Safran Lab 2

Every day, more than 80,000 commercial flights take place around the world, operated by hundreds of airlines. For all aircraft take-off weight exceeding 27 tons, a regulatory constraint requires companies to systematically record and analyse all flight data, for the purpose of improving the safety of flights. Flight Data Monitoring strives to detect and prioritize deviations from standards set by the aircraft manufacturers, the authorities of civil aviation in the country, or even companies themselves. Such deviations, called events, are used to populate a database that enables companies to identify and monitor the risks inherent to these operations.

This notebook is designed to let you manipulate real aeronautical data, provided by the Safran Group. It is divided in two parts: the first part deals with data exploration, data visualization, the use case, analysis of distributions and simple linear models to predict the fuel consumption of a flight. The second part deals with more complex models, optimization of parameters, interpretation of the results, and models to predict the fuel consumption of each flight phase and finally conclude by the objective of giving pieces of advice to the pilot so that he optimizes the consumption of fuel the next time.

Load the cell below for overall set up

In [2]:
```
# set up
BASE_DIR = "/mnt/safran/TP2/data/"

import time

import glob

import matplotlib as mpl
import matplotlib.pylab as plt
%matplotlib inline
import matplotlib.dates as mdates
mpl.rcParams['axes.grid'] = True

import numpy as np
import scipy as sp
import pandas as pd

pd.options.display.max_columns = 23

from datetime import datetime

from sklearn import tree, linear_model, model_selection, preprocessing, decomposition
from sklearn.metrics import mean_squared_error


# read_pickle
dfs = []
files = glob.glob(BASE_DIR + "flights/*.pkl")

p = 0
for idx, file in enumerate(files):
    if idx % int(len(files) / 10) == 0:
        print(str(p * 10) + "%: [" + "#" * p + " " * (10 - p) + "]", end="\r")
        p += 1
    dfs.append(pd.read_pickle(file))


# Load global values data, Summarising global values in a dataframe

file_features_df = BASE_DIR + "features_df.pkl"
file_output_df = BASE_DIR + "output_df.pkl"

features_df = pd.read_pickle(file_features_df)
output_df = pd.read_pickle(file_output_df)

# flight_phases

flight_phases = ['APPROACH', 'CLIMB', 'CRUISE', 'DESCENT', 'ENG START', 'FINAL APP',
                 'FLARE', 'INIT CLIMB', 'LANDING', 'TAKE OFF', 'TAXI IN', 'TAXI OUT', 'TOUCH N GO',
                 'LVL CHANGE', 'GO AROUND']
```

```
100%: [##########]
```

1 Know & understand the data

Context

You are provided with nearly 3000 flights operating different routes.

Each flight data is a collection of time series resumed in a dataframe, the sample rate is 1Hz, the columns variables are described in the schema below:

Schema

VAR	DESCRIPTION	UNIT
ORIGIN	Flight departure airport	NA
RUNWAY_TO	Flight origin runway	NA
DESTINATION	Flight arrival airport	NA
RUNWAY_LD	Flight destination runway	NA
DATE_HF	High rate date computation	%d/%m/%y (UTC)
TIME_HF	High rate time computation	%H:%M:%S (UTC)
FLIGHT_PHASE	Current flight-phase	NA
ALT_STD_C	Standard altitude corrected	feet
HEAD_MAG	Magnetic heading	deg
IAS_C	Indicated air speed corrected	knot
RALTC	Radio altitude computed from different sources	feet
PITCH_C	Pitch attitude corrected	deg
ROLL_C	Bank angle corrected	deg
FOB	Fuel on board	kg
TORQ1_C	Torque corrected (engine 1)	%
TORQ2_C	Torque corrected (engine 2)	%
NH1_C	NH corrected (engine 1)	%
NH2_C	NH corrected (engine 2)	%
NL1	NL Left from frequency input	%
NL2	NL Right from frequency input (NL2)	%
GW_C	Gross weight corrected	kg

Here are some links to get expertise on some variables:

- torque (http://www.experimentalaircraft.info/articles/aircraft-engine-performance-1.php)
- aicraft fuel consumption (https://en.wikipedia.org/wiki/Fuel_economy_in_aircraft#Airline_fuel_efficiency)
- about FOB and fuel flow (http://www.experimentalaircraft.info/articles/aircraft-engine-instruments-1.php)

Question 1.1

- What variables are categorical?
- What variables are numerical?

In [3]:
```
features_df.head()
```

Out[3]:

	DATE_HF	ORIGIN	DESTINATION	RUNWAY_TO	RUNWAY_LD	MAX_FOB	MAX_GW	TIME_APPROACH	TIME_CLIMB	TIME_CRUISE	TIME_DE
0	03/12/15	ARPT0	ARPT1	08	26	2820	20620.0	106	857	1123	762
1	03/12/15	ARPT0	ARPT1	08	26	2752	18480.0	219	1129	649	933
2	22/06/15	ARPT0	ARPT3	24	28	2026	17780.0	152	1139	2418	366
3	10/08/15	ARPT0	ARPT3	08	28	1930	18300.0	32	749	2676	619
4	21/08/16	ARPT0	ARPT4	20	33	2054	21540.0	62	1038	1040	1210

In [18]:
```
features_df.head()
labels = []
for i in features_df:
    labels.append(i)
print(labels)
```

```
['DATE_HF', 'ORIGIN', 'DESTINATION', 'RUNWAY_TO', 'RUNWAY_LD', 'MAX_FOB', 'MAX_GW', 'TIME_APPROACH', 'TIME_CLIMB', 'TIME_CRUIS
E', 'TIME_DESCENT', 'TIME_ENG START', 'TIME_FINAL APP', 'TIME_FLARE', 'TIME_GO AROUND', 'TIME_INIT CLIMB', 'TIME_LANDING', 'TIM
E_LVL CHANGE', 'TIME_TAKE OFF', 'TIME_TAXI IN', 'TIME_TAXI OUT', 'TIME_TOUCH N GO', 'TIME_TOTAL']
```

In [28]:
```
type(features_df[labels[5]][0])
```

Out[28]: numpy.int64

In [32]:
```
# Your code goes here
features_df['DATE_HF'][0]
result = np.zeros(len(flight_phases))
for i in range(len(labels)):

    try:
        bla = float(features_df[labels[i]][0])
        result[i] = 1
    except:
        pass
print (result)
```

```
[ 0.  0.  0.  1.  1.  1.  1.  1.  1.  1.  1.  1.  1.  1.  1.]
```

Answer

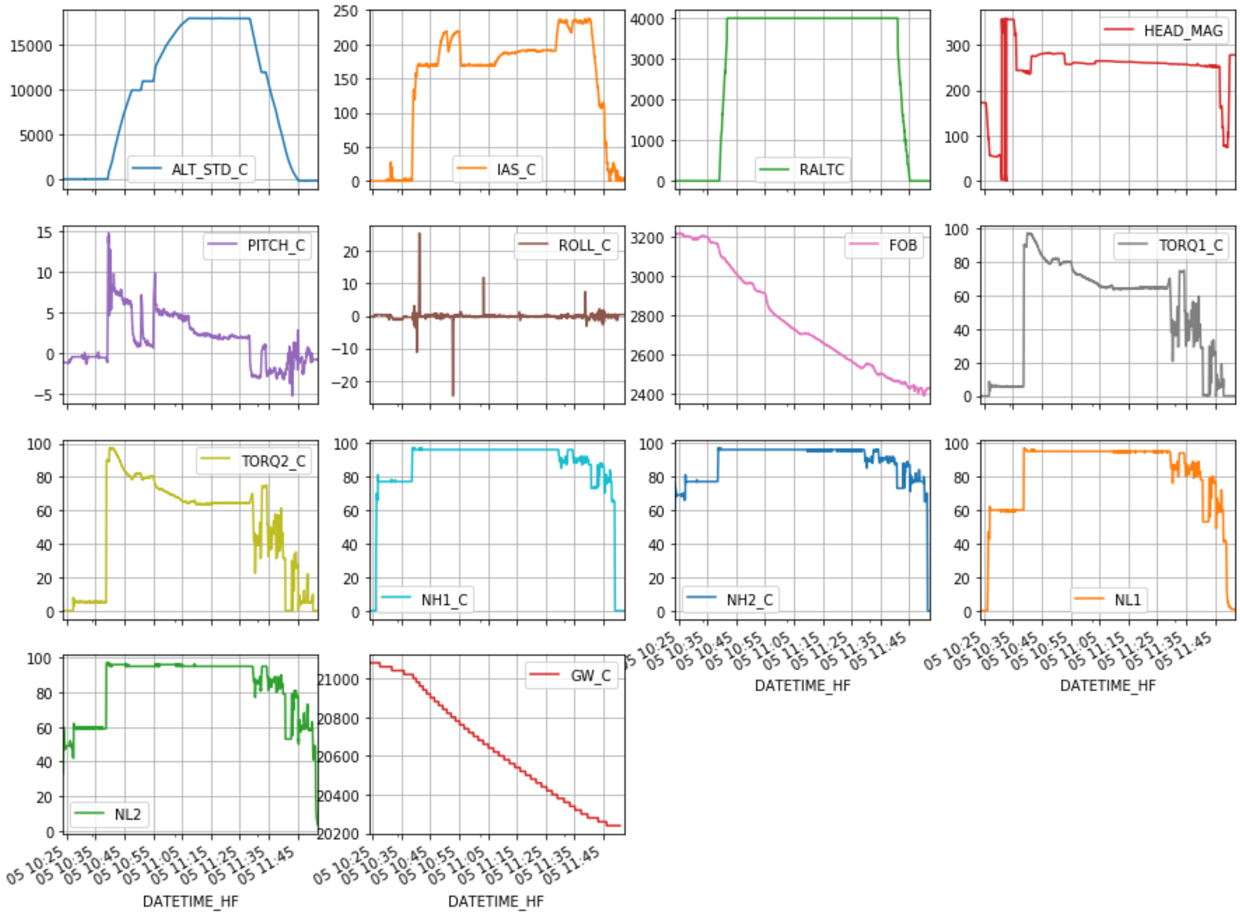
As the variable"result "shows, the first 3 feature is categorical, others are numeric

