

Project Report

Optimization of Airport Waiting Time

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1 Introduction

When traveling from one country to another by airplane, people usually need to pass for the custom clearance through service booths at the airport. This procedure is crucial in legalizing their arrival in the foreign country or their reentering their home country. Therefore, optimizing the service booth allocation is essential to improve overall well-being of travelers.

However, crossing the border is not always an enjoyable experience because people may wait in queues for a long time. To solve this problem, the U.S. Customs and Border Protection(CBP) needs to consider the trade-off between booth operating cost and passenger waiting time, which is illustrated in below graph.

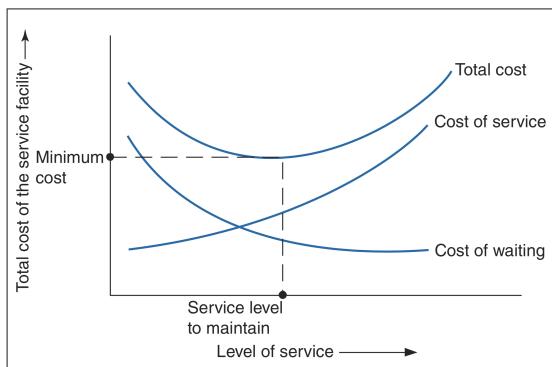


Figure 1: Cost trade-off for service levels. (Taylor, 2007)

We therefore seek to construct a model that efficiently allocates the number of service booths at the custom to best accommodate incoming passengers at every time interval. To this end, we want to minimize the number of customers waiting longer than 30 minutes for their clearance at the custom.

2 Methodology

The notion of waiting line is essential in analyzing and optimizing airport operations. A waiting line can be defined in terms of the arrival rate of customers, the rate at which customers are served by service providers, and the number of service providers. We study the optimization problem under the framework of M/M/c queueing model(See Appendix A). Hence we follow the commonly-used assumptions in queueing theory, which are:

1. Arrival of customers follows the law of Poisson process.
2. Service time follows an exponential distribution.

We will input the waiting time of respective intervals to obtain approximations of the parameter for the Poisson process. With the number of booths as the decision variable, we intend to minimize the average waiting time for incoming customers. Main constraints include a maximum capacity of operating booths. A mathematical expression for the optimization statement is as follows:

In this model, L denotes the number of average customers in the system, λ denotes the average number of customers arrived per hour, and W denotes the average waiting time customer spends in the system. c denotes the serves provided by booths in use and c_m denotes the total capacity of all booths.

$$\begin{aligned} \min U &= (\sum_{t=1}^{t=24} U_t)/24 \\ \text{subject to } c_t &\leq c_m \\ U_t &= u_1 * \frac{L_t}{\lambda_t} + u_2 * c_t \\ P_{0t} &= \frac{1}{\left[\sum_{n=0}^{n=c-1} \frac{1}{n!} \left(\frac{\lambda_t}{\mu_t} \right)^n \right] + \frac{1}{c_t!} \left(\frac{\lambda_t}{\mu_t} \right)^{c_t} \left(\frac{c_t \mu_t}{c_t \mu_t - \lambda_t} \right)} \quad (1) \\ L_t &= \frac{\lambda_t \mu (\lambda_t / \mu)^{c_t}}{(c_t - 1)! (c_t \mu - \lambda_t)^2} P_{0t} + \frac{\lambda_t}{\mu} \quad (2) \\ c_t &\geq 0 \end{aligned}$$

3 Data Source and Description

We used open data from the U.S. Customs and Border Protection (CBP), one of the largest law enforcement organization. CBP closely monitors the flight processing times, commonly referred to as wait times, for arriving flights at the busiest international airports. The data provided by CBP shows the number of passengers processed on flights arriving in each hour based on how long it took for those passengers to clear Passport Control. Moreover, they also displays their average compensation for employers on their websites, which serves as a budget benchmark in our model

Considering our computational constraint, we only focused on John F. Kennedy International Airport since it is the most crowded international airport in the world. Moreover, to probe into the general working pattern of airports, we set the duration of our data time span to three month, namely from January 2019 to April 2019.

In terms of the operating budget, we only considered the salary for the entry-level workers since they are those officers working at the booth. According to CBP's open information, the average base income for Grade G5 (the most junior position) is \$29350. Assuming that they work

for 260 days per year and 8 hours per day, their hourly wage would be \$14.11. In our model, we rounded it as approximation. Furthermore, based on the border security's "Report to Congressional Requesters" in 2011, CBP air and marine operations has \$814.5 million budget per year to cover their 300 entry ports in the US. Roughly, the daily budget for one entry port is \$7,600. To simplify our calculation, we estimated its daily budget to be \$10,000 since JFK is such a busy and important station.

4 Data Preprocessing and Solution Algorithm

To get feasible values of average customer arrival (which is dependent on the timing of the day), average service time, we run several statistics of the CBP airport waiting time dataset over a month and get the a few representative graphs:

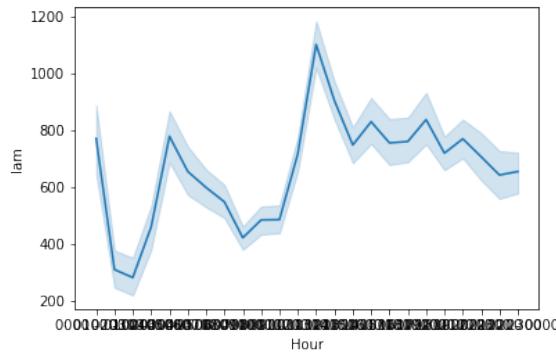


Figure 2: Arrival distribution of passengers in one day period.

The above graph delineates the arrival characteristics of number of customers arriving at the airport, from which there is rush hours between 5 – 6am and one around 12pm. We then get an approximate arrival rate $\lambda(t)$ which depends on the hour of the day. Note that for simplicity reasons, $\lambda(t)$ is a step function whose value in each hour interval is constant.

Now we need to specify the average service rate μ (the number of customers a booth process in one hour) over the whole day period, which is 47.9047. We also obtained the average number of operating booths c_t graph, as follows.

