Analysis of FAA Air Incidents Data

Data set source: https://www.kaggle.com/prathamsharma123/aviation-accidents-and-incidents-ntsb-faa-waas?select=faa_incidents_data.csv

IN3061/INM430 Principles of Data Science | RAJANI MOHAN JANIPALLI | City University of London

About Data set

Data set is a record for general aviation and commercial air incidents from the year 1978 to 2015, collected from FAA's AIDS website.

Import useful libraries.

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Load the data. Code reference: lab week two feedback.

In [2]:

```
av_data = pd.read_csv('faa_incidents_data.csv', encoding = 'ISO-8859-1')
```

```
C:\Users\jraja\anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3444: DtypeWarning: Columns (12,14) have mixed types.S
pecify dtype option on import or set low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

Have a glance of data frame. Code reference: Data camp course on data manipulation with pandas.

In [3]:

```
av_data.head()
```

Out[3]:

	AIDS Report Number	Local Event Date	Event City	Event State	Event Airport	Event Type	Aircraft Damage	Flight Phase	Aircraft Make	Aircraft Model	...	Total Injuries	Aircraft Engine Make	Aircraft Engine Model	Engin Grou Cod
0	19780101000019I	01-JAN-78	WAHPETON	ND	BRECKENRIDGE	INCIDENT	MINOR	ROLL-OUT (FIXED WING)	CESSNA	182	...	0	NaN	NaN	Na
1	19780101000029I	01-JAN-78	FAIRBANKS	AK	FAIRBANKS INTL	INCIDENT	MINOR	ROLL-OUT (FIXED WING)	PIPER	PA18	...	0	NaN	NaN	Na
2	19780101000039I	01-JAN-78	BRUNSWICK	GA	JEKYLL ISLAND	INCIDENT	NaN	NORMAL CRUISE	BEECH	35	...	0	NaN	NaN	Na
3	19780101000049I	01-JAN-78	CARLSBAD	CA	MC CLELLAN-PALOMAR	INCIDENT	MINOR	LEVEL OFF TOUCHDOWN	CESSNA	310	...	0	NaN	NaN	Na
4	19780101000059I	01-JAN-78	TROUTDALE	OR	TROUTDALE MUNI	INCIDENT	MINOR	GROUND TAXI, OTHER AIRPLANE	CESSNA	172	...	0	NaN	NaN	Na

5 rows × 27 columns

Check the number of rows and columns of the data frame. Code reference: data camp course on data manipulation with pandas.

In [4]:

```
av_data.shape
```

Out[4]:

```
(100000, 27)
```

Data frame Information - Check the names, data type and the number of non-missing values for all the columns in the data frame. Code reference: data camp course on data manipulation with pandas.

In [5]:

```
av_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 27 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   AIDS Report Number              100000 non-null  object
 1   Local Event Date                100000 non-null  object
 2   Event City                      91364 non-null   object
 3   Event State                     99234 non-null   object
 4   Event Airport                   81398 non-null   object
 5   Event Type                      100000 non-null  object
 6   Aircraft Damage                 71199 non-null   object
 7   Flight Phase                    99758 non-null   object
 8   Aircraft Make                   97441 non-null   object
```

```
 9   Aircraft Model                  96928 non-null   object
 10  Aircraft Series                 96927 non-null   object
 11  Operator                        29974 non-null   object
 12  Primary Flight Type             89906 non-null   object
 13  Flight Conduct Code             99858 non-null   object
 14  Flight Plan Filed Code          87088 non-null   object
 15  Aircraft Registration Nbr       100000 non-null  object
 16  Total Fatalities                100000 non-null  int64
 17  Total Injuries                  100000 non-null  int64
 18  Aircraft Engine Make            36395 non-null   object
 19  Aircraft Engine Model           36399 non-null   object
 20  Engine Group Code               30102 non-null   object
 21  Nbr of Engines                  93004 non-null   float64
 22  PIC Certificate Type            91474 non-null   object
 23  PIC Flight Time Total Hrs       79807 non-null   float64
 24  PIC Flight Time Total Make-Model 85053 non-null  float64
 25                                  83803 non-null   float64
 26   .1                             60737 non-null   float64
dtypes: float64(5), int64(2), object(20)
memory usage: 20.6+ MB
```

The first thing observed from Date frame Information is that the "Local Event Date" column which contains the dates of the incident, is of object data type. But it should be of datetime data type.

Preliminary data cleaning.

So, the "Local Event Date" column has to be converted from object data type to datetime data type. Code reference: https://www.youtube.com/watch?v=yCgJGsg0Xa4

In [6]:

```
av_data['Local Event Date'] = pd.to_datetime(av_data['Local Event Date'])
```

View data frame information again to check if the changes have been implemented.

In [7]:

```
av_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 27 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   AIDS Report Number              100000 non-null  object
 1   Local Event Date                100000 non-null  datetime64[ns]
 2   Event City                      91364 non-null   object
 3   Event State                     99234 non-null   object
 4   Event Airport                   81398 non-null   object
 5   Event Type                      100000 non-null  object
 6   Aircraft Damage                 71199 non-null   object
 7   Flight Phase                    99758 non-null   object
 8   Aircraft Make                   97441 non-null   object
 9   Aircraft Model                  96928 non-null   object
 10  Aircraft Series                 96927 non-null   object
 11  Operator                        29974 non-null   object
 12  Primary Flight Type             89906 non-null   object
 13  Flight Conduct Code             99858 non-null   object
 14  Flight Plan Filed Code          87088 non-null   object
 15  Aircraft Registration Nbr       100000 non-null  object
 16  Total Fatalities                100000 non-null  int64
 17  Total Injuries                  100000 non-null  int64
 18  Aircraft Engine Make            36395 non-null   object
 19  Aircraft Engine Model           36399 non-null   object
 20  Engine Group Code               30102 non-null   object
 21  Nbr of Engines                  93004 non-null   float64
 22  PIC Certificate Type            91474 non-null   object
 23  PIC Flight Time Total Hrs       79807 non-null   float64
 24  PIC Flight Time Total Make-Model 85053 non-null  float64
 25                                  83803 non-null   float64
 26   .1                             60737 non-null   float64
dtypes: datetime64[ns](1), float64(5), int64(2), object(19)
memory usage: 20.6+ MB
```

Have a glance of data frame again to check how the “Local Event Date” column data appears after the change of data type.

In [8]:

```
av_data.head()
```

Out[8]:

	AIDS Report Number	Local Event Date	Event City	Event State	Event Airport	Event Type	Aircraft Damage	Flight Phase	Aircraft Make	Aircraft Model	...	Total Injuries	Aircraft Engine Make	Aircraft Engine Model	Engin Grou Cod
0	19780101000019I	1978-01-01	WAHPETON	ND	BRECKENRIDGE	INCIDENT	MINOR	ROLL-OUT (FIXED WING)	CESSNA	182	...	0	NaN	NaN	Nal
1	19780101000029I	1978-01-01	FAIRBANKS	AK	FAIRBANKS INTL	INCIDENT	MINOR	ROLL-OUT (FIXED WING)	PIPER	PA18	...	0	NaN	NaN	Nal
2	19780101000039I	1978-01-01	BRUNSWICK	GA	JEKYLL ISLAND	INCIDENT	NaN	NORMAL CRUISE	BEECH	35	...	0	NaN	NaN	Nal

	AIDS Report Number	Local Event Date	Event City	Event State	Event Airport	Event Type	Aircraft Damage	Flight Phase	Aircraft Make	Aircraft Model	...	Total Injuries	Aircraft Engine Make	Aircraft Engine Model	Engin Grou Code
3	19780101000049I	1978-01-01	CARLSBAD	CA	MC CLELLAN-PALOMAR	INCIDENT	MINOR	LEVEL OFF TOUCHDOWN	CESSNA	310	...	0	NaN	NaN	Na
4	19780101000059I	1978-01-01	TROUTDALE	OR	TROUTDALE MUNI	INCIDENT	MINOR	GROUND TAXI, OTHER AIRPLANE	CESSNA	172	...	0	NaN	NaN	Na

5 rows × 27 columns

Check missing values. Code reference: https://www.kaggle.com/itssuru/eda-cristiano-ronaldo-s-career

In [9]:
```
missing_originaldata = pd.DataFrame({'total_missing': av_data.isnull().sum(),
                                     'perc_missing': (av_data.isnull().sum()/av_data.shape[0])*100})
missing_originaldata
```

Out[9]:

	total_missing	perc_missing
AIDS Report Number	0	0.000
Local Event Date	0	0.000
Event City	8636	8.636
Event State	766	0.766
Event Airport	18602	18.602
Event Type	0	0.000
Aircraft Damage	28801	28.801
Flight Phase	242	0.242
Aircraft Make	2559	2.559
Aircraft Model	3072	3.072
Aircraft Series	3073	3.073
Operator	70026	70.026
Primary Flight Type	10094	10.094
Flight Conduct Code	142	0.142
Flight Plan Filed Code	12912	12.912
Aircraft Registration Nbr	0	0.000
Total Fatalities	0	0.000
Total Injuries	0	0.000
Aircraft Engine Make	63605	63.605
Aircraft Engine Model	63601	63.601
Engine Group Code	69898	69.898
Nbr of Engines	6996	6.996
PIC Certificate Type	8526	8.526
PIC Flight Time Total Hrs	20193	20.193
PIC Flight Time Total Make-Model	14947	14.947
	16197	16.197
.1	39263	39.263

Exploratory data analysis.

Data preparation

Checking of missing values has shown that there are a lot of missing values in many columns and also the names of the last two columns are also missing. To confirm, column names of the data frame are to be checked exclusively.

Check column names of the data frame. Code reference: data camp course on data manipulation with pandas.

In [10]:
```
av_data.columns
```

Out[10]:
```
Index(['AIDS Report Number', 'Local Event Date', 'Event City', 'Event State',
       'Event Airport', 'Event Type', 'Aircraft Damage', 'Flight Phase',
       'Aircraft Make', 'Aircraft Model', 'Aircraft Series', 'Operator',
       'Primary Flight Type', 'Flight Conduct Code', 'Flight Plan Filed Code',
       'Aircraft Registration Nbr', 'Total Fatalities', 'Total Injuries',
```