Visualize all time series for one flight

Let's visualize all the numerical time series for one flight, for example `dfs[0]`, to have a sense of how the time series vary.

In [33]:
```
# Give an alias to dfs[0] for convenience
df = dfs[0]

df.plot(kind="line", subplots=True, layout=(4, 4), figsize=(15, 12));
```



In [40]:
```
len(df)
```

Out[40]: 5300

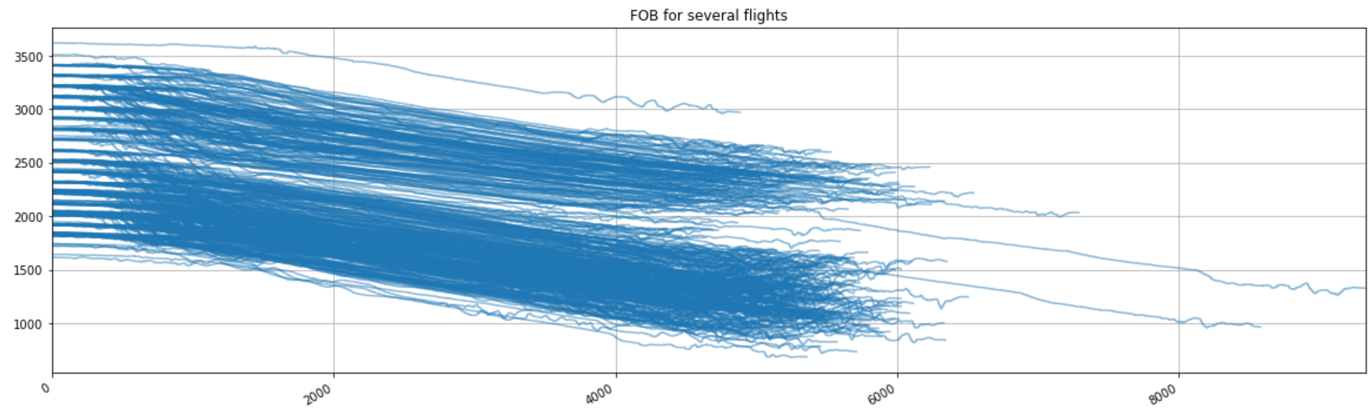
Question 1.2

Comment this visualization of FOB for several flights.

- Is there a pattern?
- Do you notice anything strange?

In [41]:
```
# Create a figure and one subplot
fig, ax = plt.subplots(figsize=(20, 6))

for df in dfs[:500]:
    df.FOB.plot(use_index=False, color="C0", ax=ax, title="FOB for several flights", alpha=0.5)
```



Answer

pattern: 1.in general, the FOB decreases along with the flight phase

1. THe initial FOB is classified to several classes. i.e. the initial Fuel is descrete, not continues. Strange: The FOB the FOB can fluctuate among the whole process. i.e. the fuel on board may increase somtimes when flight is in the air, which is strange.

About FLIGHT_PHASE column

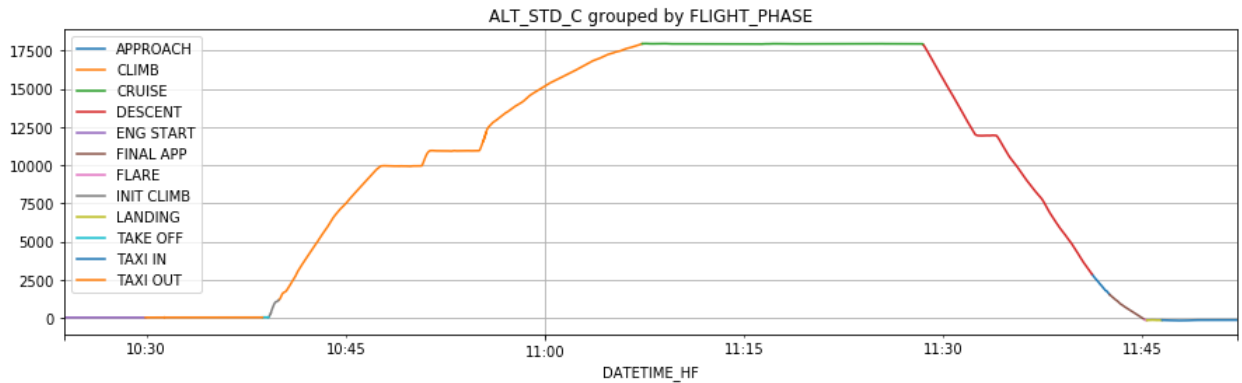
Observe how ALT_STD_C varies for each phase

In [42]:
```
# Create a figure and one subplot
fig, ax = plt.subplots(figsize=(15, 4))

# Give an alias to dfs[0]
df = dfs[0]

df.groupby("FLIGHT_PHASE").ALT_STD_C.plot(title="ALT_STD_C grouped by FLIGHT_PHASE", ax=ax);
ax.legend()
```

Out[42]: <matplotlib.legend.Legend at 0x7f4a0d72bbe0>



Typical chronology of cruise phases:

```
- ENG START
- TAXI OUT
- TAKE OFF
- INIT CLIMB
- CLIMB
- CRUISE
- DESCENT
- APPROACH
- FINAL APP
- FLARE
- LANDING
- TAXI IN
```

Phases that exist only for some flights:

```
- LVL CHANGE
- GO AROUND
- TOUCH N GO
```

About DELTA_FOB

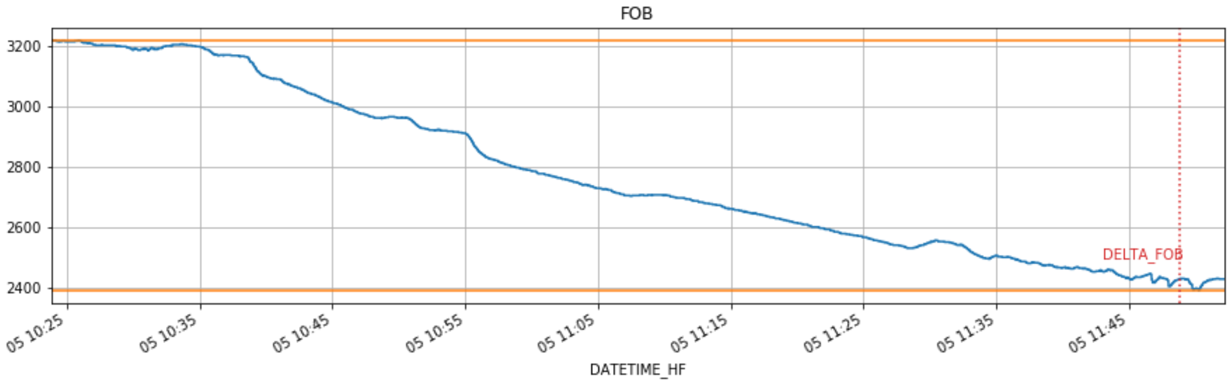
- `MAX_FOB`: FOB at the beginning of the flight
- `MIN_FOB`: FOB at the end of the flight
- `DELTA_FOB`: `MAX_FOB` - `MIN_FOB` the amount of fuel consumed during the whole flight

