SanOperation

April 27, 2019

```
In [1]: import seaborn as sns
        import csv
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import zipfile
        from pathlib import Path
        from datetime import datetime
```

1 San Diego International Airport (SAN) Performance Analysis

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2 Introduction

2.0.1 1. Data Source:

(1) The 2011 and 2018 San Diego Airport Operation Data comes from the Department of Transportation's public data. No confidential data are involved in this analysis.

(2) Aircrafts' performance data are downloaded from Beoing and Airbus's official website. (Click to see the link).
2. Objectives:

(3) Examine airports' operation data and analyze the trend; provide information about airport's performance

(4) **Critical Aircraft** analysis (critical aircraft: the most demanding aircraft type, or grouping of aircraft with similar characteristics, that make the regular use of the airport (regualr use: > 500 anual operations)).

(5) **Runway requirements**

(6) **Average Weekday Peak Month(AWPM)** Analysis for 2011 data. AWPM: one weekday representative of the month with peak operation counts

(7) **Forcasting** the growth

(8) **2018** Paerformance Analysis

(9) **Discussion**: on possible influence seen by passengers, FAA and the airport

2.0.2 Data Preparation

```
In [3]: san_old = pd.read_csv('2011_SAN_OAG.csv')
        san_new = pd.read_csv('2018_SAN_OAG.csv')

In [4]: san_old['dt'] = pd.to_datetime(san_old['Dep_Date'] + " " + san_old['Dep_Time'])

In [5]: san_old['at'] = pd.to_datetime(san_old['Arr_Date'] + " " + san_old['Arr_Time'])

In [6]: san_old_dept = san_old[san_old['Dep Airport Code'] =='SAN']
        san_old_arr = san_old[san_old['Arr Airport Code'] =='SAN']
        san_old_dept_monthday = pd.read_csv('./output/san_old_dept_monthday.csv').iloc[:,1:]
        day_counts = pd.read_csv('./output/day_counts.csv').iloc[:,1:]
        day_counts = pd.read_csv('./output/day_counts.csv').iloc[:,1:]

In [7]: rolling_18 = pd.read_csv('./output/rolling_18.csv').iloc[:,1:]

In [8]: san_18_actype = pd.read_csv('./output/san_18_actype.csv')

In [9]: aircraft_type_2011 = san_old['Specific Aircraft Name'].value_counts().to_frame()

In [10]: san_2011_actype = pd.read_csv('./output/aircraft_type_2011.csv')

In [11]: san_new_summ = pd.read_csv('./output/san_new_summ.csv').iloc[:,1:]

In [12]: awpm_17_summ = pd.read_csv('./output/awpm_17_summ.csv').iloc[:,1:]

In [13]: awpm_17_summ['total operation count'] = awpm_17_summ['dept count'] + awpm_17_summ['ar

In [14]: grouped_seats = san_old['Seats'].value_counts().to_frame().rename(columns = {'Seats':
         grouped_seats = grouped_seats.rename(columns = {'index': 'Seats Number'})
         grouped_seats = grouped_seats.sort_values('Count', ascending = False)

In [15]: by_seats_and_type = san_old[['Seats', 'Specific Aircraft Name']].groupby(['Seats', 'S

In [16]: by_seats_and_type = by_seats_and_type.rename(columns = {0: 'Counts'})

In [17]: san_new_by_seats = pd.read_csv('./output/san_new_by_seats.csv').iloc[:,1:]
```

2.1 Part I: 2011 Design Aircraft

Definition of **critical aircraft**: the most demanding aircraft type, or grouping of aircraft with similar characteristics, that make the regular use of the airport (regualr use: > 500 anual operations).

MOTIVATION: although it is reasonable to group the aircrafts by their total seats number, the aircraft producers (e.g. Boeing and Airbus) provide detailed data on aircraft characteristics based on aircraft type. The data source for the Rayload charts is also the motivation behind the grouping by aircraft type in order to determine deterministic aircraft type of airport planning.

2.1.1 1. Number of operations by aircraft type

```
In [18]: san_2011_actype
```

Out[18]:

	Aircraft Type	Count
0	Boeing 737-700 Passenger	41928
1	Boeing 737-300 Passenger	22095
2	Airbus A320	16758
3	Boeing 737-800 Passenger	8594
4	Boeing 737-800 (winglets) Passenger	7939
5	Airbus A319	7429
6	Embraer RJ140	7144
7	Embraer 120 Brasilia	6344
8	Canadair Regional Jet	5370
9	Boeing 757-200 Passenger	4930
10	Boeing (douglas) MD-80	4359
11	Boeing 757 (Passenger)	4331
12	Airbus A321	4297
13	Boeing 737-500 Passenger	3759
14	Canadair Regional Jet 700	3086
15	Boeing 737-900 Passenger	2936
16	Boeing 737-400 Passenger	2191
17	Boeing (douglas) MD-83	1638
18	Canadair Regional Jet 900	1338
19	Boeing 767-300 Passenger	1284
20	Embraer 190	1116
21	Boeing (douglas) MD-90	591
22	Airbus A318	486
23	Boeing 777 Passenger	424
24	Boeing 737-700 (winglets) Passenger	424
25	Airbus A318 /319 /320 /321	269
26	Boeing 757-300 Passenger	48
27	Boeing 767-200 Passenger	36
28	Embraer 170	16
29	Boeing 767-400 Passenger	2
30	Boeing 737-600 Passenger	2

2.1.2 2. Design aircraft

Approach I: grouping by aircraft type Answer: **Boeing 767-300 Passenger** (without grouping) and **Boeing 777 Passenger** (after grouping)

MOTIVATION: Runway length requirements, Airport Design Group, and other airport design requirements are determined by aircraft type. Therefore, grouping by aircraft type might produce meaningful data summary that can be meaninigful to the airport planning decision making.

```
In [19]: san_2011_actype['Percentage(%)'] = (san_2011_actype['Count']/len(san_old)) * 100
         san_2011_actype
```

Out[19]:

	Aircraft Type	Count	Percentage(%)
0	Boeing 737-700 Passenger	41928	26.015736

1	Boeing 737-300 Passenger	22095	13.709637
2	Airbus A320	16758	10.398104
3	Boeing 737-800 Passenger	8594	5.332456
4	Boeing 737-800 (winglets) Passenger	7939	4.926038
5	Airbus A319	7429	4.609590
6	Embraer RJ140	7144	4.432752
7	Embraer 120 Brasilia	6344	3.936363
8	Canadair Regional Jet	5370	3.332010
9	Boeing 757-200 Passenger	4930	3.058996
10	Boeing (douglas) MD-80	4359	2.704698
11	Boeing 757 (Passenger)	4331	2.687325
12	Airbus A321	4297	2.666228
13	Boeing 737-500 Passenger	3759	2.332407
14	Canadair Regional Jet 700	3086	1.914820
15	Boeing 737-900 Passenger	2936	1.821747
16	Boeing 737-400 Passenger	2191	1.359485
17	Boeing (douglas) MD-83	1638	1.016356
18	Canadair Regional Jet 900	1338	0.830210
19	Boeing 767-300 Passenger	1284	0.796704
20	Embraer 190	1116	0.692462
21	Boeing (douglas) MD-90	591	0.366707
22	Airbus A318	486	0.301556
23	Boeing 777 Passenger	424	0.263086
24	Boeing 737-700 (winglets) Passenger	424	0.263086
25	Airbus A318 /319 /320 /321	269	0.166911
26	Boeing 757-300 Passenger	48	0.029783
27	Boeing 767-200 Passenger	36	0.022337
28	Embraer 170	16	0.009928
29	Boeing 767-400 Passenger	2	0.001241
30	Boeing 737-600 Passenger	2	0.001241

(1) **Without Grouping**
According to the data summary in Q1 and refering to the aircraft characteristics data, among all the aircraft types that excede an anual operations of more than 500, **Boeing 767-300 Passenger** would be the design aircraft.

(2) **Grouping**
However, there are several variants of Boeing 767 in the group. Also, the grouping will take the aircraft with similar features together. **Boeing 777 passenger**, with 424 total operations each year, will be included in this group for the following reason:

(3) Boeing 777 is larger in size and has more demanding requirements for airport design.

(4) Boeing 777 is designed as the enlarged version of 767. They share many similarity. See the link
Although Boeing 777 alone does not achieve the 500 operations per year requirements, grouping Boeing 777 with 767 meet the 500 annual operations requirement by FAA. Therefore, after grouping, **Boeing 777** will be the desigh aircraft.

The following is total number of operations by **Boeing 767-300**:

```
In [20]: sum(san_2011_actype[san_2011_actype['Aircraft Type'] == 'Boeing 767-300 Passenger']['C
```

```
Out[20]: 1284
```

The following is total number of operations by **Boeing 777 and Boeing 767**:

```
In [21]: sum(san_2011_actype[(san_2011_actype['Aircraft Type'] >= 'Boeing 767')&(san_2011_actyp
```

```
Out[21]: 1746
```

```
In [22]: san_2011_actype[(san_2011_actype['Aircraft Type'] >= 'Boeing 767')&(san_2011_actype['A
```

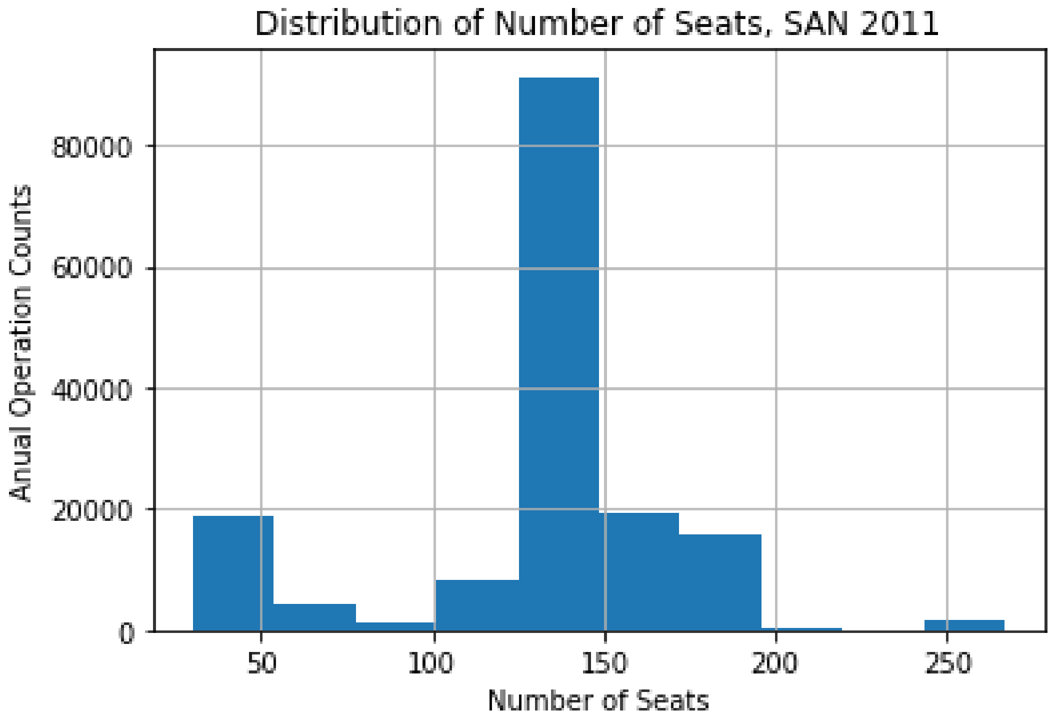
Out[22]:

	Aircraft Type	Count	Percentage(%)
19	Boeing 767-300 Passenger	1284	0.796704
23	Boeing 777 Passenger	424	0.263086
27	Boeing 767-200 Passenger	36	0.022337
29	Boeing 767-400 Passenger	2	0.001241

Approach II: grouping by seats number *MOTIVATION*: It is reasonable to draw a positive correlation between total number of seats on the aircraft and the airport planning requirements.