```
        'Aircraft Engine Make', 'Aircraft Engine Model', 'Engine Group Code',
        'Nbr of Engines', 'PIC Certificate Type', 'PIC Flight Time Total Hrs',
        'PIC Flight Time Total Make-Model', ' ', ' .1'],
       dtype='object')
```

So, it is confirmed that the names of last two columns are missing. Temporary names of those two columns are to be assigned in order to make them callable. Code Reference: https://www.youtube.com/watch?v=0uBirYFhizE

In [11]:
```
av_data.rename(columns={' ':'UC1',' .1':'UC2'}, inplace=True)
```

Check if the changes in column names have been implemented.

In [12]:
```
av_data.columns
```

Out[12]:
```
Index(['AIDS Report Number', 'Local Event Date', 'Event City', 'Event State',
       'Event Airport', 'Event Type', 'Aircraft Damage', 'Flight Phase',
       'Aircraft Make', 'Aircraft Model', 'Aircraft Series', 'Operator',
       'Primary Flight Type', 'Flight Conduct Code', 'Flight Plan Filed Code',
       'Aircraft Registration Nbr', 'Total Fatalities', 'Total Injuries',
       'Aircraft Engine Make', 'Aircraft Engine Model', 'Engine Group Code',
       'Nbr of Engines', 'PIC Certificate Type', 'PIC Flight Time Total Hrs',
       'PIC Flight Time Total Make-Model', 'UC1', 'UC2'],
      dtype='object')
```

Explore the data of the penultimate column. Code reference: https://www.kaggle.com/itssuru/eda-cristiano-ronaldo-s-career

In [13]:
```
av_data.UC1.value_counts()
```

Out[13]:
```
0.0        20908
30.0        3128
20.0        3112
10.0        2386
50.0        2358
           ...
465.0          1
948.0          1
456.0          1
458.0          1
99999.0        1
Name: UC1, Length: 458, dtype: int64
```

With 458 different values, the data in this column is difficult to correlate and understand the relationship with other columns in the data frame and there is no further information about this column. Hence it is better to drop this column.

Explore the date of the last column.

In [14]:
```
av_data.UC2.value_counts()
```

Out[14]:
```
0.0      19796
20.0      2513
10.0      2319
30.0      2255
15.0      1975
         ...
356.0        1
389.0        1
753.0        1
337.0        1
715.0        1
Name: UC2, Length: 390, dtype: int64
```

With 390 different values, the data in this column is difficult to correlate and understand the relationship with other columns in the data frame and there is no further information about this column. Hence it is better to drop this column.

Drop the penultimate column of the Data Frame. Code reference: https://www.kaggle.com/itssuru/eda-cristiano-ronaldo-s-career

In [15]:
```
av_data.drop('UC1',axis=1,inplace=True)
```

Drop the last column of the Data Frame.

In [16]:
```
av_data.drop('UC2',axis=1,inplace=True)
```

Check the change in number of columns of the data frame.

In [17]:
```
av_data.shape
```

Out[17]:
```
(100000, 25)
```

Number of columns of the data frame changed from 27 to 25.

Explore all columns of the data frame and drop unnecessary columns.

Explore the first column of the data frame.

In [18]:
```
av_data['AIDS Report Number'].value_counts()
```

Out[18]:
```
197801010000191    1
199610080458491    1
199610120402691    1
199610120381091    1
199610120376491    1
                  ..
198610010644791    1
198610010634091    1
198610010568791    1
198610010564191    1
201512180241821    1
Name: AIDS Report Number, Length: 100000, dtype: int64
```

It can be seen that each observation of this column is a unique ID number and it cannot be used for any further analysis. Hence it is better to drop this column.

In [19]:
```
av_data.drop('AIDS Report Number',axis=1,inplace=True)
```

Check the change in number of columns of the data frame.

In [20]:
```
av_data.shape
```

Out[20]:
```
(100000, 24)
```

Changes in the column numbers are reflected.

Explore "Local Event Date" column.

In [21]:
```
av_data['Local Event Date'].value_counts()
```

Out[21]:
```
1996-06-01    31
1980-07-19    29
1978-06-25    29
1979-07-29    28
1978-03-10    28
              ..
2011-09-19     1
2014-10-18     1
1984-10-19     1
2007-05-17     1
2008-11-08     1
Name: Local Event Date, Length: 13736, dtype: int64
```

With 13736 unique values this column will be difficult to plot and do further exploratory analysis. A better idea would be to create a column containing only year's so that the number of unique values will be low enough that it can be plotted easily and also explored further.

Data derivation

Create a new column from "Local Event Date" column that would contain only the year and not the date and month.Code reference: https://www.youtube.com/watch?v=yCgJGsg0Xa4

In [22]:
```
av_data['Year'] = av_data['Local Event Date'].dt.year
```

Check the addition of column in the Data frame.

In [23]:
```
av_data.head()
```

Out[23]:

	Local Event Date	Event City	Event State	Event Airport	Event Type	Aircraft Damage	Flight Phase	Aircraft Make	Aircraft Model	Aircraft Series	...	Total Fatalities	Total Injuries	Aircraft Engine Make	Aircra Engir Mod
0	1978-01-01	WAHPETON	ND	BRECKENRIDGE	INCIDENT	MINOR	ROLL-OUT (FIXED WING)	CESSNA	182	UNDESIGNATED SERIES	...	0	0	NaN	Na
1	1978-01-01	FAIRBANKS	AK	FAIRBANKS INTL	INCIDENT	MINOR	ROLL-OUT (FIXED WING)	PIPER	PA18	150	...	0	0	NaN	Na
2	1978-01-01	BRUNSWICK	GA	JEKYLL ISLAND	INCIDENT	NaN	NORMAL CRUISE	BEECH	35	B35	...	0	0	NaN	Na
3	1978-01-01	CARLSBAD	CA	MC CLELLAN-PALOMAR	INCIDENT	MINOR	LEVEL OFF TOUCHDOWN	CESSNA	310	L	...	0	0	NaN	Na
4	1978-01-01	TROUTDALE	OR	TROUTDALE MUNI	INCIDENT	MINOR	GROUND TAXI, OTHER AIRPLANE	CESSNA	172	UNDESIGNATED SERIES	...	0	0	NaN	Na

5 rows × 25 columns

In [24]:
```
av_data.shape
```

Out[24]:
```
(100000, 25)
```

Data preparation

Since the year column is created the “local event date column can be dropped.

In [25]:
```
av_data.drop('Local Event Date',axis=1,inplace=True)
```

Check the changes in the number of columns.

In [26]:
```
av_data.shape
```

Out[26]:
```
(100000, 24)
```

Explore “Event Type” column.

In [27]:
```
av_data['Event Type'].value_counts()
```

Out[27]:
```
INCIDENT    100000
Name: Event Type, dtype: int64
```

It can be seen that all the observations are the same i.e., INCIDENT and it cannot be used for any further analysis. Hence it is better to drop this column.

In [28]:
```
av_data.drop('Event Type',axis=1,inplace=True)
```

Check the changes in the number of columns.

Explore “Aircraft Registration Nbr” column.

In [29]:
```
av_data['Aircraft Registration Nbr'].value_counts()
```

Out[29]:
```
UNKNO    308
NONE     202
115BS     20
116BS     18
2718Y     16
        ...
8305D      1
95955      1
6114U      1
37356      1
902AR      1
Name: Aircraft Registration Nbr, Length: 75883, dtype: int64
```

Explore “Total Fatalities” column.

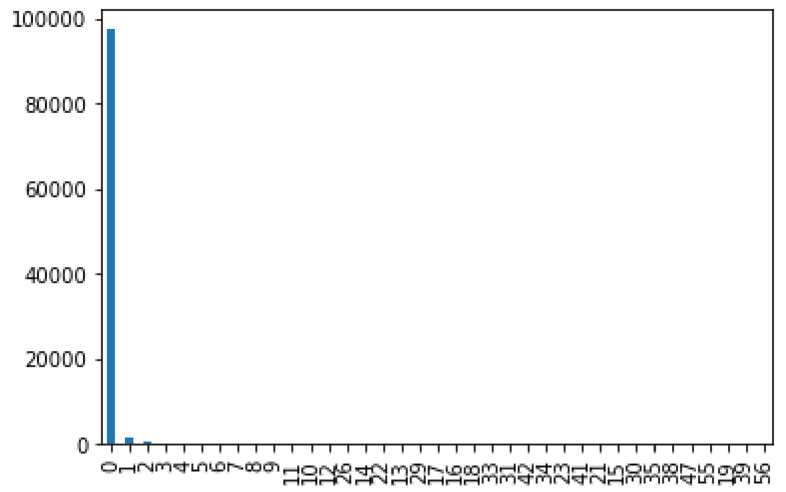
In [30]:
```
av_data['Total Fatalities'].value_counts()
```

Out[30]:
```
0    99227
1      730
2       39
3        3
5        1
Name: Total Fatalities, dtype: int64
```

Explore “Total Injuries” column.

In [31]:
```
av_data['Total Injuries'].value_counts().plot.bar()
```

Out[31]:
```
<AxesSubplot:>
```



Check the number of possible observations for a combination of values of total fatalities and total injuries which can be categorized as severe. Code reference: data camp course on data manipulation with pandas.

In [32]:
```
av_data[(av_data['Total Fatalities'] >= 1) & (av_data['Total Injuries'] == 0)]
```

Out[32]:

	Event City	Event State	Event Airport	Aircraft Damage	Flight Phase	Aircraft Make	Aircraft Model	Aircraft Series	Operator	Primary Flight Type	...	Total Fatalities	Total Injuries	A I
582	ZEPHYRHILLS	FL	ZEPHYRHILLS MUNI	NaN	DESCENT	BEECH	18	D18S	NaN	OTHER	...	1	0	
638	COOLIDGE	AZ	FLORENCE MUNI	NaN	DESCENT	CESSNA	182	A	NaN	OTHER	...	1	0	
933	HENDERSON	NC	OXFORD COUNTY RGNL	NaN	LEVEL OFF TOUCHDOWN	DOUGLAS	DC3	C	NaN	OTHER	...	1	0	
1095	NaN	CA	SKYLARK FIELD	NaN	LEVEL OFF TOUCHDOWN	NaN	NaN	NaN	NaN	OTHER	...	1	0	
1121	TULSA	OK	TULSA INTL	SUBSTANTIAL	GROUND TAXI, OTHER AIRPLANE	BOEING	727	200	CONTINENTAL AIRLINES INC	SCHEDULED AIR CARRIER	...	5	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
99790	TRES PINOS	CA	NaN	NONE	OTHER-SPECIFY	PAC	750XL	NO SERIES EXISTS	NaN	NaN	...	1	0	
99814	SEBASTIAN	FL	SEBASTIAN MUNI	NONE	CRUISE-LEVEL FLIGHT	DE HAVILLAND	DHC6	200	NaN	NaN	...	1	0	
99874	LATROBE	PA	ARNOLD PALMER RGNL	NONE	UNKNOWN	GRUMMAN	G1159	NO SERIES EXISTS	NaN	NaN	...	1	0	I
99880	OSAGE CITY	KS	OSAGE CITY MUNI	NONE	CRUISE-LEVEL FLIGHT	CESSNA	U206	F	NaN	NaN	...	1	0	
99882	MADERA	CA	MADERA MUNI	NONE	DESCENT	NaN	NaN	NaN	NaN	NaN	...	1	0	

733 rows × 23 columns

Data derivation

Create new Boolean column named "Severe" such that if the total number of fatalities is greater than equal to 1 and the total number of injuries is equal to or greater than 0, then the value is in "Severe" is 1, else it is 0. Code reference lab week three feedback.

In [33]:
```
av_data['Severe'] = np.where((av_data['Total Fatalities'] >= 1) & (av_data['Total Injuries'] >= 0),1,0)
```

Check the changes in the number of columns.

In [34]:
```
av_data.shape
```

Out[34]:
```
(100000, 24)
```

In [35]:
```
av_data.head()
```

Out[35]:

	Event City	Event State	Event Airport	Aircraft Damage	Flight Phase	Aircraft Make	Aircraft Model	Aircraft Series	Operator	Primary Flight Type	...	Total Injuries	Aircraft Engine Make	Aircraft Engine Model	Eng Gr C
0	WAHPETON	ND	BRECKENRIDGE	MINOR	ROLL-OUT (FIXED WING)	CESSNA	182	UNDESIGNATED SERIES	NaN	PERSONAL	...	0	NaN	NaN	I
1	FAIRBANKS	AK	FAIRBANKS INTL	MINOR	ROLL-OUT (FIXED WING)	PIPER	PA18	150	NaN	PERSONAL	...	0	NaN	NaN	I
2	BRUNSWICK	GA	JEKYLL ISLAND	NaN	NORMAL CRUISE	BEECH	35	B35	NaN	PERSONAL	...	0	NaN	NaN	I
3	CARLSBAD	CA	MC CLELLAN-PALOMAR	MINOR	LEVEL OFF TOUCHDOWN	CESSNA	310	L	NaN	PERSONAL	...	0	NaN	NaN	I
4	TROUTDALE	OR	TROUTDALE MUNI	MINOR	GROUND TAXI, OTHER AIRPLANE	CESSNA	172	UNDESIGNATED SERIES	NaN	PERSONAL	...	0	NaN	NaN	I

5 rows × 24 columns

Explore "Severe" column.

In [36]:
```
av_data.Severe.value_counts()
```

Out[36]:
```
0    99227
1      773
Name: Severe, dtype: int64
```

Data preparation

Continue to explore remaining columns of the data frame.

Explore “Flight Conduct Code” column.

In [37]:
```
av_data['Flight Conduct Code'].value_counts()
```

Out[37]:
```
GENERAL OPERATING RULES                69912
AIR CARRIER/COMMERCIAL                 16012
AIR TAXI/COMMUTER                      10094
AGRICULTURAL                            1278
PARACHUTE JUMPING                        972
PILOT SCHOOLS                            922
FOREIGN AIR CARRIER                      436
ROTORCRAFT EXTERNAL LOAD OPERATIONS       98
PART 125 OPERATOR                         66
ULTRALIGHT VEHICLES                       60
TRAVEL CLUB                                6
SCHEDULED AIRCRAFT/HELICOPTER              2
Name: Flight Conduct Code, dtype: int64
```

Explore “Flight Phase” column.

In [38]:
```
av_data['Flight Phase'].value_counts()
```

Out[38]:
```
LEVEL OFF TOUCHDOWN                       17084
ROLL-OUT (FIXED WING)                     16224
FCD/PREC LDG FROM CRUISE                   9523
NORMAL CRUISE                              9244
GROUND TAXI, OTHER AIRPLANE                7666
                                          ...  
SIMULATED FORCED LANDING/TAKEOFF CLIMB        9
FORMATION FLYING                              9
ROLL-OUT (ROTORCRAFT)                         8
SLOPE LANDING                                 7
PINNACLE LANDING                              1
Name: Flight Phase, Length: 75, dtype: int64
```

Explore “Flight Plan Filed Code” column.

In [39]:
```
av_data['Flight Plan Filed Code'].value_counts()
```

Out[39]:
```
NONE                          35771
INSTRUMENT FLIGHT RULES       25814
UNKNOWN                       15527
VISUAL FLIGHT RULES            9633
AIR TAXI FLIGHT FOLLOWING       204
SPECIAL VISUAL FLIGHT RULES      42
DEFENSE VISUAL FLIGHT RULES      40
VISUAL FLIGHT FOLLOWING          32
MILITARY CONTROL                 23
VISUAL FLIGHT RULES ON TOP        2
Name: Flight Plan Filed Code, dtype: int64
```

Explore “PIC Certificate Type” column.

In [40]:
```
av_data['PIC Certificate Type'].value_counts()
```

Out[40]:
```
PRIVATE PILOT                             29963
AIRLINE TRANSPORT                         23573
COMMERCIAL PILOT                          18614
COMMERCIAL PILOT FLIGHT INSTRUCTOR         7512
STUDENT                                    5780
AIRLINE TRANSPORT PILOT FLIGHT INSTRUCTOR  4249
UNKNOWN/FOREIGN                            1338
PILOT NOT CERTIFICATED                      228
PRIVATE PILOT FLIGHT INSTRUCTOR             184
RECREATIONAL PILOT                           22
SPECIAL PURPOSE                              11
Name: PIC Certificate Type, dtype: int64
```

Explore “PIC Flight Time Total Hrs” column.

In [41]:
```
av_data['PIC Flight Time Total Hrs'].value_counts()
```

Out[41]:
```
0.0        1712
3000.0     1147
2000.0     1080
4000.0     1020
5000.0      995
           ... 
20215.0       1
```