In [43]:
```
# Create a figure and one subplot
fig, ax = plt.subplots(figsize=(15, 4))

# Give an alias to dfs[0]
df = dfs[0]

df.FOB.plot(title="FOB")
plt.axhline(df.FOB.max(), color="C1")
plt.axhline(df.FOB.min(), color="C1")
plt.axvline(df.FOB.index[-200], linestyle=":", color="C3")
plt.text(df.FOB.index[-550], 2500, "DELTA_FOB", color="C3")
```

Out[43]:
```
&lt;matplotlib.text.Text at 0x7f4a12223978&gt;
```



From this FOB signal we will only be interested in deltas, that is the amount of fuel consumed over a certain time period. The first approach will focus on predicting the delta of all the flight, the second approach will be predicting the deltas of each flight phase

2 Use case

The story

A company asks you to help them optimize the fuel consumption of their fleet. They've been collecting data from their flights for 2 years, operating on four different routes. They do not understand why sometimes the pilots consume 800 kilograms of fuel and sometimes 600 kg for the same route. The company provided you with all their flights.

Your objective is two-fold:

- Create a model of the quantity of fuel consumed
- Tell the company how their pilots should fly the aircraft to optimize their fuel consumption

In this part we will only use some summarised features of each flight, not the whole time series. Here are the features we will be using:

features_df

VAR	DESCRIPTION
DATE_HF	date
DESTINATION	destination airport
ORIGIN	origin airport
RUNWAY_LD	runway landing
RUNWAY_TO	runway take-off
MAX_FOB	FOB at origin
MAX_GW	Gross weigth at origin
TIME_APPROACH	Approach length
TIME_CLIMB	Climb length
TIME_CRUISE	Cruise length

VAR	DESCRIPTION
TIME_DESCENT	Descent length
TIME_ENG START	Eng start length
TIME_FINAL APP	Final app length
TIME_FLARE	Flare length
TIME_GO AROUND	Go around length
TIME_INIT CLIMB	Init climb length
TIME_LANDING	Landing length
TIME_LVL CHANGE	Lvl change length
TIME_TAKE OFF	Take off length
TIME_TAXI IN	Taxi in length
TIME_TAXI OUT	Taxi out length
TIME_TOUCH N GO	Touch n go length
TIME_TOTAL	Total length

From these features we want to predict the amount of fuel consumed during the whole flight, that is `DELTA_FOB`. Imagine that at the end of flight the sensor that measures FOB broke and that we cannot know how much fuel we have left.

output_df

VAR	DESCRIPTION
DELTA_FOB	FOB conso

The `features_df` containing all the features described above has been computed for you, as well as `output_df`.

In [44]:
```
features_df = pd.read_pickle(file_features_df)
features_df.head()
```

Out[44]:

	DATE_HF	ORIGIN	DESTINATION	RUNWAY_TO	RUNWAY_LD	MAX_FOB	MAX_GW	TIME_APPROACH	TIME_CLIMB	TIME_CRUISE	TIME_DI
0	03/12/15	ARPT0	ARPT1	08	26	2820	20620.0	106	857	1123	762
1	03/12/15	ARPT0	ARPT1	08	26	2752	18480.0	219	1129	649	933
2	22/06/15	ARPT0	ARPT3	24	28	2026	17780.0	152	1139	2418	366
3	10/08/15	ARPT0	ARPT3	08	28	1930	18300.0	32	749	2676	619
4	21/08/16	ARPT0	ARPT4	20	33	2054	21540.0	62	1038	1040	1210

In [45]:
```
output_df = pd.read_pickle(file_output_df)
output_df.head()
```

Out[45]:

	DELTA_FOB
0	668
1	630
2	1072
3	1000
4	926

Question 2.1

In this question we compute some statistics about the population of flights:

- How many different origin airports?
- How many different destination airports?
- How many routes? How many flights per route?

In [73]:
```
# Your code goes here
#origin airport
n1 = len(features_df['ORIGIN'].unique())
n2 = len(features_df['DESTINATION'].unique())
print("No. of original airports:",n1)
#dest airport
print("No. of dest airports:",n2)
print("No. of routes:",n1*n2)\

for i in range(4):
    print(features_df.groupby("DESTINATION").count().iloc[i][0])
```

```
No. of original airports: 1
No. of dest airports: 4
No. of routes: 4
415
956
929
442
```

Answer

1.No. of original airports: 1
2.No. of dest airports: 4
3.No. of routes: 4
No. of flight per route: 415
956
929
442

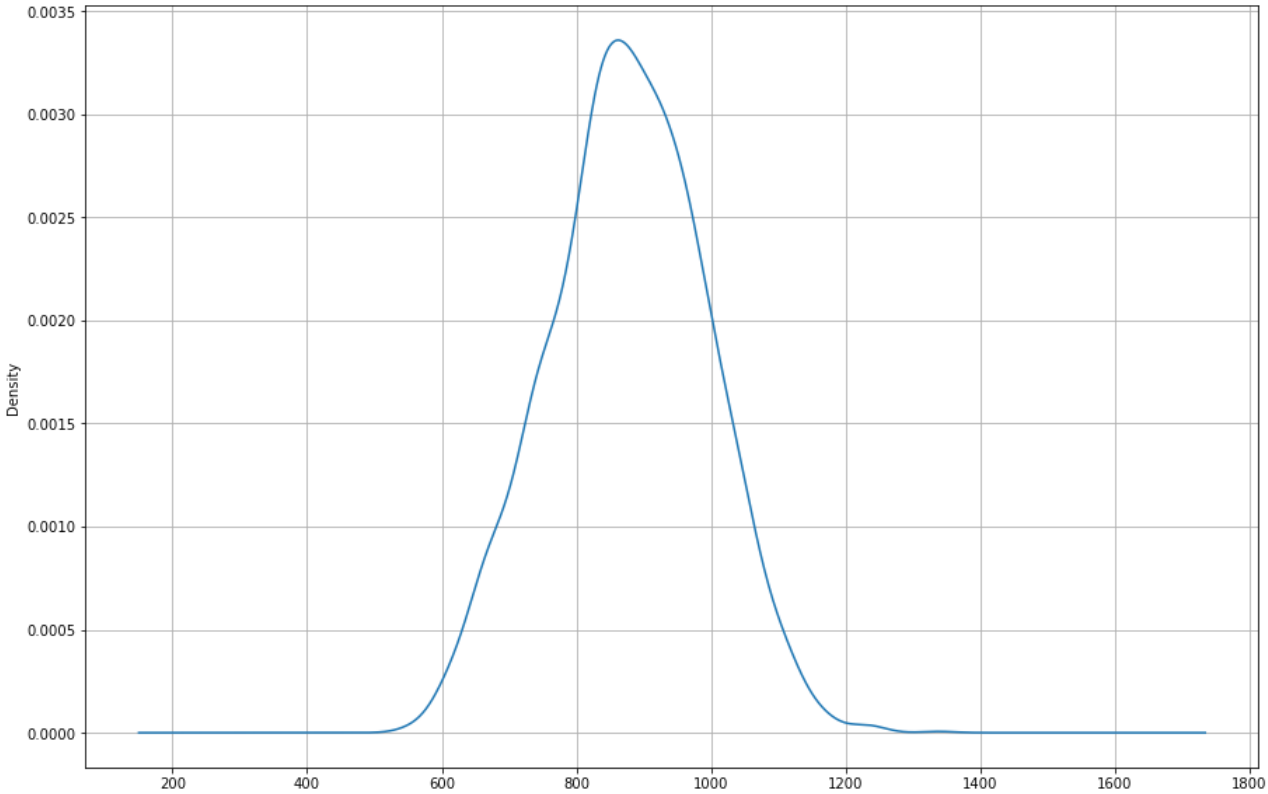
Question 2.2

In this question we focus on the output we want to predict: `DELTA_FOB` in dataframe `output_df`

- Plot the DELTA_FOB distribution and comment.
- What influences the most DELTA_FOB according to you? There is no right or wrong answer.