In the data visualization below, we can observe that there is a peak in the operation counts for aircraft with around 140 seats.

```
In [23]: san_old[['Seats']].hist()
         plt.xlabel('Number of Seats')
         plt.ylabel('Anual Operation Counts')
         plt.title('Distribution of Number of Seats, SAN 2011')
         plt.show()
```



According to the data visualization, there are group of aircrafts with more than 250 seats. Do they exceed the total operations of 500 per year? **Yes**

```
In [38]: by_seats_and_type1 = san_old.groupby(['Seats','Specific Aircraft Name']).agg(len)['Fl
         by_seats_and_type1 = by_seats_and_type1.rename(columns = {'Flight No': 'Counts'})
         by_seats_and_type1
```

Out[38]:

	Seats	Specific Aircraft Name	Counts
0	30	Embraer 120 Brasilia	6344
1	44	Embraer RJ140	7144
2	50	Canadair Regional Jet	5370
3	66	Canadair Regional Jet 700	2266
4	70	Canadair Regional Jet 700	820
5	70	Canadair Regional Jet 900	288
6	76	Canadair Regional Jet 900	1050
7	76	Embraer 170	16
8	93	Embraer 190	730
9	98	Embraer 190	370
10	99	Embraer 190	16
11	114	Airbus A318	478
12	114	Boeing 737-500 Passenger	152
13	119	Airbus A319	70
14	119	Boeing 737-600 Passenger	2
15	120	Airbus A318	8
16	120	Airbus A319	2477
17	122	Boeing 737-500 Passenger	3607
18	124	Airbus A319	406
19	124	Boeing 737-700 (winglets) Passenger	2
20	124	Boeing 737-700 Passenger	1250
21	126	Airbus A319	1011
22	126	Boeing 737-700 Passenger	234
23	129	Boeing 737-700 Passenger	34
24	132	Airbus A319	1819
25	134	Boeing 737-300 Passenger	12
26	136	Boeing 737-700 (winglets) Passenger	422
27	136	Boeing 737-700 Passenger	10036
28	137	Boeing 737-300 Passenger	22083
29	137	Boeing 737-700 Passenger	30374
..	...	...	...
47	150	Boeing (douglas) MD-90	591
48	157	Boeing 737-800 (winglets) Passenger	3212
49	157	Boeing 737-800 Passenger	4180
50	160	Boeing 737-800 (winglets) Passenger	2475
51	160	Boeing 737-800 Passenger	745
52	162	Airbus A320	98
53	162	Boeing 737-800 Passenger	22

```
54     166                Boeing 757-200 Passenger      22
55     168                Boeing 767-200 Passenger      36
56     172                Boeing 737-900 Passenger     636
57     173                Boeing 737-900 Passenger    2300
58     174                             Airbus A320       6
59     175                Boeing 757-200 Passenger       4
60     180  Boeing 737-800 (winglets) Passenger       3
61     182                Boeing 757-200 Passenger    4240
62     183                             Airbus A321    4297
63     183                  Boeing 757 (Passenger)    3532
64     183                Boeing 757-200 Passenger       2
65     183                Boeing 767-300 Passenger       1
66     188                  Boeing 757 (Passenger)     799
67     190                Boeing 757-200 Passenger     662
68     216                Boeing 757-300 Passenger      44
69     216                Boeing 767-300 Passenger     172
70     224                Boeing 757-300 Passenger       2
71     235                Boeing 767-400 Passenger       2
72     244                Boeing 767-300 Passenger       5
73     252                Boeing 757-300 Passenger       2
74     252                Boeing 767-300 Passenger     730
75     262                Boeing 767-300 Passenger     376
76     267                    Boeing 777 Passenger     424

[77 rows x 3 columns]
```

```
In [39]: sum(by_seats_and_type1[by_seats_and_type1['Seats']>250]['Counts'])
```

```
Out[39]: 1532
```

Therefore, the design aircraft if we group using number of seats is the aircraft that is most demanding among the group of aircrafts **with more than 250 seats**; there are **1532** operations at total.

```
In [40]: by_seats_and_type1[by_seats_and_type1['Seats']>250]
```

```
Out[40]:     Seats    Specific Aircraft Name  Counts
        73     252  Boeing 757-300 Passenger       2
        74     252  Boeing 767-300 Passenger     730
        75     262  Boeing 767-300 Passenger     376
        76     267      Boeing 777 Passenger     424
```

Among the group, **Boeing 777** is the most demanding aircraft, with a total anual operation of **424**.

Both approaches produce the same results. Therefore, we can use **Boeing 777** as our desigh aircraft.

2.1.3 3. Key Dimensions of Aircrafts

Four key dimensions: (1) Wingspan (2) Tail height (3) Fulselage length (4) Wheel span

According to the document AC 150/5000-17, if there are variants within the group, take the maximal of each dimensions for consideration.

Using **Boeing 777** as the design aircraft, we examine the variant in Boeing 777 that has the largest dimension requirement.

Max Wingspan: 64.80 m (212 ft 7 in) (from 777-300ER)
Tail height: 18.85 m (61 ft 10 in) (from 777-300ER)
Length: 73.86 m (242 ft 4 in) (from 777-300ER)
Wheel span: 10.97 m (36 ft 0 in)

ADG Group for Boeing 777(-300ER)
by **FAA**: **V**
by **ICAO**: **E**

2.1.4 4. Discussion

The results using the official definition of design aircraft would be the same as the result of using seats, as shwon in part 2. That is, the design aircraft determined by aircraft type or total seats number are the same.

2.2 II Runway requirements for 2011

2.2.1 5. Determine the runway length requirements

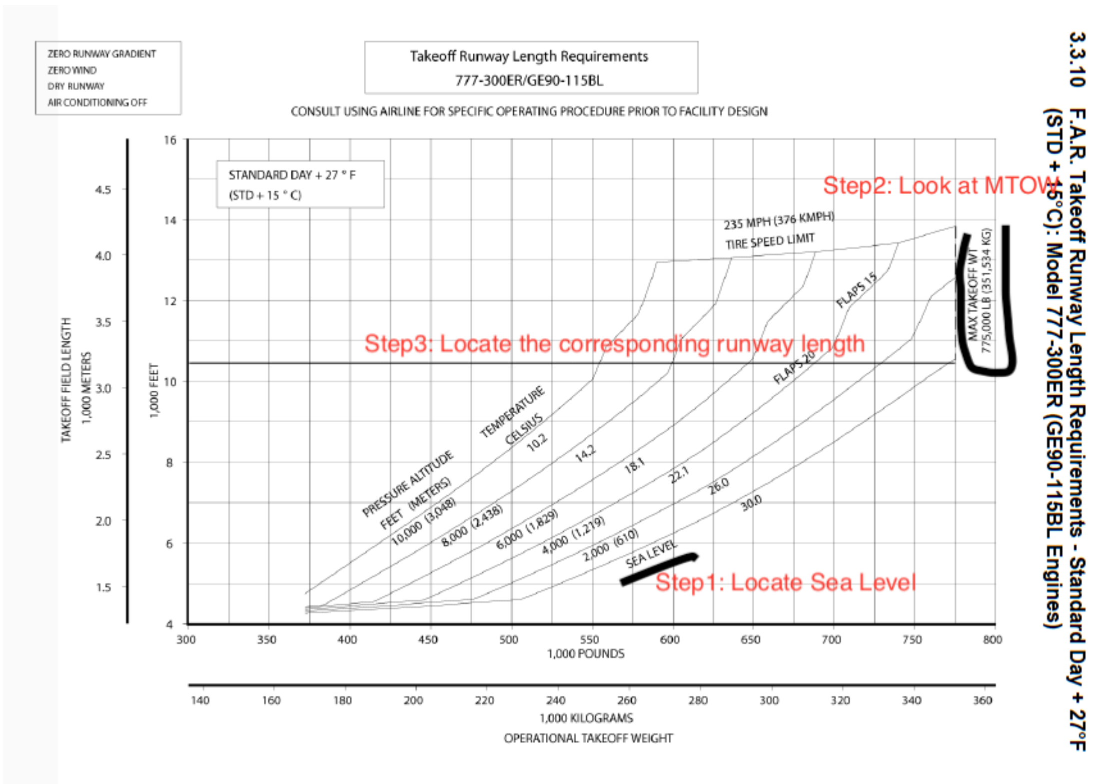
Use **Boeing 777-300ER** as the design aircraft.