```
11921.0       1
8288.0        1
10594.0       1
16372.0       1
Name: PIC Flight Time Total Hrs, Length: 8314, dtype: int64
```

Explore “PIC Flight Time Total Make-Model” column.

In [42]:
```
av_data['PIC Flight Time Total Make-Model'].value_counts()
```

Out[42]:
```
0.0        8543
200.0      2383
100.0      2239
300.0      2200
500.0      2050
           ...
1029.0        1
3956.0        1
7046.0        1
11300.0       1
863.0         1
Name: PIC Flight Time Total Make-Model, Length: 3698, dtype: int64
```

Data preparation

Handling Missing Values.

After checking the missing values, it is realized that there are no missing values in numeric columns and there are missing values only in categorical non numeric columns. Imputing categorical non numeric values using the common methods like label encoding, label mapping, etc, may not be suitable for the data, as there are large number of unique values for almost all the categorical columns. So, there was no imputation of missing values for the categorical columns as imputation using the above-mentioned methods would give inconsistent results. Also, it is not appropriate 2 impute the missing values through most frequent value, for this data taken from FAA.

Data preparation

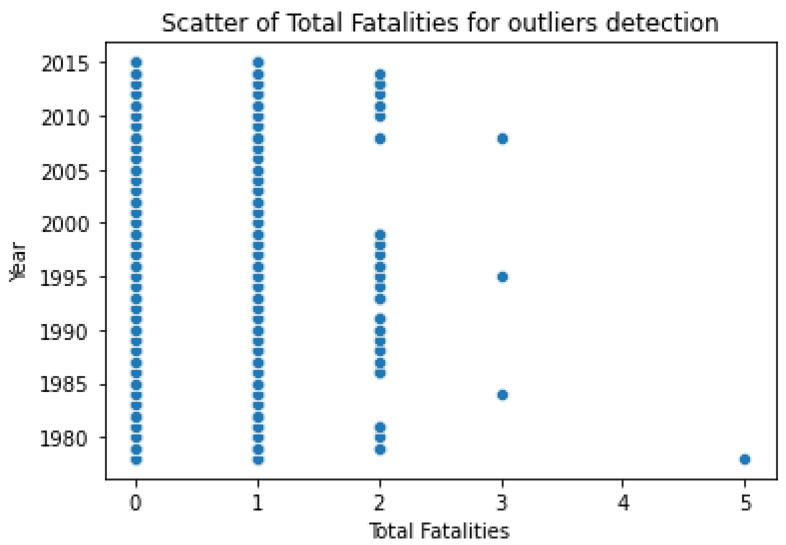
Handling Outliers

Identify outliers in continuous numeric variables and remove them where needed.

Identify outliers in “Total Fatalities” column visually through a scatterplot. Code reference lab week three feedback.

In [43]:
```
sns.scatterplot(x=av_data['Total Fatalities'],y=av_data.Year)
plt.title('Scatter of Total Fatalities for outliers detection')
```

Out[43]:
```
Text(0.5, 1.0, 'Scatter of Total Fatalities for outliers detection')
```

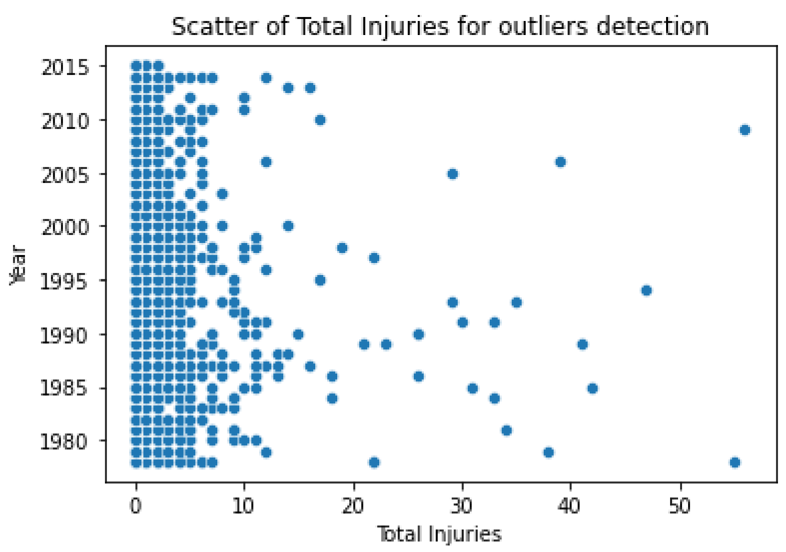


Since all the values are realistic, they cannot be identified as outliers.

Identify outliers in “Total Injuries” column visually through a scatterplot.

In [44]:
```
sns.scatterplot(x=av_data['Total Injuries'],y=av_data.Year)
plt.title('Scatter of Total Injuries for outliers detection')
```

Out[44]:
```
Text(0.5, 1.0, 'Scatter of Total Injuries for outliers detection')
```



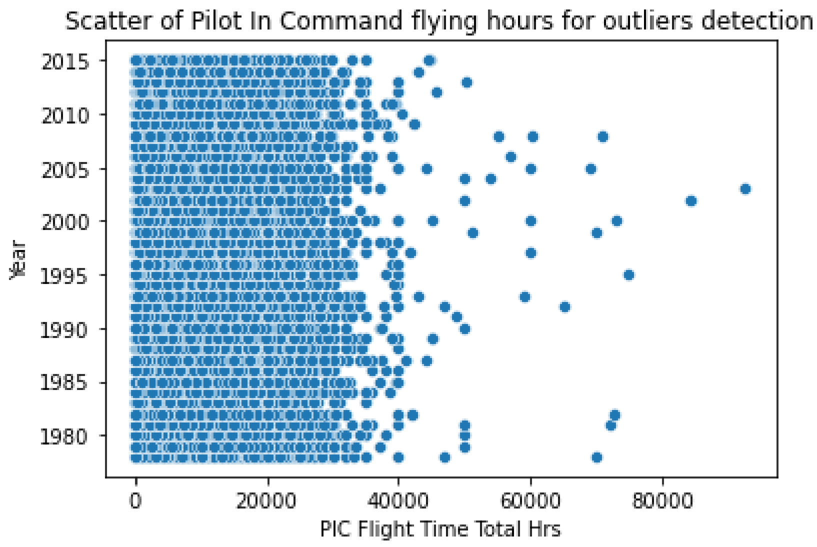
Since the maximum value is not clear visually it's better to check it through code.

In [45]:
```
av_data['Total Injuries'].max()
```
Out[45]:
```
56
```

Since all the values are realistic, they cannot be identified as outliers.

Identify outliers in "PIC Flight Time Total Hrs" column visually through a scatterplot.

In [46]:
```
sns.scatterplot(x=av_data['PIC Flight Time Total Hrs'],y=av_data.Year)
plt.title('Scatter of Pilot In Command flying hours for outliers detection')
```
Out[46]:
```
Text(0.5, 1.0, 'Scatter of Pilot In Command flying hours for outliers detection')
```



Visually there seems to be presence of some outliers. So, it should be tried to identify outliers using rules of thumb method.

Calculate mean and standard deviation of the column. Code reference lab week three feedback.

In [47]:
```
meanPICFTTH = av_data['PIC Flight Time Total Hrs'].mean()
stdPICFTTH = av_data['PIC Flight Time Total Hrs'].std()
```

Check the value of mean.

In [48]:
```
meanPICFTTH
```
Out[48]:
```
3838.574962096057
```

Check the value of standard deviation.

In [49]:
```
stdPICFTTH
```
Out[49]:
```
5508.412809379743
```

Check the value of twice the mean and if it is greater than the standard deviation.

In [50]:
```
2*meanPICFTTH
```
Out[50]:
```
7677.149924192114
```

Clearly the value of twice the mean is greater than the standard deviation.

But visually it can be seen that a major chunk of the values is greater than this value. Also, this is a data given by FAA which is very much reliable source. As per visual analysis of the scatter plot it is clear that majority of the values are below 40,000. Before considering 40,000 as the limit for considering outlier, it's better to check how many observations are below the 40,000 value.

In [51]:
```
av_data[av_data['PIC Flight Time Total Hrs'] < 40000].shape
```
Out[51]:
```
(79744, 24)
```

Clearly majority of the observations are below the 40,000 value. So we can consider values equal to or above 40,000 as outliers.

Remove observations which fall under the outlier's category for this column.

In [52]:
```
av_data = av_data[av_data['PIC Flight Time Total Hrs'] < 40000]
```

Check the changes in the number of rows.

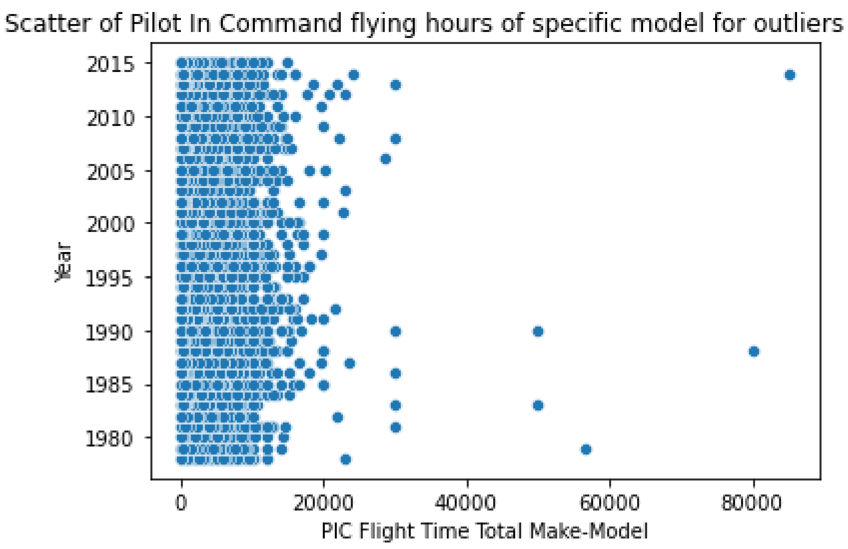
In [53]:
```
av_data.shape
```
Out[53]:
```
(79744, 24)
```

Now check the maximum value of the column from which the outliers have been removed.

In [54]:
```
av_data['PIC Flight Time Total Hrs'].max()
```
Out[54]:
```
39960.0
```

Identify outliers in "PIC Flight Time Total Make-Model" column visually through a scatterplot.

In [55]:
```
sns.scatterplot(x=av_data['PIC Flight Time Total Make-Model'],y=av_data.Year)
plt.title('Scatter of Pilot In Command flying hours of specific model for outliers detection')
```
Out[55]:
```
Text(0.5, 1.0, 'Scatter of Pilot In Command flying hours of specific model for outliers detection')
```



Visually there seems to be presence of some outliers. So, it should be tried to identify outliers using rules of thumb method.

Calculate mean and standard deviation of the column. Code reference lab week three feedback.

In [56]:
```
meanPICFTTMM = av_data['PIC Flight Time Total Make-Model'].mean()
stdPICFTTMM = av_data['PIC Flight Time Total Make-Model'].std()
```

Check the value of mean.

In [57]:
```
meanPICFTTMM
```
Out[57]:
```
749.6852065839818
```

Check the value of standard deviation.

In [58]:
```
stdPICFTTMM
```
Out[58]:
```
1629.2628862677227
```

Check the value of twice the mean and if it is greater than the standard deviation.

In [59]:
```
2*meanPICFTTMM
```
Out[59]:
```
1499.3704131679635
```

Clearly the value of twice the mean is lesser than the standard deviation.

Check the value of thrice the mean and if it is greater than the standard deviation.

In [60]:
```
3*meanPICFTTMM
```
Out[60]:
```
2249.0556197519454
```

Clearly the value of thrice the mean is greater than the standard deviation.

But visually it can be seen that a major chunk of the values is greater than this value. Also, this is a data given by FAA which is very much reliable source. As per visual analysis of the scatter plot it is clear that majority of the values are below 20,000. Before considering 20,000 as the limit for considering outlier, it's better to check how many observations are below the 20,000 value.

In [61]:
```
av_data[av_data['PIC Flight Time Total Make-Model'] < 20000].shape
```
Out[61]:
```
(77854, 24)
```

Clearly majority of the observations are below the 20,000 value. So we can consider values equal to or above 20,000 as outliers.

Remove observations which fall under the outlier's category for this column.

In [62]:
```
av_data = av_data[av_data['PIC Flight Time Total Make-Model'] < 20000]
```

Check the changes in the number of rows.

In [63]:
```
av_data.shape
```

Out[63]:
```
(77854, 24)
```

Now check the maximum value of the column from which the outliers have been removed.

In [64]:
```
av_data['PIC Flight Time Total Make-Model'].max()
```

Out[64]:
```
19500.0
```

It can be clearly observed that removal of observations based on outliers have reduced the number of observations of the data frame by more than 20%. The column "Severe" is a useful column that has been derived from the original data and it's a good idea to check the changes in that column, as a result of the removal of observations.

In [65]:
```
av_data.Severe.value_counts()
```

Out[65]:
```
0    77565
1      289
Name: Severe, dtype: int64