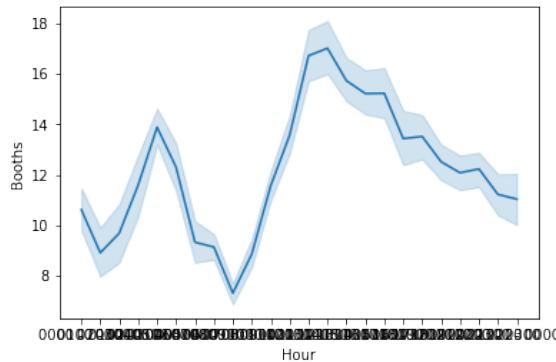


Figure 3: Average number of operating booths in one day period.

After getting preliminary values for λ and μ , we then went on to figure out the relationship between our objective function (i.e., the utility function which consists of average waiting time and booth operating cost) and number of opening booths. To do this, we ran several plots with given λ and μ in Mathematica, with the equation specified in optimization statement. We noticed that even with different λ, μ value pairs, the structure of the graph of utility function against number of opening booths is very similar, and only the values of vertical asymptotes differ.

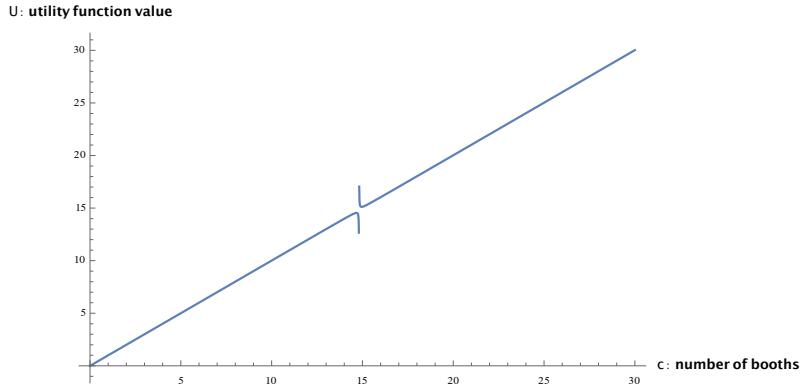


Figure 4: Graph of the utility function value versus number of booth, taking λ and μ to be their mean, which are 711 and 48, respectively.

We also plotted the difference between the objective function and our proposed simplified function, which indeed verified our speculation.

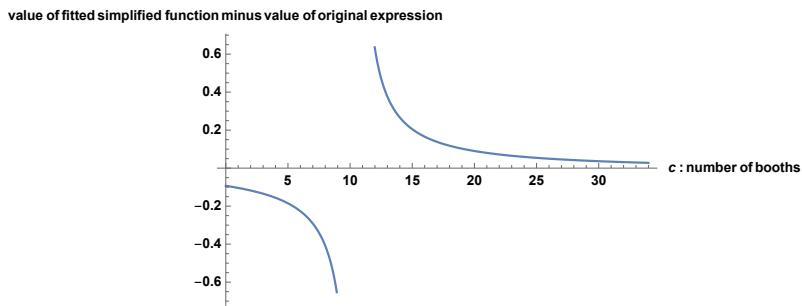


Figure 5: Graph of the difference between the original utility function expression and simplified expression, taking λ and μ to be their mean, which are 711 and 48, respectively.

Given the above information about the graph, we decided to regress U_t on c_t and $\frac{1}{c_t}$ to get best approximation results for every operating hour, which is summarized in the following table.

| time | Booths_params | booth_in_params | R_square | max_c |
|------|---------------|-----------------|----------|-------|
| 1 | 2.38452 | 110.294 | 0.921876 | 16 |
| 2 | 2.54965 | 88.8538 | 0.962271 | 17 |
| 3 | 2.77804 | 88.5761 | 0.942388 | 14 |
| 4 | 2.65307 | 53.4147 | 0.95566 | 17 |
| 5 | 1.91944 | 93.5562 | 0.981156 | 21 |
| 6 | 1.98047 | 105.11 | 0.953806 | 20 |
| 7 | 2.6546 | 63.9199 | 0.964709 | 15 |
| 8 | 2.96579 | 77.4236 | 0.927836 | 18 |
| 9 | 3.13254 | 88.9573 | 0.928013 | 14 |
| 10 | 2.87069 | 101.269 | 0.919259 | 16 |
| 11 | 2.73734 | 99.9679 | 0.933754 | 19 |
| 12 | 2.41814 | 99.377 | 0.966189 | 24 |
| 13 | 2.28977 | 105.725 | 0.963803 | 31 |
| 14 | 2.37313 | 134.09 | 0.942585 | 34 |
| 15 | 2.12654 | 175.246 | 0.941537 | 32 |
| 16 | 2.10257 | 188.151 | 0.941453 | 32 |
| 17 | 2.24244 | 214.409 | 0.93327 | 32 |
| 18 | 1.71045 | 219.73 | 0.913348 | 30 |
| 19 | 2.36134 | 107.525 | 0.942327 | 24 |
| 20 | 2.48574 | 107.436 | 0.902682 | 24 |
| 21 | 2.47652 | 114.653 | 0.908519 | 20 |
| 22 | 2.23202 | 178 | 0.921931 | 18 |
| 23 | 2.64025 | 147.771 | 0.933482 | 17 |
| 24 | 1.89465 | 135.824 | 0.950789 | 22 |

Figure 6: Summary of regression models for all time intervals.

It can be observed from the table above that our proposed regression model is an excellent approximation (with average explanation power 93.9%, see Appendix B for details) of the complicated expression we had in the optimization formulation. After simplification, our final model became as follows.

$$\min U = \left(\sum_{t=1}^{t=24} U_t \right) / 24$$

$$\text{s.t. } c_t \leq c_m$$

$$U_t = u_1 * \frac{1}{c_t} + u_2 * c_t$$

$$c_t \geq 0$$

Based on the simplified regression model of U_t on c_t and $\frac{1}{c_t}$, the convexity of the objective function becomes apparent. In particular, U_t is convex on the positive real line. We can thus input the coefficients as parameters and combining these information with the previous budget to formulate a complete optimization model that can be comprehended by algebraic modeling language (e.g. GAMS).