Because **SAN** is roughly at sea level, when taking look at the Payload chart for **Runway Length Requirement** at Maximum Take Off Weight, the 777-300ER variant with the greatest runway length requirement is roughly 3200 m (10,500 ft).

```
In [41]: from IPython.display import Image
```

```
In [42]: Image('./output/runwaylength.png')
```

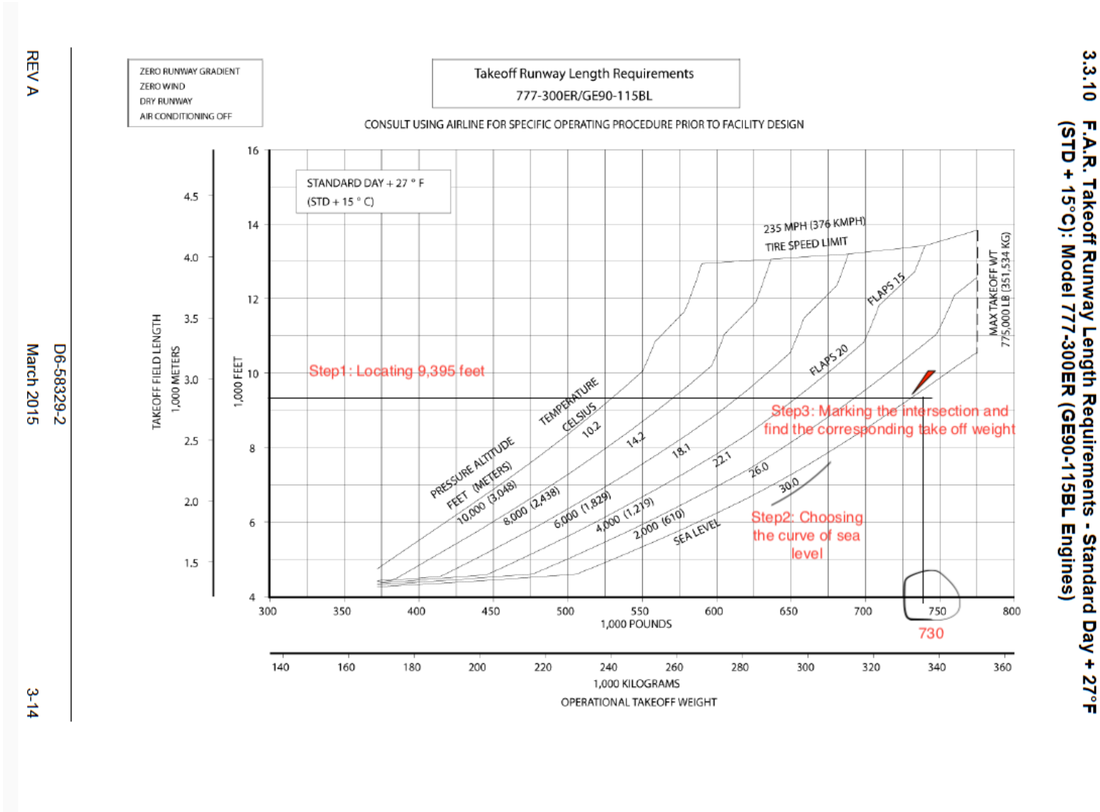
```
Out[42]:
```



2.2.2 6. Determining the Runway Length Requirement

In [43]:
```
Image('./output/q9.png')
```

Out[43]:



No, it is not sufficient for the **Boeing 777-300ER** to take off at its MTOW. The maximum take off weight that this runway can accomodate is **730,000 pounds**.

2.3 III Calculation for the average weekday peak month for 2011

2.3.1 7. 2011 SAN Operations Summary

```
In [44]: monthly_dept = san_old[san_old['Dep Airport Code'] =='SAN'].groupby(san_old['dt'].dt.r
```

```
In [45]: san_old_dept = san_old[san_old['Dep Airport Code'] =='SAN']
         san_old_arr = san_old[san_old['Arr Airport Code'] == 'SAN']
```

```
In [46]: san_old_dept_count = san_old_dept.groupby(san_old_dept['dt'].dt.month)['dt'].agg(len)
```

```
In [47]: san_old_dept_count = san_old_dept_count.to_frame().rename(columns = {'dt':'Departure C
```

```
In [48]: san_old_arr_count = san_old_arr.groupby(san_old_arr['at'].dt.month)['at'].agg(len)
```

```
In [49]: san_old_arr_count = san_old_arr_count.to_frame().rename(columns = {'at':'Arrival Coun
```

```
In [50]: san_old_count_summary = san_old_dept_count.merge(san_old_arr_count, left_index=True, r
```

```
In [51]: san_old_count_summary = san_old_count_summary.reset_index().rename(columns = {'dt':'Mo
```

```
In [52]: san_old_count_summary['Total Operation Count'] = san_old_count_summary['Departure Coun
```

```
In [53]: san_old_count_summary
```

```
Out[53]:     Month  Departure Count  Arrival Count  Total Operation Count
         0       1             6562           6559                  13121
         1       2             5983           5982                  11965
         2       3             6806           6806                  13612
         3       4             6512           6515                  13027
         4       5             6846           6841                  13687
         5       6             6964           6965                  13929
         6       7             7233           7234                  14467
         7       8             7164           7164                  14328
         8       9             6558           6562                  13120
         9      10             6752           6752                  13504
         10     11             6417           6419                  12836
         11     12             6783           6785                  13568
```

```
In [54]: hourly_summary = san_old_dept.groupby(san_old['dt'].dt.hour)['dt'].agg(len).to_frame()
         hourly_summary = hourly_summary.reset_index().rename(columns = {'dt': 'departure hour
```

```
In [55]: hourly_summary = hourly_summary.set_index('departure hour')
```

```
In [56]: arrival_summary = san_old_arr.groupby(san_old['at'].dt.hour)['at'].agg(len).to_frame()
         arrival_summary = arrival_summary.reset_index().rename(columns = {'at': 'arrival hour
         arrival_summary = arrival_summary.set_index('arrival hour')
```

2.3.2 8. Peak Month

```
In [57]: san_old_count_summary = pd.read_csv('./output/q8_summary.csv')
         san_old_count_summary['Operation Per Day'] = san_old_count_summary['Total Operation Co
         san_old_count_summary.iloc[:, 2:]
```

```
Out[57]:     Month  Departure Count  Arrival Count  Total Operation Count  \
         0       1             6562           6559                  13121
         1       2             5983           5982                  11965
         2       3             6806           6806                  13612
         3       4             6512           6515                  13027
         4       5             6846           6841                  13687
         5       6             6964           6965                  13929
         6       7             7233           7234                  14467
         7       8             7164           7164                  14328
         8       9             6558           6562                  13120
         9      10             6752           6752                  13504
         10     11             6417           6419                  12836
         11     12             6783           6785                  13568
```

```
    Departure Per Day  Arrivals Per Day  Operation Per Day
0          211.677419        211.580645         423.258065
1          213.678571        213.642857         427.321429
2          219.548387        219.548387         439.096774
3          217.066667        217.166667         434.233333
4          220.838710        220.677419         441.516129
5          232.133333        232.166667         464.300000
6          233.322581        233.354839         466.677419
7          231.096774        231.096774         462.193548
8          218.600000        218.733333         437.333333
9          217.806452        217.806452         435.612903
10         213.900000        213.966667         427.866667
11         218.806452        218.870968         437.677419
```

The month with the greatest number of daily operations is **July**

2.3.3 Q9 Opeartion Summary for the Peak Month: July

```
In [58]: july_daily_sum = pd.read_csv('./output/q9_daily_sum_july.csv')
```

```
In [59]: july_daily_sum
```

```
Out[59]:     day  daily arrival count  daily departure count  \
         0     1                  239                    239
         1     2                  212                    211
         2     3                  177                    178
         3     4                  220                    220
         4     5                  239                    239
         5     6                  240                    240
         6     7                  242                    242
         7     8                  239                    239
         8     9                  214                    213
         9    10                  233                    234
         10   11                  242                    242
         11   12                  239                    239
         12   13                  240                    240
         13   14                  242                    242
         14   15                  241                    241
         15   16                  216                    215
         16   17                  235                    235
         17   18                  243                    243
         18   19                  241                    241
         19   20                  242                    242
         20   21                  244                    244
         21   22                  241                    241
         22   23                  216                    215
         23   24                  235                    236
         24   25                  243                    243
         25   26                  241                    241
```

```
26   27                    242                     242
27   28                    244                     244
28   29                    241                     241
29   30                    216                     215
30   31                    235                     236

    total operation daily count
0                           478
1                           423
2                           355
3                           440
4                           478
5                           480
6                           484
7                           478
8                           427
9                           467
10                          484
11                          478
12                          480
13                          484
14                          482
15                          431
16                          470
17                          486
18                          482
19                          484
20                          488
21                          482
22                          431
23                          471
24                          486
25                          482
26                          484
27                          488
28                          482
29                          431
30                          471
```

2.3.4 10. Average of Daily Operation

In [60]:
```
july_days = san_old[san_old['dt'].dt.month == 7].loc[:,['dt']]
july_days['weekday'] = july_days['dt'].dt.weekday
july_days['day'] = july_days['dt'].dt.day
july_days = july_days.iloc[:, 1:]
july_day = july_days.groupby('day').agg(np.mean)
july_weekday = july_day.iloc[:, 0]
july_daily_sum['weekday'] = july_weekday.reset_index()['weekday']
```

(1) All days Average Daily Arrival: 233.3548387096774
Average Daily Departure: 233.32258064516128
Average Daily Total Operation: 466.6774193548387
(2) Weekdays Average Daily Arrival: 240.23809523809524
Average Daily Departure: 240.23809523809524
Average Daily Total Operation: 480.4761904761905

```
In [61]: july_daily_sum[july_daily_sum['weekday'] < 5]
```

```
Out[61]:     day  daily arrival count  daily departure count  \
        0     1                  239                    239
        3     4                  220                    220
        4     5                  239                    239
        5     6                  240                    240
        6     7                  242                    242
        7     8                  239                    239
        10   11                  242                    242
        11   12                  239                    239
        12   13                  240                    240
        13   14                  242                    242
        14   15                  241                    241
        17   18                  243                    243
        18   19                  241                    241
        19   20                  242                    242
        20   21                  244                    244
        21   22                  241                    241
        24   25                  243                    243
        25   26                  241                    241
        26   27                  242                    242
        27   28                  244                    244
        28   29                  241                    241

            total operation daily count  weekday
        0                           478        4
        3                           440        0
        4                           478        1
        5                           480        2
        6                           484        3
        7                           478        4
        10                          484        0
        11                          478        1
        12                          480        2
        13                          484        3
        14                          482        4
        17                          486        0
        18                          482        1
        19                          484        2
        20                          488        3
```

```
21                              482        4
24                              486        0
25                              482        1
26                              484        2
27                              488        3
28                              482        4
```

2.3.5 11. AWPM

The day would be **July 13** because it has daily arrival counts, departure counts and total oepration counts very close to the average of weekdays.

2.4 PART IV AWPM Analysis

2.4.1 12. Operations by Hour

Before diving into the answer, first take a look at the overall data summary for the whole year.

