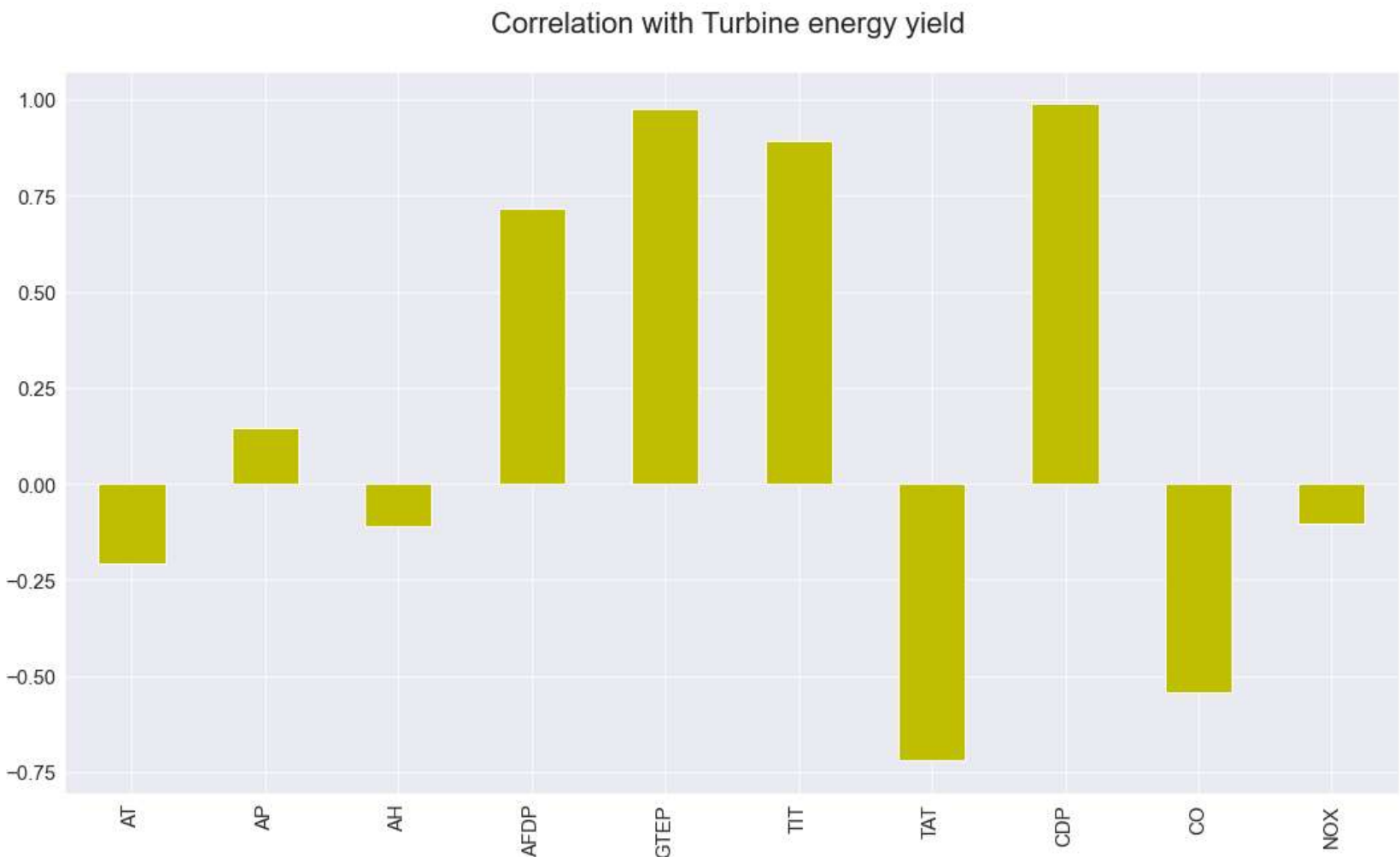
```
In [9]: # correlation with TEY

data2 = X.copy()

correlations = data2.corrwith(gas_turbines["TEY"])
correlations = correlations[correlations!=1]
positive_correlations = correlations[correlations >0].sort_values(ascending = False)
negative_correlations =correlations[correlations<0].sort_values(ascending = False)

correlations.plot.bar(
    figsize = (18, 10),
    fontsize = 15,
    color = 'y',
    rot = 90, grid = True)
plt.title('Correlation with Turbine energy yield \n',
horizontalalignment="center", fontstyle = "normal",
fontsize = "22", fontfamily = "sans-serif")
```