5 Results and Discussion

We input our convex optimization model into GAMS to get final results. In particular, we used SCIP mixed-integer non-linear solver to solve our problem.

```
---- 106 VARIABLE c.L  number of booths to open at hour t
1   7.000,    2   6.000,    3   6.000,    4   4.000,    5   7.000,    6   7.000
7   5.000,    8   5.000,    9   5.000,    10  6.000,   11  6.000,   12  3.000
13  7.000,   14  8.000,   15  9.000,   16  9.000,   17 10.000,   18 11.000
19  7.000,   20  3.000,   21  7.000,   22  9.000,   23  8.000,   24  8.000

---- 106 VARIABLE u.L                      =      34.144  utility function
```

Figure 7: GAMS output.

The above output indicates the optimal strategy to arrange the number of opening booths at each hour interval throughout the day, based on the criterion that minimize the utility function (cost). The results verifies the hypothesis that it's generally more efficient to operate more booths during 14pm-24pm as opposed to operate more booths in the morning.

6 Concluding Remarks

In this project, we provided an model assessing the overall operating efficiency of airport customs, based on the data in all terminals of New York JFK airport, using M/M/c queueing framework. We simplified the objective function by speculating the graph of the function and tried regression upon the observation. We obtained a transformed approximation model which has a high explanation power of over 93%. After that, we input the simplified expression into GAMS and applied SCIP nonlinear mixed integer solver, and obtained our optimized strategy to a list of opening booths according to the hour of the day.

Space for future improvement include more rigorous proof of the mathematical approximation, maybe introducing methods of spline approximation when doing the simplification of the objective function. Moreover, more budget specifications should be obtained to improve accuracy of constraints calculation.

Appendix A M/M/c queueing model

M/M/c is a multi-server system with customers arrival follows a poisson process and exponential service time. When a customer enters an Empty system, he gets the service at once. If the system is non-empty the incoming customer joins the Queue (Sundari and Srinivasan, 2011). In this system, λ denotes the average number of customers arrived per hour, μ denotes the average number of customers served per hour, and c denotes the serves provided by booths in use.

Here we list a few formulas that would be useful in characterizing our optimization model:

First, P_0 denotes the probability that there are no customers in system:

$$P_0 = \frac{1}{\sum_{n=0}^{n=c-1} \frac{1}{n!} \left(\frac{\lambda}{\mu}\right)^n + \frac{1}{c!} \left(\frac{\lambda}{\mu}\right)^c \left(\frac{c\mu}{c\mu-\lambda}\right)} \quad (3)$$

L denotes the number of average customers in the system:

$$L = \frac{\lambda\mu(\lambda/\mu)^c}{(c-1)!(c\mu-\lambda)^2} P_0 + \frac{\lambda}{\mu} \quad (4)$$

Finally, our objective function, W , which denotes the average waiting time customer spends in the system, is expressed as

$$W = \frac{L}{\lambda} \quad (5)$$

$$W = \frac{\mu \left(\frac{\lambda}{\mu}\right)^c}{\left(\frac{e}{c-1}\right)^{c-1} (c\mu-\lambda)^2 \left(\sum_{n=1}^{c-1} \frac{\left(\frac{e}{n}\right)^n \left(\frac{\lambda}{\mu}\right)^n}{\sqrt{2\pi n}} + \frac{\left(\frac{e}{c}\right)^c c\mu \left(\frac{\lambda}{\mu}\right)^c}{\sqrt{2\pi c(c\mu-\lambda)}} + 1 \right)} \quad (6)$$

Appendix B Ordinary Least Squares Regression Results

| OLS Regression Results | | | | | | |
|---|------------------|---------------------|----------|--------|--------|---------|
| Dep. Variable: | utility | R-squared: | 0.922 | | | |
| Model: | OLS | Adj. R-squared: | 0.918 | | | |
| Method: | Least Squares | F-statistic: | 218.3 | | | |
| Date: | Wed, 08 May 2019 | Prob (F-statistic): | 3.28e-21 | | | |
| Time: | 11:14:59 | Log-Likelihood: | -147.70 | | | |
| No. Observations: | 39 | AIC: | 299.4 | | | |
| Df Residuals: | 37 | BIC: | 302.7 | | | |
| Df Model: | 2 | | | | | |
| Covariance Type: | nonrobust | | | | | |
| coef | std err | t | P> t | [0.025 | 0.975] | |
| Booths | 2.3845 | 0.314 | 7.606 | 0.000 | 1.749 | 3.020 |
| booth_in | 110.2937 | 32.334 | 3.411 | 0.002 | 44.779 | 175.808 |
| Omnibus: | 9.459 | Durbin-Watson: | 1.903 | | | |
| Prob(Omnibus): | 0.009 | Jarque-Bera (JB): | 8.537 | | | |
| Skew: | 1.082 | Prob(JB): | 0.0140 | | | |
| Kurtosis: | 3.758 | Cond. No. | 202. | | | |
| Warnings: | | | | | | |
| [1] Standard Errors assume that the covariance matrix of the errors is correctly specified. | | | | | | |

Figure 8: Summary of regression model for o:oo-1:00.

```

OLS Regression Results
=====
Dep. Variable: utility R-squared: 0.962
Model: OLS Adj. R-squared: 0.960
Method: Least Squares F-statistic: 382.6
Date: Wed, 08 May 2019 Prob (F-statistic): 4.47e-22
Time: 11:15:01 Log-Likelihood: -106.40
No. Observations: 32 AIC: 216.8
Df Residuals: 30 BIC: 219.7
Df Model: 2
Covariance Type: nonrobust
=====

      coef    std err      t      P>|t|      [0.025      0.975]
Booths     2.5497    0.230   11.103      0.000      2.081      3.019
booth_in   88.8538   16.361     5.431      0.000     55.440    122.267
=====
Omnibus:          8.281 Durbin-Watson: 1.921
Prob(Omnibus):  0.016 Jarque-Bera (JB): 6.884
Skew:           1.080 Prob(JB): 0.0320
Kurtosis:        3.703 Cond. No. 124.
=====

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

Figure 9: Summary of regression model for 1:00-2:00.