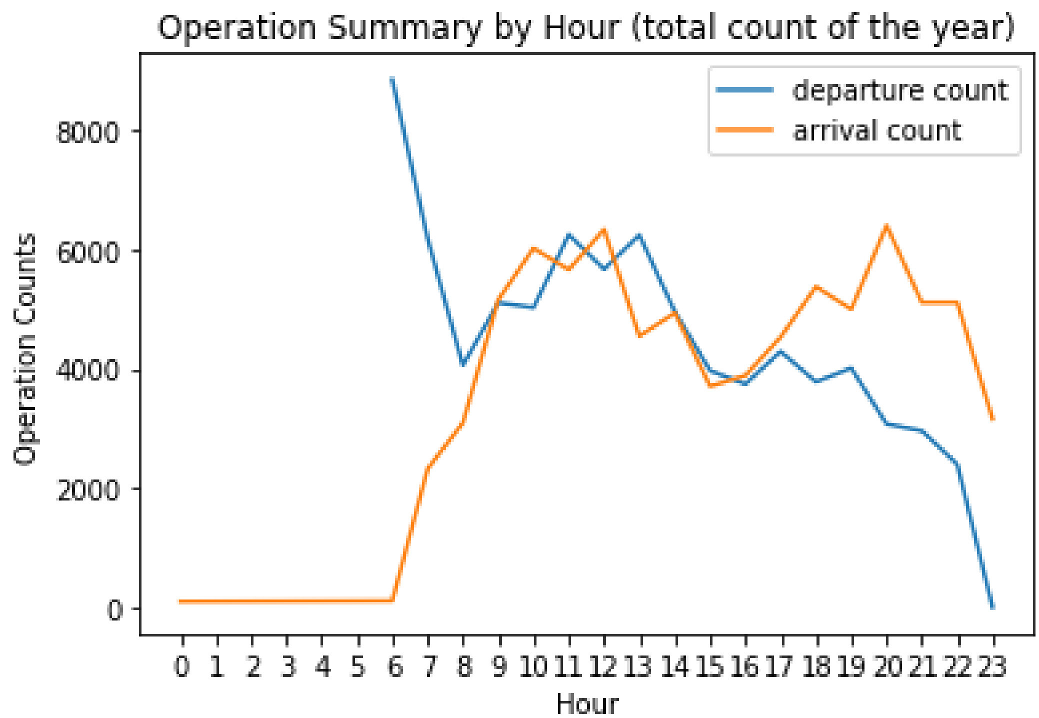
```
In [62]: by_hr = hourly_summary.join(arrival_summary, how = 'outer').reset_index().rename(colu
         by_hr['departure count'] = by_hr['departure count'].fillna(0.0).astype(int)
         by_hr['total operations count'] = by_hr['departure count'] + by_hr['arrival count']
         by_hr
```

Out[62]:

	Hour	departure count	arrival count	total operations count
0	0	0	100	100
1	6	8849	111	8960
2	7	6185	2323	8508
3	8	4058	3093	7151
4	9	5109	5158	10267
5	10	5027	6020	11047
6	11	6249	5661	11910
7	12	5669	6337	12006
8	13	6242	4547	10789
9	14	4960	4939	9899
10	15	3969	3706	7675
11	16	3744	3888	7632
12	17	4291	4533	8824
13	18	3781	5379	9160
14	19	4012	4999	9011
15	20	3074	6402	9476
16	21	2960	5114	8074
17	22	2397	5114	7511
18	23	4	3160	3164

```
In [63]: plt.plot(hourly_summary['departure count'])
         plt.plot(arrival_summary['arrival count'])
         plt.xticks([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20,
```

```
plt.legend()
plt.xlabel('Hour')
plt.ylabel('Operation Counts')
plt.title('Operation Summary by Hour (total count of the year)')
plt.show()
```



Key obeservation: Departure peaks at early morning(around 6 and 7) and the arrival seems to peak around noon and night (8 pm to 9 pm).

Now: focus on July 13

```
In [64]: july_13_daily_summ = pd.read_csv('./output/july_13_daily_summ.csv').iloc[:,1:]
```

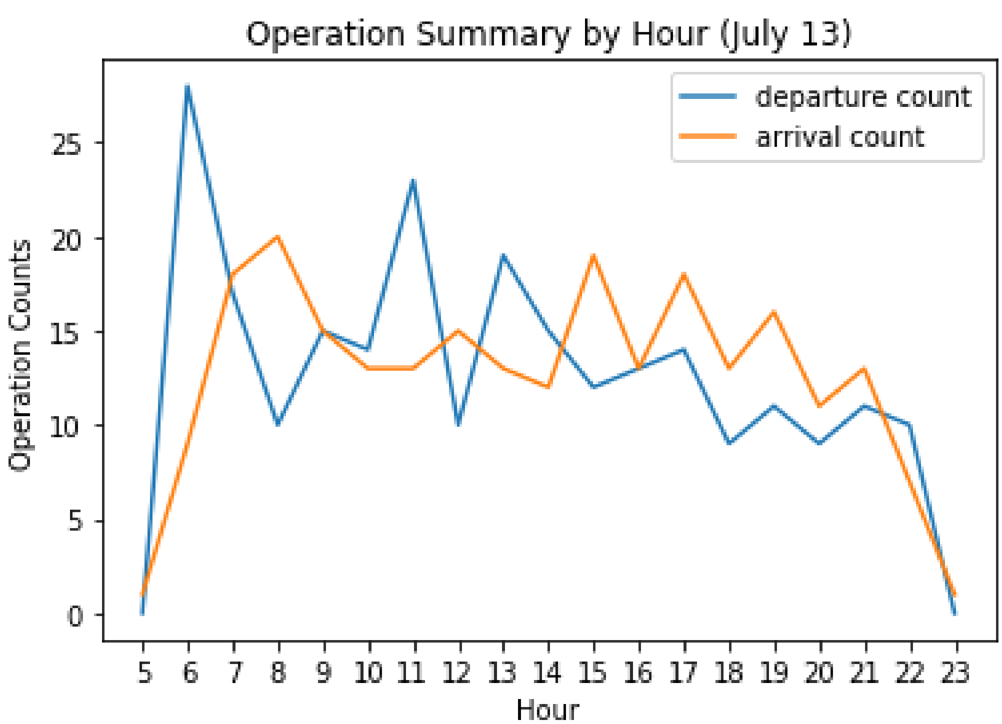
```
In [65]: july_13_daily_summ
```

Out[65]:

	hour	departure count	arrival count	opeartion count
0	5	0	1	1
1	6	28	9	37
2	7	17	18	35
3	8	10	20	30
4	9	15	15	30
5	10	14	13	27
6	11	23	13	36
7	12	10	15	25
8	13	19	13	32
9	14	15	12	27

```
10     15            12            19            31
11     16            13            13            26
12     17            14            18            32
13     18             9            13            22
14     19            11            16            27
15     20             9            11            20
16     21            11            13            24
17     22            10             7            17
18     23             0             1             1
```

```
In [66]: plt.plot(july_13_daily_summ['hour'], july_13_daily_summ['departure count'])
         plt.plot(july_13_daily_summ['hour'], july_13_daily_summ['arrival count'])
         plt.xticks([5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23])
         plt.legend()
         plt.xlabel('Hour')
         plt.ylabel('Operation Counts')
         plt.title('Operation Summary by Hour (July 13)')
         plt.show()
```



2.4.2 13. Peak Counts

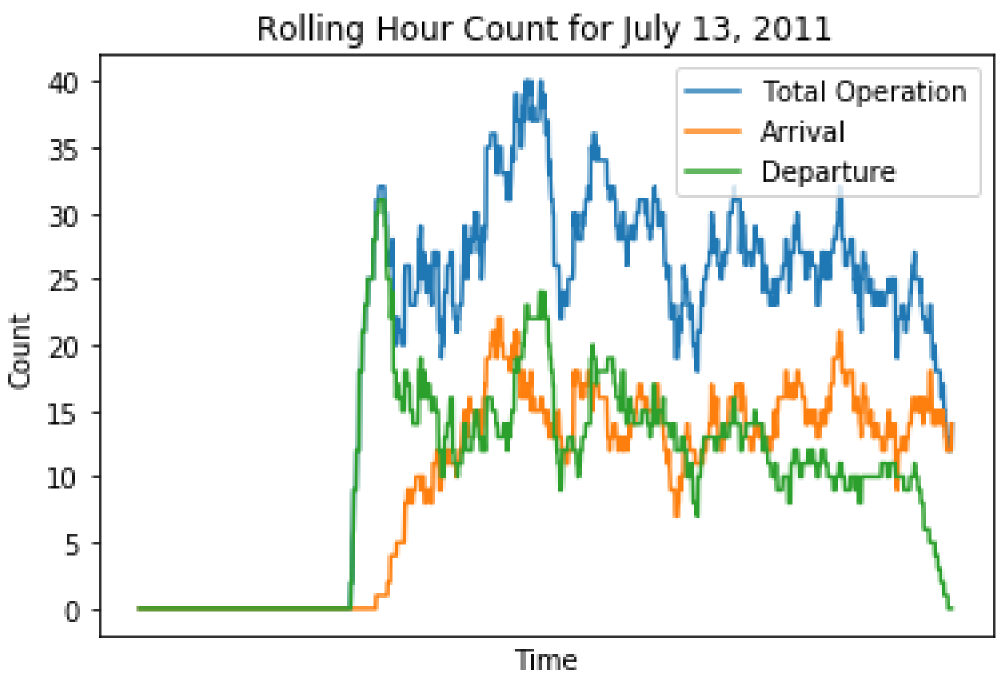
Maximum Departure Count: 28 happen in **6am**
Maximum Arrival Count: 10 happen in **8am**
Maximum Total Operation Count: 37 happen in **6am**

The trend and the peak for AWPM is consistent with the trend and peak for total count over the year of 2011.