Out[9]: Text(0.5, 1.0, 'Correlation with Turbine energy yield \n')



```
In [10]: # split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=1)
```

```
In [11]: #feature selecton

def select_features(X_train, y_train, X_test):

    # configure to select all features
    features = SelectKBest(score_func=mutual_info_regression, k='all')

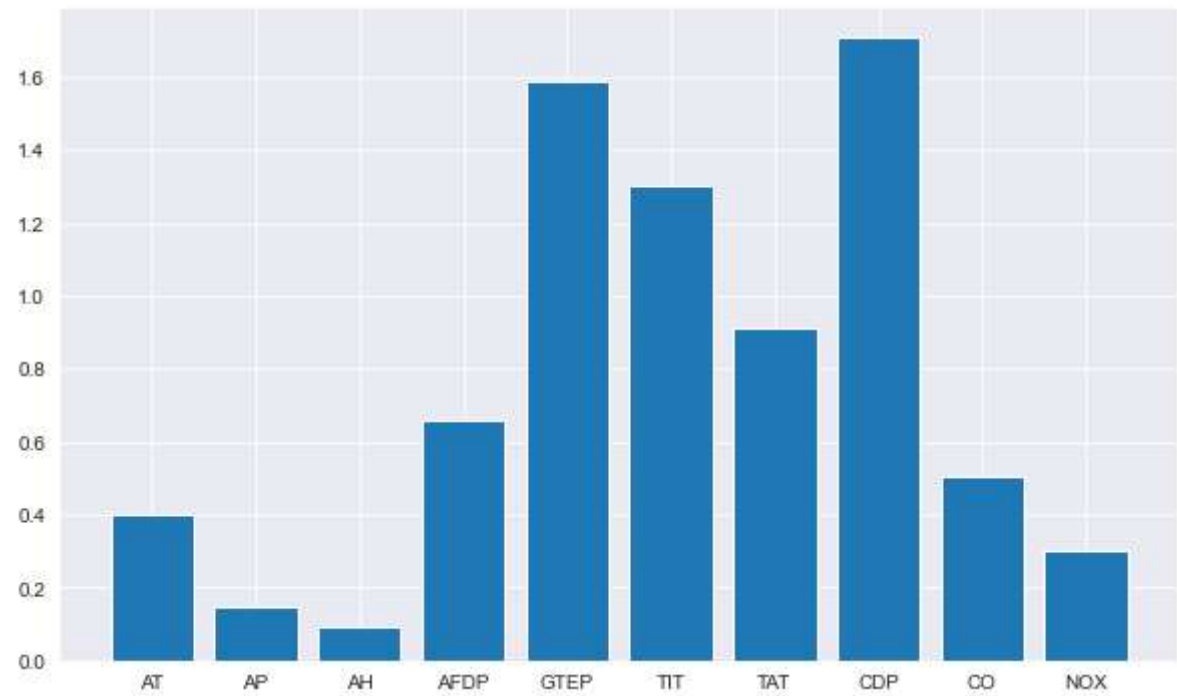
    # Relationships from training data
    features.fit(X_train, y_train)

    # transform train data
    X_train_f = features.transform(X_train)

    # transform test data
    X_test_f = features.transform(X_test)

    return X_train_f, X_test_f, features
```

```
In [12]: X_train_f, X_test_f, features = select_features(X_train, y_train, X_test)
fig, axes = plt.subplots(figsize=(10, 6))
plt.bar([i for i in range(len(features.scores_))], features.scores_)
axes.set_xticks([0,1,2,3,4,5,6,7,8,9])
axes.set_xticklabels(X.columns.values)
plt.show()
```



```
In [13]: y_copy = gas_turbines["TEY"]
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
y_ = StandardScaler().fit_transform(y_copy.values.reshape(len(y_copy),1))[:,0]

X1 = gas_turbines.drop(['TEY', 'AT', 'AP', 'AH', 'CO', 'NOX'], axis = 1)
scaler.fit(X1)

#X_copy = X[['AFDP', 'GTEP', 'TIT', 'TAT', 'CDP']]
features_scaler=scaler.fit_transform(X1)
X_=pd.DataFrame(features_scaler,columns=X[['AFDP', 'GTEP', 'TIT', 'TAT', 'CDP']].columns)
X_.head()
```