```

OLS Regression Results
=====
Dep. Variable: utility R-squared: 0.942
Model: OLS Adj. R-squared: 0.936
Method: Least Squares F-statistic: 139.0
Date: Wed, 08 May 2019 Prob (F-statistic): 2.91e-11
Time: 11:13:55 Log-Likelihood: -68.997
No. Observations: 19 AIC: 142.0
Df Residuals: 17 BIC: 143.9
Df Model: 2
Covariance Type: nonrobust
=====

      coef    std err      t      P>|t|      [0.025      0.975]
Booths     2.7780    0.442    6.279      0.000      1.845      3.712
booth_in   88.5761   38.107     2.324      0.033      8.177    168.975
=====
Omnibus:          7.517 Durbin-Watson: 1.161
Prob(Omnibus):  0.023 Jarque-Bera (JB): 5.051
Skew:           1.207 Prob(JB): 0.0800
Kurtosis:        3.743 Cond. No. 172.
=====

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

Figure 10: Summary of regression model for 2:00-3:00.

```

OLS Regression Results
=====
Dep. Variable: utility R-squared: 0.956
Model: OLS Adj. R-squared: 0.950
Method: Least Squares F-statistic: 161.6
Date: Wed, 08 May 2019 Prob (F-statistic): 7.10e-11
Time: 11:13:41 Log-Likelihood: -59.004
No. Observations: 17 AIC: 122.0
Df Residuals: 15 BIC: 123.7
Df Model: 2
Covariance Type: nonrobust
=====

      coef    std err      t      P>|t|      [0.025      0.975]
-----
Booths     2.6531    0.370     7.168     0.000      1.864     3.442
booth_in   53.4147   46.633     1.145     0.270     -45.980    152.810
=====
Omnibus:            2.702 Durbin-Watson: 1.096
Prob(Omnibus):      0.259 Jarque-Bera (JB): 1.481
Skew:                0.722 Prob(JB): 0.477
Kurtosis:             3.074 Cond. No. 276.
=====

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

Figure ii: Summary of regression model for 3:00-4:00.

```

OLS Regression Results
=====
Dep. Variable: utility R-squared: 0.981
Model: OLS Adj. R-squared: 0.980
Method: Least Squares F-statistic: 1041.
Date: Wed, 08 May 2019 Prob (F-statistic): 3.19e-35
Time: 11:13:58 Log-Likelihood: -124.46
No. Observations: 42 AIC: 252.9
Df Residuals: 40 BIC: 256.4
Df Model: 2
Covariance Type: nonrobust
=====

      coef    std err      t      P>|t|      [0.025      0.975]
-----
Booths     1.9194    0.147     13.072     0.000      1.623     2.216
booth_in   93.5562   27.291     3.428     0.001     38.400    148.713
=====
Omnibus:            10.664 Durbin-Watson: 2.035
Prob(Omnibus):      0.005 Jarque-Bera (JB): 10.166
Skew:                1.017 Prob(JB): 0.00620
Kurtosis:             4.293 Cond. No. 520.
=====

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

Figure i2: Summary of regression model for 4:00-5:00.

```

OLS Regression Results
=====
Dep. Variable: utility R-squared: 0.954
Model: OLS Adj. R-squared: 0.952
Method: Least Squares F-statistic: 526.5
Date: Wed, 08 May 2019 Prob (F-statistic): 8.85e-35
Time: 11:14:02 Log-Likelihood: -182.15
No. Observations: 53 AIC: 368.3
Df Residuals: 51 BIC: 372.2
Df Model: 2
Covariance Type: nonrobust
=====
      coef    std err      t   P>|t|   [0.025   0.975]
-----
Booths     1.9805   0.134   14.812   0.000    1.712    2.249
booth_in  105.1105  17.305   6.074   0.000   70.370  139.851
=====
Omnibus:          6.948 Durbin-Watson: 2.159
Prob(Omnibus):  0.031 Jarque-Bera (JB): 6.757
Skew:           0.875 Prob(JB): 0.0341
Kurtosis:        3.016 Cond. No. 210.
=====
```

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 13: Summary of regression model for 5:00-6:00.

```

OLS Regression Results
=====
Dep. Variable: utility R-squared: 0.965
Model: OLS Adj. R-squared: 0.964
Method: Least Squares F-statistic: 888.4
Date: Wed, 08 May 2019 Prob (F-statistic): 6.30e-48
Time: 11:14:05 Log-Likelihood: -219.27
No. Observations: 67 AIC: 442.5
Df Residuals: 65 BIC: 446.9
Df Model: 2
Covariance Type: nonrobust
=====
      coef    std err      t   P>|t|   [0.025   0.975]
-----
Booths     2.6546   0.114   23.197   0.000    2.426    2.883
booth_in  63.9199   8.077    7.914   0.000   47.789   80.051
=====
Omnibus:          0.549 Durbin-Watson: 2.196
Prob(Omnibus):  0.760 Jarque-Bera (JB): 0.472
Skew:           0.199 Prob(JB): 0.790
Kurtosis:        2.896 Cond. No. 101.
=====
```

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 14: Summary of regression model for 6:00-7:00.

```

OLS Regression Results
=====
Dep. Variable: utility R-squared:          0.928
Model:           OLS   Adj. R-squared:      0.926
Method:          Least Squares F-statistic:     649.3
Date:            Wed, 08 May 2019 Prob (F-statistic): 2.21e-58
Time:             11:14:08 Log-Likelihood:    -386.09
No. Observations: 103   AIC:                  776.2
Df Residuals:    101   BIC:                  781.5
Df Model:        2
Covariance Type: nonrobust
=====

      coef    std err      t      P>|t|      [0.025      0.975]
-----+-----+-----+-----+-----+-----+-----+
Booths    2.9658    0.181    16.372    0.000      2.606      3.325
booth_in  77.4236   13.183     5.873    0.000     51.272    103.575
-----+-----+-----+-----+-----+-----+-----+
Omnibus:           15.449 Durbin-Watson:       1.812
Prob(Omnibus):    0.000 Jarque-Bera (JB):    18.114
Skew:              0.839 Prob(JB):          0.000117
Kurtosis:          4.185 Cond. No.         123.
=====

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

Figure 15: Summary of regression model for 7:00-8:00.

```

OLS Regression Results
=====
Dep. Variable: utility R-squared:          0.928
Model:           OLS   Adj. R-squared:      0.927
Method:          Least Squares F-statistic:     818.6
Date:            Wed, 08 May 2019 Prob (F-statistic): 2.73e-73
Time:             11:14:11 Log-Likelihood:    -482.80
No. Observations: 129   AIC:                  969.6
Df Residuals:    127   BIC:                  975.3
Df Model:        2
Covariance Type: nonrobust
=====

      coef    std err      t      P>|t|      [0.025      0.975]
-----+-----+-----+-----+-----+-----+-----+
Booths    3.1325    0.198    15.861    0.000      2.742      3.523
booth_in  88.9573   9.341     9.523    0.000     70.472    107.442
-----+-----+-----+-----+-----+-----+-----+
Omnibus:           14.752 Durbin-Watson:       2.182
Prob(Omnibus):    0.001 Jarque-Bera (JB):    16.097
Skew:              0.804 Prob(JB):          0.000320
Kurtosis:          3.637 Cond. No.         79.2
=====

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

Figure 16: Summary of regression model for 8:00-9:00.