2.4.3 14. Rolling hour

```
In [67]: import datetime

In [68]: datetime.timedelta(minutes=60)

Out[68]: datetime.timedelta(0, 3600)

In [69]: july_13_opt = san_old[san_old['dt'].dt.month == 7]
         july_13_opt = july_13_opt[july_13_opt['dt'].dt.day == 13]

In [70]: hour = []
         minute = []

In [71]: for i in range(24):
             for j in range(60):
                 hour = np.append(hour, i)
                 minute = np.append(minute, j)

In [72]: rolling = pd.DataFrame(hour).astype(int)
         rolling['min'] = minute.astype(int)
         rolling = rolling.rename(columns = {0:'h'})

In [73]: san_july13_dept = san_old_dept[san_old_dept['dt'].dt.month == 7]
         san_july13_dept = san_july13_dept[san_july13_dept['dt'].dt.day == 13]
         san_july13_arr = san_old_arr[san_old_arr['at'].dt.month == 7]
         san_july13_arr = san_july13_arr[san_july13_arr['at'].dt.day == 13]

In [74]: san_july13_dept['hour'] = san_july13_dept['dt'].dt.hour
         san_july13_dept['min'] = san_july13_dept['dt'].dt.minute

In [75]: san_july13_arr['hour'] = san_july13_arr['at'].dt.hour
         san_july13_arr['min'] = san_july13_arr['at'].dt.minute

In [76]: rolling = pd.read_csv('./output/rolling.csv').iloc[:,1:]

In [77]: dtobj = []
         for i in range(len(rolling)):
             dth = hour[i]
             dtm = minute[i]
             dtobject = datetime.timedelta(minutes = dtm, hours = dth)
             dtobj = np.append(dtobj, dtobject)

In [78]: rolling['time'] = dtobj
```

```
In [79]: plt.plot(rolling['time'], rolling['Operation Count'], label = 'Total Operation')
         plt.plot(rolling['time'], rolling['Arrival Count'], label = 'Arrival')
         plt.plot(rolling['time'], rolling['Departure Count'], label = 'Departure')
         plt.xticks([])
         plt.title('Rolling Hour Count for July 13, 2011')
         plt.ylabel('Count')
         plt.xlabel('Time')
         plt.legend()
         plt.show()
```



2.4.4 15. Peak Counts

Maximum Departure: 31 from **07:05** to **07:14**
Maximum Arrival: 22 from **10:35** to **10:41**
Maximum Total Opeartions: 40 from **11:25** to **11:26**, **11:29**, **11:34** and **11:51** to **11:52**

2.5 Part V Forecasting Growth in 2018

2.5.1 a)

```
In [80]: base_year_dept = len(san_old[san_old['Dep Airport Code'] == 'SAN'])
```

```
In [81]: base_year_arr = len(san_old[san_old['Arr Airport Code'] == 'SAN'])
```

In [82]:
```
year_list = np.arange(2011, 2019)
```

In [83]:
```
year_list
```

Out[83]:
```
array([2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018])
```

In [84]:
```
forcasting = pd.DataFrame(year_list).rename(columns = {0: 'Year'})
```

In [85]:
```
dept_for = []
arr_for = []

for i in range(len(forcasting)):
    multiplier = 1.028 ** i
    dept_for = np.append(dept_for, multiplier * base_year_dept)
    arr_for = np.append(arr_for, multiplier * base_year_arr)
```

In [86]:
```
forcasting['departure forecasting'] = dept_for
forcasting['arrival forecasting'] = arr_for
```

In [87]:
```
forcasting['total operation forecasting'] = forcasting['departure forecasting'] + fore
```

In [88]:
```
forcasting
```

Out[88]:
```
   Year  departure forecasting  arrival forecasting  \
0  2011           80580.000000         80584.000000
1  2012           82836.240000         82840.352000
2  2013           85155.654720         85159.881856
3  2014           87540.013052         87544.358548
4  2015           89991.133418         89995.600587
5  2016           92510.885153         92515.477404
6  2017           95101.189938         95105.910771
7  2018           97764.023256         97768.876273

   total operation forecasting
0                161164.000000
1                165676.592000
2                170315.536576
3                175084.371600
4                179986.734005
5                185026.362557
6                190207.100709
7                195532.899529
```

2.5.2 b)

In [89]:
```
san_2012_actype = san_2011_actype
san_2012_actype['Count'] = san_2011_actype['Count'] * 1.028
```

In [90]:
```
san_2013_actype = san_2012_actype
san_2013_actype['Count'] = san_2012_actype['Count'] * 1.028
```

In [91]:
```
san_2014_actype = san_2013_actype
san_2014_actype['Count'] = san_2014_actype['Count'] * 1.028
```

In [92]:
```
san_2015_actype = san_2014_actype
san_2015_actype['Count'] = san_2015_actype['Count'] * 1.028
```

In [93]:
```
san_2016_actype = san_2015_actype
san_2016_actype['Count'] = san_2016_actype['Count'] * 1.028
```

In [94]:
```
san_2017_actype = san_2016_actype
san_2017_actype['Count'] = san_2017_actype['Count'] * 1.028
```

In [95]:
```
san_2018_actype_f = san_2017_actype
san_2018_actype_f['Count'] = san_2018_actype_f['Count'] * 1.028
```

In [96]:
```
san_2018_actype_f
```

Out[96]:

	Aircraft Type	Count	Percentage(%)
0	Boeing 737-700 Passenger	50869.322004	26.015736
1	Boeing 737-300 Passenger	26806.851500	13.709637
2	Airbus A320	20331.713846	10.398104
3	Boeing 737-800 Passenger	10426.706576	5.332456
4	Boeing 737-800 (winglets) Passenger	9632.025076	4.926038
5	Airbus A319	9013.265435	4.609590
6	Embraer RJ140	8667.487989	4.432752
7	Embraer 120 Brasilia	7696.884631	3.936363
8	Canadair Regional Jet	6515.175042	3.332010
9	Boeing 757-200 Passenger	5981.343195	3.058996
10	Boeing (douglas) MD-80	5288.575048	2.704698
11	Boeing 757 (Passenger)	5254.603931	2.687325
12	Airbus A321	5213.353288	2.666228
13	Boeing 737-500 Passenger	4560.622529	2.332407
14	Canadair Regional Jet 700	3744.102454	1.914820
15	Boeing 737-900 Passenger	3562.114325	1.821747
16	Boeing 737-400 Passenger	2658.239947	1.359485
17	Boeing (douglas) MD-83	1987.310376	1.016356
18	Canadair Regional Jet 900	1623.334117	0.830210
19	Boeing 767-300 Passenger	1557.818390	0.796704
20	Embraer 190	1353.991685	0.692462
21	Boeing (douglas) MD-90	717.033231	0.366707
22	Airbus A318	589.641540	0.301556
23	Boeing 777 Passenger	514.419780	0.263086
24	Boeing 737-700 (winglets) Passenger	514.419780	0.263086
25	Airbus A318 /319 /320 /321	326.365379	0.166911
26	Boeing 757-300 Passenger	58.236201	0.029783
27	Boeing 767-200 Passenger	43.677151	0.022337
28	Embraer 170	19.412067	0.009928
29	Boeing 767-400 Passenger	2.426508	0.001241
30	Boeing 737-600 Passenger	2.426508	0.001241

Without grouping, according to the above forecasting, **Boeing 777 passenger** surpass the 500 annual operation floor and it should be considered the design aircraft (the same reason as for Q3). The design aircraft does not change according to the forecasting.

2.5.3 c)

In [98]:
```
awpm_2012 = july_13_daily_summ
awpm_2012['forecasted departure'] = awpm_2012['departure count'] * 1.028
awpm_2012['forecasted arrival'] = awpm_2012['arrival count'] * 1.028
awpm_2012['forecasted total'] = awpm_2012['opeartion count'] * 1.028
awpm_2012 = awpm_2012.iloc[:, 4:7]
```

In [99]:
```
awpm_2013 = awpm_2012
awpm_2013['forecasted departure'] = awpm_2013['forecasted departure'] * 1.028
awpm_2013['forecasted arrival'] = awpm_2013['forecasted arrival'] * 1.028
awpm_2013['forecasted total'] = awpm_2013['forecasted total'] * 1.028
```

In [100]:
```
awpm_2014 = awpm_2013
awpm_2014['forecasted departure'] = awpm_2014['forecasted departure'] * 1.028
awpm_2014['forecasted arrival'] = awpm_2014['forecasted arrival'] * 1.028
awpm_2014['forecasted total'] = awpm_2014['forecasted total'] * 1.028
```

In [101]:
```
awpm_2015 = awpm_2014
awpm_2015['forecasted departure'] = awpm_2015['forecasted departure'] * 1.028
awpm_2015['forecasted arrival'] = awpm_2015['forecasted arrival'] * 1.028
awpm_2015['forecasted total'] = awpm_2015['forecasted total'] * 1.028
```

In [102]:
```
awpm_2016 = awpm_2015
awpm_2016['forecasted departure'] = awpm_2016['forecasted departure'] * 1.028
awpm_2016['forecasted arrival'] = awpm_2016['forecasted arrival'] * 1.028
awpm_2016['forecasted total'] = awpm_2016['forecasted total'] * 1.028
```

In [103]:
```
awpm_2017 = awpm_2016
awpm_2017['forecasted departure'] = awpm_2017['forecasted departure'] * 1.028
awpm_2017['forecasted arrival'] = awpm_2017['forecasted arrival'] * 1.028
awpm_2017['forecasted total'] = awpm_2017['forecasted total'] * 1.028
```

In [104]:
```
awpm_2018_f = awpm_2017
awpm_2018_f['forecasted departure'] = awpm_2018_f['forecasted departure'] * 1.028
awpm_2018_f['forecasted arrival'] = awpm_2018_f['forecasted arrival'] * 1.028
awpm_2018_f['forecasted total'] = awpm_2018_f['forecasted total'] * 1.028
```

In [105]:
```
awpm_2012
```

Out[105]:

	forecasted departure	forecasted arrival	forecasted total
0	0.000000	1.213254	1.213254
1	33.971118	10.919288	44.890405
2	20.625321	21.838576	42.463897
3	12.132542	24.265084	36.397626

4	18.198813	18.198813	36.397626
5	16.985559	15.772305	32.757863
6	27.904847	15.772305	43.677151
7	12.132542	18.198813	30.331355
8	23.051830	15.772305	38.824134
9	18.198813	14.559050	32.757863
10	14.559050	23.051830	37.610880
11	15.772305	15.772305	31.544609
12	16.985559	21.838576	38.824134
13	10.919288	15.772305	26.691592
14	13.345796	19.412067	32.757863
15	10.919288	13.345796	24.265084
16	13.345796	15.772305	29.118101
17	12.132542	8.492779	20.625321
18	0.000000	1.213254	1.213254

```
In [106]: awpm_2013
```

Out[106]:

	forecasted departure	forecasted arrival	forecasted total
0	0.000000	1.213254	1.213254
1	33.971118	10.919288	44.890405
2	20.625321	21.838576	42.463897
3	12.132542	24.265084	36.397626
4	18.198813	18.198813	36.397626
5	16.985559	15.772305	32.757863
6	27.904847	15.772305	43.677151
7	12.132542	18.198813	30.331355
8	23.051830	15.772305	38.824134
9	18.198813	14.559050	32.757863
10	14.559050	23.051830	37.610880
11	15.772305	15.772305	31.544609
12	16.985559	21.838576	38.824134
13	10.919288	15.772305	26.691592
14	13.345796	19.412067	32.757863
15	10.919288	13.345796	24.265084
16	13.345796	15.772305	29.118101
17	12.132542	8.492779	20.625321
18	0.000000	1.213254	1.213254

```
In [107]: awpm_2014
```

Out[107]:

	forecasted departure	forecasted arrival	forecasted total
0	0.000000	1.213254	1.213254
1	33.971118	10.919288	44.890405
2	20.625321	21.838576	42.463897
3	12.132542	24.265084	36.397626
4	18.198813	18.198813	36.397626
5	16.985559	15.772305	32.757863
6	27.904847	15.772305	43.677151