```

It can be seen that the number of observations with a positive severe value have reduced to a great extent. So, it's better not to remove observations any further at overall level but do it only at a subset level. At overall level the data is prepared enough to answer the first research question.

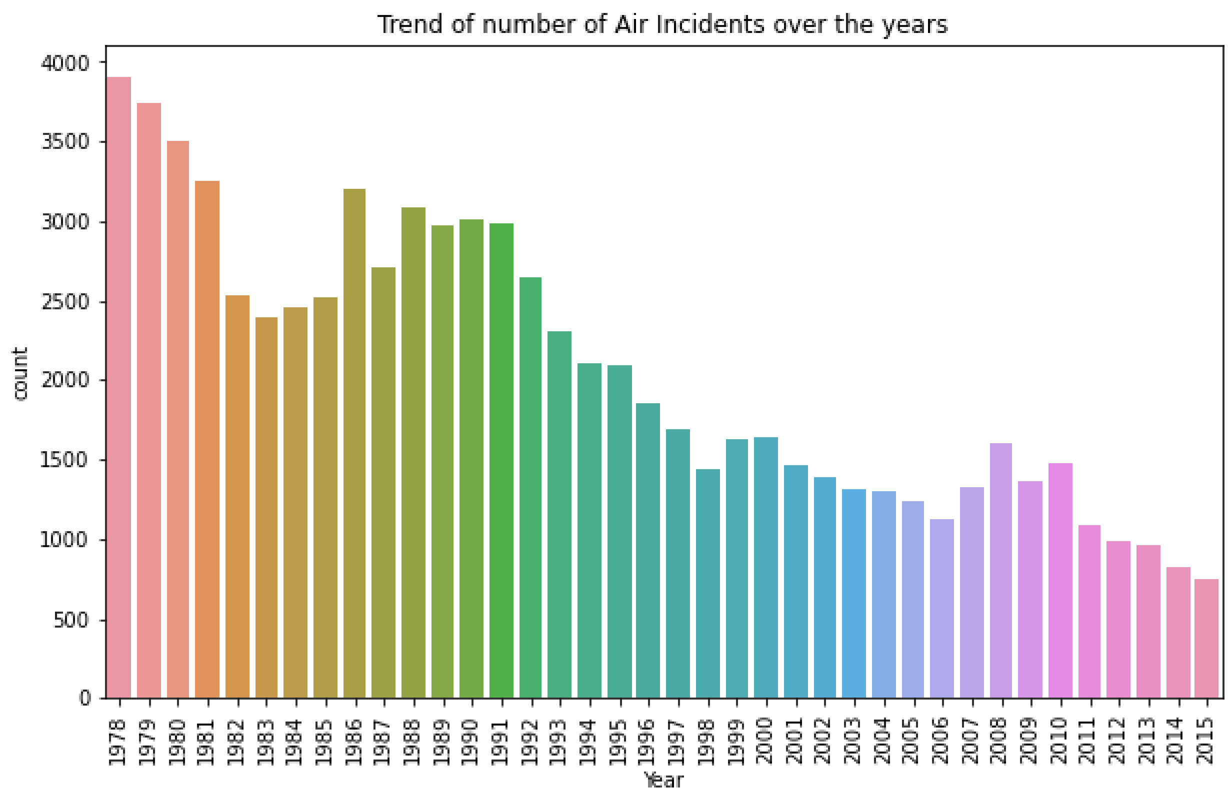
Research Question 1

What was the trend of number of accidents over the years? From the available data what could be a possible factor for that trend.

Since each observation is an incident, one of the good ideas to answer this research question is bye showing the count plot of the years. Code reference: https://seaborn.pydata.org/generated/seaborn.countplot.html

In [66]:
```
plt.figure(figsize=(10,6))
yr = sns.countplot(x=av_data.Year)
yr.set_xticklabels(yr.get_xticklabels(), rotation=90);
plt.title('Trend of number of Air Incidents over the years')
```

Out[66]:
```
Text(0.5, 1.0, 'Trend of number of Air Incidents over the years')
```

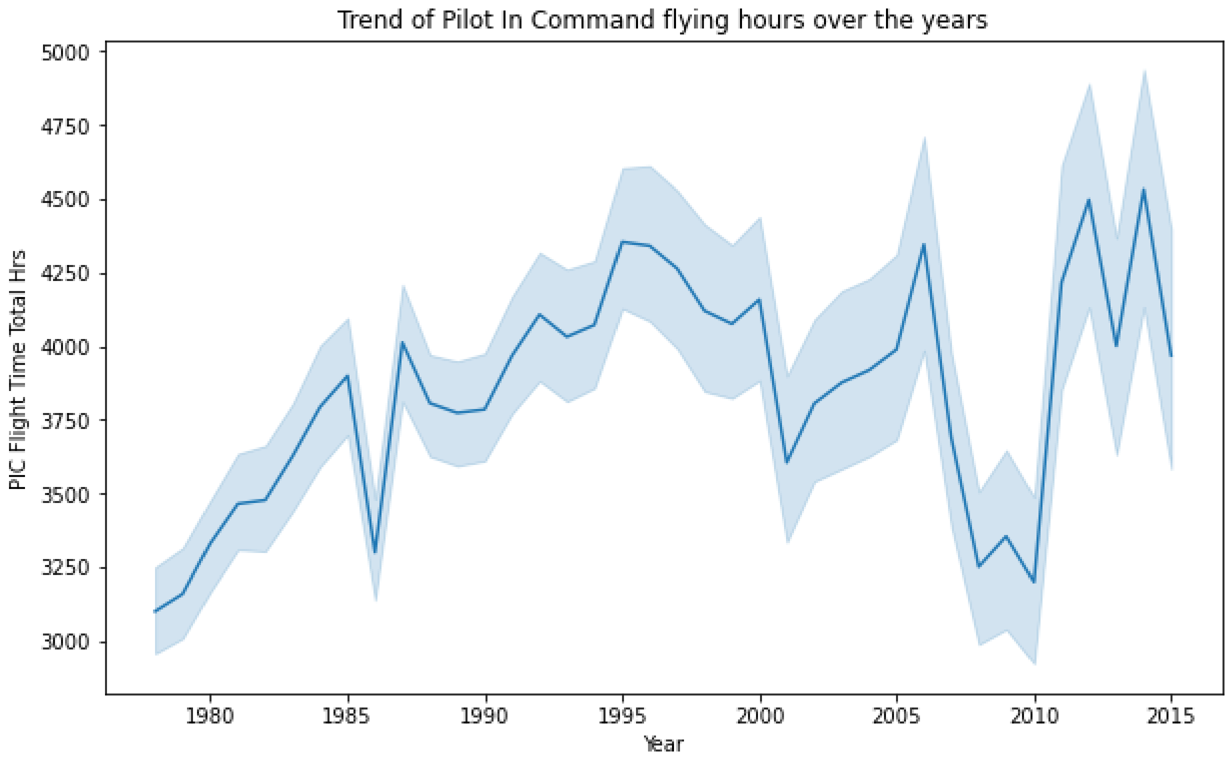


As per the plot the number of incidents has decreased over the time in general, although there have been some surges intermittently.

The experience of the pilot in command is one of the common factors available in the given data and it is represented here in the column "PIC Flight Time Total Hrs". It's a nice idea to plot this column and try to correlate it with the trend of number of incidents.

In [67]:
```
plt.figure(figsize=(10,6))
sns.lineplot(x=av_data.Year,y=av_data['PIC Flight Time Total Hrs'])
plt.title('Trend of Pilot In Command flying hours over the years')
```

Out[67]:
```
Text(0.5, 1.0, 'Trend of Pilot In Command flying hours over the years')
```

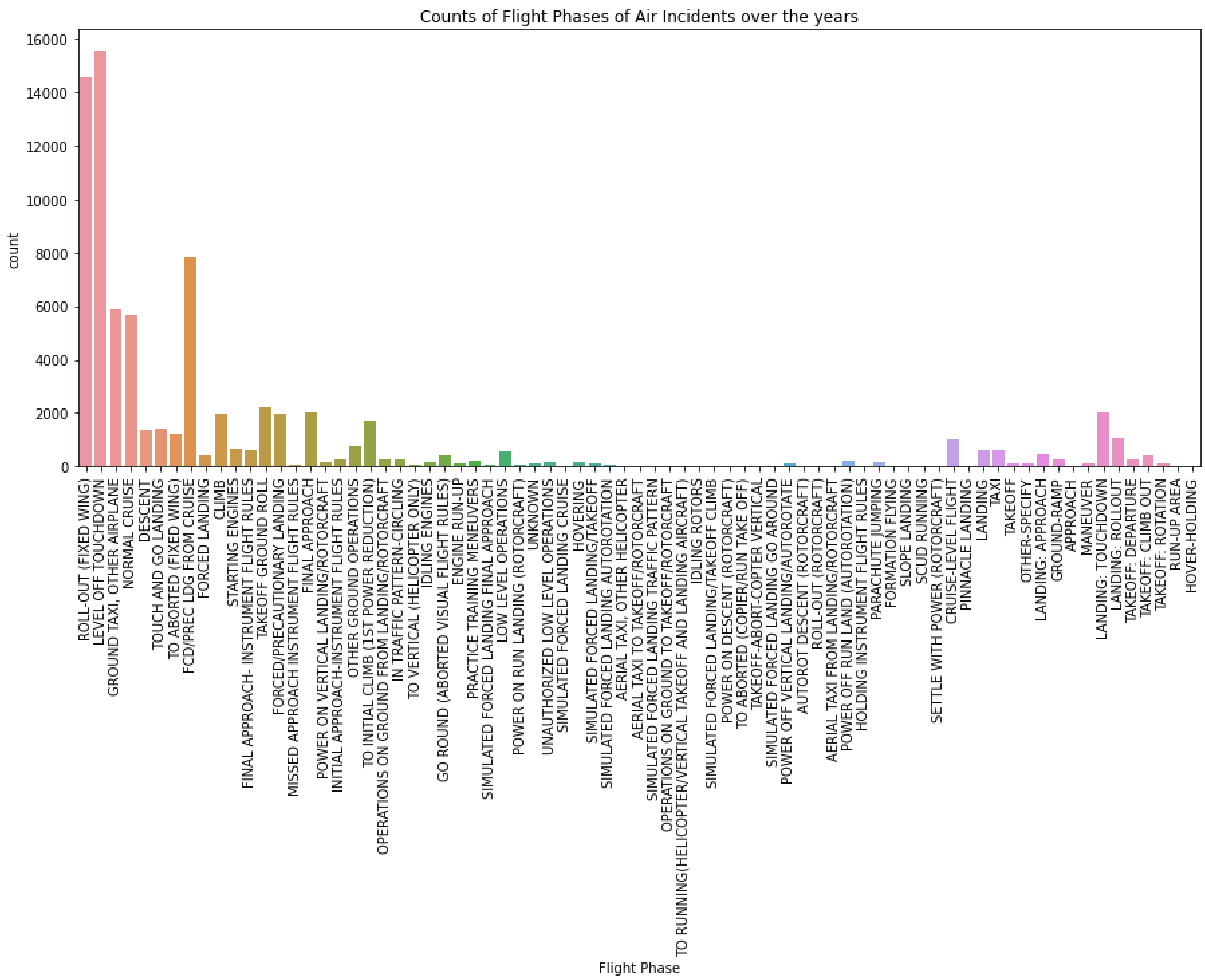


Trying to correlate both the plots, one can clearly observe that whenever there was a surge in the number of incidents there was a dip in the experience of the pilot in command. So, the experience of the pilot in command could be one of the key factors for the cause of the incidents.

The flight phase is another common factor available in the given data and it is represented here in the column "Flight Phase".

In [68]:
```
plt.figure(figsize=(15,6))
ovrlfp = sns.countplot(x=av_data['Flight Phase'])
ovrlfp.set_xticklabels(ovrlfp.get_xticklabels(), rotation=90);
plt.title('Counts of Flight Phases of Air Incidents over the years')
```

Out[68]:
```
Text(0.5, 1.0, 'Counts of Flight Phases of Air Incidents over the years')
```



The plot indicates that the level off touchdown is the phase in which the most number of incidents happened. This phase is part of landing procedure. From the answer of the first research question, a point to check is the experience of pilot in command for the incidents with this flight phase.

Data derivation

Create a subset of data frame where the flight phase is level of touchdown.

In [69]:
```
lvl_touch_data = pd.DataFrame(av_data.loc[av_data['Flight Phase'] == 'LEVEL OFF TOUCHDOWN', 'PIC Flight Time Total Hrs'])
```

Have a glance of the subset data frame.

In [70]:
```
lvl_touch_data.head()
```

Out[70]:

	PIC Flight Time Total Hrs
3	2000.0
11	2300.0
12	2300.0
23	4400.0
34	4000.0

Check the majority values of the column. Code reference: https://www.youtube.com/watch?v=7sJaRHF03K8

In [71]:
```
lvl_touch_data["PIC Flight Time Total Hrs"].quantile(0.75)
```

Out[71]:
```
3000.0
```

So, the experience of majority of pilots in command for the incidents where the flight phase was level off touchdown, is less than the mean value of the experience of pilot in command in overall. This concurs with the answer of the first research question.

From the count plot of years, it can be seen that there was a surge in number of incidents between the years 1978 and 1980. Investigate the flight phase and experience of pilot in command during this period.

Data derivation

Create a subset of data for years between 1978 and 1980.

In [72]:
```
yrs_3high = av_data[(av_data.Year >= 1978) & (av_data.Year <= 1980)]
```

Check the dimensions of the subset data frame.

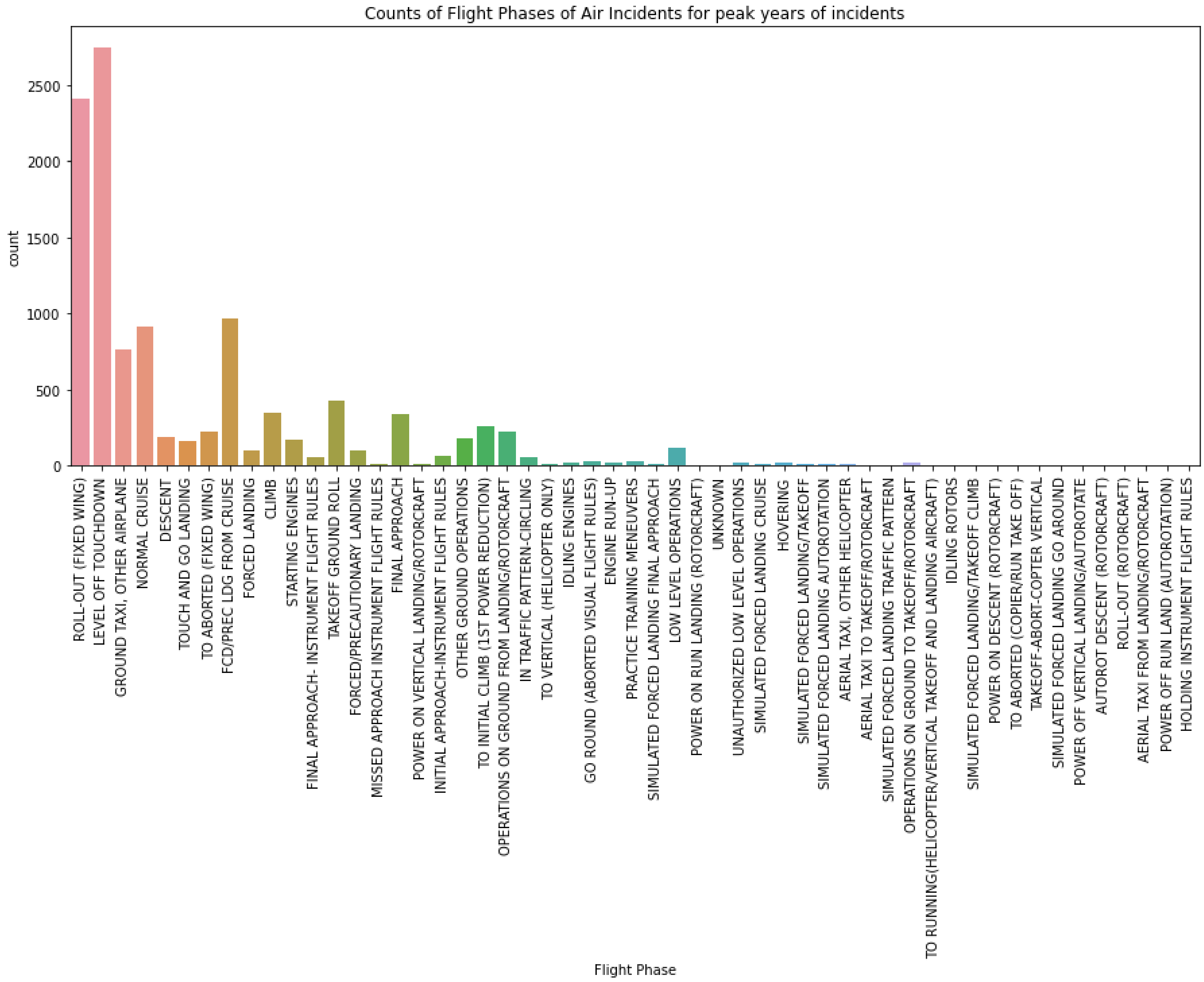
In [73]:
```
yrs_3high.shape
```

Out[73]:
```
(11163, 24)
```

Explore the flight phase of the subset through count plot.

In [74]:
```
plt.figure(figsize=(15,6))
y3hfp = sns.countplot(x=yrs_3high['Flight Phase'])
y3hfp.set_xticklabels(y3hfp.get_xticklabels(), rotation=90);
plt.title('Counts of Flight Phases of Air Incidents for peak years of incidents')
```

Out[74]:
```
Text(0.5, 1.0, 'Counts of Flight Phases of Air Incidents for peak years of incidents')
```



In this period too, the level off touchdown is the phase in which the most number of incidents happened. Explore the experience of pilot in command for this period too.

Data derivation

Create a further subset of the subset data frame where the flight phase is level of touchdown.

In [75]:
```
lvl_touch_data_1 = pd.DataFrame(yrs_3high.loc[yrs_3high['Flight Phase'] == 'LEVEL OFF TOUCHDOWN', 'PIC Flight Time Total Hrs'])
```

Have a glance of the subset data frame.

In [76]:
```
lvl_touch_data_1.head()
```

Out[76]:

	PIC Flight Time Total Hrs
3	2000.0
11	2300.0
12	2300.0
23	4400.0
34	4000.0

Check the majority values of the column.

In [77]:
```
lvl_touch_data_1['PIC Flight Time Total Hrs'].quantile(0.75)
```

Out[77]:
```
2601.5
```

Again, the experience of pilot in command is less than the mean of the experience of pilot in command in overall.

From the count plot of years, it can be seen that there was a surge in the number of incidents between the years 1986 and 1981. So, repeat the above procedure for this period too to check if the flight phase and experience of the pilot in command display a similar trend.

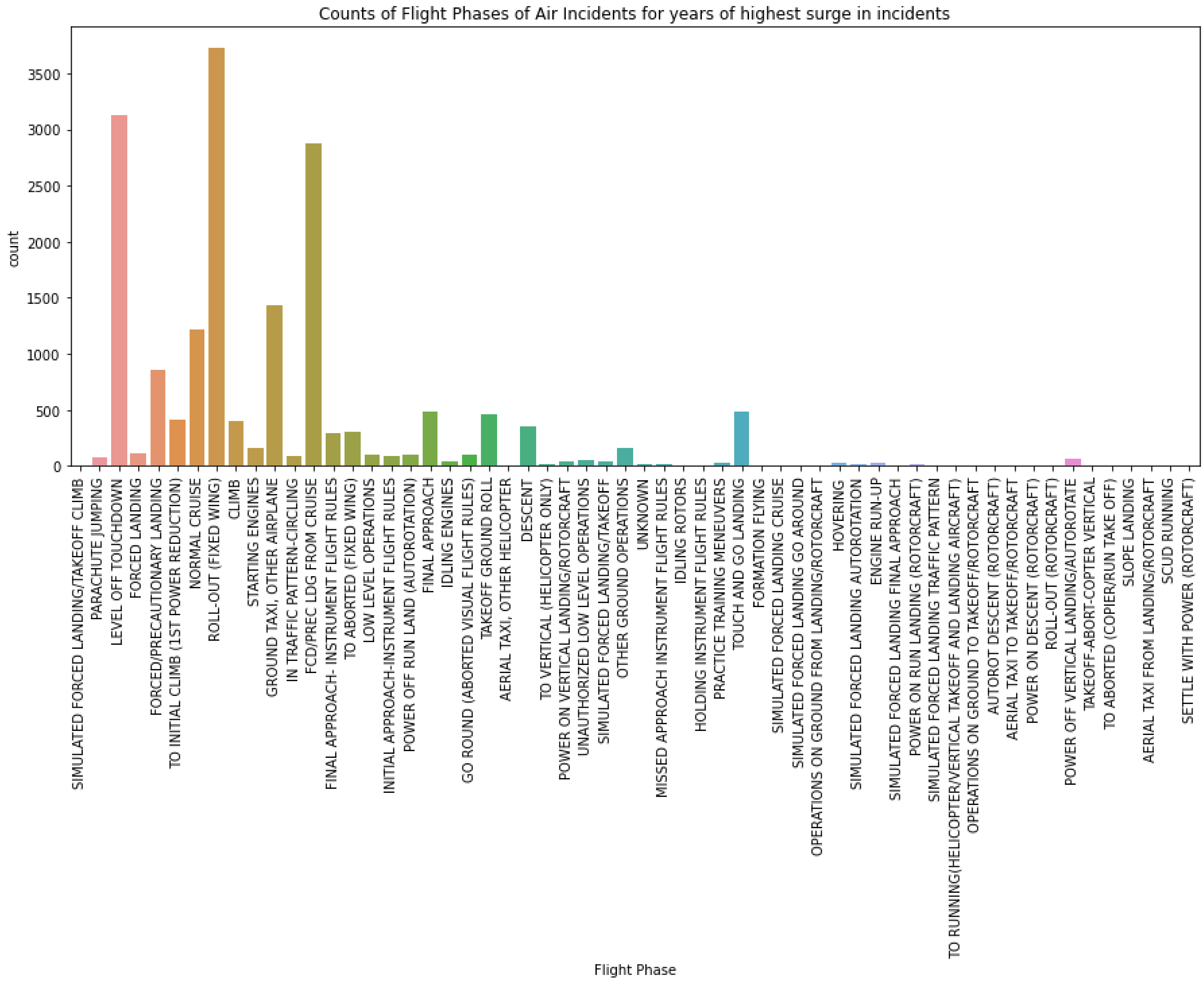
In [78]:
```
yrs_surge1 = av_data[(av_data.Year >= 1986) & (av_data.Year <= 1991)]
```

In [79]:
```
yrs_surge1.shape
```

Out[79]:
```
(17968, 24)
```

In [80]:
```
plt.figure(figsize=(15,6))
ysfp1 = sns.countplot(x=yrs_surge1['Flight Phase'])
ysfp1.set_xticklabels(ysfp1.get_xticklabels(), rotation=90);
plt.title('Counts of Flight Phases of Air Incidents for years of highest surge in incidents')
```

Out[80]:
```
Text(0.5, 1.0, 'Counts of Flight Phases of Air Incidents for years of highest surge in incidents')
```



Interestingly for this period, roll out fixed wing was the flight phase in which most of the incidents occurred. But again, this is also a part of landing procedure and so it makes sense to check the pilot experience for this case too.

In [81]:
```
rollout_data = pd.DataFrame(yrs_3high.loc[yrs_3high['Flight Phase'] == 'ROLL-OUT (FIXED WING)', 'PIC Flight Time Total Hrs'])
```

In [82]:
```
rollout_data.head()
```

Out[82]:

	PIC Flight Time Total Hrs
0	245.0
1	200.0
9	90.0
18	200.0
30	5500.0

In [83]:
```
rollout_data['PIC Flight Time Total Hrs'].quantile(0.75)
```

Out[83]:
```
3108.0
```

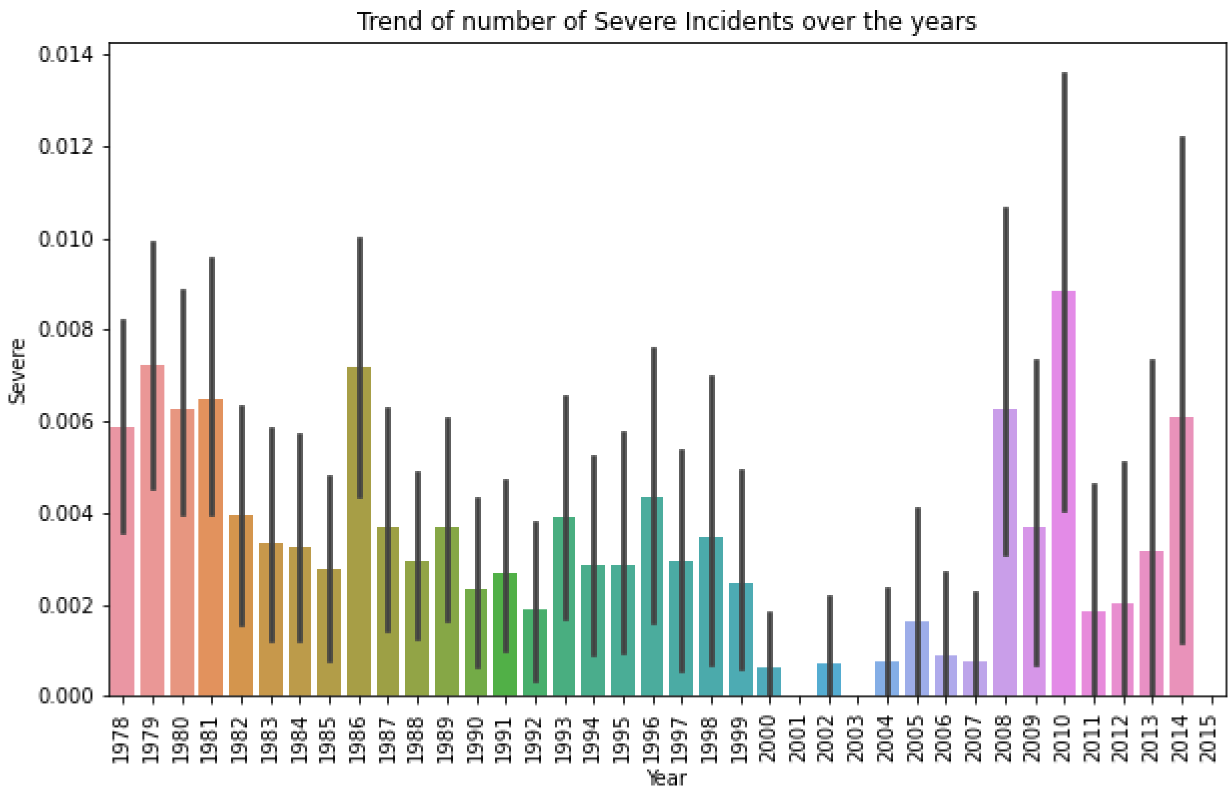
The experience of pilot in command is again showing a similar trend as for the above cases.

So, it could be possible that the answer to the first research question might have been influenced by these different periods of incidents.

Check the trend of number of severe incidents over the years and the type of damage caused to the aircrafts in these cases.

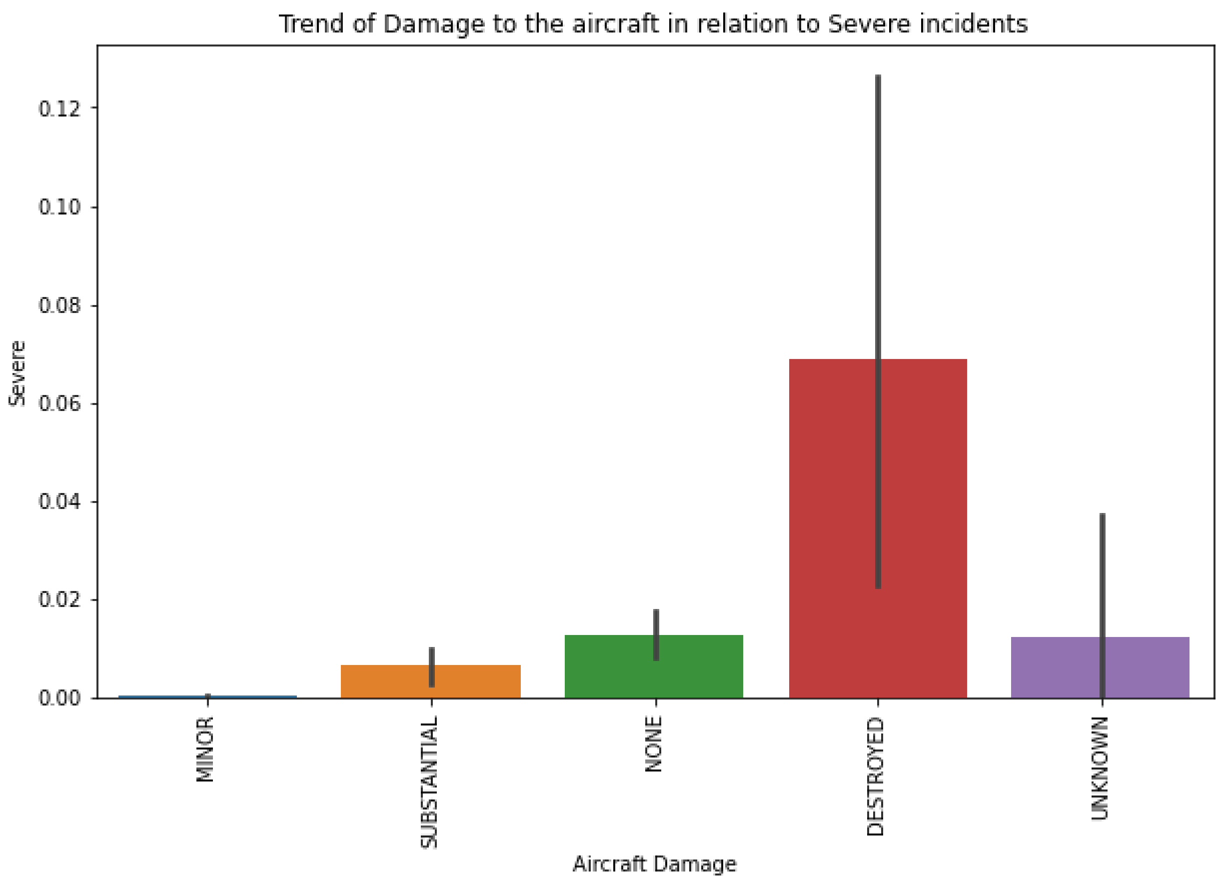
In [84]:
```
plt.figure(figsize=(10,6))
yr_sr = sns.barplot(x=av_data.Year,y=av_data.Severe)
yr_sr.set_xticklabels(yr_sr.get_xticklabels(), rotation = 90);
plt.title('Trend of number of Severe Incidents over the years')
```

Out[84]:
```
Text(0.5, 1.0, 'Trend of number of Severe Incidents over the years')
```



In [85]:
```
