Predictive maintenance of Naval Propulsion Plants Data Set

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Abstract

This report describes the analysis steps conducted on the the Naval Propulsion Plants Data Set available in the UCI machine learning repository. Goal of the analysis is to predict values of the two output variables 'GT Compressor decay state coefficient' and 'GT turbine decay state coefficient' based on the values of 16 features representing measurements in a vessel and specifically the engine compartment. Basic data exploration steps were conducted, the dataset was cleaned and normalized. Dataset was split into train and test dataset, a linear regression and a decision tree regression model were applied. Both algorithms performed well on the given test dataset. Accuracy of the algorithms was measured by the mean squared error. Results of the analysis can be used to evaluate the engine state and to implement condition based or predictive maintenance on the system.

Motivation

The Naval Propulsion Plants Data Set yields interesting opportunities for machine learning applications. The application of regression algorithms like Linear regression, decision trees, GLM, GAM, quantile regression or SVM as well as a combination of several models could be the basis of a system able to assist companies in maintaining production machines. Predictive maintenance is a hot topic nowadays for any company with machines that cost a lot of money when not producing goods. Implementing a system that is able to predict a possible machine failure in time (=before it happens) can cut down repair costs and be an important part of a efficient production environment.

Dataset(s)

The Naval Propulsion Plants Data Set from [1] includes 11934 observations consisting of 18 measurements of different engine properties respectively.

- 14 features were used for prediction
- 2 features were dropped due to no or low variance
- 2 variables are our outcome variables which were predicted by the models, these are:
    - Gas turbine Compressor decay state coefficient (GT_comp_decay) and
    - Gas turbine Turbine decay state coefficient (GT_turbine_decay)

Data Preparation and Cleaning

The following data cleaning steps were conducted on the dataset:

- Drop NA values (drop those observations which had a NA value in any column)
- Drop two features, that is GT Compressor inlet air temperature and GT Compressor inlet air pressure due to no or very low variance
- Scale all 14 predictor variables using the standard scaler from sklearn due to differences in units and properties.

Research Question(s)

Based on 14 features from the Naval Propulsion Plants Data Set, is it possible to predict the value of two system-critical key indicators, GT_comp_decay and GT_turbine_decay?

If yes - how accurate are regression models able to predict the actual values of the two output variables mentioned above?

Methods

Multivariate linear regression and decision tree regression was used in order to tackle the supervised machine learning problem formulated in the research question.

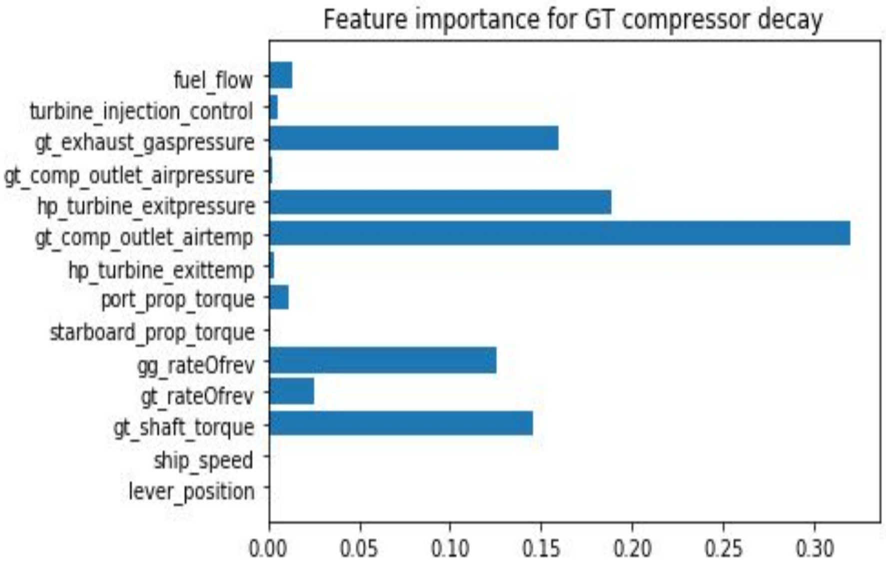
The dataset was split into training and test datasets, the models were fitted on the training set and afterwards evaluated on the test set. Accuracy of the models was evaluated by calculating the round mean squared error. RSME was calculated for the first (gt_comp_decay) and the second outcome variable (gt_turbine_decay) separately.