In [8]:
```
# Your code goes here
output_df['DELTA_FOB'].plot(figsize = (15,10),kind = 'kde')
```

Out[8]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f404c22ee48>`



Answer

According to the figure, the DELTA_FOB has the general value range from 600 to 1200. THe most frequent DELTA_FOB among all the flights is between [800,1000] We think the key factor than influencing the DELTA_FOB is the distance and the flying time. THe longer the distance, the more time you take, the flight will consume a higher delta FOB

Question 2.2

In this question we work on the distributions of `DELTA_FOB` conditionned on `DESTINATION` and (optional) `RUNWAY_LD`

- Plot `DELTA_FOB` distribution conditionned on `DESTINATION` airport and comment.
- (optional) Plot `DELTA_FOB` distribution conditionned on `DESTINATION` airport and `RUNWAY_LD` and comment.

In [12]:

```
# Your code goes here
'''
join the two table
'''
result = features_df.join(output_df,how = 'inner')
result.head()
```

Out[12]:

	DATE_HF	ORIGIN	DESTINATION	RUNWAY_TO	RUNWAY_LD	MAX_FOB	MAX_GW	TIME_APPROACH	TIME_CLIMB	TIME_CRUISE	TIME_DE
0	03/12/15	ARPT0	ARPT1	08	26	2820	20620.0	106	857	1123	762
1	03/12/15	ARPT0	ARPT1	08	26	2752	18480.0	219	1129	649	933
2	22/06/15	ARPT0	ARPT3	24	28	2026	17780.0	152	1139	2418	366
3	10/08/15	ARPT0	ARPT3	08	28	1930	18300.0	32	749	2676	619
4	21/08/16	ARPT0	ARPT4	20	33	2054	21540.0	62	1038	1040	1210

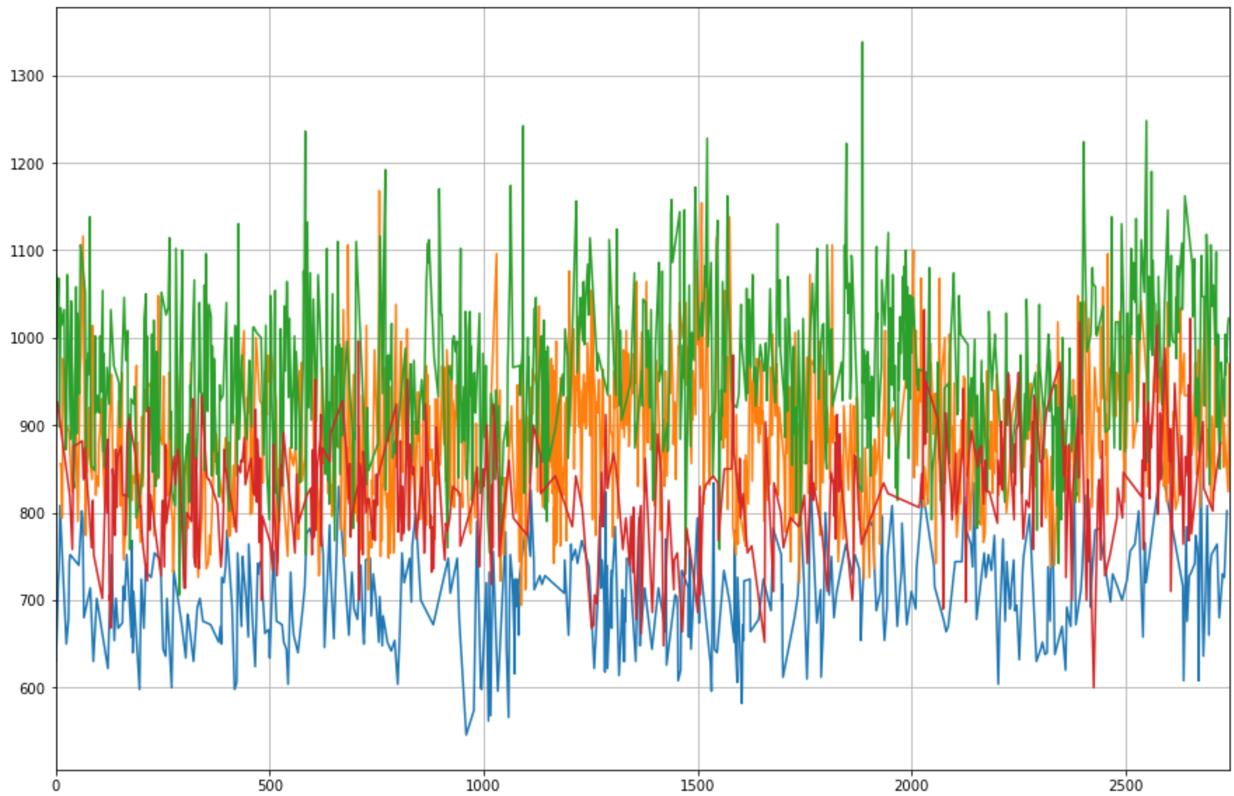
5 rows × 24 columns

In [26]:

```
result.groupby('DESTINATION').DELTA_FOB.plot(figsize = (15,10))
```

Out[26]:

```
DESTINATION
ARPT1    Axes(0.125,0.125;0.775x0.755)
ARPT2    Axes(0.125,0.125;0.775x0.755)
ARPT3    Axes(0.125,0.125;0.775x0.755)
ARPT4    Axes(0.125,0.125;0.775x0.755)
Name: DELTA_FOB, dtype: object
```



Answer

THe result shows that different destination airport has a clearly different value of DELTA_FOB. The flight heading to the same destination has the same DELTA_FOB

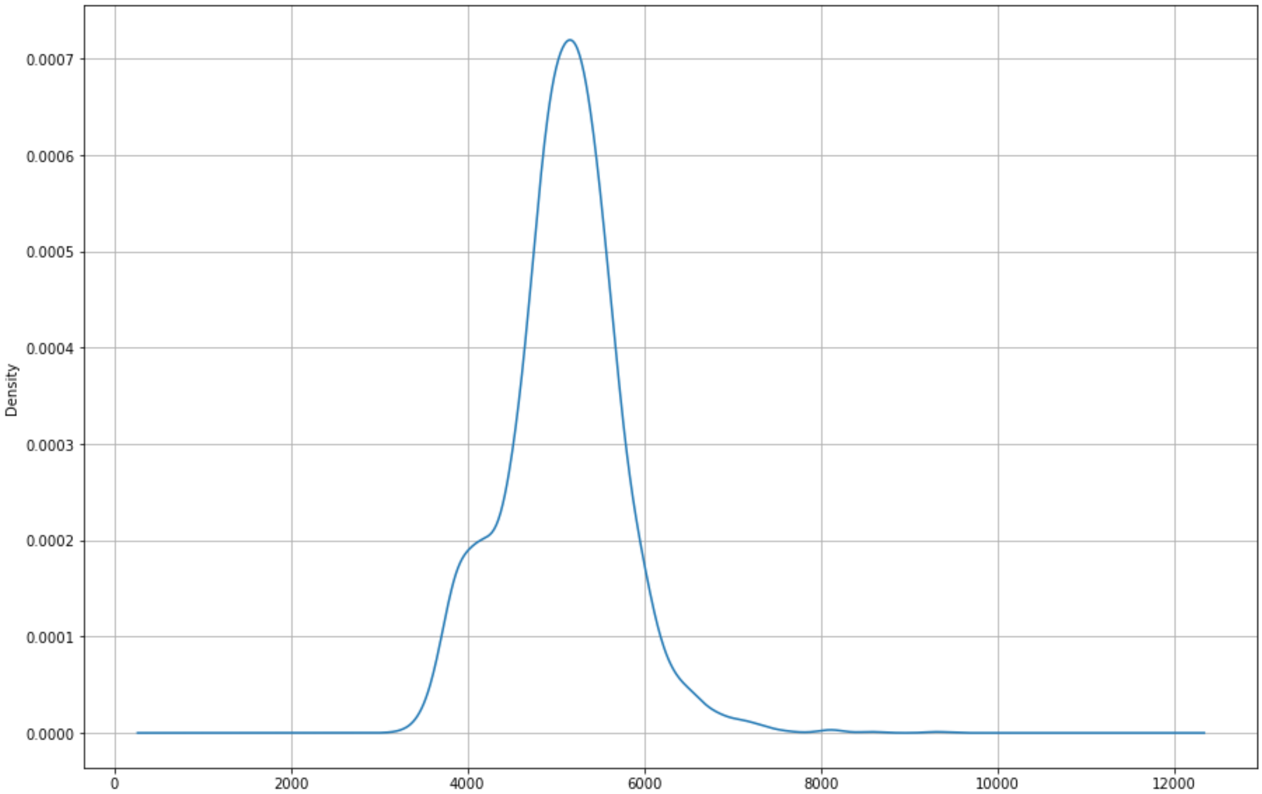
Question 2.3

Finally let's work with two important features: the total duration of the flight `TOTAL_TIME` and the quantity of fuel at the beginning of the flight `MAX_FOB`.