7	12.132542	18.198813	30.331355
8	23.051830	15.772305	38.824134
9	18.198813	14.559050	32.757863
10	14.559050	23.051830	37.610880
11	15.772305	15.772305	31.544609
12	16.985559	21.838576	38.824134
13	10.919288	15.772305	26.691592
14	13.345796	19.412067	32.757863
15	10.919288	13.345796	24.265084
16	13.345796	15.772305	29.118101
17	12.132542	8.492779	20.625321
18	0.000000	1.213254	1.213254

In [108]: awpm_2015

Out[108]:

	forecasted departure	forecasted arrival	forecasted total
0	0.000000	1.213254	1.213254
1	33.971118	10.919288	44.890405
2	20.625321	21.838576	42.463897
3	12.132542	24.265084	36.397626
4	18.198813	18.198813	36.397626
5	16.985559	15.772305	32.757863
6	27.904847	15.772305	43.677151
7	12.132542	18.198813	30.331355
8	23.051830	15.772305	38.824134
9	18.198813	14.559050	32.757863
10	14.559050	23.051830	37.610880
11	15.772305	15.772305	31.544609
12	16.985559	21.838576	38.824134
13	10.919288	15.772305	26.691592
14	13.345796	19.412067	32.757863
15	10.919288	13.345796	24.265084
16	13.345796	15.772305	29.118101
17	12.132542	8.492779	20.625321
18	0.000000	1.213254	1.213254

In [109]: awpm_2016

Out[109]:

	forecasted departure	forecasted arrival	forecasted total
0	0.000000	1.213254	1.213254
1	33.971118	10.919288	44.890405
2	20.625321	21.838576	42.463897
3	12.132542	24.265084	36.397626
4	18.198813	18.198813	36.397626
5	16.985559	15.772305	32.757863
6	27.904847	15.772305	43.677151
7	12.132542	18.198813	30.331355
8	23.051830	15.772305	38.824134
9	18.198813	14.559050	32.757863

10	14.559050	23.051830	37.610880
11	15.772305	15.772305	31.544609
12	16.985559	21.838576	38.824134
13	10.919288	15.772305	26.691592
14	13.345796	19.412067	32.757863
15	10.919288	13.345796	24.265084
16	13.345796	15.772305	29.118101
17	12.132542	8.492779	20.625321
18	0.000000	1.213254	1.213254

In [110]:
```
awpm_2017
```

Out[110]:

	forecasted departure	forecasted arrival	forecasted total
0	0.000000	1.213254	1.213254
1	33.971118	10.919288	44.890405
2	20.625321	21.838576	42.463897
3	12.132542	24.265084	36.397626
4	18.198813	18.198813	36.397626
5	16.985559	15.772305	32.757863
6	27.904847	15.772305	43.677151
7	12.132542	18.198813	30.331355
8	23.051830	15.772305	38.824134
9	18.198813	14.559050	32.757863
10	14.559050	23.051830	37.610880
11	15.772305	15.772305	31.544609
12	16.985559	21.838576	38.824134
13	10.919288	15.772305	26.691592
14	13.345796	19.412067	32.757863
15	10.919288	13.345796	24.265084
16	13.345796	15.772305	29.118101
17	12.132542	8.492779	20.625321
18	0.000000	1.213254	1.213254

In [111]:
```
awpm_2018_f
```

Out[111]:

	forecasted departure	forecasted arrival	forecasted total
0	0.000000	1.213254	1.213254
1	33.971118	10.919288	44.890405
2	20.625321	21.838576	42.463897
3	12.132542	24.265084	36.397626
4	18.198813	18.198813	36.397626
5	16.985559	15.772305	32.757863
6	27.904847	15.772305	43.677151
7	12.132542	18.198813	30.331355
8	23.051830	15.772305	38.824134
9	18.198813	14.559050	32.757863
10	14.559050	23.051830	37.610880
11	15.772305	15.772305	31.544609
12	16.985559	21.838576	38.824134

```
13             10.919288           15.772305          26.691592
14             13.345796           19.412067          32.757863
15             10.919288           13.345796          24.265084
16             13.345796           15.772305          29.118101
17             12.132542            8.492779          20.625321
18              0.000000            1.213254           1.213254
```

2.5.4 d)

```
In [112]: base_year_max_dep = max(july_13_daily_summ['departure count'])
          base_year_max_arr = max(july_13_daily_summ['arrival count'])
          base_year_max_total = max(july_13_daily_summ['opeartion count'])
```

```
In [113]: dept_for = []
          arr_for = []

          for i in range(len(forcasting)):
              multiplier = 1.028 ** i
              dept_for = np.append(dept_for, multiplier * base_year_dept)
              arr_for = np.append(arr_for, multiplier * base_year_arr)
```

```
In [114]: forcasting_peak_hour = forcasting
```

```
In [115]: dept_hour_for = []
          arr_hour_for = []
          total_hour_for = []

          for i in np.arange(0,8):
              multiplier = 1.028 ** i
              dept_hour_for = np.append(dept_hour_for, multiplier * base_year_max_dep)
              arr_hour_for = np.append(arr_hour_for, multiplier * base_year_max_arr)
              total_hour_for = np.append(total_hour_for, multiplier * base_year_max_total)
```

```
In [116]: forcasting_peak_hour['peak departure forecast'] = dept_hour_for
          forcasting_peak_hour['peak arrival forecast'] = arr_hour_for
          forcasting_peak_hour['peak total operation forecast'] = total_hour_for
```

```
In [117]: forcasting_peak_hour = forcasting_peak_hour.iloc[:, [0, 4, 5, 6]]
```

```
In [118]: forcasting_peak_hour
```

```
Out[118]:    Year  peak departure forecast  peak arrival forecast  \
          0  2011                28.000000              20.000000
          1  2012                28.784000              20.560000
          2  2013                29.589952              21.135680
          3  2014                30.418471              21.727479
          4  2015                31.270188              22.335848
          5  2016                32.145753              22.961252
          6  2017                33.045834              23.604167
```

```
7  2018                 33.971118              24.265084

   peak total operation forecast
0                       37.000000
1                       38.036000
2                       39.101008
3                       40.195836
4                       41.321320
5                       42.478317
6                       43.667709
7                       44.890405
```

2.5.5 e)

```
In [119]: rolling_hour_forcasting = forcasting_peak_hour
```

```
In [120]: base_year_max_dep_rh = 31
          base_year_max_arr_rh = 22
          base_year_max_total_rh = 40
```

```
In [121]: dept_hour_for_rh = []
          arr_hour_for_rh = []
          total_hour_for_rh = []

          for i in np.arange(0,8):
              multiplier = 1.028 ** i
              dept_hour_for_rh = np.append(dept_hour_for_rh, multiplier * base_year_max_dep_rh)
              arr_hour_for_rh = np.append(arr_hour_for_rh, multiplier * base_year_max_arr_rh)
              total_hour_for_rh = np.append(total_hour_for_rh, multiplier * base_year_max_tota
```

```
In [122]: rolling_hour_forcasting['peak departure (rolling hour)'] = dept_hour_for_rh
```

```
/Users/hanzhong/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:1: SettingWithCopy
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """Entry point for launching an IPython kernel.
```

```
In [123]: rolling_hour_forcasting['peak arrival (rolling hour)'] = arr_hour_for_rh
```

```
/Users/hanzhong/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:1: SettingWithCopy
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """Entry point for launching an IPython kernel.
```

```
In [124]: rolling_hour_forcasting['peak total (rolling hour)'] = total_hour_for_rh

In [125]: rolling_hour_forcasting = rolling_hour_forcasting.iloc[:, [0, 4, 5, 6]]

In [126]: rolling_hour_forcasting
```

```
Out[126]:    Year  peak departure (rolling hour)  peak arrival (rolling hour)  \
          0  2011                      31.000000                    22.000000
          1  2012                      31.868000                    22.616000
          2  2013                      32.760304                    23.249248
          3  2014                      33.677593                    23.900227
          4  2015                      34.620565                    24.569433
          5  2016                      35.589941                    25.257377
          6  2017                      36.586459                    25.964584
          7  2018                      37.610880                    26.691592

             peak total (rolling hour)
          0                  40.000000
          1                  41.120000
          2                  42.271360
          3                  43.454958
          4                  44.671697
          5                  45.922504
          6                  47.208335
          7                  48.530168
```

2.6 Part VI Evaluate the actual 2018 SAN Schedule

2.6.1 17. 2018 SAN Schedule

```
In [127]: san_new['dt'] = pd.to_datetime(san_new['Dep_Date'] + " " + san_new['Dep_Time'])
          san_new['at'] = pd.to_datetime(san_new['Arr_Date'] + " " + san_new['Arr_Time'])

In [128]: len(san_new[san_new['Dep Airport Code'] == 'SAN'])

Out[128]: 100127

In [129]: len(san_new[san_new['Arr Airport Code'] == 'SAN'])

Out[129]: 100102
```

There are **100127** departures, **100102** arrivals and **200229** total operations in 2018

2.6.2 18. Design Aircraft (2018)

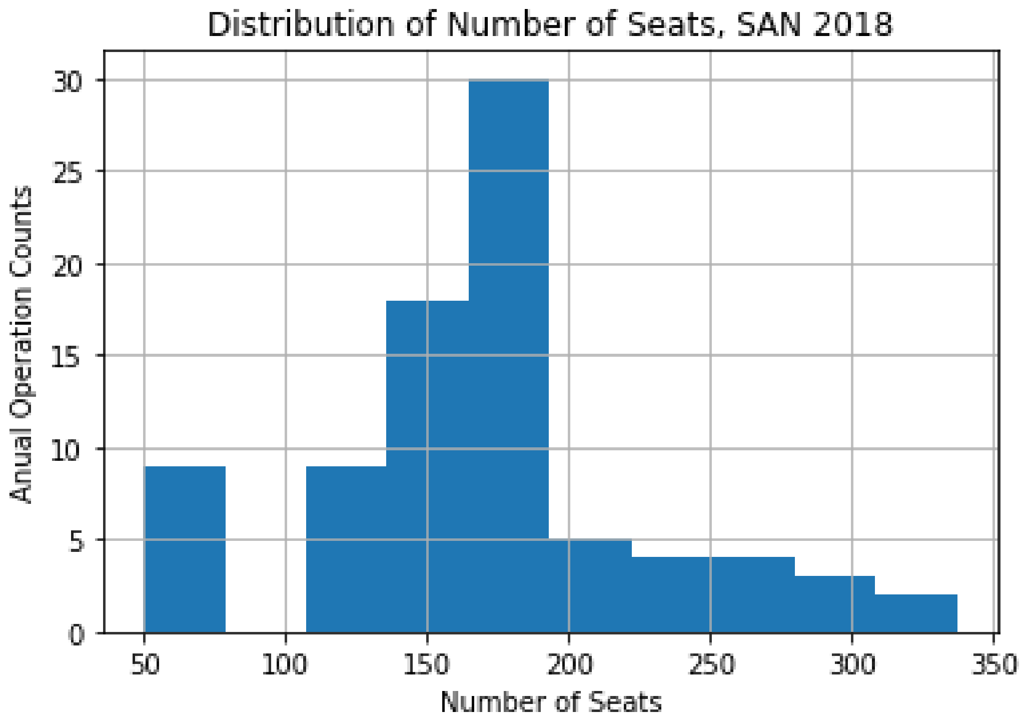
```
In [130]: san_18_actype = san_18_actype.rename(columns = {'Unnamed: 0': 'Aircraft Type'})
          san_18_actype
```