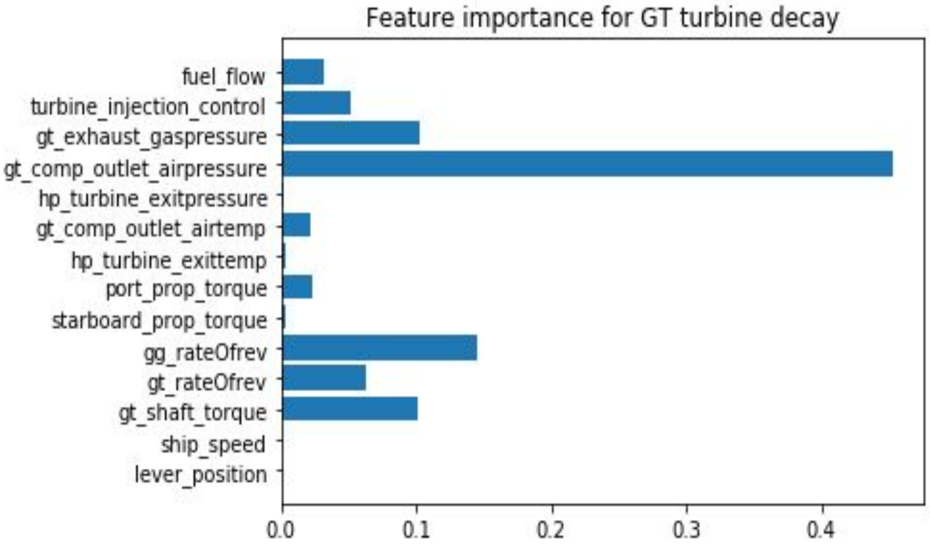
Findings

RMSE of the two models linear regression and decision tree regressor was calculated for both of the outcome variables gt_comp_decay and gt_turbine_decay. Here is the result: (rounded to 6 decimal numbers)

RSME Linear Regression GT comp decay	RSME Desc. Tree GT comp decay	RSME Linear Regression GT turbine decay	RSME Desc. Tree GT turbine decay
0.005949	0.002194	0.001527	0.001408

The difference in RSME is very small for GT turbine decay (only about 0.0002) and a little larger for GT compressor decay (0.0038).We see that decision tree regressor performs better to predict the GT compressor decay and only a little better on the turbine decay state. Next we want to investigate which variables were the most important ones for the decision tree predictor in order to predict our two output variables GT compressor decay and GT turbine decay. We do this by plotting the features importances from the predictor as barplots on the next slide.





We see in the plots above that the decision tree regressor uses features differently for predicting our two output variables. For GT compressor decay it is the variable 'gt_comp_outlet_airtemp' that is most important for the algorithm. 'gt_comp_outlet_airpressure' is of highest importance for predicting GT turbine decay.

Limitations

For the next micromasters course, machine learning, I would like to implement other regression models on the Naval Propulsion Plants Data Set like GLM,GAM, quantile regression or SVM. I would also like to do a combination of models in order to further minimize RMSE.

I know that this report lacks of elegant visualizations but I couldn’t think of any plots that yield a better understanding of the analysis steps conducted so I preferred not to include more color to this presentation just for the sake of doing it.

I am happy to receive feedback from you - maybe you can leave some ideas for plots in your review!

Conclusions

Both algorithms, linear regression and decision tree regression provide good results in predicting the values of our two output variables based on the 14 features available in the dataset used.

The difference in RSME is very small for GT turbine decay (only about 0.0002) and a little larger for GT compressor decay (0.0038).We see that decision tree regressor performs better to predict the GT compressor decay and only a little better on the turbine decay state.

Acknowledgements

The analysis this presentation is based on was conducted by me alone. I used code and information from the micromasters course ‘Python for Data Science’ from UCSD. Data was obtained from UCI machine learning repository, see references on the next slide.