OLS Regression Results

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | utility | R-squared: | 0.919 |
| Model: | OLS | Adj. R-squared: | 0.917 |
| Method: | Least Squares | F-statistic: | 461.1 |
| Date: | Wed, 08 May 2019 | Prob (F-statistic): | 5.46e-45 |
| Time: | 11:14:15 | Log-Likelihood: | -319.41 |
| No. Observations: | 83 | AIC: | 642.8 |
| Df Residuals: | 81 | BIC: | 647.7 |
| Df Model: | 2 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------|----------|---------|--------|-------|--------|---------|
| Booths | 2.8707 | 0.236 | 12.147 | 0.000 | 2.400 | 3.341 |
| booth_in | 101.2686 | 16.560 | 6.115 | 0.000 | 68.320 | 134.217 |

| | | | |
|----------------|--------|-------------------|----------|
| Omnibus: | 39.697 | Durbin-Watson: | 1.945 |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 114.019 |
| Skew: | 1.582 | Prob(JB): | 1.74e-25 |
| Kurtosis: | 7.792 | Cond. No. | 122. |

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 17: Summary of regression model for 9:00-10:00.

OLS Regression Results

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | utility | R-squared: | 0.934 |
| Model: | OLS | Adj. R-squared: | 0.932 |
| Method: | Least Squares | F-statistic: | 641.3 |
| Date: | Wed, 08 May 2019 | Prob (F-statistic): | 2.30e-54 |
| Time: | 11:14:18 | Log-Likelihood: | -355.09 |
| No. Observations: | 93 | AIC: | 714.2 |
| Df Residuals: | 91 | BIC: | 719.2 |
| Df Model: | 2 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------|---------|---------|--------|-------|--------|---------|
| Booths | 2.7373 | 0.188 | 14.560 | 0.000 | 2.364 | 3.111 |
| booth_in | 99.9679 | 22.966 | 4.353 | 0.000 | 54.349 | 145.587 |

| | | | |
|----------------|--------|-------------------|----------|
| Omnibus: | 14.127 | Durbin-Watson: | 2.283 |
| Prob(Omnibus): | 0.001 | Jarque-Bera (JB): | 16.449 |
| Skew: | 1.029 | Prob(JB): | 0.000268 |
| Kurtosis: | 3.101 | Cond. No. | 237. |

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 18: Summary of regression model for 10:00-11:00.

OLS Regression Results

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | utility | R-squared: | 0.966 |
| Model: | OLS | Adj. R-squared: | 0.965 |
| Method: | Least Squares | F-statistic: | 1372. |
| Date: | Wed, 08 May 2019 | Prob (F-statistic): | 2.48e-71 |
| Time: | 11:14:20 | Log-Likelihood: | -339.19 |
| No. Observations: | 98 | AIC: | 682.4 |
| Df Residuals: | 96 | BIC: | 687.6 |
| Df Model: | 2 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------|---------|---------|--------|-------|--------|---------|
| <hr/> | | | | | | |
| Booths | 2.4181 | 0.113 | 21.358 | 0.000 | 2.193 | 2.643 |
| booth_in | 99.3770 | 19.353 | 5.135 | 0.000 | 60.962 | 137.792 |

| | | | |
|----------------|--------|-------------------|----------|
| Omnibus: | 23.114 | Durbin-Watson: | 1.432 |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 33.874 |
| Skew: | 1.077 | Prob(JB): | 4.41e-08 |
| Kurtosis: | 4.912 | Cond. No. | 345. |

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 19: Summary of regression model for 11:00-12:00.

OLS Regression Results

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | utility | R-squared: | 0.964 |
| Model: | OLS | Adj. R-squared: | 0.963 |
| Method: | Least Squares | F-statistic: | 1771. |
| Date: | Wed, 08 May 2019 | Prob (F-statistic): | 1.42e-96 |
| Time: | 11:14:23 | Log-Likelihood: | -489.29 |
| No. Observations: | 135 | AIC: | 982.6 |
| Df Residuals: | 133 | BIC: | 988.4 |
| Df Model: | 2 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------|----------|---------|--------|-------|--------|---------|
| <hr/> | | | | | | |
| Booths | 2.2898 | 0.067 | 34.205 | 0.000 | 2.157 | 2.422 |
| booth_in | 105.7251 | 15.706 | 6.731 | 0.000 | 74.659 | 136.792 |

| | | | |
|----------------|--------|-------------------|----------|
| Omnibus: | 22.342 | Durbin-Watson: | 1.585 |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 29.706 |
| Skew: | 0.916 | Prob(JB): | 3.54e-07 |
| Kurtosis: | 4.387 | Cond. No. | 354. |

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 20: Summary of regression model for 12:00-13:00.

```

OLS Regression Results
=====
Dep. Variable: utility R-squared: 0.943
Model: OLS Adj. R-squared: 0.942
Method: Least Squares F-statistic: 1330.
Date: Wed, 08 May 2019 Prob (F-statistic): 3.03e-101
Time: 11:14:26 Log-Likelihood: -650.32
No. Observations: 164 AIC: 1305.
Df Residuals: 162 BIC: 1311.
Df Model: 2
Covariance Type: nonrobust
=====

      coef    std err      t   P>|t|   [0.025   0.975]
-----
Booths     2.3731    0.072   32.872   0.000     2.231    2.516
booth_in  134.0902   16.149    8.303   0.000    102.201   165.980
=====
Omnibus: 25.558 Durbin-Watson: 2.015
Prob(Omnibus): 0.000 Jarque-Bera (JB): 35.767
Skew: 0.882 Prob(JB): 1.71e-08
Kurtosis: 4.457 Cond. No. 297.
=====

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

Figure 21: Summary of regression model for 13:00-14:00.