- Plot the distributions of the following variables:
  - `MAX_FOB`
  - `TIME_TOTAL`
- Comment these distributions

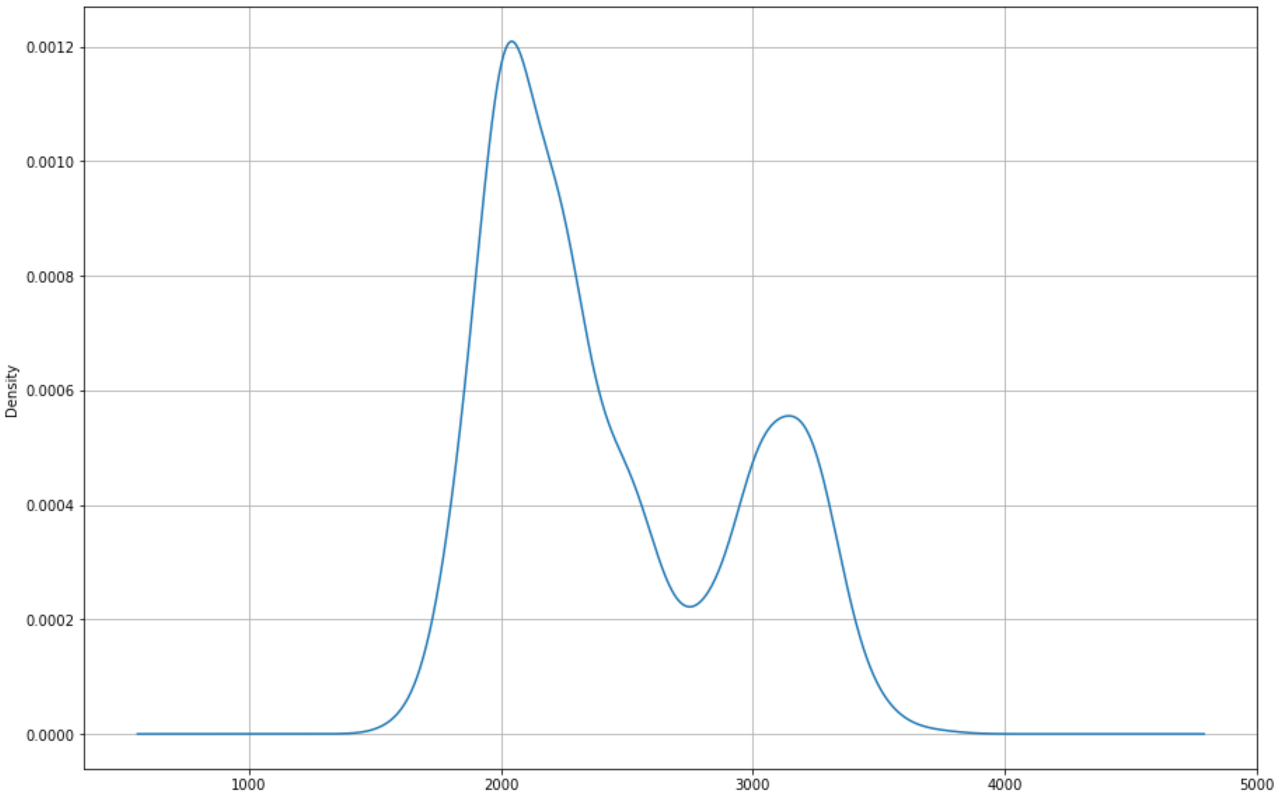
In [35]:
```
# Your code goes here
features_df['TIME_TOTAL'].plot(figsize = (15,10),kind = 'kde')
```

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x7f404297d198>



In [37]:
```
features_df['MAX_FOB'].plot(figsize = (15,10),kind = 'kde')
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7f40427822b0>



Answer Most of the flights experience the flying time ranging from [4000,6000]; And there are 2 comman value of MAX_FOB: 2000 and 3000

3 Model DELTA_FOB

We use sklearn (http://scikit-learn.org/stable/documentation.html) for models.

Question 3.1

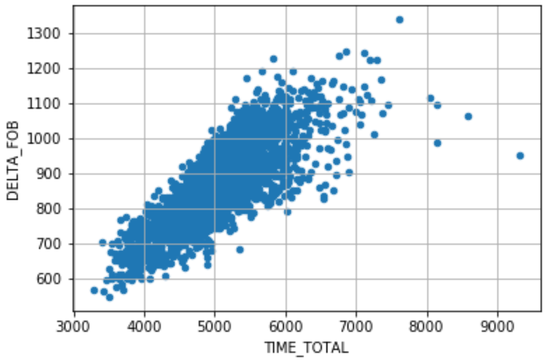
- Scatter plot `TIME_TOTAL` against `DELTA_FOB`.
- Is there any relationship?

In [42]:
```
# Your code goes here

result.plot.scatter(x= 'TIME_TOTAL',y = 'DELTA_FOB')
```

Out[42]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f404266b198>
```

```
<matplotlib.figure.Figure at 0x7f4042f80470>
```



Answer

THe scatter figure above shows there is a rough linear relationship between DELTA-FOB and TIME_TOTAL

Let's explore the predictive power of `TIME_TOTAL` on `DELTA_FOB`. Our first model is the following linear regression:

- algorithm: `LinearRegression` from sklearn package `linear_model` (reference (http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html))
- input: `TIME_TOTAL`
- output: `DELTA_FOB`

Follow the code below, in the following questions you will extensively use this template code and adapt it.

Question 3.2

Comment briefly the results, the following questions can help you:

- What is the score method implemented by sklearn?
- How do you relate it to the mse?
- What is best to interprete the quality of the estimator?

In [43]:
```
# This is template code for setting up a sklearn regression model

X = features_df[["TIME_TOTAL"]].as_matrix()

y = output_df[["DELTA_FOB"]].as_matrix()

test_size = 0.2
random_state = 42

# Split the features and output in training and test sets
X_train, X_test, y_train, y_test = model_selection.train_test_split(X, y, test_size=test_size, random_state=random_state)

# Create linear regression object
estimator = linear_model.LinearRegression()

# Train the model using the training sets
estimator.fit(X_train, y_train)

# Test the model on tests sets
print("score", estimator.score(X_test, y_test))
```

```
score 0.606144364551
```

Answer The score method returns the coefficient of determination R^2 of the prediction.
The coefficient R^2 is defined as (1 - u/v), where u is the regression sum of squares ((y_true - y_pred)^2).sum() and v is the residual sum of squares ((y_true - y_true.mean()) ^2).sum().
While $$MSE = ((y\_true - y\_pred)^2).sum()/N$$

Question 3.3

- Adapt the code above for the following model
  - algorithm: `LinearRegression`
  - input: `TIME_TOTAL`, `MAX_FOB`
  - output: `DELTA_FOB`
- Compare the score with the results of the previous regression
  - is it getting better?
  - which variable has the most predictive power among `TIME_TOTAL` and `MAX_FOB`?