plt.figure(figsize=(10,6))
dam_sr = sns.barplot(x=av_data['Aircraft Damage'],y=av_data.Severe)
dam_sr.set_xticklabels(dam_sr.get_xticklabels(), rotation = 90);
plt.title('Trend of Damage to the aircraft in relation to Severe incidents')
```

Out[85]:
```
Text(0.5, 1.0, 'Trend of Damage to the aircraft in relation to Severe incidents')
```



From the above two plots it is not so clear, so it's better to create a subset of data for severe incidents and then explore the same.

Data derivation

Create a subset of data for severe incidents with only the year, the severe and the aircraft damage columns.

In [86]:
```
years_sever = pd.DataFrame({'Year':av_data.Year,'Severe':av_data.Severe,'Aircraft Damage':av_data['Aircraft Damage']})
```

In [87]:
```
years_sever = years_sever[years_sever.Severe == 1]
```

Check the dimensions of this subset data frame.

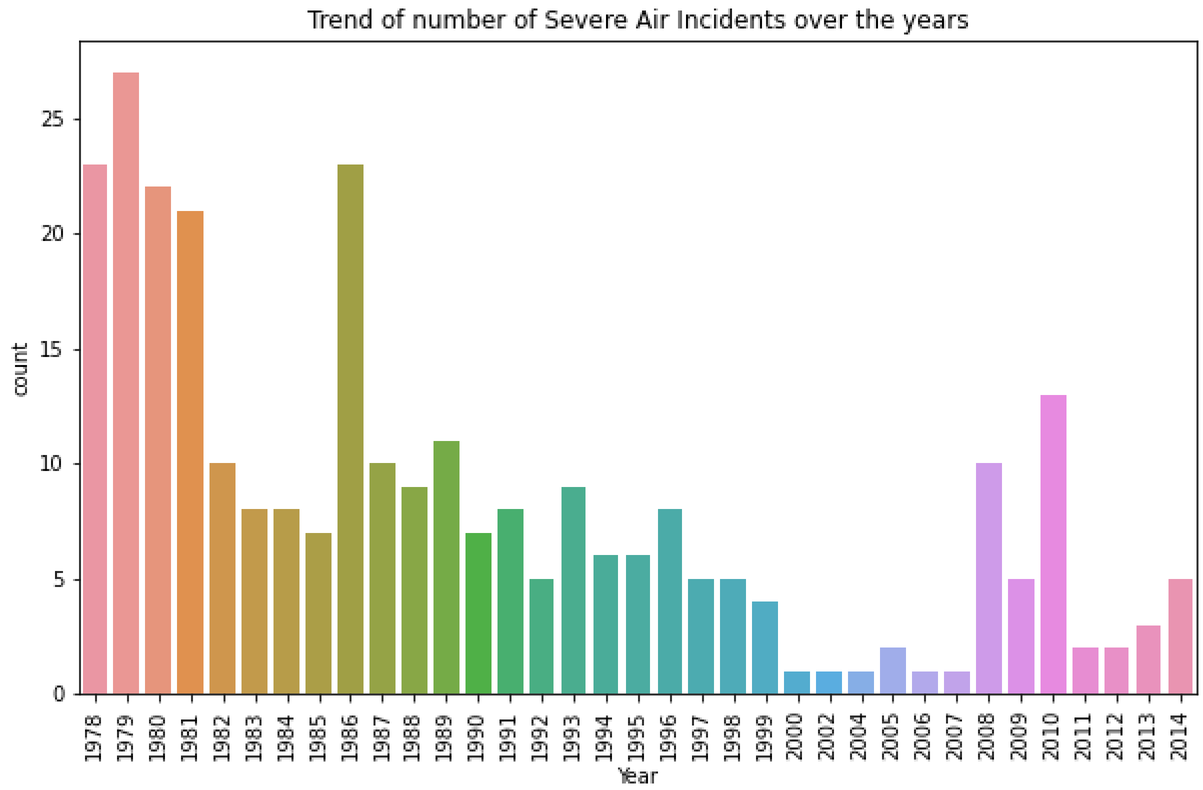
In [88]:
```
years_sever.shape
```

Out[88]:
```
(289, 3)
```

Check the trends of incidents over years and type of aircraft damage for this subset.

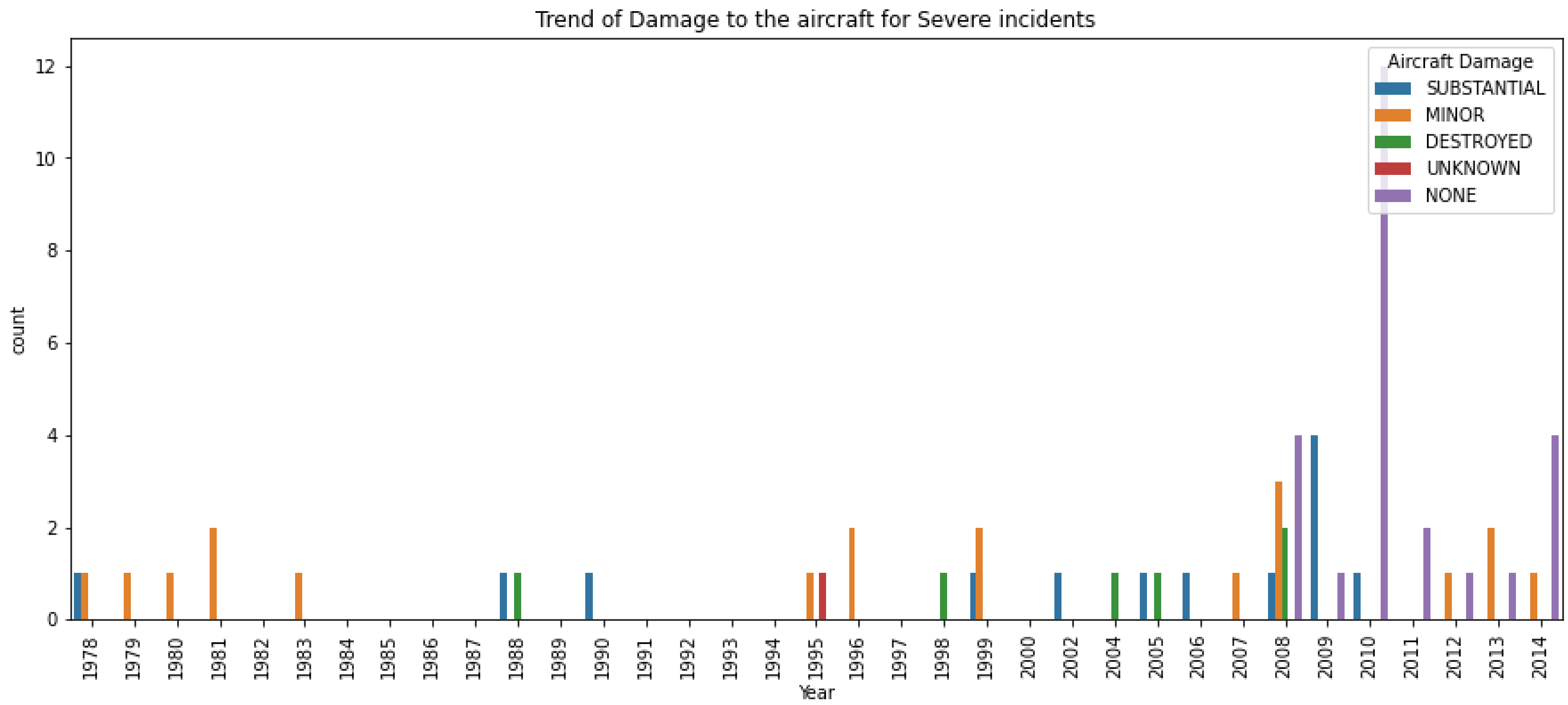
In [89]:
```
plt.figure(figsize=(10,6))
yrsr_count = sns.countplot(x=years_sever.Year)
yrsr_count.set_xticklabels(yrsr_count.get_xticklabels(), rotation=90);
plt.title('Trend of number of Severe Air Incidents over the years')
```

Out[89]:
```
Text(0.5, 1.0, 'Trend of number of Severe Air Incidents over the years')
```



In [90]:
```
plt.figure(figsize=(15,6))
yrsr_dam = sns.countplot(data=years_sever,x=years_sever.Year,hue="Aircraft Damage")
yrsr_dam.set_xticklabels(yrsr_dam.get_xticklabels(), rotation=90);
plt.title('Trend of Damage to the aircraft for Severe incidents')
```

Out[90]:
```
Text(0.5, 1.0, 'Trend of Damage to the aircraft for Severe incidents')
```



The trend of number of severe incidents over the years is very different from that of all the incidents in general.

Answer to Researh Question 1.

From all the above observations, the answer to the first research question is that the trend of number of incidents has decreased over the time in overall, although there were some surges intermittently. From the given data the factor that appears to create this trend is the increase and/or decrease in the flight hours of the pilot in command.

The remaining research questions are not based on the whole data in general but are specific to group of variables on different basis. So, further analysis would be done on different basis and hence will be done over subsets of data with different groups of features.

For this purpose, a true copy of the data set is created.

In [91]:
```
av_data_copy = av_data.copy()
```

Have a glance and check the copy data frame.

Research Question 2 - location basis

Which was the most dangerous location and what could be the possible factors from the given data due to which that location was the most dangerous.

To answer this question, we choose the event airport as the main column and create a subset of data with all the relevant columns.

In [92]:
```
loc_basis_data = av_data_copy[['Event City','Event Airport','Aircraft Damage','Flight Phase','Primary Flight Type',
            'Flight Conduct Code','Flight Plan Filed Code','Aircraft Registration Nbr','Year','Severe']]
```

Have a glance of the created subset.

In [93]:
```
loc_basis_data.head()
```

Out[93]:

Event City	Event Airport	Aircraft Damage	Flight Phase	Primary Flight Type	Flight Conduct Code	Flight Plan Filed Code	Aircraft Registration Nbr	Year	Severe

	Event City	Event Airport	Aircraft Damage	Flight Phase	Primary Flight Type	Flight Conduct Code	Flight Plan Filed Code	Aircraft Registration Nbr	Year	Severe
0	WAHPETON	BRECKENRIDGE	MINOR	ROLL-OUT (FIXED WING)	PERSONAL	GENERAL OPERATING RULES	NONE	2691Q	1978	0
1	FAIRBANKS	FAIRBANKS INTL	MINOR	ROLL-OUT (FIXED WING)	PERSONAL	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	4073E	1978	0
3	CARLSBAD	MC CLELLAN-PALOMAR	MINOR	LEVEL OFF TOUCHDOWN	PERSONAL	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	2250F	1978	0
4	TROUTDALE	TROUTDALE MUNI	MINOR	GROUND TAXI, OTHER AIRPLANE	PERSONAL	GENERAL OPERATING RULES	NONE	738FD	1978	0
7	LAFAYETTE	PURDUE UNIVERSITY	NaN	NORMAL CRUISE	OTHER	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	27196	1978	0

In [94]:
```
loc_basis_data.shape
```

Out[94]:
```
(77854, 10)
```

Check missing values for the created subset. Code reference: https://www.kaggle.com/itssuru/eda-cristiano-ronaldo-s-career

In [95]:
```
loc_basis_data.isnull().sum()
```

Out[95]:
```
Event City                   6552
Event Airport               15123
Aircraft Damage             16828
Flight Phase                  108
Primary Flight Type          8182
Flight Conduct Code            44
Flight Plan Filed Code       9891
Aircraft Registration Nbr       0
Year                            0
Severe                          0
dtype: int64
```

It can be seen that the key column event airport has a lot of missing values which needs to be dropped. But this may also lead to drop in the number of observations which are severe. So instead of dropping the missing values in the subset, it's better to do the analysis of the subset in two different sections, that is one for not severe cases and the other for severe cases.

Check the count of not severe and severe incidents.

In [96]:
```
loc_basis_data.Severe.value_counts()
```

Out[96]:
```
0    77565
1      289
Name: Severe, dtype: int64
```

Create a further subset of not severe incidents.

In [97]:
```
loc_basis_notsevere = loc_basis_data[loc_basis_data.Severe == 0]
```

Find the airport with highest number of incidents for not severe incidents. Code reference: https://www.youtube.com/watch?v=FdudxZN6rIo

In [98]:
```
loc_basis_notsevere['Event Airport'].value_counts().index[0]
```

Out[98]:
```
'DENVER INTL'
```

Create a further subset data frame exclusively for this airport.

In [99]:
```
High_Inci_Airpt = loc_basis_notsevere[loc_basis_notsevere['Event Airport'] ==
                                      loc_basis_notsevere['Event Airport'].value_counts().index[0]]
```

Check the data for him exclusive to this airport.

In [100…
```
High_Inci_Airpt
```

Out[100…

	Event City	Event Airport	Aircraft Damage	Flight Phase	Primary Flight Type	Flight Conduct Code	Flight Plan Filed Code	Aircraft Registration Nbr	Year	Severe
1079	DENVER	DENVER INTL	MINOR	GROUND TAXI, OTHER AIRPLANE	BUSINESS	GENERAL OPERATING RULES	NONE	19RF	1978	0
1272	DENVER	DENVER INTL	MINOR	LEVEL OFF TOUCHDOWN	PERSONAL	GENERAL OPERATING RULES	NONE	1751W	1978	0
1708	DENVER	DENVER INTL	MINOR	GROUND TAXI, OTHER AIRPLANE	EXECUTIVE	GENERAL OPERATING RULES	INSTRUMENT FLIGHT RULES	69489	1978	0
2149	DENVER	DENVER INTL	MINOR	TO ABORTED (FIXED WING)	AIR TAXI (SCHEDULED-NOT COMMUTER)	AIR TAXI/COMMUTER	INSTRUMENT FLIGHT RULES	33FE	1978	0

	Event City	Event Airport	Aircraft Damage	Flight Phase	Primary Flight Type	Flight Conduct Code	Flight Plan Filed Code	Aircraft Registration Nbr	Year	Severe
3100	DENVER	DENVER INTL	NaN	CLIMB	PERSONAL	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	5612P	1978	0
...	...	...	...	...	...	...	...	...	...	...
97858	DENVER	DENVER INTL	NONE	LANDING: APPROACH	NaN	AIR CARRIER/COMMERCIAL	NaN	644RW	2014	0
98661	DENVER	DENVER INTL	MINOR	TAKEOFF: ROTATION	NaN	GENERAL OPERATING RULES	NaN	694ES	2014	0
99459	DENVER	DENVER INTL	NONE	LANDING: TOUCHDOWN	NaN	AIR CARRIER/COMMERCIAL	NaN	200NN	2015	0
99588	MAX	DENVER INTL	MINOR	CRUISE-LEVEL FLIGHT	NaN	AIR CARRIER/COMMERCIAL	NaN	332NW	2015	0
99776	DENVER	DENVER INTL	MINOR	LANDING: TOUCHDOWN	NaN	AIR TAXI/COMMUTER	NaN	5079E	2015	0

317 rows × 10 columns

Explore various columns of this data frame and note the observations.

In [101…