References

The dataset used was obtained by:

[1] A. Coraddu, L. Oneto, A. Ghio, S. Savio, D. Anguita, M. Figari, Machine Learning Approaches for Improving Condition Based Maintenance of Naval Propulsion Plants, Journal of Engineering for the Maritime Environment, 2014, DOI: 10.1177/1475090214540874, (In Press)

Dataset was downloaded from UCI machine learning repository:

https://archive.ics.uci.edu/ml/datasets/Condition+Based+Maintenance+of+Naval+Propulsion+Plants

Abstract

This report describes the analysis steps conducted on the the Naval Propulsion Plants Data Set available in the UCI machine learning repository. Goal of the analysis is to predict values of the two output variables 'GT Compressor decay state coefficient' and 'GT turbine decay state coefficient' based on the values of 16 features representing meassurements in the vessel and specifically the engine compartment. Basic data exploration steps were conducted, the dataset was cleaned and normalized. After that the dataset was split into train and test dataset. The machine learning models applied were trained on the training set and then evaluated on the test dataset. Results of the analysis can be used to evaluate the state the engine, specifically the gas turbine compressor and turbines and to implement condition based or predictive maintenance on the vessel system. Algorithms applied were linear regression and descision tree regressor. Both algorithms performed well on the given test dataset. Decision tree based regression predicted the values of the outcome variables better that linear regression. Accuracy of the algorithms was measured by the mean squared error.

Description of the dataset

A. Coraddu, L. Oneto, A. Ghio, S. Savio, D. Anguita, M. Figari, Machine Learning Approaches for Improving Condition Based Maintenance of Naval Propulsion Plants, Journal of Engineering for the Maritime Environment, 2014, DOI: 10.1177/1475090214540874, (In Press)

"The experiments have been carried out by means of a numerical simulator of a naval vessel (Frigate) characterized by a Gas Turbine (GT) propulsion plant. The different blocks forming the complete simulator (Propeller, Hull, GT, Gear Box and Controller) have been developed and fine tuned over the year on several similar real propulsion plants. In view of these observations the available data are in agreement with a possible real vessel. In this release of the simulator it is also possible to take into account the performance decay over time of the GT components such as GT compressor and turbines. The propulsion system behaviour has been described with this parameters:

- Ship speed (linear function of the lever position lp).
- Compressor degradation coefficient kMc.
- Turbine degradation coefficient kMt. so that each possible degradation state can be described by a combination of this triple (lp,kMt,kMc). The range of decay of compressor and turbine has been sampled with an uniform grid of precision 0.001 so to have a good granularity of representation. In particular for the compressor decay state discretization the kMc coefficient has been investigated in the domain [1; 0.95], and the turbine coefficient in the domain [1; 0.975]. Ship speed has been investigated sampling the range of feasible speed from 3 knots to 27 knots with a granularity of representation equal to tree knots. A series of measures (16 features) which indirectly represents of the state of the system subject to performance decay has been acquired and stored in the dataset over the parameter's space."

The data can be downloaded from here: https://archive.ics.uci.edu/ml/datasets/Condition+Based+Maintenance+of+Naval+Propulsion+Plants (https://archive.ics.uci.edu/ml/datasets/Condition+Based+Maintenance+of+Naval+Propulsion+Plants) It consists of two .txt files containing data and headings respectivly.

In [5]:

```
import pandas as pd
import numpy as np
from numpy import *
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.metrics import accuracy_score
from math import sqrt
```

Lets have a quick look at the dataset and check out the names and units of the 16 predictor variables and the two output variables

In [6]:

```
featuredescription = pd.read_csv("C:/Features.txt", header=None)
featuredescription
```

Out[6]:

	0
0	1 - Lever position (lp) [ ]
1	2 - Ship speed (v) [knots]
2	3 - Gas Turbine shaft torque (GTT) [kN m]
3	4 - Gas Turbine rate of revolutions (GTn) [rpm]
4	5 - Gas Generator rate of revolutions (GGn) [rpm]
5	6 - Starboard Propeller Torque (Ts) [kN]
6	7 - Port Propeller Torque (Tp) [kN]
7	8 - HP Turbine exit temperature (T48) [C]
8	9 - GT Compressor inlet air temperature (T1) [C]
9	10 - GT Compressor outlet air temperature (T2)...
10	11 - HP Turbine exit pressure (P48) [bar]
11	12 - GT Compressor inlet air pressure (P1) [bar]
12	13 - GT Compressor outlet air pressure (P2) [bar]
13	14 - Gas Turbine exhaust gas pressure (Pexh) [...
14	15 - Turbine Injecton Control (TIC) [%]
15	16 - Fuel flow (mf) [kg/s]
16	17 - GT Compressor decay state coefficient.
17	18 - GT Turbine decay state coefficient.