In [97]:
```
# Your code goes here
# This is template code for setting up a sklearn regression model

X_33 = features_df[["TIME_TOTAL", "MAX_FOB"]].as_matrix()
X_2 = features_df[["MAX_FOB"]].as_matrix()
# X_33 = np.hstack((X1,X2))


y = output_df[["DELTA_FOB"]].as_matrix()

test_size = 0.2
random_state = 42

# Split the features and output in training and test sets
X_train, X_test, y_train, y_test = model_selection.train_test_split(X_33, y, test_size=test_size, random_state=random_state)

# Create linear regression object
estimator = linear_model.LinearRegression()

# Train the model using the training sets
estimator.fit(X_train, y_train)

# Test the model on tests sets
print("score", estimator.score(X_test, y_test))
```

```
score 0.708710764451
```

In [98]:
```
X_train, X_test, y_train, y_test = model_selection.train_test_split(X_2, y, test_size=test_size, random_state=random_state)

# Create linear regression object
estimator = linear_model.LinearRegression()

# Train the model using the training sets
estimator.fit(X_train, y_train)

# Test the model on tests sets
print("score", estimator.score(X_test, y_test))
```

```
score 0.0797671623189
```

Answer

The result(score) is better then the single input. As computed above, the 'TIME_TOTAL' is more predictive to the DELTA_FOB because the score is higer than MAX-FOB

Before moving on and adding more features to our models, let's compare our linear regressions to a simple non-linear model:

- algorithm: `DecisionTreeRegressor` from sklearn package `tree` (reference (http://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeRegressor.html))
- input: `TIME_TOTAL`, `MAX_FOB`
- output: `DELTA_FOB`

Question 3.4

- Adapt the code for the model described above.
- What is the default behavior for `max_depth` parameter?
- With a default behavior, is the score better than with linear regression?
- Split in 10 validation sets and optimize `max_depth` parameter (you can use the template code below)
  - plot `max_depth` parameters against the score
  - why is it not OK to optimize parameters only with train and test sets?
- What attributes can you use to you interprete the tree?

In [132]:
```
'''
default maxdepth
'''
estimator =  tree.DecisionTreeRegressor()
X_train, X_test, y_train, y_test = model_selection.train_test_split(X_33, y, test_size=test_size, random_state=random_state)
estimator.fit(X_train, y_train)
score = estimator.score(X_test, y_test)
print(score)
```

```
0.588388532083
```

Answer

- With a default behavior, the score is 0.0109289617486, which worse than linear regression

- With only train and test data, the model is easily to get overfitting, so we need cross validation to modifier the model. Also, after applying cross validation, we can use every data bunch to train and tune the model, so the data set more efficiently used.

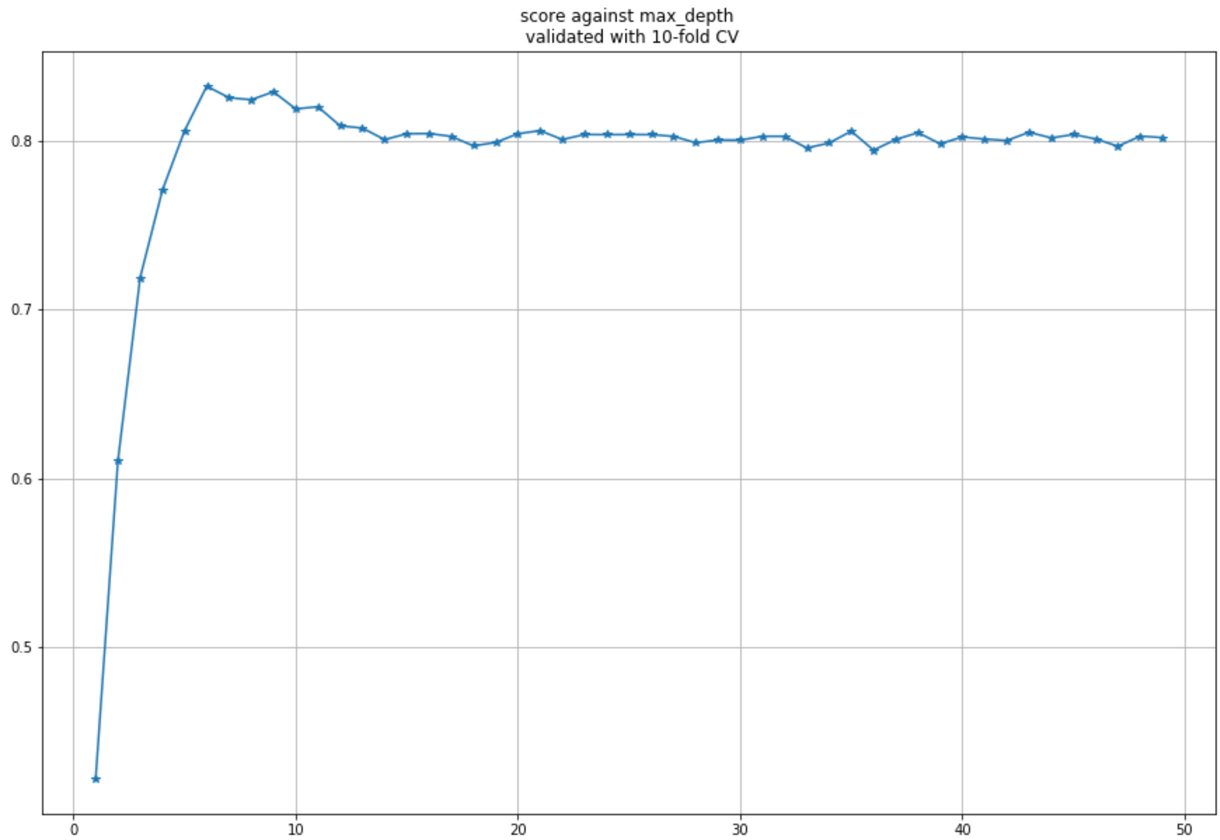
In [134]:
```
# This is the template code for cross validation, fill in the blanks

max_depths = range(1,50)

kFold = model_selection.KFold(n_splits=10)
scores = []

for max_depth in max_depths:
    estimator.set_params(max_depth=max_depth)
    score = []
    folds = kFold.split(X_33)
    for fold in folds:
        # Unpack train and test indices
        train, test = fold
        # Split in train and test sets
        X_train, X_test, y_train, y_test = X[train], X[test], y[train], y[test]
        estimator.fit(X_train, y_train)
        score.append(estimator.score(X_test, y_test))
    scores.append(np.mean(score))
plt.figure(figsize = (15,10))
plt.plot(max_depths,scores, marker="*")
plt.title("score against max_depth \n validated with 10-fold CV")
```

Out[134]:
```
<matplotlib.text.Text at 0x7f40213bb7f0>
```



Answer

According to the result, the best depth of the tree is 6. After around 14, the model converges to local minmum and has no improvement.

Let's add all the other numeric features.

In [77]:
```
numeric_features = ['MAX_FOB',
                    'MAX_GW',
                    'TIME_APPROACH',
                    'TIME_CLIMB',
                    'TIME_CRUISE',
                    'TIME_DESCENT',
                    'TIME_ENG START',
                    'TIME_FINAL APP',
                    'TIME_FLARE',
                    'TIME_GO AROUND',
                    'TIME_INIT CLIMB',
                    'TIME_LANDING',
                    'TIME_LVL CHANGE',
                    'TIME_TAKE OFF',
                    'TIME_TAXI IN',
                    'TIME_TAXI OUT',
                    'TIME_TOUCH N GO',
                    'TIME_TOTAL']
```

Question 3.5

In Question 3.5 we will use regularized regression. In this question we take a preliminary step and rescale the features.

We use the `StandardScaler` from sklearn `preprocessing` package (reference (http://scikit-learn.org/stable/modules/preprocessing.html)).

- Give one reason for rescaling the features before doing regularized regression
- Fill in the blanks in the code below and observe the results printed out
- Why the first feature of `X_test_transformed` does not have a std of 1?

In [84]:
```
# This is the template code for rescaling the features, fill in the blanks
X = features_df[numeric_features].as_matrix()

y = output_df[["DELTA_FOB"]].as_matrix()

test_size = 0.2
random_state = 42
X_train, X_test, y_train, y_test = model_selection.train_test_split(X, y, test_size=test_size, random_state=random_state)


scaler = preprocessing.StandardScaler()

scaler.fit(X_train) # Fill in the blanks

X_train_transformed = scaler.transform(X_train) # Fill in the blanks
X_test_transformed = scaler.transform(X_test) # Fill in the blanks

print("X_train_transformed first feature,", "mean:", X_train_transformed[:, 0].mean(), "std:", X_train_transformed[:, 0].std())
print("X_test_transformed first feature,", "mean:", X_test_transformed[:, 0].mean(), "std:", X_test_transformed[:, 0].std())
```

```
X_train_transformed first feature, mean: -1.36892068335e-16 std: 1.0
X_test_transformed first feature, mean: 0.0510960710978 std: 1.03838428734
```

Answer

- Because different feature has different range of numerical value, so in order to avoid some feature has strong impact on the result while other feature with low numerical value has no contributio on the model, we should rescale eache value of feature to ensure their value to be in the similar, comparable range.
- Why the first feature of X_test_transformed does not have a std 1?
  Because the scaler.fit() funcion is used on X_train, so when we implement the scalar.transform, the `X_train` will have std = 1 but X_test won't

The last question of this part focus on regularized linear regression.