```
High_Inci_Airpt['Flight Phase'].value_counts()
```

Out[101…

```
ROLL-OUT (FIXED WING)                         46
LEVEL OFF TOUCHDOWN                           43
GROUND TAXI, OTHER AIRPLANE                   42
CLIMB                                         23
TAKEOFF GROUND ROLL                           19
FCD/PREC LDG FROM CRUISE                      19
NORMAL CRUISE                                 17
FINAL APPROACH                                13
TO INITIAL CLIMB (1ST POWER REDUCTION)        12
TO ABORTED (FIXED WING)                       10
OTHER GROUND OPERATIONS                       10
FORCED/PRECAUTIONARY LANDING                   8
CRUISE-LEVEL FLIGHT                            6
DESCENT                                        5
INITIAL APPROACH-INSTRUMENT FLIGHT RULES       4
FINAL APPROACH- INSTRUMENT FLIGHT RULES        4
LANDING: TOUCHDOWN                             3
LANDING: APPROACH                              3
TOUCH AND GO LANDING                           3
SIMULATED FORCED LANDING AUTOROTATION          2
LANDING: ROLLOUT                               2
IDLING ENGINES                                 2
TAKEOFF: CLIMB OUT                             2
TAKEOFF: ROTATION                              2
OPERATIONS ON GROUND FROM LANDING/ROTORCRAFT   2
GROUND-RAMP                                    2
ENGINE RUN-UP                                  1
POWER OFF RUN LAND (AUTOROTATION)              1
TAKEOFF                                        1
LANDING                                        1
OTHER-SPECIFY                                  1
UNAUTHORIZED LOW LEVEL OPERATIONS              1
STARTING ENGINES                               1
POWER ON RUN LANDING (ROTORCRAFT)              1
TO VERTICAL (HELICOPTER ONLY)                  1
SIMULATED FORCED LANDING CRUISE                1
FORCED LANDING                                 1
HOVERING                                       1
TAXI                                           1
Name: Flight Phase, dtype: int64
```

In [102…

```
High_Inci_Airpt['Flight Conduct Code'].value_counts()
```

Out[102…

```
GENERAL OPERATING RULES    135
AIR CARRIER/COMMERCIAL     110
AIR TAXI/COMMUTER           71
TRAVEL CLUB                  1
Name: Flight Conduct Code, dtype: int64
```

In [103…

```
High_Inci_Airpt['Flight Plan Filed Code'].value_counts()
```

Out[103…

```
INSTRUMENT FLIGHT RULES    174
NONE                        69
VISUAL FLIGHT RULES         31
UNKNOWN                     18
Name: Flight Plan Filed Code, dtype: int64
```

In [104…

```
High_Inci_Airpt['Aircraft Registration Nbr'].value_counts()
```

Out[104…

```
3149Z     2
```

```
67TC     2
32017    2
100UX    2
2MM      2
        ..
5832L    1
33LK     1
52655    1
9277V    1
5079E    1
Name: Aircraft Registration Nbr, Length: 311, dtype: int64
```

In [105…

```
High_Inci_Airpt.Year.value_counts()
```

Out[105…

```
1981    29
1983    29
1982    22
1979    20
1984    19
1986    18
1985    16
1978    13
1992    13
1988    11
1993     8
1997     8
1989     7
2009     7
2010     7
1980     7
1999     6
1991     6
1994     6
2008     6
2005     6
1996     5
1998     5
1995     5
1987     5
2001     4
2003     4
2011     4
2000     3
2006     3
2007     3
1990     3
2012     3
2015     3
2014     2
2004     1
Name: Year, dtype: int64
```

After exploring various columns, a notable observation is that except for flight phase column, all the other columns seem to have indeterminant indications. Although the flight phase indications seem to be in line with the answer to the first research question, but in context of the airport this may also mean the poor infrastructure and maintenance of the airport.

Repeat the above steps for severe incidents and note the observations.

In [106…

```
loc_basis_severe = loc_basis_data[loc_basis_data.Severe == 1]
```

In [107…

```
loc_basis_severe['Event Airport'].value_counts().index[0]
```

Out[107…

```
'RENO/STEAD'
```

In [108…

```
Most_Sev_Airpt = loc_basis_severe[loc_basis_severe['Event Airport'] ==
                                  loc_basis_severe['Event Airport'].value_counts().index[0]]
```

In [109…

```
Most_Sev_Airpt
```

Out[109…

	Event City	Event Airport	Aircraft Damage	Flight Phase	Primary Flight Type	Flight Conduct Code	Flight Plan Filed Code	Aircraft Registration Nbr	Year	Severe
10005	RENO	RENO/STEAD	NaN	NORMAL CRUISE	OTHER	GENERAL OPERATING RULES	NaN	28378	1980	1
55239	RENO	RENO/STEAD	NaN	PARACHUTE JUMPING	OTHER	GENERAL OPERATING RULES	NONE	4912D	1992	1
90286	RENO	RENO/STEAD	DESTROYED	TO INITIAL CLIMB (1ST POWER REDUCTION)	NaN	GENERAL OPERATING RULES	UNKNOWN	4235T	2008	1

In [110…

```
Most_Sev_Airpt['Flight Phase'].value_counts()
```

Out[110…

```
NORMAL CRUISE                1
PARACHUTE JUMPING            1
```

```
TO INITIAL CLIMB (1ST POWER REDUCTION)    1
Name: Flight Phase, dtype: int64
```

In [111…

```
Most_Sev_Airpt['Flight Conduct Code'].value_counts()
```

Out[111…

```
GENERAL OPERATING RULES    3
Name: Flight Conduct Code, dtype: int64
```

The first thing to note for severe incidents is that the airport with most incidents is different from that of not severe incidents. The number of observations for severe incidents are very low due to which it is not appropriate to figure out a particular possibility for the cause, from the given data.

Answer to Research Question 2

From all the above observations, the answer to the second research question was DENVER INTL is the most dangerous airport for not severe incidents and RENO/STEAD was the most dangerous airport for severe incidents. For the not severe incidents, the airport infrastructure seems to be one of the possible reasons for such status to the airport. For the severe incidents, the number of observations are very low and as a result the possible reasons for the status of the airport are inconclusive.

Research Question 3 - aircraft basis

Which was the most dangerous aircraft and what could be the possible factors from the given data due to which that aircraft was the most dangerous.

To answer this question, we choose the aircraft model as the main column and create a subset of data with all the relevant columns.

In [112…

```
aircraft_basis_data = av_data_copy[['Aircraft Make','Aircraft Model','Aircraft Series','Primary Flight Type',
                                   'Flight Conduct Code','Aircraft Engine Model','PIC Flight Time Total Hrs', 'Severe']]
```

Have a glance of the created subset.

In [113…

```
aircraft_basis_data.head()
```

Out[113…

	Aircraft Make	Aircraft Model	Aircraft Series	Primary Flight Type	Flight Conduct Code	Aircraft Engine Model	PIC Flight Time Total Hrs	Severe
0	CESSNA	182	UNDESIGNATED SERIES	PERSONAL	GENERAL OPERATING RULES	NaN	245.0	0
1	PIPER	PA18	150	PERSONAL	GENERAL OPERATING RULES	NaN	200.0	0
3	CESSNA	310	L	PERSONAL	GENERAL OPERATING RULES	NaN	2000.0	0
4	CESSNA	172	UNDESIGNATED SERIES	PERSONAL	GENERAL OPERATING RULES	NaN	300.0	0
7	PIPER	PA31	350	OTHER	GENERAL OPERATING RULES	NaN	2700.0	0

Check missing values for the created subset.

In [114…

```
aircraft_basis_data.isnull().sum()
```

Out[114…

```
Aircraft Make                 1762
Aircraft Model                2198
Aircraft Series               2199
Primary Flight Type           8182
Flight Conduct Code             44
Aircraft Engine Model        48173
PIC Flight Time Total Hrs        0
Severe                           0
dtype: int64
```

The situation again resembles to that of analysis to the second research question. So, repeat the whole process that was done as part of analysis for the second research question and note the observations.

In [115…