In [10]:

```
#Read the dataset and check out the variables
data = pd.read_csv("C:/data.txt",sep=" ")
data.describe()
```

Out[10]:

	lever_position	ship_speed	gt_shaft_torque	gt_rateOfrev	gg_rateOfrev	starboard_p
count	11934.000000	11934.000000	11934.000000	11934.000000	11934.000000	11
mean	5.166667	15.000000	27247.498685	2136.289256	8200.947312	
std	2.626388	7.746291	22148.613155	774.083881	1091.315507	
min	1.138000	3.000000	253.547000	1307.675000	6589.002000	
25%	3.144000	9.000000	8375.883750	1386.758000	7058.324000	
50%	5.140000	15.000000	21630.659000	1924.326000	8482.081500	
75%	7.148000	21.000000	39001.426750	2678.079000	9132.606000	
max	9.300000	27.000000	72784.872000	3560.741000	9797.103000	

In [11]:

```
data.head()
```

Out[11]:

	lever_position	ship_speed	gt_shaft_torque	gt_rateOfrev	gg_rateOfrev	starboard_prop_to
0	1.138	3.0	289.964	1349.489	6677.380	7
1	2.088	6.0	6960.180	1376.166	6828.469	28
2	3.144	9.0	8379.229	1386.757	7111.811	60
3	4.161	12.0	14724.395	1547.465	7792.630	113
4	5.140	15.0	21636.432	1924.313	8494.777	175

In [12]:

```
data.shape
```

Out[12]:

```
(11934, 18)
```

Data cleaning and preparation

In [14]:

```
#Remove NA values
data = data.dropna()
data.isna().any()
```

Out[14]:

```
lever_position                  False
ship_speed                      False
gt_shaft_torque                 False
gt_rateOfrev                    False
gg_rateOfrev                    False
starboard_prop_torque           False
port_prop_torque                False
hp_turbine_exittemp             False
gt_comp_inlet_airtemp           False
gt_comp_outlet_airtemp          False
hp_turbine_exitpressure         False
gt_comp_inlet_airpressure       False
gt_comp_outlet_airpressure      False
gt_exhaust_gaspressure          False
turbine_injection_control       False
fuel_flow                       False
gt_comp_decay                   False
gt_turbine_decay                False
dtype: bool
```

In [16]:

```
#Check out variance in of the features
data.var()
```

Out[16]:

```
lever_position                  6.897912e+00
ship_speed                      6.000503e+01
gt_shaft_torque                 4.905611e+08
gt_rateOfrev                    5.992059e+05
gg_rateOfrev                    1.190970e+06
starboard_prop_torque           4.019860e+04
port_prop_torque                4.019860e+04
hp_turbine_exittemp             3.016493e+04
gt_comp_inlet_airtemp           0.000000e+00
gt_comp_outlet_airtemp          5.281784e+03
hp_turbine_exitpressure         1.176726e+00
gt_comp_inlet_airpressure       6.419307e-26
gt_comp_outlet_airpressure      2.848835e+01
gt_exhaust_gaspressure          1.079587e-04
turbine_injection_control       6.677760e+02
fuel_flow                       2.571825e-01
gt_comp_decay                   2.166848e-04
gt_turbine_decay                5.625471e-05
dtype: float64
```

gt_comp_inlet_airtemp doesn't have any variance across observations so we remove it because it won't be a good predictor in our models.

In [17]:

```
del data["gt_comp_inlet_airtemp"]
```

Also gt_comp_inlet_airpressure doesn't seem to have a high variance, let's check it out.

In [24]:

```
min(data["gt_comp_inlet_airpressure"])
```

Out[24]:

```
0.998
```

In [26]:

```
max(data["gt_comp_inlet_airpressure"])
```

Out[26]:

```
0.998
```

In [27]:

```
del data["gt_comp_inlet_airpressure"]
```

We also removed gt_comp_inlet_airpressure due to no variance and end up with 14 features for the prediction models. It should be noted that the dataset includes 2 output variables, "gt_comp_decay" and "gt_turbine_decay". They will be both be predicted seperatly. The features used for prediction are same for the two output variables:

In [29]:

```
features = ["lever_position","ship_speed","gt_shaft_torque","gt_rateOfrev","gg_rateOfre
v","starboard_prop_torque",
            "port_prop_torque","hp_turbine_exittemp","gt_comp_outlet_airtemp","hp_turbi
ne_exitpressure",
            "gt_comp_outlet_airpressure","gt_exhaust_gaspressure","turbine_injection_co
ntrol",
            "fuel_flow"]
target1=["gt_comp_decay"]
target2=["gt_turbine_decay"]
```

Due to differences in units and properties of the 14 prediction features, they will be scaled using the StandardScaler from sklearn. Also the dataset will be further prepared for the algorithms applied later. We form a set with features and output variables.