Out[130]:

	Aircraft Type	Count
0	Boeing 737-700 (winglets) Passenger	58576
1	Boeing 737-800 (winglets) Passenger	23467
2	Embraer 175	22294
3	Boeing 737-800 Passenger	15998
4	Airbus A321	12865
5	Airbus A320	12136
6	Boeing 737-900 Passenger	11470
7	Boeing 737-900 (winglets) Passenger	6768
8	Airbus A321 (Sharklets)	5768
9	Airbus A319	4904
10	Canadair Regional Jet 700	3224
11	Airbus A318/319/320/321	3066
12	Airbus A320 (Sharklets)	2381
13	Embraer 175 (Enhanced Winglets)	2305
14	Canadair Regional Jet 900	2053
15	Boeing 717-200	1577
16	Boeing 757-200 Passenger	1515
17	Canadair Regional Jet	1372
18	Boeing 737MAX 8 Passenger	1182
19	Boeing 757 (Passenger)	817
20	Boeing 737-700 Passenger	787
21	Boeing 787-8	730
22	Airbus A330-200	728
23	DHvilld-Bombardier DHC8 Dsh 8-400/8Q	710
24	Boeing 757-200 (winglets) Passenger	688
25	Boeing 757-300 Passenger	686
26	Airbus A340-300	490
27	Boeing 777 Passenger	432
28	Boeing 737MAX 9 Passenger	338
29	Boeing 747-400 (Passenger)	292
30	Boeing (douglas) MD-90	263
31	Boeing 767-300 Passenger	148
32	Canadair CRJ Series 705	119
33	Boeing 737-600 Passenger	34
34	Boeing (douglas) MD-80	24
35	Boeing 767-400 Passenger	14
36	Airbus A340-600	4
37	Boeing 777-300ER Passenger	4

In [131]:

```
san_new_by_seats[['Seats']].hist()
plt.xlabel('Number of Seats')
plt.ylabel('Anual Operation Counts')
plt.title('Distribution of Number of Seats, SAN 2018')
plt.show()
```



If we focus on the aircrafts with more than 270 seats:

```
In [132]: large_aircraft = san_new_by_seats[san_new_by_seats['Seats'] > 270]
          large_aircraft
```

Out[132]:

	Seats	Specific Aircraft Name	count
76	275	Boeing 747-400 (Passenger)	288
77	278	Airbus A330-200	728
78	279	Airbus A340-300	390
79	281	Airbus A340-600	4
80	296	Boeing 777-300ER Passenger	4
81	297	Boeing 777 Passenger	430
82	314	Airbus A340-300	100
83	337	Boeing 747-400 (Passenger)	4

Although only A330-200 achieves an annual operation number more than 500, grouping all the aircraft with more than 270 seats together, they achieve a total annual operation more than 500. **Motivation for grouping:** according to the ADG Group by Airbus and by Boeing, all the aircrafts with more than 270 seats belong to ADG Group **V** (by FAA) or **E** (by ICAO).

The design aircraft changes in 2018.

Take a closer look at the change, copared to 2011, the chagne is due to the Lufthansa's new commercial flight between **FRA** and **SAN**, which mostly use **Airbus A340-300 and A340-600**; Edelweiss's flight to **ZRH** using **Airbus A340-300**;and British Airways' use of **747-400** in the flight between **LHR** and **SAN**.

It is meaningful to ensure the opeartion requirements for the new design aircraft type. Lufthansa makes a total number of 394 operations,British Airways makes 724 operations and Edelweiss, 100, during 2018. Indeed, **FRA**, **LHR** and **ZRH** are the only three non-stop European destinations.

```
In [133]: len(san_new[san_new['Carrier Code'] == 'WK'])
```

```
Out[133]: 100
```

```
In [134]: len(san_new[san_new['Carrier Code'] == 'BA'])
```

```
Out[134]: 724
```

```
In [135]: len(san_new[san_new['Carrier Code'] == 'LH'])
```

```
Out[135]: 394
```

Looking at the dimensions for all the aircrafts in the group with 270 and more seats, **Boeing 747-400 has the maximal tail height (19.59 m / 64 ft 3 in) and wheel span (11 m / 36 ft 1 in), while Boeing 777-300ER has the greatest length (73.08 m / 239 ft 4 in) and wingspan (64.80 m / 212 ft 7 in).** However, **A340-600** has the maximal runway length requirement at the sea level (where SAN is located), maximal take off weight on a standard day.

Therefore, when tail height and wheel span are needed for design, **Boeing 747-400** should be the design aircraft.

When length and wingspan needed for design, **Boeing 777-300ER** should be considered the design aircraft.

When planning for runway, **Boeing 777-300ER and Boeing 747-400** should be the design aircraft (because they have similar runway length requirement at their MTOW)

Calculating New Runway Length Because **SAN** is roughly at sea level, when taking look at the Payload chart for **Runway Length Requirement** at Maximum Take Off Weight, the 777-300ER variant with the greatest runway length requirement is roughly 3200 m (10,500 ft). The 747-400 variant with the greatest runway length requirement at the Maximum Take Off Weight is also around 3200 m (10,500 ft).

Although we have to take into consideration of new design aircraft for runway length, the calculated runway length does not change. It reamins the **same**.

2.6.3 19. Performance Summary

```
In [136]: days = np.array([31, 28, 31, 30, 31, 30, 31, 31, 30, 31, 30, 31])
```

```
In [137]: san_new_summ['Average Daily Arrival Count'] = san_new_summ['Arrival Count']/days
```

```
In [138]: san_new_summ['Average Daily Departure Count'] = san_new_summ['Departure Count']/days
```

```
In [139]: san_new_summ['Average Daily Operation Count'] = san_new_summ['Total Operation Count'
```

```
In [140]: san_new_summ
```

Out[140]:

```
    Month  Arrival Count  Departure Count  Total Operation Count  \
0       1           7836             7836                  15672
1       2           7023             7023                  14046
2       3           8213             8213                  16426
3       4           8188             8192                  16380
4       5           8568             8568                  17136
5       6           8759             8761                  17520
6       7           9159             9159                  18318
7       8           9033             9035                  18068
8       9           8248             8251                  16499
9      10           8548             8545                  17093
10     11           8172             8171                  16343
11     12           8380             8348                  16728

    Average Daily Arrival Count  Average Daily Departure Count  \
0                    252.774194                     252.774194
1                    250.821429                     250.821429
2                    264.935484                     264.935484
3                    272.933333                     273.066667
4                    276.387097                     276.387097
5                    291.966667                     292.033333
6                    295.451613                     295.451613
7                    291.387097                     291.451613
8                    274.933333                     275.033333
9                    275.741935                     275.645161
10                   272.400000                     272.366667
11                   270.322581                     269.290323

    Average Daily Operation Count
0                      505.548387
1                      501.642857
2                      529.870968
3                      546.000000
4                      552.774194
5                      584.000000
6                      590.903226
7                      582.838710
8                      549.966667
9                      551.387097
10                     544.766667
11                     539.612903
```

Therefore, the **PEAK MONTH** is **JULY** for 2018.
Take a look at the July data.

In [141]:

```
san_17_dept = san_new[san_new['Dep Airport Code'] == 'SAN']
san_17_arr = san_new[san_new['Arr Airport Code'] == 'SAN']
```

In [142]:

```
san_17_dept_july = san_17_dept[san_17_dept['dt'].dt.month == 7]
```

```
san_17_arr_july = san_17_arr[san_17_arr['at'].dt.month == 7]
```

```
In [143]: san_17_dept_july['weekday'] = san_17_dept_july['dt'].dt.weekday
          san_17_arr_july['weekday'] = san_17_arr_july['at'].dt.weekday
```

```
/Users/hanzhong/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:1: SettingWithCopyW
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """Entry point for launching an IPython kernel.
/Users/hanzhong/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyW
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

Average number of arrivals, departures and total operations for weekdays in July, 2018

```
In [144]: san_17_dept_july[san_17_dept_july['weekday']<5]['dt'].dt.day.value_counts()
```

```
Out[144]: 20    308
          13    308
          30    307
          23    306
          16    306
          19    305
          12    305
          26    305
          9     305
          27    305
          11    301
          24    300
          10    300
          25    300
          18    300
          17    298
          31    298
          6     296
          5     291
          2     288
          3     265
          4     253
          Name: dt, dtype: int64
```

The **average weekday arrivals** is:

```
In [145]: np.mean(san_17_dept_july[san_17_dept_july['weekday']<5]['dt'].dt.day.value_counts())
```

```
Out[145]: 297.72727272727275
```

The **average weekday departures** is:

```
In [146]: np.mean(san_17_arr_july[san_17_arr_july['weekday']<5]['at'].dt.day.value_counts())
```

```
Out[146]: 297.6363636363636
```

Therefore, the **average daily total operation is:** 595

Because according to the data summary, **July 17, 2018** has similar daily number of arrivals, departures and total operation for average weekday counts, therefore, we choose **July 17, 2018** as the **average weekday**.