- algorithm: `Ridge` for sklearn package `linear_model` (reference (http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.Ridge.html))
- input: `numeric_features` of `features_df`
- output: `DELTA_FOB`

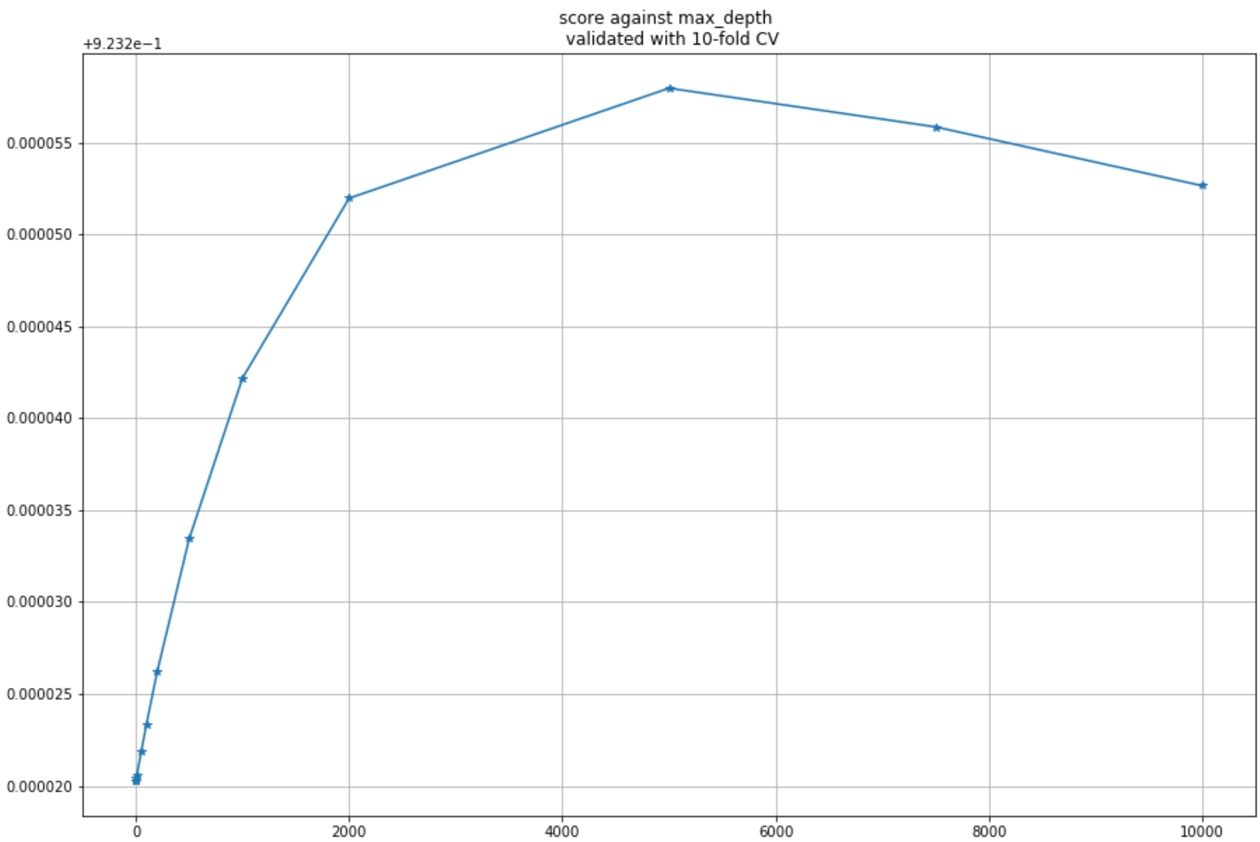
Question 3.6

- Use the previous template codes and adapt it to set up the models described above and rescale the features
- Split in validation sets and optimize `alpha` parameter
- Interprete the coefficients of your best estimator

In [135]:
```
# This is the template code for cross validation, fill in the blanks
estimator = linear_model.Ridge()
# alphas = np.array(range(20))/10
# alphas = alphas.tolist()
alphas = [0.1,0.5,1,5,10,50,100,200,500,1000,2000,5000,7500,10000]

kFold = model_selection.KFold(n_splits=10)
scores = []
for alpha in alphas:
    estimator.set_params(alpha = alpha)
    score = []
    folds = kFold.split(X)
    for fold in folds:
        # Unpack train and test indices
        train, test = fold
        # Split in train and test sets
        X_train, X_test, y_train, y_test = X[train], X[test], y[train], y[test]
        estimator.fit(X_train, y_train)
        score.append(estimator.score(X_test, y_test))
    scores.append(np.mean(score))
plt.figure(figsize = (15,10))
plt.plot(alphas,scores, marker="*")
plt.title("score against max_depth \n validated with 10-fold CV")
```

Out[135]: <matplotlib.text.Text at 0x7f4021339c18>



In [139]:
```
estimator.coef_[0]
```

Out[139]:
```
array([-0.08888783,  0.00600624,  0.09832672,  0.04966331,  0.09802506,
        0.11027636, -0.07504029,  0.03718645, -0.24265935,  0.05536181,
        0.17781385, -0.33446976,  0.17986239,  0.05173224, -0.07871405,
       -0.01964498,  0.        ,  0.10771976])
```

Answer

THe graph above shows that the score of Ridge Regression is quite low, and changing alpha doesn't make an evident improvement on the score. Therefore, Ridge Regression is not a suitable method on this dataset, linear regression is a better choice.

4 Feature engineering & model delta_fob for each phase

We will add a lot of information with engine-related time series:

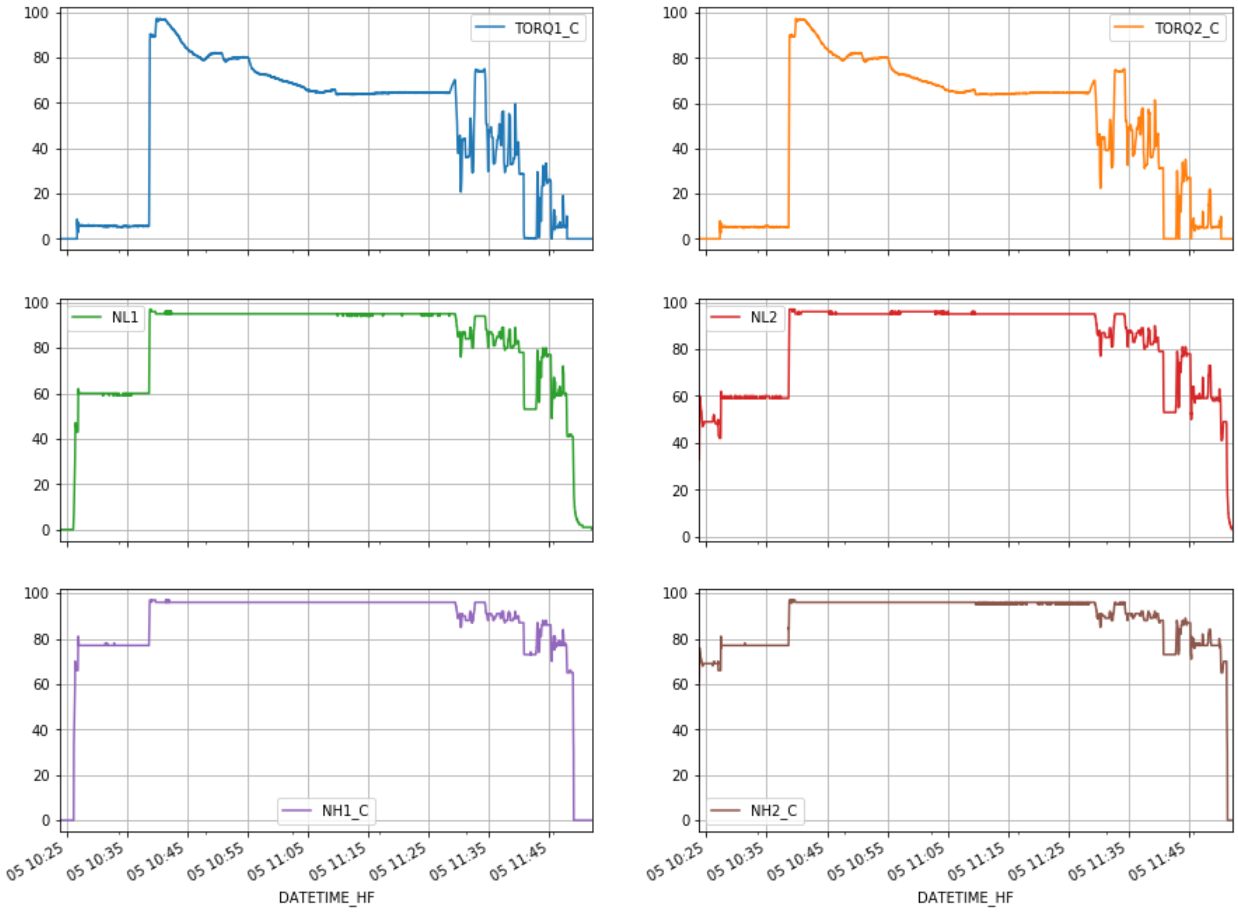
- TORQ1_C, TORQ2_C
- NL1, NL2
- NH1_C, NH2_C