In [31]:

```
X = StandardScaler().fit_transform(data[features])
y1=data[target1]
y2=data[target2]
```

Linear Regression

The dataset will be split in training and test datasets, the model will then be fitted on the training set and afterwards evaluated on the test set. We evaluate the accuracy of the model by calculating the round mean squared error. We calculate the rmse for our first (gt_comp_decay) and our second outcome variable (gt_turbine_decay).

gt_comp_decay:

In [33]:

```
X_train, X_test, y1_train, y1_test = train_test_split(X,y1,test_size=0.2,random_state=3
24)
regressor=LinearRegression()
regressor.fit(X_train,y1_train)
y1_prediction=regressor.predict(X_test)
rmse1 = sqrt(mean_squared_error(y_true=y1_test,y_pred=y1_prediction))
#Print the mean ssquared prediction error
print(rmse1)
```

```
0.005949103989763792
```

gt_turbine_decay:

In [35]:

```
X_train, X_test, y2_train, y2_test = train_test_split(X,y2,test_size=0.2,random_state=3
24)
regressor=LinearRegression()
regressor.fit(X_train,y2_train)
y2_prediction=regressor.predict(X_test)
rmse2 = sqrt(mean_squared_error(y_true=y2_test,y_pred=y2_prediction))
print(rmse2)
```

```
0.0021941897143928205
```

Decision tree regressor

As a comparison to the linear regression model from above we build a second model using decision tree regression. Let's check out if this model performes even better.

gt_comp_decay:

In [36]:

```
dtregressor1=DecisionTreeRegressor(max_depth=20)
dtregressor1.fit(X_train,y1_train)
y1dt_prediction=dtregressor1.predict(X_test)
rmse_DT1 = sqrt(mean_squared_error(y_true=y1_test,y_pred=y1dt_prediction))
print(rmse_DT1)
```

```
0.0015108187086251663
```

gt_turbine_decay:

In [38]:

```
dtregressor2=DecisionTreeRegressor(max_depth=20)
dtregressor2.fit(X_train,y2_train)
y2dt_prediction=dtregressor2.predict(X_test)
rmse_DT2 = sqrt(mean_squared_error(y_true=y2_test,y_pred=y2dt_prediction))
print(rmse_DT2)
```

```
0.0013551785958606434
```

Results and visualization

Let's compare accuracy of the two models regarding the prediction of the two outcome variables. Values represent the rmse values of the models applied above.

In [49]:

```
resultsdata = np.array([["Linear Regression GT comp decay","Desc. Tree GT comp decay",
                         "Linear Regression GT turbine decay","Desc. Tree GT turbine de
cay"],
                        [rmse1,rmse2,rmse_DT1,rmse_DT2]])
res_df = pd.DataFrame(resultsdata)
res_df.columns = ['']*res_df.shape[1]
print(res_df.to_string(index=False))
```

```
 Linear Regression GT comp decay  Desc. Tree GT comp decay  Linear Regre
ssion GT turbine decay  Desc. Tree GT turbine decay
            0.005949103989763792      0.0021941897143928205
0.0015108187086251663        0.0013551785958606434
```

We see that decision tree regressor performes better to predict the GT compressor decay and only a little better on the turbine decay state. Next we want to investigate which variables were the most important ones for the decision tree predictor in order to predict our two output variables GT compressor decay and GT turbine decay. We do this by plotting the features importances from the predictor as barplots.

In [50]:

```
feat_importances1 = pd.Series(dtregressor1.feature_importances_)
feat_importance1_df = pd.DataFrame(feat_importances1)
feat_importance1_df["feature"]=features
feat_importances2 = pd.Series(dtregressor2.feature_importances_)
feat_importance2_df = pd.DataFrame(feat_importances2)
feat_importance2_df["feature"]=features
```