Out[13]:

|   | AFDP      | GTEP      | TIT       | TAT      | CDP       |
|---|-----------|-----------|-----------|----------|-----------|
| 0 | -0.921232 | -1.379101 | -1.488376 | 0.585240 | -1.357331 |
| 1 | -0.921495 | -1.363528 | -1.482325 | 0.585240 | -1.363676 |
| 2 | -0.944385 | -1.351309 | -1.476275 | 0.568715 | -1.360957 |
| 3 | -0.946884 | -1.348194 | -1.464173 | 0.583969 | -1.356424 |
| 4 | -0.924389 | -1.354663 | -1.458123 | 0.582698 | -1.350985 |

```
In [14]: # Splitting data into test data and train data

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X1, y_, test_size=0.3, random_state=1)
```

```
In [15]: print('Shape of x_train: ', X_train.shape)
print('Shape of x_test: ', X_test.shape)
print('Shape of y_train: ', y_train.shape)
print('Shape of y_test: ', y_test.shape)

Shape of x_train: (10527, 5)
Shape of x_test: (4512, 5)
Shape of y_train: (10527,)
Shape of y_test: (4512,)
```

```
In [16]: ▶ model = Sequential()
model.add(Dense(28, input_dim=5, kernel_initializer='uniform', activation='tanh'))
model.add(Dense(50, kernel_initializer='uniform', activation='tanh'))
model.add(Dense(50, kernel_initializer='uniform', activation='tanh'))
model.add(Dense(1, kernel_initializer='uniform', activation='linear'))

# Compile model
model.compile(loss='mean_squared_error', optimizer='adam',
              metrics=['mean_squared_error', 'mean_absolute_error', 'mean_absolute_percentage_error', 'cosine_proximity'])
```

```
In [17]: ▶ model.summary()

Model: "sequential"

Layer (type)                 Output Shape              Param #
=====
dense (Dense)                (None, 28)                168
-----
dense_1 (Dense)              (None, 50)               1450
-----
dense_2 (Dense)              (None, 50)               2550
-----
dense_3 (Dense)              (None, 1)                 51
=====
Total params: 4,219
Trainable params: 4,219
Non-trainable params: 0
=====
```