Visualization of engine-related time series for one flight

In [140]:
```
# Five an alias to dfs[0]
df = dfs[0]

engine_features = ['TORQ1_C', 'TORQ2_C',
                   'NL1', 'NL2',
                   'NH1_C', 'NH2_C']

df[engine_features].plot(subplots=True, layout=(3, 2), figsize=(15, 12));
```



Question 4.1

We will extract few numbers out of each phase for all engine variables (`TORQ1_C`, `TORQ2_C`, `NL1`, `NL2`, `NH1_C`, `NH2_C`)

- Feature engineering
  - get `TORQ1_C` of one phase of one flight, do a linear regression by index and plot the result
  - is it OK to resume the signal by a straight line? what other features would you add?

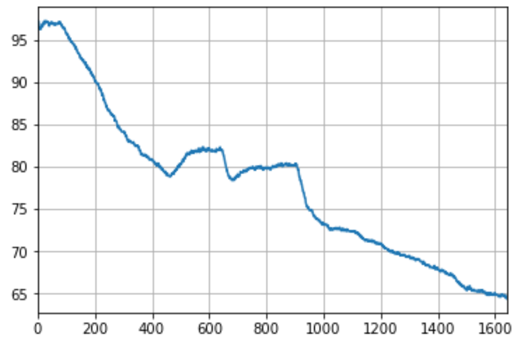
In [175]:
```
# Your code goes here
df_c = df[['FLIGHT_PHASE','TORQ1_C']].as_matrix()
df_cc = []
for i in df_c:

    if i[0] == 'CLIMB':
        df_cc.append(i)
df_cc = np.array(df_cc)
print(df_cc)
```

```
[['CLIMB' 96.9]
 ['CLIMB' 96.9]
 ['CLIMB' 97.2]
 ...,
 ['CLIMB' 64.5]
 ['CLIMB' 64.4]
 ['CLIMB' 64.4]]
```

In [180]:
```
df_ccc = pd.DataFrame(data = df_cc)
df_ccc[1].plot()
```

Out[180]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f4020f20b70>`



Answer

It's basically distributed linearly, but a little bit fluctuate

These features have been created for you in the `features2_df` dataframe.

Recap features2_df

In [181]:
```
file_features2 = BASE_DIR + "features2_df.pkl"

features2_df = pd.read_pickle(file_features2)

numeric_features2 = list(features2_df.columns.values)
numeric_features2.remove("DATE_HF")
numeric_features2.remove("ORIGIN")
numeric_features2.remove("DESTINATION")
numeric_features2.remove("RUNWAY_TO")
numeric_features2.remove("RUNWAY_LD")

features2_df.describe()
```

Out[181]:

	MAX_FOB	MAX_GW	TIME_APPROACH	TIME_CLIMB	TIME_CRUISE	TIME_DESCENT	TIME_ENG START	TIME_FINAL APP	TIME_FLARE	TI AP
count	2742.000000	2742.000000	2742.000000	2742.000000	2742.000000	2742.000000	2742.000000	2742.000000	2742.000000	27
mean	2439.663020	20495.557987	143.109044	1190.589351	1568.312181	745.985412	496.062728	193.513494	8.628009	3.4
std	482.857964	1161.616565	94.942888	258.253887	581.133001	182.289871	307.850561	78.275612	2.584759	54
min	1616.000000	17300.000000	1.000000	85.000000	9.000000	230.000000	127.000000	65.000000	1.000000	0.0
25%	2028.000000	19640.000000	83.000000	1012.000000	1102.250000	613.000000	322.000000	143.000000	7.000000	0.0
50%	2243.000000	20540.000000	126.000000	1160.000000	1687.500000	715.000000	411.000000	174.000000	8.000000	0.0
75%	2922.000000	21400.000000	187.000000	1340.000000	1995.750000	854.000000	566.000000	216.000000	10.000000	0.0
max	3732.000000	23440.000000	1560.000000	2445.000000	3467.000000	1892.000000	5142.000000	748.000000	24.000000	17

8 rows × 468 columns

Let's be more ambitious and predict the fuel consumed by each phase. It would help a lot more to model the fuel consumption behavior for each phase when it will come to interpretation. The dataframe `output2_df` containing the fuel consumed by each phase for each flight has been created for you.

In [207]:
```
file_output2 = BASE_DIR + "output2_df.pkl"
output2_df = pd.read_pickle(file_output2)

output2_df.head()
```

Out[207]:

	APPROACH	CLIMB	CRUISE	DESCENT	ENG START	FINAL APP	FLARE	GO AROUND	INIT CLIMB	LANDING	LVL CHANGE	TAKE OFF	TAXI IN	TAXI OUT	TOUCH N GO
0	12.0	186.0	180.0	112.0	22.0	12.0	6.0	0.0	60.0	20.0	0.0	40.0	26.0	32.0	0.0
1	28.0	218.0	88.0	146.0	12.0	20.0	2.0	0.0	42.0	16.0	0.0	42.0	20.0	38.0	0.0
2	66.0	256.0	532.0	112.0	18.0	38.0	8.0	0.0	18.0	76.0	178.0	30.0	64.0	22.0	0.0
3	20.0	138.0	552.0	186.0	16.0	54.0	4.0	0.0	28.0	64.0	0.0	22.0	36.0	20.0	0.0
4	44.0	192.0	230.0	240.0	16.0	42.0	4.0	0.0	30.0	82.0	0.0	22.0	94.0	90.0	0.0

Question 4.3

In this question we make use of `output2_df` to determine the phase that consumes the most fuel per second in average.

- What flight phase consumes the most in average?
- What flight phase consumes the most per second in average?

In [183]:
```
# This is template code to extract the phases durations out of features_df and rename the columns to make them identical to outpu

phases_durations_df = features2_df[["TIME_" + fp for fp in flight_phases]]
phases_durations_df.columns = flight_phases
phases_durations_df.head()
```

Out[183]:

	APPROACH	CLIMB	CRUISE	DESCENT	ENG START	FINAL APP	FLARE	INIT CLIMB	LANDING	TAKE OFF	TAXI IN	TAXI OUT	TOUCH N GO	LVL CHANGE	GO AROUND
0	106	857	1123	762	705	203	12	49	36	26	222	295	0	0	0
1	219	1129	649	933	174	151	7	39	53	22	219	225	0	0	0
2	152	1139	2418	366	354	188	10	47	36	23	238	215	0	323	0
3	32	749	2676	619	249	243	9	34	32	21	217	182	0	0	0
4	62	1038	1040	1210	302	161	5	34	24	27	506	1016	0	0	0

In [206]:
```
# Your code goes here
'''
What flight phase consumes the most in average?
'''
desc = output2_df.describe()
means = []
for fp in flight_phases:
    means.append(desc[fp]['mean'])
idx = means.index(np.max(means))
result = flight_phases[idx]
print("%s phase consumes the most in average"%result)
```

```
CRUISE phase consumes the most in average
```

Answer

CRUISE phase consumes the most in average

Question 4.4

This last question aims to let you work with `features2_df` and `output2_df`. You can make use of any pieces of code we have worked with so far: especially to set up your models, rescale the features, optimize and validate your models... The expected outcome is to explain to the company what parameters influence the most the fuel consumption of their fleet and give them advice to consume less.

- The algorithm:
  - algorithm: you choose
  - input: `features2_df`, output: `output2_df`
- Interprete the coefficients, explain the causes of fuel consumption for each phase, give adive to the company to consume less in their following flights

In [3]:
```
# Your code goes here
```

Answer

Your answer goes here

In [ ]:
```
```