```

OLS Regression Results
=====
Dep. Variable: utility R-squared: 0.942
Model: OLS Adj. R-squared: 0.941
Method: Least Squares F-statistic: 1433.
Date: Wed, 08 May 2019 Prob (F-statistic): 1.79e-110
Time: 11:14:28 Log-Likelihood: -699.01
No. Observations: 180 AIC: 1402.
Df Residuals: 178 BIC: 1408.
Df Model: 2
Covariance Type: nonrobust
=====

      coef    std err      t   P>|t|   [0.025   0.975]
-----
Booths     2.1265    0.078   27.207   0.000     1.972    2.281
booth_in  175.2464   16.516   10.611   0.000    142.654   207.839
=====
Omnibus: 69.516 Durbin-Watson: 2.241
Prob(Omnibus): 0.000 Jarque-Bera (JB): 264.318
Skew: 1.479 Prob(JB): 4.02e-58
Kurtosis: 8.147 Cond. No. 316.
=====

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

Figure 22: Summary of regression model for 14:00-15:00.

OLS Regression Results

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | utility | R-squared: | 0.941 |
| Model: | OLS | Adj. R-squared: | 0.941 |
| Method: | Least Squares | F-statistic: | 1198. |
| Date: | Wed, 08 May 2019 | Prob (F-statistic): | 1.51e-92 |
| Time: | 11:14:31 | Log-Likelihood: | -584.65 |
| No. Observations: | 151 | AIC: | 1173. |
| Df Residuals: | 149 | BIC: | 1179. |
| Df Model: | 2 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------|----------|---------|--------|-------|---------|---------|
| Booths | 2.1026 | 0.092 | 22.737 | 0.000 | 1.920 | 2.285 |
| booth_in | 188.1508 | 18.555 | 10.140 | 0.000 | 151.485 | 224.817 |

| | | | |
|----------------|--------|-------------------|---------|
| Omnibus: | 11.894 | Durbin-Watson: | 1.934 |
| Prob(Omnibus): | 0.003 | Jarque-Bera (JB): | 12.861 |
| Skew: | 0.714 | Prob(JB): | 0.00161 |
| Kurtosis: | 3.076 | Cond. No. | 315. |

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 23: Summary of regression model for 15:00-16:00.

OLS Regression Results

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | utility | R-squared: | 0.933 |
| Model: | OLS | Adj. R-squared: | 0.932 |
| Method: | Least Squares | F-statistic: | 769.2 |
| Date: | Wed, 08 May 2019 | Prob (F-statistic): | 2.18e-65 |
| Time: | 11:14:34 | Log-Likelihood: | -450.80 |
| No. Observations: | 112 | AIC: | 905.6 |
| Df Residuals: | 110 | BIC: | 911.0 |
| Df Model: | 2 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------|----------|---------|--------|-------|---------|---------|
| Booths | 2.2424 | 0.127 | 17.639 | 0.000 | 1.991 | 2.494 |
| booth_in | 214.4093 | 25.833 | 8.300 | 0.000 | 163.214 | 265.605 |

| | | | |
|----------------|--------|-------------------|----------|
| Omnibus: | 21.286 | Durbin-Watson: | 1.920 |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 27.404 |
| Skew: | 1.013 | Prob(JB): | 1.12e-06 |
| Kurtosis: | 4.328 | Cond. No. | 323. |

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 24: Summary of regression model for 16:00-17:00.

```

OLS Regression Results
=====
Dep. Variable: utility R-squared: 0.913
Model: OLS Adj. R-squared: 0.911
Method: Least Squares F-statistic: 358.4
Date: Wed, 08 May 2019 Prob (F-statistic): 7.67e-37
Time: 11:14:37 Log-Likelihood: -277.55
No. Observations: 70 AIC: 559.1
Df Residuals: 68 BIC: 563.6
Df Model: 2
Covariance Type: nonrobust
=====

      coef  std err      t  P>|t|  [0.025  0.975]
Booths     1.7104   0.182    9.406  0.000    1.348  2.073
booth_in  219.7296  29.377    7.480  0.000   161.108 278.351
=====
Omnibus: 28.723 Durbin-Watson: 2.859
Prob(Omnibus): 0.000 Jarque-Bera (JB): 51.030
Skew: 1.500 Prob(JB): 8.30e-12
Kurtosis: 5.915 Cond. No. 270.
=====
```

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 25: Summary of regression model for 17:00-18:00.

```

OLS Regression Results
=====
Dep. Variable: utility R-squared: 0.942
Model: OLS Adj. R-squared: 0.941
Method: Least Squares F-statistic: 555.5
Date: Wed, 08 May 2019 Prob (F-statistic): 7.47e-43
Time: 11:14:41 Log-Likelihood: -261.56
No. Observations: 70 AIC: 527.1
Df Residuals: 68 BIC: 531.6
Df Model: 2
Covariance Type: nonrobust
=====

      coef  std err      t  P>|t|  [0.025  0.975]
Booths     2.3613   0.162   14.606  0.000    2.039  2.684
booth_in  107.5252  26.563    4.048  0.000   54.520 160.530
=====
Omnibus: 6.561 Durbin-Watson: 1.680
Prob(Omnibus): 0.038 Jarque-Bera (JB): 5.750
Skew: 0.635 Prob(JB): 0.0564
Kurtosis: 3.601 Cond. No. 302.
=====
```

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 26: Summary of regression model for 18:00-19:00.

```

OLS Regression Results
=====
Dep. Variable: utility R-squared: 0.903
Model: OLS Adj. R-squared: 0.901
Method: Least Squares F-statistic: 533.3
Date: Wed, 08 May 2019 Prob (F-statistic): 6.62e-59
Time: 11:14:43 Log-Likelihood: -471.08
No. Observations: 117 AIC: 946.2
Df Residuals: 115 BIC: 951.7
Df Model: 2
Covariance Type: nonrobust
=====

      coef  std err      t   P>|t|  [0.025  0.975]
-----
Booths     2.4857    0.159   15.642   0.000    2.171   2.801
booth_in  107.4356   21.829    4.922   0.000   64.197  150.674
=====
Omnibus:            32.224 Durbin-Watson:        1.714
Prob(Omnibus):      0.000 Jarque-Bera (JB):  52.340
Skew:                1.274 Prob(JB):       4.31e-12
Kurtosis:             5.061 Cond. No.        227.
=====

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

Figure 27: Summary of regression model for 19:00-20:00.