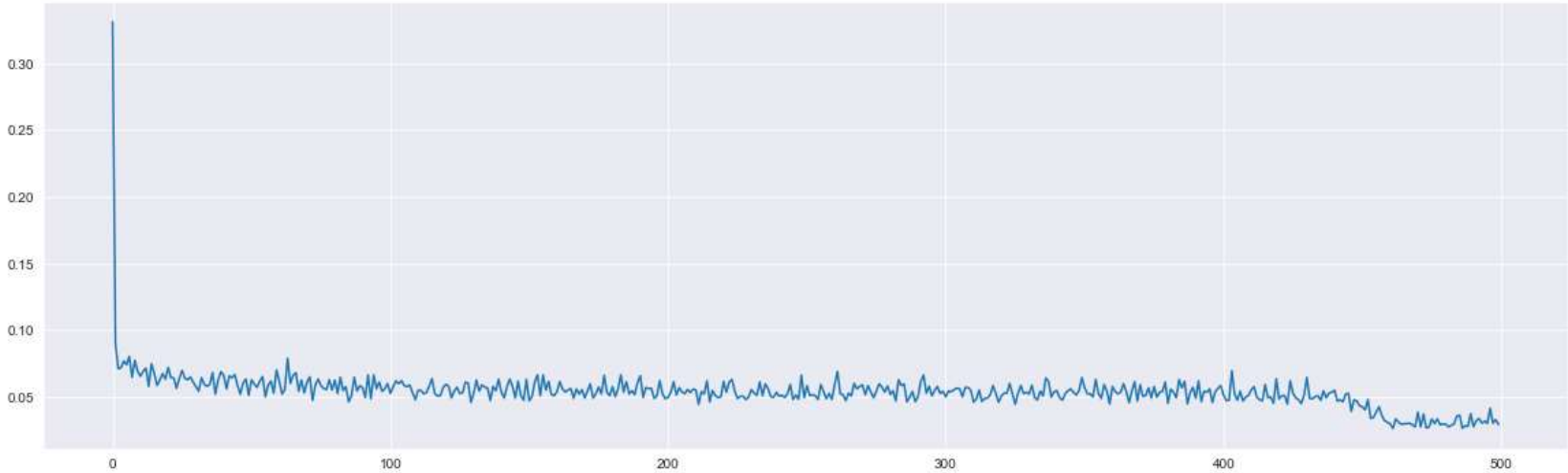
```
In [18]: ▶ # Fit the model
history = model.fit(X_train,y_train, epochs=500)

Epoch 1/500
329/329 [=====] - 1s 1ms/step - loss: 0.6445 - mean_squared_error: 0.6445 - mea
n_absolute_error: 0.5400 - mean_absolute_percentage_error: 616.8769 - cosine_proximity: 0.2770
Epoch 2/500
329/329 [=====] - 0s 1ms/step - loss: 0.0842 - mean_squared_error: 0.0842 - mea
n_absolute_error: 0.2336 - mean_absolute_percentage_error: 1140.4767 - cosine_proximity: 0.5508
Epoch 3/500
329/329 [=====] - 1s 2ms/step - loss: 0.0682 - mean_squared_error: 0.0682 - mea
n_absolute_error: 0.2092 - mean_absolute_percentage_error: 1139.7822 - cosine_proximity: 0.5699
Epoch 4/500
329/329 [=====] - 0s 1ms/step - loss: 0.0717 - mean_squared_error: 0.0717 - mea
n_absolute_error: 0.2150 - mean_absolute_percentage_error: 1303.7081 - cosine_proximity: 0.5729
Epoch 5/500
329/329 [=====] - 1s 2ms/step - loss: 0.0811 - mean_squared_error: 0.0811 - mea
n_absolute_error: 0.2291 - mean_absolute_percentage_error: 1086.9312 - cosine_proximity: 0.5669
Epoch 6/500
329/329 [=====] - 0s 1ms/step - loss: 0.0684 - mean_squared_error: 0.0684 - mea
n_absolute_error: 0.2102 - mean_absolute_percentage_error: 857.1329 - cosine_proximity: 0.5727
Epoch 7/500
329/329 [=====] - 1s 2ms/step - loss: 0.0822 - mean_squared_error: 0.0822 - mea
n_absolute_error: 0.2291 - mean_absolute_percentage_error: 1086.9312 - cosine_proximity: 0.5669
```

```
In [19]: ▶ # model evaluation
scores = model.evaluate(X_test, y_test)
print((model.metrics_names[1]))

141/141 [=====] - 1s 1ms/step - loss: 0.0299 - mean_squared_error: 0.0299 - mean_a
bsolute_error: 0.1292 - mean_absolute_percentage_error: 372.8955 - cosine_proximity: 0.7110
mean_squared_error
```

```
In [20]: ▶ fig, axes = plt.subplots(figsize=(20, 6))
# plot metrics
plt.plot(history.history['mean_squared_error'])
"""plt.plot(history.history['mean_absolute_error'])
plt.plot(history.history['mean_absolute_percentage_error'])
plt.plot(history.history['cosine_proximity'])
"""
plt.show()
```



```
In [21]: ► y2 = gas_turbines["TEY"]
data_c = gas_turbines.copy()
X2 = data_c.drop(['TEY', 'AT', 'AP', 'AH', 'CO', 'NOX'], axis = 1)

# Scaling all the features
scaler.fit(X2)
y2_ = StandardScaler().fit_transform(y2.values.reshape(len(y2),1))[:,0]

scaled_features=scaler.transform(X2)
data_head=pd.DataFrame(scaled_features,columns=X2.columns)
data_head.head()
```