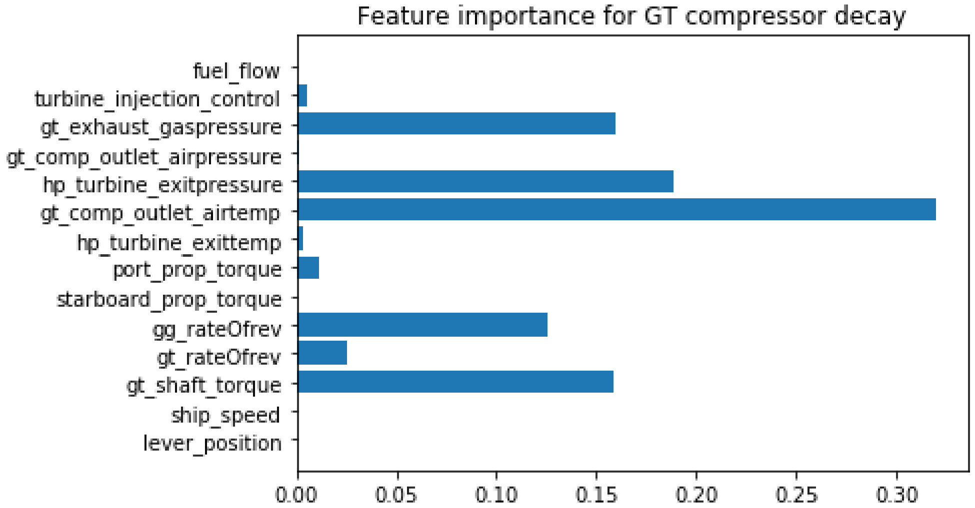
GT compressor decay:

In [51]:

```
import matplotlib.pyplot as plt
plt.barh(feat_importance1_df["feature"],feat_importance1_df[0])
plt.title("Feature importance for GT compressor decay")
```

Out[51]:

```
Text(0.5, 1.0, 'Feature importance for GT compressor decay')
```



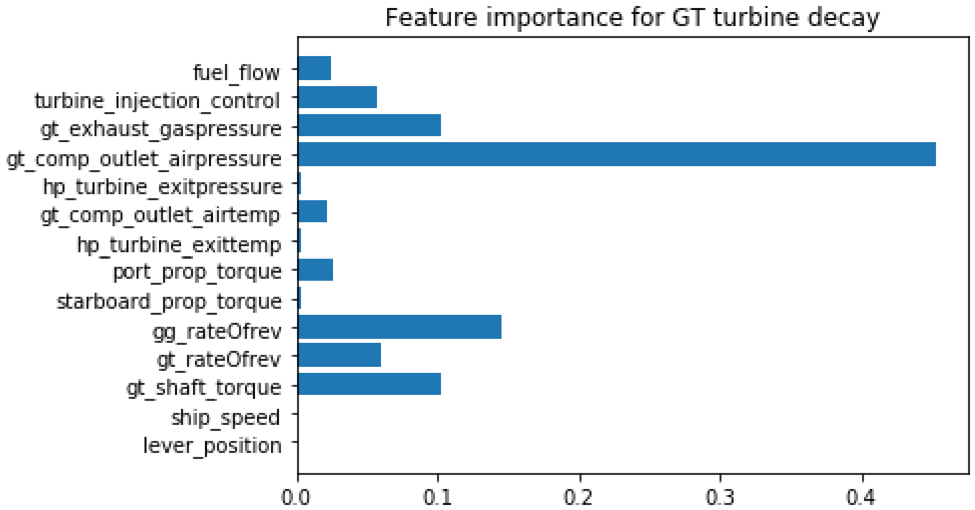
GT turbine decay:

In [52]:

```
plt.barh(feat_importance2_df["feature"],feat_importance2_df[0])
plt.title("Feature importance for GT turbine decay")
```

Out[52]:

```
Text(0.5, 1.0, 'Feature importance for GT turbine decay')
```



Conclusion

We see in the plots above that the decision tree regressor uses features differntly for predicting our two ouput variables. For GT compressor decay it is the variable 'gt_comp_outlet_airtemp' that is most important for the algorithm. 'gt_comp_outlet_airpressure' is of highest importance for predicting GT turbine decay. Both algorithms, linear regression and decision tree regression provide good results in predicting the values of our two output variables based on the 14 features available in the dataset used. The difference in RSME, our measure of accuracy for the algorithms, is very small for GT turbine decay (only about 0.0002) and a little larger for GT compressor decay (0.0038). THe Naval Propulsion Plants Data Set yields interesting opportunities for machine learning applications. The application of other regression algorithms like GLM,GAM, quantile regression or SVM as well as a combination of several models could be the basis of a system able to assist companies in maintaining production machines. Predictive maintenance is a hot topic nowadays for any company with machines that cost a lot of money when not producing goods. Implementing a system that is able to predict a possible machine failure in time can cut down repair costs and be an important part of a efficient production environment.

In [ ]:

```

```