```

OLS Regression Results
=====
Dep. Variable: utility R-squared: 0.909
Model: OLS Adj. R-squared: 0.907
Method: Least Squares F-statistic: 506.5
Date: Wed, 08 May 2019 Prob (F-statistic): 1.07e-53
Time: 11:14:47 Log-Likelihood: -413.74
No. Observations: 104 AIC: 831.5
Df Residuals: 102 BIC: 836.8
Df Model: 2
Covariance Type: nonrobust
=====

      coef  std err      t   P>|t|  [0.025  0.975]
-----
Booths     2.4765    0.180   13.754   0.000    2.119   2.834
booth_in  114.6532   23.474    4.884   0.000   68.092  161.215
=====
Omnibus:            50.244 Durbin-Watson:        1.793
Prob(Omnibus):      0.000 Jarque-Bera (JB):  135.219
Skew:                1.812 Prob(JB):       4.34e-30
Kurtosis:             7.252 Cond. No.        231.
=====

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

Figure 28: Summary of regression model for 20:00-21:00.

OLS Regression Results

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | utility | R-squared: | 0.922 |
| Model: | OLS | Adj. R-squared: | 0.920 |
| Method: | Least Squares | F-statistic: | 401.5 |
| Date: | Wed, 08 May 2019 | Prob (F-statistic): | 2.21e-38 |
| Time: | 11:14:49 | Log-Likelihood: | -275.96 |
| No. Observations: | 70 | AIC: | 555.9 |
| Df Residuals: | 68 | BIC: | 560.4 |
| Df Model: | 2 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------|----------|---------|-------|-------|---------|---------|
| Booths | 2.2320 | 0.257 | 8.686 | 0.000 | 1.719 | 2.745 |
| booth_in | 178.0004 | 35.699 | 4.986 | 0.000 | 106.765 | 249.236 |

| | | | |
|----------------|--------|-------------------|----------|
| Omnibus: | 42.319 | Durbin-Watson: | 1.858 |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 159.307 |
| Skew: | 1.764 | Prob(JB): | 2.55e-35 |
| Kurtosis: | 9.494 | Cond. No. | 296. |

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 29: Summary of regression model for 21:00-22:00.

OLS Regression Results

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | utility | R-squared: | 0.933 |
| Model: | OLS | Adj. R-squared: | 0.931 |
| Method: | Least Squares | F-statistic: | 336.8 |
| Date: | Wed, 08 May 2019 | Prob (F-statistic): | 5.63e-29 |
| Time: | 11:14:52 | Log-Likelihood: | -194.15 |
| No. Observations: | 50 | AIC: | 392.3 |
| Df Residuals: | 48 | BIC: | 396.1 |
| Df Model: | 2 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------|----------|---------|-------|-------|--------|---------|
| Booths | 2.6403 | 0.282 | 9.355 | 0.000 | 2.073 | 3.208 |
| booth_in | 147.7707 | 32.374 | 4.565 | 0.000 | 82.679 | 212.862 |

| | | | |
|----------------|-------|-------------------|-------|
| Omnibus: | 2.280 | Durbin-Watson: | 2.081 |
| Prob(Omnibus): | 0.320 | Jarque-Bera (JB): | 2.144 |
| Skew: | 0.432 | Prob(JB): | 0.342 |
| Kurtosis: | 2.468 | Cond. No. | 221. |

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 30: Summary of regression model for 22:00-23:00.

| OLS Regression Results | | | | | | |
|------------------------|------------------|---------------------|----------|--------|---------|---------|
| Dep. Variable: | utility | R-squared: | 0.951 | | | |
| Model: | OLS | Adj. R-squared: | 0.949 | | | |
| Method: | Least Squares | F-statistic: | 560.3 | | | |
| Date: | Wed, 08 May 2019 | Prob (F-statistic): | 1.17e-38 | | | |
| Time: | 11:14:55 | Log-Likelihood: | -210.04 | | | |
| No. Observations: | 60 | AIC: | 424.1 | | | |
| Df Residuals: | 58 | BIC: | 428.3 | | | |
| Df Model: | 2 | | | | | |
| Covariance Type: | nonrobust | | | | | |
| coef | std err | t | P> t | [0.025 | 0.975] | |
| Booths | 1.8946 | 0.138 | 13.771 | 0.000 | 1.619 | 2.170 |
| booth_in | 135.8240 | 14.362 | 9.457 | 0.000 | 107.075 | 164.573 |
| Omnibus: | 9.871 | Durbin-Watson: | 1.322 | | | |
| Prob(Omnibus): | 0.007 | Jarque-Bera (JB): | 9.515 | | | |
| Skew: | 0.913 | Prob(JB): | 0.00859 | | | |
| Kurtosis: | 3.688 | Cond. No. | 160. | | | |

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 31: Summary of regression model for 23:00-24:00.

Appendix C Codes

C.I Mathematica

```
In[1]:= W2 = (μ (λ / μ) ^ c) / ((c - 1)! * (c * μ - λ) ^ 2 * (1 + Sum[(n!) ^ (-1) * ((λ / μ) ^ n), {n, 1, c - 1}] + ((c!) ^ (-1) * (λ / μ) ^ c) * c * μ / ((c * μ - λ))) + 1 / μ + c)

Out[1]= c + 1/μ + ((λ/μ)^c μ)/((-λ + c μ)^2 (-1 + c) ! (c (λ/μ)^c μ + e^(λ/μ) Gamma[c, λ/μ]/Gamma[c]))
```