```
In [147]: len(san_17_dept_july[san_17_dept_july['dt'].dt.day == 17])
```

```
Out[147]: 298
```

```
In [148]: len(san_17_arr_july[san_17_arr_july['at'].dt.day == 17])
```

```
Out[148]: 299
```

Therefore, on **AWPM** (July 17), there are **298 departures, 299 arrivals, and 597 total operations**.

2.6.4 20. Hour Count for AWPM

```
In [149]: dept_awpm = san_17_dept_july[san_17_dept_july['dt'].dt.day == 17]
```

```
In [150]: arr_awpm = san_17_arr_july[san_17_arr_july['at'].dt.day == 17]
```

```
In [151]: dept_17_hour = dept_awpm['dt'].dt.hour.value_counts().to_frame().reset_index().rename
```

```
In [152]: arr_17_hour = arr_awpm['at'].dt.hour.value_counts().to_frame().reset_index().rename(
```

Maximum Arrivals Hour:

```
In [153]: awpm_17_summ[awpm_17_summ['arr count'] == max(awpm_17_summ['arr count'])]
```

```
Out[153]:     hour  dept count  arr count  total operation count
          11    22          15         25                     40
```

The **peak hour for arrivals on AWPM is 22** count: 25

Maximum Departure Hour:

```
In [154]: awpm_17_summ[awpm_17_summ['dept count'] == max(awpm_17_summ['dept count'])]
```

```
Out[154]:    hour  dept count  arr count  total operation count
          0     7          28         12                     40
```

The **peak hour for departures on AWPM is 7** count: 28

Maximum Total Operation Hour:

```
In [155]: awpm_17_summ[awpm_17_summ['total operation count'] == max(awpm_17_summ['total operati
```

```
Out[155]:    hour  dept count  arr count  total operation count
          8    10          17         24                     41
```

The **peak hour for total operation on AWPM is 10** count: 41

2.6.5 21. AWPM Analysis

```
In [156]: dtobj = []
          for i in range(len(rolling)):
              dth = hour[i]
              dtm = minute[i]
              dtobject = datetime.timedelta(minutes = dtm, hours = dth)
              dtobj = np.append(dtobj, dtobject)
```

```
In [157]: rolling_18['time'] = dtobj
```

```
In [158]: arr_awpm['xiaoshi'] = arr_awpm['at'].dt.hour
```

```
/Users/hanzhong/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:1: SettingWithCopyW
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """Entry point for launching an IPython kernel.
```

```
In [159]: arr_awpm['fenzhong'] = arr_awpm['at'].dt.minute
```

```
/Users/hanzhong/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:1: SettingWithCopyW
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """Entry point for launching an IPython kernel.
```

```
In [168]: dept_awpm['xiaoshi'] = dept_awpm['dt'].dt.hour
          dept_awpm['fenzhong'] = dept_awpm['dt'].dt.minute
```

```
/Users/hanzhong/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:1: SettingWithCopyW
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """Entry point for launching an IPython kernel.
/Users/hanzhong/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyW
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

```
In [170]: dept_c = []
          for i in range(len(rolling_18['h'])):
```

```
            dept_count = 0
            xiaoshi = rolling_18.iloc[i, 0]
            fenzhong = rolling_18.iloc[i, 1]
            for j in range(len(dept_awpm)):
                xs = dept_awpm.iloc[j, 13]
                fz = dept_awpm.iloc[j, 14]
                diff = 60 * (xiaoshi-xs) + (fenzhong - fz)
                if diff > 0:
                    if diff < 60:
                        dept_count = dept_count + 1
            dept_c = np.append(dept_c, dept_count)
```

```
In [171]: arr_c = []
          for i in range(len(rolling_18)):
              arr_count = 0
              xiaoshi = rolling_18.iloc[i, 0]
              fenzhong = rolling_18.iloc[i, 1]
              for j in range(len(arr_awpm)):
                  xs = arr_awpm.iloc[j, 13]
                  fz = arr_awpm.iloc[j, 14]
                  diff = 60 * (xiaoshi-xs) + (fenzhong - fz)
                  if diff > 0:
                      if diff < 60:
                          arr_count = arr_count + 1
              arr_c = np.append(arr_c, arr_count)
```

```
In [172]: rolling_18['departure count'] = dept_c.astype(int)
```

```
In [173]: rolling_18['arrival count'] = arr_c.astype(int)
```

```
In [174]: rolling_18['total operation'] = rolling_18['departure count'] + rolling_18['arrival c
```

The maximum departure rolling hour:

```
In [175]: rolling_18[rolling_18['departure count'] == max(rolling_18['departure count'])]
```

```
Out[175]:      h  min      time  departure count  arrival count  total operation
          433  7   13  07:13:00               36              7               43
          434  7   14  07:14:00               36              7               43
```

The maximum arrival rolling hour:

```
In [176]: rolling_18[rolling_18['arrival count'] == max(rolling_18['arrival count'])]
```

```
Out[176]:        h  min      time  departure count  arrival count  total operation
          1407  23   27  23:27:00                9             32               41
```

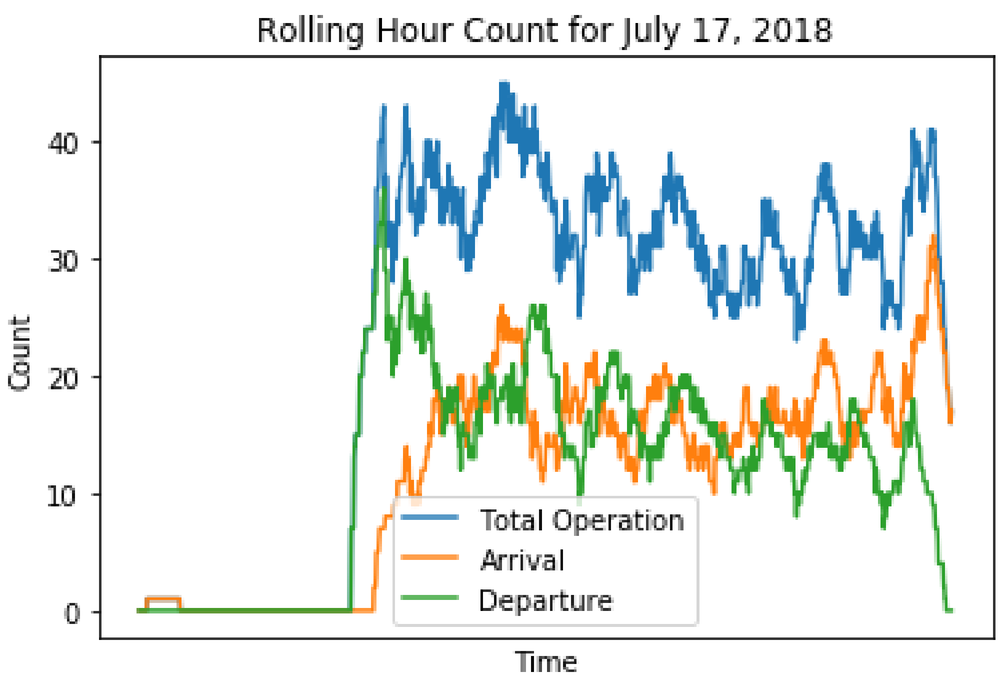
The maximum operation rolling hour:

```
In [177]: rolling_18[rolling_18['total operation'] == max(rolling_18['total operation'])]
```

Out[177]:

	h	min	time	departure count	arrival count	total operation
643	10	43	10:43:00	19	26	45
651	10	51	10:51:00	20	25	45

In [178]:
```
plt.plot(rolling_18['time'], rolling_18['total operation'], label = 'Total Operation
plt.plot(rolling_18['time'], rolling_18['arrival count'], label = 'Arrival')
plt.plot(rolling_18['time'], rolling_18['departure count'], label = 'Departure')
plt.xticks([])
plt.title('Rolling Hour Count for July 17, 2018')
plt.ylabel('Count')
plt.xlabel('Time')
plt.legend()
plt.show()
```



2.7 Part VII Discussion Questions

2.7.1 22. Operation Summary

a) Operations

In [180]:
```
forcasting
```

Out[180]:

	Year	departure forecasting	arrival forecasting	\
0	2011	80580.000000	80584.000000	

```
1  2012          82836.240000        82840.352000
2  2013          85155.654720        85159.881856
3  2014          87540.013052        87544.358548
4  2015          89991.133418        89995.600587
5  2016          92510.885153        92515.477404
6  2017          95101.189938        95105.910771
7  2018          97764.023256        97768.876273

   total operation forecasting  peak departure forecast  \
0                161164.000000                28.000000
1                165676.592000                28.784000
2                170315.536576                29.589952
3                175084.371600                30.418471
4                179986.734005                31.270188
5                185026.362557                32.145753
6                190207.100709                33.045834
7                195532.899529                33.971118

   peak arrival forecast  peak total operation forecast
0              20.000000                      37.000000
1              20.560000                      38.036000
2              21.135680                      39.101008
3              21.727479                      40.195836
4              22.335848                      41.321320
5              22.961252                      42.478317
6              23.604167                      43.667709
7              24.265084                      44.890405
```

There are **100127** departures, **100102** arrivals and **200229** total operations in 2018.
According to the forecasting, there are **97764** departures and **97764** arrivals, which is very close to the true counts of operations.

b) Design Aircraft (1)The design aircraft by forecasting is Boeing 777. In fact, the design aircraft is Boeing 777 and Boeing 747.
(2)The forecasting does not consider the introduction of the new aircraft type.
(3)However, the forecasting is still effective because it still consider Boeing 777 as its design aircraft, which would give the same result for runway length requirement.

c) Peak Hour AWPM According to the forecasting, the max hour departure is 34, arrival is 24 and total operation is 44 on AWPM. In fact, max hour departure is 28, arrival is 25 and total operation is 41 on AWPM.
The forecasting overestimate the max departure by around 20%, but almost correctly predict the max hourly arrivals and total operations.
Therefore, the result of the forecasting is reasonably reliable.

d) Peak Rolling Hour AWPM 37 26 48 According to the forecasting, the max rolling hour departure is 37, arrival is 26 and total operation is 48 on AWPM. In fact, max hour departure is 36,

arrival is 32 and total operation is 45 on AWPM.
The forecasting underestimates the max rolling hour arrivals by around 27%, but almost correctly predict the max rolling hour arrivals and total operations.
Therefore, the result of the forecasting is reasonably reliable.

2.7.2 23. Under Built

According to the data summary in 22, while the forecasting almost correctly predict the total operations, with slightly underestimation, it overestimates the max hourly departures on AWPM and underestimates the max rolling hour arrivals.
While other forecasting is precise, if I built an airport based on forecasting, it will be slightly **under built**.

2.7.3 24. Perspectives

Passenger perspective:
1. The airport has seen a growth of operations from around 8000 departures, 8000 arrivals and 16,000 total operations to 10,000 departures, 10,000 arrivals and 20,000 total operations. The growth of operations would mean more choices of flights to passengers. To be more specific, **more time flexibility and more destinations** choices. For example, while in 2011 there were only 1 intercontinental flight, from SAN to LHR, in 2018, there are three non-stop routes to Europe.
2. However, the airport is more crowded. While there is a growth in operations, the runway remains the same. Therefore, the passengers would reasonably expect more traffic and crowd. This would means possibly more delays, more crowded waiting rooms and more waiting time etc.

Airline perspective:
1. The airport has seen and increase in operations. Therefore, the airline would expect **more passengers**. Moreover, more operations might influence the pricing strategies, aircraft type choices and adjustment for scheduling etc.
2. The airport might encounter increased burden during the peak rolling hour. Therefore, the airlines should be prepared.

FAA perspective: 1. The biggest challenge for FAA is to make sure the safety of the airport operations. More operations in the airport while the runway remains the same require more coordination from ATC.
2. According to the growth, the airport might be under built in the future. Therefore, FAA might consider the future expansion and construction.