Out[21]:

|   | AFDP      | GTEP      | TIT       | TAT      | CDP       |
|---|-----------|-----------|-----------|----------|-----------|
| 0 | -0.921232 | -1.379101 | -1.488376 | 0.585240 | -1.357331 |
| 1 | -0.921495 | -1.363528 | -1.482325 | 0.585240 | -1.363676 |
| 2 | -0.944385 | -1.351309 | -1.476275 | 0.568715 | -1.360957 |
| 3 | -0.946884 | -1.348194 | -1.464173 | 0.583969 | -1.356424 |
| 4 | -0.924389 | -1.354663 | -1.458123 | 0.582698 | -1.350985 |

```
In [22]: ► from sklearn.model_selection import train_test_split
from keras.optimizers import Adam

x_train, x_test, y_train, y_test = train_test_split(X2, gas_turbines["TEY"], test_size=0.3, random_state=42)
```

In [ ]: 

```
def create_model(learning_rate,dropout_rate,activation_function,init,neuron1,neuron2):
    model = Sequential()
    model.add(Dense(neuron1,input_dim = 5,kernel_initializer = init,activation = activation_function))
    model.add(Dropout(dropout_rate))
    model.add(Dense(neuron2,input_dim = neuron1,kernel_initializer = init,activation = activation_function))
    model.add(Dropout(dropout_rate))
    model.add(Dense(1,activation = 'linear'))

    adam=Adam(learning_rate = learning_rate)
    model.compile(loss = 'mean_squared_error',optimizer = adam, metrics = ['mse'])
    return model

# Create the model

model = KerasClassifier(build_fn = create_model,verbose = 0)

# Define the grid search parameters

batch_size = [20,40]
epochs = [100,500]
learning_rate = [0.01,0.1]
dropout_rate = [0.1,0.2]
activation_function = ['softmax','relu','tanh','linear']
init = ['uniform','normal']
neuron1 = [4,8,16]
neuron2 = [2,4,8]

# Make a dictionary of the grid search parameters

param_grids = dict(batch_size = batch_size,epochs = epochs,learning_rate = learning_rate,dropout_rate = dropout_rate,
                    activation_function = activation_function,init = init,neuron1 = neuron1,neuron2 = neuron2)

# Build and fit the GridSearchCV

grid = GridSearchCV(estimator = model,param_grid = param_grids,cv = KFold(),verbose = 10, scoring='neg_mean_squared_error')
grid_result = grid.fit(x_train, y_train)

# Summarize the results
print('Best : {}, using {}'.format(grid_result.best_score_,grid_result.best_params_))
```

Fitting 5 folds for each of 1152 candidates, totalling 5760 fits  
[CV] activation\_function=softmax, batch\_size=20, dropout\_rate=0.1, epochs=100, init=uniform, learning\_rate=0.01, neuron1=4, neuron2=2

[Parallel(n\_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

[CV] activation\_function=softmax, batch\_size=20, dropout\_rate=0.1, epochs=100, init=uniform, learning\_rate=0.01, neuron1=4, neuron2=2, score=-1426.468, total= 30.3s  
[CV] activation\_function=softmax, batch\_size=20, dropout\_rate=0.1, epochs=100, init=uniform, learning\_rate=0.01, neuron1=4, neuron2=2

[Parallel(n\_jobs=1)]: Done 1 out of 1 | elapsed: 30.2s remaining: 0.0s

[CV] activation\_function=softmax, batch\_size=20, dropout\_rate=0.1, epochs=100, init=uniform, learning\_rate=0.01, neuron1=4, neuron2=2, score=-1388.876, total= 29.3s  
[CV] activation\_function=softmax, batch\_size=20, dropout\_rate=0.1, epochs=100, init=uniform, learning\_rate=0.01, neuron1=4, neuron2=2

[Parallel(n\_jobs=1)]: Done 2 out of 2 | elapsed: 59.6s remaining: 0.0s

[CV] activation\_function=softmax, batch\_size=20, dropout\_rate=0.1, epochs=100, init=uniform, learning\_rate=0.01, neuron1=4, neuron2=2

Reference: Keras classification and regression metrics  
<https://machinelearningmastery.com/custom-metrics-deep-learning-keras-python/> (<https://machinelearningmastery.com/custom-metrics-deep-learning-keras-python/>).