```
aircraft_basis_data.Severe.value_counts()
```

Out[115…

```
0    77565
1      289
Name: Severe, dtype: int64
```

In [116…

```
aircraft_basis_notsevere = aircraft_basis_data[aircraft_basis_data.Severe == 0]
```

In [117…

```
aircraft_basis_notsevere['Aircraft Model'].value_counts().index[0]
```

Out[117…

```
'172'
```

In [118…

```
High_Inci_Model = aircraft_basis_notsevere[aircraft_basis_notsevere['Aircraft Model'] ==
                                            aircraft_basis_notsevere['Aircraft Model'].value_counts().index[0]]
```

In [119…

```
High_Inci_Model
```

Out[119…

	Aircraft Make	Aircraft Model	Aircraft Series	Primary Flight Type	Flight Conduct Code	Aircraft Engine Model	PIC Flight Time Total Hrs	Severe

	Aircraft Make	Aircraft Model	Aircraft Series	Primary Flight Type	Flight Conduct Code	Aircraft Engine Model	PIC Flight Time Total Hrs	Severe
4	CESSNA	172	UNDESIGNATED SERIES	PERSONAL	GENERAL OPERATING RULES	NaN	300.0	0
9	CESSNA	172	UNDESIGNATED SERIES	BUSINESS	GENERAL OPERATING RULES	NaN	90.0	0
77	CESSNA	172	UNDESIGNATED SERIES	BUSINESS	GENERAL OPERATING RULES	NaN	1800.0	0
97	CESSNA	172	UNDESIGNATED SERIES	PERSONAL	GENERAL OPERATING RULES	NaN	180.0	0
181	CESSNA	172	UNDESIGNATED SERIES	INSTRUCTION	GENERAL OPERATING RULES	NaN	46.0	0
...	...	...	...	...	...	...	...	...
99877	CESSNA	172	N	NaN	GENERAL OPERATING RULES	0-320 SERIES	445.0	0
99890	CESSNA	172	P	NaN	GENERAL OPERATING RULES	0-320 SERIES	786.0	0
99901	CESSNA	172	K	NaN	GENERAL OPERATING RULES	0-300 SER	120.0	0
99945	CESSNA	172	P	NaN	PILOT SCHOOLS	O-320-D2J	1480.0	0
99975	CESSNA	172	R	NaN	PILOT SCHOOLS	I0360 SER A&C	880.0	0

3943 rows × 8 columns

In [120…
```
High_Inci_Model["Aircraft Make"].value_counts()
```
Out[120…
```
CESSNA    3943
Name: Aircraft Make, dtype: int64
```
In [121…
```
High_Inci_Model["Aircraft Engine Model"].value_counts()
```
Out[121…
```
O320H2AD        294
O320E2D         242
0-320 SERIES    168
O320*           167
O300D           162
               ...
O320D2C           1
O320E3D           1
IO520*            1
O320A2B           1
O-320-D2J         1
Name: Aircraft Engine Model, Length: 69, dtype: int64
```
In [122…
```
High_Inci_Model["Primary Flight Type"].value_counts()
```
Out[122…
```
PERSONAL                                                   2346
INSTRUCTION                                                 883
BUSINESS                                                    125
INDUSTRIAL/SPECIAL                                           53
OTHER                                                        52
AIR TAXI (NON-SCHEDULED)                                     20
FOR HIRE                                                      6
AIR TAXI COMMUTER (SCHEDULED 5 OR MORE ROUNDTRIPS PER WEEK)   5
ILLEGAL DRUG, STOLEN AIRCRAFT, ETC.                           3
EXECUTIVE                                                     1
AIR TAXI (SCHEDULED- NOT COMMUTER)                            1
SUPPLEMENTAL OR COMMERCIAL OPERATOR                           1
Name: Primary Flight Type, dtype: int64
```
In [123…
```
High_Inci_Model["Flight Conduct Code"].value_counts()
```
Out[123…
```
GENERAL OPERATING RULES    3802
PILOT SCHOOLS               110
AIR TAXI/COMMUTER            26
PARACHUTE JUMPING             3
Name: Flight Conduct Code, dtype: int64
```
In [124…
```
High_Inci_Model["PIC Flight Time Total Hrs"].quantile(0.75)
```
Out[124…
```
750.0
```
After exploring various columns, two key observations were that the make of the most dangerous aircraft model for not severe incidents is the same and also most of flight types for this was personal.

In [125…
```
aircraft_basis_severe = aircraft_basis_data[aircraft_basis_data.Severe == 1]
```

In [126…
```
aircraft_basis_severe['Aircraft Model'].value_counts().index[0]
```
Out[126…
```
'182'
```

In [127…
```
Most_Sev_Model = aircraft_basis_severe[aircraft_basis_severe['Aircraft Model'] ==
                                       aircraft_basis_severe['Aircraft Model'].value_counts().index[0]]
```

In [128…
```
Most_Sev_Model
```
Out[128…

	Aircraft Make	Aircraft Model	Aircraft Series	Primary Flight Type	Flight Conduct Code	Aircraft Engine Model	PIC Flight Time Total Hrs	Severe
638	CESSNA	182	A	OTHER	GENERAL OPERATING RULES	NaN	750.0	1
1926	CESSNA	182	UNDESIGNATED SERIES	OTHER	PARACHUTE JUMPING	NaN	1500.0	1
2290	CESSNA	182	B	PERSONAL	GENERAL OPERATING RULES	NaN	340.0	1
2331	CESSNA	182	A	PERSONAL	GENERAL OPERATING RULES	NaN	135.0	1
2448	CESSNA	182	UNDESIGNATED SERIES	OTHER	PARACHUTE JUMPING	NaN	900.0	1
...	...	...	...	...	...	...	...	...
69325	CESSNA	182	UNDESIGNATED SERIES	INDUSTRIAL/SPECIAL	PARACHUTE JUMPING	NaN	4200.0	1
70571	CESSNA	182	B	INDUSTRIAL/SPECIAL	GENERAL OPERATING RULES	O470U	2400.0	1
89852	CESSNA	182	F	OTHER	GENERAL OPERATING RULES	NaN	0.0	1
92398	CESSNA	182	UNDESIGNATED SERIES	NaN	PARACHUTE JUMPING	O-470 SERIES	0.0	1
93312	CESSNA	182	C	NaN	GENERAL OPERATING RULES	O-470 SERIES	0.0	1

111 rows × 8 columns

In [129…
```
Most_Sev_Model['Aircraft Make'].value_counts()
```
Out[129…
```
CESSNA    111
Name: Aircraft Make, dtype: int64
```

In [130…
```
Most_Sev_Model['Aircraft Engine Model'].value_counts()
```
Out[130…
```
O470L          10
O470*           3
O-470 SERIES    2
O470R           1
O470U           1
Name: Aircraft Engine Model, dtype: int64
```

In [131…
```
Most_Sev_Model['Primary Flight Type'].value_counts()
```
Out[131…
```
OTHER                 98
PERSONAL               6
INDUSTRIAL/SPECIAL     4
INSTRUCTION            1
Name: Primary Flight Type, dtype: int64
```

In [132…
```
Most_Sev_Model['Flight Conduct Code'].value_counts()
```
Out[132…
```
PARACHUTE JUMPING          89
GENERAL OPERATING RULES    22
Name: Flight Conduct Code, dtype: int64
```

In [133…
```
Most_Sev_Model['PIC Flight Time Total Hrs'].quantile(0.75)
```
Out[133…
```
1350.0
```

For the severe incidents it can be observed that the most dangerous aircraft make is same as that for the not severe incidents. Unlike the not severe incidents, here the factors which might be the possible cause were not so clear.

Answer to Research Question 3

From all the above observations, the answer to the third research question is that the most dangerous aircraft model for not severe incidents was 172 and that for severe incidents was 182, both of which are CESSNA make. So, aircraft make could possibly be a factor that might have made those two models the most dangerous. The flight type could also be another factor, but it doesn't appear to be as clear as the aircraft make.

Research Question 4 - operator basis

Which was the most dangerous operator and what could be the possible factors from the given data due to which that operator was the most dangerous.

To answer this question, the operator would obviously be the main column and create a subset of data with all the relevant columns.

In [134…

```
operator_basis_data = av_data_copy[['Aircraft Make','Aircraft Model','Operator','Flight Conduct Code',
                                    'Flight Plan Filed Code','Aircraft Registration Nbr','PIC Certificate Type']]
```

Have a glance of the created subset.

In [135…

```
operator_basis_data
```

Out[135…

	Aircraft Make	Aircraft Model	Operator	Flight Conduct Code	Flight Plan Filed Code	Aircraft Registration Nbr	PIC Certificate Type
0	CESSNA	182	NaN	GENERAL OPERATING RULES	NONE	2691Q	PRIVATE PILOT
1	PIPER	PA18	NaN	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	4073E	STUDENT
3	CESSNA	310	NaN	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	2250F	COMMERCIAL PILOT FLIGHT INSTRUCTOR
4	CESSNA	172	NaN	GENERAL OPERATING RULES	NONE	738FD	COMMERCIAL PILOT
7	PIPER	PA31	NaN	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	27196	COMMERCIAL PILOT
...	...	...	...	...	...	...	...
99988	AVIAT	A1	NaN	GENERAL OPERATING RULES	NaN	143HP	PRIVATE PILOT
99992	CESSNA	172RG	NaN	GENERAL OPERATING RULES	NaN	9647B	COMMERCIAL PILOT FLIGHT INSTRUCTOR
99996	CESSNA	550	NaN	GENERAL OPERATING RULES	NaN	363CA	UNKNOWN/FOREIGN
99997	CESSNA	172RG	NaN	GENERAL OPERATING RULES	NaN	6545V	PRIVATE PILOT
99998	PIPER	PA28	NaN	GENERAL OPERATING RULES	NaN	8338W	STUDENT

77854 rows × 7 columns

Check missing values for the created subset.

In [136…

```
operator_basis_data.isnull().sum()
```

Out[136…

```
Aircraft Make                 1762
Aircraft Model                2198
Operator                     61362
Flight Conduct Code             44
Flight Plan Filed Code        9891
Aircraft Registration Nbr        0
PIC Certificate Type          1239
dtype: int64
```

From the missing values it can be seen that too much of data for the operator column is missing. So, unlike approach for previous two research questions, here the missing values are to be dropped and the analysis is to be done without segregating data into severe and not severe incidents.

Before dropping the columns, it is better to create a copy of the created subset.

In [137…

```
operator_basis_data_copy = operator_basis_data.copy()
```

Drop observations with missing values in the operator column. Code reference: https://www.kaggle.com/itssuru/eda-cristiano-ronaldo-s-career

In [138…

```
operator_basis_data_copy = operator_basis_data_copy.dropna(subset=['Operator'])
```

Check the data frame.

In [139…

```
operator_basis_data_copy
```

Out[139…

	Aircraft Make	Aircraft Model	Operator	Flight Conduct Code	Flight Plan Filed Code	Aircraft Registration Nbr	PIC Certificate Type
27	BELL	206	PETROLEUM HELICOPTERS	AIR TAXI/COMMUTER	INSTRUMENT FLIGHT RULES	9979K	COMMERCIAL PILOT
29	BELL	206	AIR LOGISTICS	AIR TAXI/COMMUTER	NONE	59516	COMMERCIAL PILOT
30	BEECH	18	MOUNTAIN AIR CARGO	AIR TAXI/COMMUTER	INSTRUMENT FLIGHT RULES	703M	COMMERCIAL PILOT
34	CESSNA	310	SKYCRAFT INC	AIR TAXI/COMMUTER	INSTRUMENT FLIGHT RULES	8240Q	COMMERCIAL PILOT
46	PIPER	PA34	SOLDOTNA AIR SERVICE	AIR TAXI/COMMUTER	VISUAL FLIGHT RULES	41960	COMMERCIAL PILOT

	Aircraft Make	Aircraft Model	Operator	Flight Conduct Code	Flight Plan Filed Code	Aircraft Registration Nbr	PIC Certificate Type
...	...	...	...	...	...	...	...
99945	CESSNA	172	WAYMAN AVIATION SERVICE INC	PILOT SCHOOLS	NaN	5352K	PRIVATE PILOT FLIGHT INSTRUCTOR
99960	BEECH	99	FREIGHT RUNNERS EXPRESS INC	AIR TAXI/COMMUTER	NaN	699CZ	PRIVATE PILOT FLIGHT INSTRUCTOR
99975	CESSNA	172	AMERICAN FLYERS CO INC	PILOT SCHOOLS	NaN	72AF	PRIVATE PILOT FLIGHT INSTRUCTOR
99978	TECNAM	P2006T	UPPER LIMIT AVIATION	GENERAL OPERATING RULES	NaN	245TA	PRIVATE PILOT
99982	ROBINSON	R44	CLOUD 9 HELICOPTERS LLC	GENERAL OPERATING RULES	NaN	4427H	PRIVATE PILOT

16492 rows × 7 columns

Find the operator with highest number of incidents.

In [140…
```
operator_basis_data_copy.Operator.value_counts().index[0]
```
Out[140…
```
'DELTA AIR LINES INC'
```

Create a further subset data frame exclusively for this operator.

In [141…
```
High_Inci_Operator = operator_basis_data_copy[operator_basis_data_copy.Operator ==
                                               operator_basis_data_copy.Operator.value_counts().index[0]]
```

Check the data for him exclusive to this operator.

In [142…
```
High_Inci_Operator
```
Out[142…

	Aircraft Make	Aircraft Model	Operator	Flight Conduct Code	Flight Plan Filed Code	Aircraft Registration Nbr	PIC Certificate Type
311	DOUGLAS	DC9	DELTA AIR LINES INC	AIR CARRIER/COMMERCIAL	INSTRUMENT FLIGHT RULES	1289L	AIRLINE TRANSPORT
3146	DOUGLAS	DC8	DELTA AIR LINES INC	AIR CARRIER/COMMERCIAL	INSTRUMENT FLIGHT RULES	809E	AIRLINE TRANSPORT
5791	DOUGLAS	DC9	DELTA AIR LINES INC	AIR CARRIER/COMMERCIAL	INSTRUMENT FLIGHT RULES	NR181	AIRLINE TRANSPORT
9545	LOCKHEED	L1011 385	DELTA AIR LINES INC	FOREIGN AIR CARRIER	INSTRUMENT FLIGHT RULES	714DA	AIRLINE TRANSPORT
9713	DOUGLAS	DC8	DELTA AIR LINES INC	AIR CARRIER/COMMERCIAL	INSTRUMENT FLIGHT RULES	823E	AIRLINE TRANSPORT
...	...	...	...	...	...	...	...
96532	DOUGLAS	DC9	DELTA AIR LINES INC	AIR CARRIER/COMMERCIAL	NaN	770NC	COMMERCIAL PILOT
97026	MCDONNELL DOUGLAS	MD90	DELTA AIR LINES INC	AIR CARRIER/COMMERCIAL	NaN	963DN	AIRLINE TRANSPORT
97817	MCDONNELL DOUGLAS	MD88	DELTA AIR LINES INC	AIR CARRIER/COMMERCIAL	NaN	912DE	COMMERCIAL PILOT FLIGHT INSTRUCTOR
98546	MCDONNELL DOUGLAS	MD88	DELTA AIR LINES INC	AIR CARRIER/COMMERCIAL	NaN	903DE	AIRLINE TRANSPORT
99588	AIRBUS	A320	DELTA AIR LINES INC	AIR CARRIER/COMMERCIAL	NaN	332NW	AIRLINE TRANSPORT

401 rows × 7 columns

Explore various columns of this data frame and note the observations.

In [143…
```
High_Inci_Operator['Aircraft Model'].value_counts()
```
Out[143…
```
727          89
MD88         81
757          52
737          48
L1011 385    48
767          24
DC9          21
MD90         14
DC8           6
A320          5
MD11          4
747           2
DC10          1
```

```
1329          1
TB10          1
777           1
A330          1
Name: Aircraft Model, dtype: int64
```

In [144…

```
High_Inci_Operator['Aircraft Make'].value_counts()
```

Out[144…

```
BOEING                 216
MCDONNELL DOUGLAS      100
LOCKHEED                49
DOUGLAS                 27
AIRBUS                   6
SOCATA                   1
Name: Aircraft Make, dtype: int64
```

In [145…

```
High_Inci_Operator['Flight Conduct Code'].value_counts()
```

Out[145…

```
AIR CARRIER/COMMERCIAL     397
FOREIGN AIR CARRIER          2
GENERAL OPERATING RULES      2
Name: Flight Conduct Code, dtype: int64
```

In [146…

```
High_Inci_Operator['Flight Plan Filed Code'].value_counts()
```

Out[146…

```
INSTRUMENT FLIGHT RULES    351
UNKNOWN                     13
VISUAL FLIGHT RULES          2
NONE                         1
Name: Flight Plan Filed Code, dtype: int64
```

In [147…

```
High_Inci_Operator['PIC Certificate Type'].value_counts()
```

Out[147…

```
AIRLINE TRANSPORT                             354
AIRLINE TRANSPORT PILOT FLIGHT INSTRUCTOR      22
COMMERCIAL PILOT                                8
PRIVATE PILOT                                   1
COMMERCIAL PILOT FLIGHT INSTRUCTOR              1
Name: PIC Certificate Type, dtype: int64
```

In [148…

```
High_Inci_Operator['Aircraft Registration Nbr'].value_counts()
```

Out[148…

```
953DL     3
982DL     3
831L      3
735D      3
543DA     3
         ..
964DL     1
754DL     1
320DL     1
809E      1
903DE     1
Name: Aircraft Registration Nbr, Length: 318, dtype: int64
```

Answer to Research Question 4

From all the observations, the answer to the fourth research question is that the most dangerous operator it was DELTA AIR LINES INC. One of the possible factors due to which this was the most dangerous operator is the aircraft make that is most possessed by the operator. Whether or not the operating procedures of the operator is another possible factor, is inconclusive.

Research Question 5 - flight type basis

Which was the most dangerous flight type and what could be the possible factors from the given data due to which that flight type was the most dangerous.

To answer this question, the primary flight type would obviously be the main column and create a subset of data with all the relevant columns.

In [149…

```
flighttype_basis_data = av_data_copy[['Primary Flight Type','Flight Conduct Code','Flight Plan Filed Code',
                                     'Aircraft Model','PIC Certificate Type','PIC Flight Time Total Hrs']]
```

Have a glance of the created subset.

In [150…

```
flighttype_basis_data
```

Out[150…

	Primary Flight Type	Flight Conduct Code	Flight Plan Filed Code	Aircraft Model	PIC Certificate Type	PIC Flight Time Total Hrs
0	PERSONAL	GENERAL OPERATING RULES	NONE	182	PRIVATE PILOT	245.0
1	PERSONAL	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	PA18	STUDENT	200.0
3	PERSONAL	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	310	COMMERCIAL PILOT FLIGHT INSTRUCTOR	2000.0
4	PERSONAL	GENERAL OPERATING RULES	NONE	172	COMMERCIAL PILOT	300.0
7	OTHER	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	PA31	COMMERCIAL PILOT	2700.0

	Primary Flight Type	Flight Conduct Code	Flight Plan Filed Code	Aircraft Model	PIC Certificate Type	PIC Flight Time Total Hrs
...	...	...	...	...	...	...
99988	NaN	GENERAL OPERATING RULES	NaN	A1	PRIVATE PILOT	935.0
99992	NaN	GENERAL OPERATING RULES	NaN	172RG	COMMERCIAL PILOT FLIGHT INSTRUCTOR	2200.0
99996	NaN	GENERAL OPERATING RULES	NaN	550	UNKNOWN/FOREIGN	5500.0
99997	NaN	GENERAL OPERATING RULES	NaN	172RG	PRIVATE PILOT	267.0
99998	NaN	GENERAL OPERATING RULES	NaN	PA28	STUDENT	18.0

77854 rows × 6 columns

Check missing values for the created subset.

In [151…

```
flighttype_basis_data.isnull().sum()
```

Out[151…

```
Primary Flight Type          8182
Flight Conduct Code            44
Flight Plan Filed Code       9891
Aircraft Model               2198
PIC Certificate Type         1239
PIC Flight Time Total Hrs       0
dtype: int64
```

The situation again resembles to that of analysis to the fourth research question. So, repeat the whole process that was done as part of analysis for the fourth research question and note the observations.

In [152…

```
flighttype_basis_data_copy = flighttype_basis_data.dropna(subset=['Primary Flight Type'])
```

In [153…

```
flighttype_basis_data_copy
```

Out[153…

	Primary Flight Type	Flight Conduct Code	Flight Plan Filed Code	Aircraft Model	PIC Certificate Type	PIC Flight Time Total Hrs
0	PERSONAL	GENERAL OPERATING RULES	NONE	182	PRIVATE PILOT	245.0
1	PERSONAL	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	PA18	STUDENT	200.0
3	PERSONAL	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	310	COMMERCIAL PILOT FLIGHT INSTRUCTOR	2000.0
4	PERSONAL	GENERAL OPERATING RULES	NONE	172	COMMERCIAL PILOT	300.0
7	OTHER	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	PA31	COMMERCIAL PILOT	2700.0
...	...	...	...	...	...	...
90254	SCHEDULED AIR CARRIER	AIR CARRIER/COMMERCIAL	INSTRUMENT FLIGHT RULES	737	NaN	0.0
90272	EXECUTIVE	GENERAL OPERATING RULES	UNKNOWN	1125	NaN	0.0
90284	PERSONAL	GENERAL OPERATING RULES	UNKNOWN	36	PRIVATE PILOT	1000.0
90289	PERSONAL	GENERAL OPERATING RULES	NONE	TAIFUN17E	PRIVATE PILOT	300.0
90291	PERSONAL	GENERAL OPERATING RULES	UNKNOWN	TR182	COMMERCIAL PILOT	3000.0

69672 rows × 6 columns

In [154…

```
flighttype_basis_data_copy['Primary Flight Type'].value_counts().index[0]
```

Out[154…

```
'PERSONAL'
```

In [155…

```
High_Inci_Flighttype = flighttype_basis_data_copy[flighttype_basis_data_copy['Primary Flight Type'] ==
                                                   flighttype_basis_data_copy['Primary Flight Type'].value_counts().index[0]]
```

In [156…

```
High_Inci_Flighttype
```

Out[156…

	Primary Flight Type	Flight Conduct Code	Flight Plan Filed Code	Aircraft Model	PIC Certificate Type	PIC Flight Time Total Hrs
0	PERSONAL	GENERAL OPERATING RULES	NONE	182	PRIVATE PILOT	245.0
1	PERSONAL	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	PA18	STUDENT	200.0
3	PERSONAL	GENERAL OPERATING RULES	VISUAL FLIGHT RULES	310	COMMERCIAL PILOT FLIGHT INSTRUCTOR	2000.0
4	PERSONAL	GENERAL OPERATING RULES	NONE	172	COMMERCIAL PILOT	300.0
8	PERSONAL	GENERAL OPERATING RULES	NONE	150	PRIVATE PILOT	450.0
...	...	...	...	...	...	...
90244	PERSONAL	GENERAL OPERATING RULES	UNKNOWN	NaN	PILOT NOT CERTIFICATED	0.0
90249	PERSONAL	GENERAL OPERATING RULES	UNKNOWN	CHALLENGER	PRIVATE PILOT	1200.0
90284	PERSONAL	GENERAL OPERATING RULES	UNKNOWN	36	PRIVATE PILOT	1000.0
90289	PERSONAL	GENERAL OPERATING RULES	NONE	TAIFUN17E	PRIVATE PILOT	300.0
90291	PERSONAL	GENERAL OPERATING RULES	UNKNOWN	TR182	COMMERCIAL PILOT	3000.0

36115 rows × 6 columns

In [157…

```
High_Inci_Flighttype['Primary Flight Type'].value_counts()
```

Out[157…

```
PERSONAL    36115
Name: Primary Flight Type, dtype: int64
```

In [158…

```
High_Inci_Flighttype['Flight Conduct Code'].value_counts()
```

Out[158…

```
GENERAL OPERATING RULES    36044
PILOT SCHOOLS                 23
ULTRALIGHT VEHICLES           21
AIR TAXI/COMMUTER             10
PARACHUTE JUMPING              8
AIR CARRIER/COMMERCIAL         5
AGRICULTURAL                   2
Name: Flight Conduct Code, dtype: int64
```

In [159…

```
High_Inci_Flighttype['Flight Plan Filed Code'].value_counts()
```

Out[159…

```
NONE                           19843
UNKNOWN                         7420
VISUAL FLIGHT RULES             4529
INSTRUMENT FLIGHT RULES         2752
SPECIAL VISUAL FLIGHT RULES       19
VISUAL FLIGHT FOLLOWING           10
DEFENSE VISUAL FLIGHT RULES        9
MILITARY CONTROL                   9
AIR TAXI FLIGHT FOLLOWING          7
Name: Flight Plan Filed Code, dtype: int64
```

In [160…

```
High_Inci_Flighttype['Aircraft Model'].value_counts()
```

Out[160…

```
172         2349
PA28        2297
35          1316
182         1293
150         1090
            ... 
69A            1
N65            1
CH47           1
1101           1
VENTUS B       1
Name: Aircraft Model, Length: 811, dtype: int64
```

In [161…

```
High_Inci_Flighttype['PIC Certificate Type'].value_counts()
```

Out[161…

```
PRIVATE PILOT                             21558
COMMERCIAL PILOT                           7891
AIRLINE TRANSPORT                          2150
COMMERCIAL PILOT FLIGHT INSTRUCTOR         1762
STUDENT                                    1198
AIRLINE TRANSPORT PILOT FLIGHT INSTRUCTOR   735
UNKNOWN/FOREIGN                             458
PILOT NOT CERTIFICATED                       64
```

```
PRIVATE PILOT FLIGHT INSTRUCTOR              20
RECREATIONAL PILOT                            9
SPECIAL PURPOSE                               7
Name: PIC Certificate Type, dtype: int64
```

In [162…
```
High_Inci_Flighttype['PIC Flight Time Total Hrs'].value_counts()
```

Out[162…
```
2000.0    639
3000.0    575
1000.0    570
500.0     551
1500.0    521
         ...
3685.0      1
6459.0      1
3337.0      1
2290.0      1
3401.0      1
Name: PIC Flight Time Total Hrs, Length: 3519, dtype: int64
```

Answer to Research Question 5

From all the observations above, the answer to the fifth research question is that the most dangerous flight type was PERSONAL. One of the possible factors due to which this was the most dangerous flight type is the experience of the pilot in command. The observations regarding pilot experience are similar to the analysis done for the third research question and the analysis for both third and fifth research questions seem to be supporting each other.

Research Question 6 - engine basis

Which was the most dangerous engine and what could be the possible factors from the given data due to which that engine was the most dangerous.

To answer this question, we choose the engine model as the main column and create a subset off data with all the relevant columns.

In [163…
```
engine_basis_data = av_data_copy[['Aircraft Engine Make','Aircraft Engine Model','Engine Group Code','Nbr of Engines']]
```

Have a glance of the created subset.

In [164…
```
engine_basis_data
```

Out[164…

	Aircraft Engine Make	Aircraft Engine Model	Engine Group Code	Nbr of Engines
0	NaN	NaN	NaN	1.0
1	NaN	NaN	NaN	1.0
3	NaN	NaN	NaN	2.0
4	NaN	NaN	NaN	1.0
7	NaN	NaN	NaN	2.0
...	...	...	...	...
99988	LYCOMI	0-320 SERIES	NaN	NaN
99992	LYCOMI	O&VO-360 SER	360	1.0
99996	P&W CA	PW530A	NaN	2.0
99997	LYCOMI	O&VO-360 SER	NaN	1.0
99998	LYCOMI	O&VO-360 SER	NaN	NaN

77854 rows × 4 columns

Check missing values for the created subset.

In [165…
```
engine_basis_data.isnull().sum()
```

Out[165…
```
Aircraft Engine Make     48179
Aircraft Engine Model    48173
Engine Group Code        53128
Nbr of Engines            4703
dtype: int64
```

The situation again resembles to that of analysis to the fourth and fifth research question. So, repeat the whole process that was done as part of analysis for the fourth and fifth research question and note the observations.

In [166…
```
engine_basis_data_copy = engine_basis_data.dropna(subset=['Aircraft Engine Model'])
```

In [167…
```
engine_basis_data_copy
```

Out[167…

	Aircraft Engine Make	Aircraft Engine Model	Engine Group Code	Nbr of Engines
17	CONT	IO470E	O470	1.0
20	CONT	O200A	O200	1.0
27	ALLSN	250C20B	250C	1.0
52	LYC	O540E4B5	O540	1.0
56	LYC	O360A2A	O360	1.0

	Aircraft Engine Make	Aircraft Engine Model	Engine Group Code	Nbr of Engines
...	...	...	...	...
99988	LYCOMI	0-320 SERIES	NaN	NaN
99992	LYCOMI	O&VO-360 SER	360	1.0
99996	P&W CA	PW530A	NaN	2.0
99997	LYCOMI	O&VO-360 SER	NaN	1.0
99998	LYCOMI	O&VO-360 SER	NaN	NaN

29681 rows × 4 columns

In [168…

```
engine_basis_data_copy['Aircraft Engine Model'].value_counts().index[0]
```

Out[168…

```
'O235L2C'
```

In [169…

```
High_Inci_Engine = engine_basis_data_copy[engine_basis_data_copy['Aircraft Engine Model'] ==
                                          engine_basis_data_copy['Aircraft Engine Model'].value_counts().index[0]]
```

In [170…

```
High_Inci_Engine
```

Out[170…

	Aircraft Engine Make	Aircraft Engine Model	Engine Group Code	Nbr of Engines
3722	LYC	O235L2C	O235	1.0
3730	LYC	O235L2C	O235	1.0
5966	LYC	O235L2C	O235	1.0
6134	LYC	O235L2C	O235	1.0
6842	LYC	O235L2C	O235	1.0
...	...	...	...	...
89493	LYC	O235L2C	O235	1.0
89960	LYC	O235L2C	O235	1.0
90006	LYC	O235L2C	O235	1.0
90591	LYC	O235L2C	O235	1.0
91882	LYC	O235L2C	O235	1.0

961 rows × 4 columns

In [171…

```
High_Inci_Engine['Aircraft Engine Make'].value_counts()
```

Out[171…

```
LYC    961
Name: Aircraft Engine Make, dtype: int64
```

In [172…

```
High_Inci_Engine['Engine Group Code'].value_counts()
```

Out[172…

```
O235    961
Name: Engine Group Code, dtype: int64
```

In [173…

```
High_Inci_Engine['Nbr of Engines'].value_counts()
```

Out[173…

```
1.0    959
Name: Nbr of Engines, dtype: int64
```

Answer to Research Question 6

From all the observations above the answer to the sixth research question is that the most dangerous engine model was O235L2C, which is of LYC make. One of the possible factors due to which this was the most dangerous engine is the make of the engine.

All the Research questions have been answered through the analysis of the data.