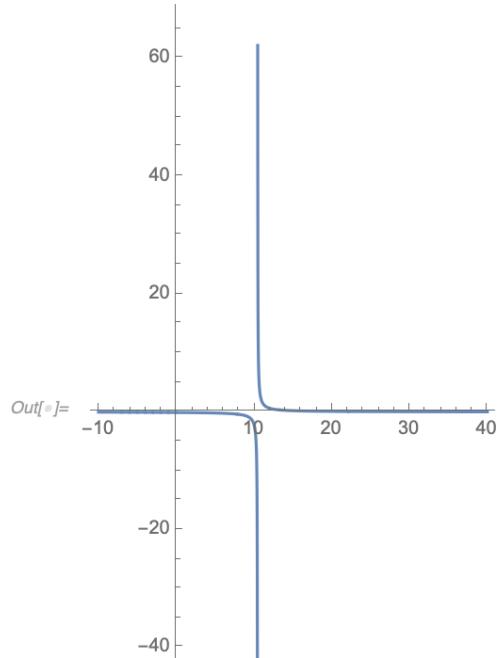
```
In[2]:= p2 = W2 /. λ → 711
m2 = p2 /. μ → 68
Plot[m2, {c, 0, 20}]

Out[2]= c + 1/μ + ((711^c (λ/μ)^(-1+c))/((-711 + c μ)^2 (-1 + c) ! (c (711^c (λ/μ)^(-1+c)) + e^(711/μ) Gamma[c, 711/μ]/Gamma[c])))
```

```
In[3]:= 68^(1-c) 711^c/((-711 + 68 c)^2 (-1 + c) ! (68^(1-c) 711^c c + e^(711/68) Gamma[c, 711/68]/Gamma[c]))
```

```
p1 = c - 711/68 + 1/(c - 711/68) + 711/68
Plot[p1 - m2, {c, -10, 40}, AspectRatio -> 2, PlotRange -> All]
```

$$Out[=] = \frac{1}{-\frac{711}{68} + c}$$



C.2 Calculate parameters for regression (Jupyter Notebook)

Calculate Parameters

May 10, 2019

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import statsmodels.api as sm
        import seaborn as sns
%matplotlib inline

In [2]: jfk_3_4 = pd.read_excel("JFK3-4.xlsx")
        jfk_2_3 = pd.read_excel("JFK2-3.xlsx")
        jfk_1_2 = pd.read_excel("JFK1-2.xlsx")
        frames = [jfk_1_2, jfk_2_3, jfk_3_4]

In [3]: jfk_raw = pd.concat(frames)
        print(jfk_raw.shape)
        jfk_raw.head()

(7282, 21)

Out[3]:   Airport    Terminal      Date       Hour  US_Avg_Wait_t  US_Max_Wait_t \
0      JFK  Terminal 1 2019-01-14  0100 - 0200          0             0
1      JFK  Terminal 1 2019-01-14  0800 - 0900         15            28
2      JFK  Terminal 1 2019-01-14  0900 - 1000          7            13
3      JFK  Terminal 1 2019-01-14  1000 - 1100          9            29
4      JFK  Terminal 1 2019-01-14  1100 - 1200          9            21

           NonUS_Avg_Wait_t  NonUS_Max_Wait_t  Avg_Wait_t  Max_Wait_t  ...  16-30 \
0                  8                 12          8          12  ...     0
1                 19                 31          16          31  ...   138
2                 11                 22          10          22  ...    63
3                 14                 33          12          33  ...  159
4                 12                 25          10          25  ...    84

      31-45  46-60  61-90  91-120  120 plus  Excluded  Total  Flights  Booths
0      0      0      0      0      0          0         1      15       1       1
1      2      0      0      0      0          0         8     249       1       8
2      0      0      0      0      0          0        11     321       2      12
3     19      0      0      0      0          0        19     673       2      12
```

```

4      0      0      0      0      0      21     573      3      15
[5 rows x 21 columns]

In [4]: jfk = jfk_raw[["Terminal", "Date", "Hour", "Avg_Wait_t", "Booths"]]
jfk["passed_in_one_hour"] = jfk_raw["0-15"]+jfk_raw["16-30"]+jfk_raw["31-45"]+jfk_raw["4"]
jfk["total_arrival"] = jfk_raw.Total - jfk_raw.Excluded

/Users/mac/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarning
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#
/Users/mac/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:3: SettingWithCopyWarning
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#
This is separate from the ipykernel package so we can avoid doing imports until

In [5]: def Cal_P(lam,c,mu):
    denominator = 0
    #error_term = 0.0001
    for i in range(c):
        denominator += (1/np.math.factorial(i))*((lam/mu)**i)
    denominator += (1/np.math.factorial(c))*((lam/mu)**c)*(c*mu/(c*mu-lam))
    #print(denominator)
    result = 1/denominator
    return result

def Cal_L(lam,c,mu,P):
    result = (lam*mu*((lam/mu)**c)*P)/(np.math.factorial(c-1)*((c*mu-lam)**2)) + lam
    return result

In [6]: jfk = jfk[jfk.passed_in_one_hour != jfk.total_arrival]
print(jfk.shape)
jfk.head()

(2058, 7)

Out[6]:      Terminal      Date      Hour  Avg_Wait_t  Booths  \
6      Terminal 1 2019-01-14  1300 - 1400      29      25
11     Terminal 1 2019-01-14  1800 - 1900      28      15
12     Terminal 1 2019-01-14  1900 - 2000      34      15
13     Terminal 1 2019-01-14  2000 - 2100      22      15
28  Terminal 4 (IAT) 2019-01-14  1100 - 1200      19      19

```

```

passed_in_one_hour total_arrival
6 1426 1466
11 1326 1486
12 280 352
13 977 1020
28 780 793

In [7]: jfk["mu"] = (jfk.passed_in_one_hour/jfk.Booths).astype(int)
jfk["lam"] = jfk.total_arrival
jfk["P_0"] = jfk.apply(lambda x: Cal_P(x.lam,x.Booths,x.mu), axis=1)
jfk["L"] = jfk.apply(lambda x: Cal_L(x.lam,x.Booths,x.mu,x.P_0), axis=1)

jfk["W"] = (jfk.L/jfk.total_arrival) * 60
jfk.head()

Out[7]:
Terminal Date Hour Avg_Wait_t Booths \
6 Terminal 1 2019-01-14 1300 - 1400 29 25
11 Terminal 1 2019-01-14 1800 - 1900 28 15
12 Terminal 1 2019-01-14 1900 - 2000 34 15
13 Terminal 1 2019-01-14 2000 - 2100 22 15
28 Terminal 4 (IAT) 2019-01-14 1100 - 1200 19 19

passed_in_one_hour total_arrival mu lam P_0 L \
6 1426 1466 57 1466 -2.917354e-12 1423.810694
11 1326 1486 88 1486 -1.054026e-07 1471.148500
12 280 352 18 352 -4.864973e-08 339.699808
13 977 1020 65 1020 -8.558506e-08 992.306341
28 780 793 41 793 -8.626067e-10 730.974530

W
6 58.273289
11 59.400343
12 57.903376
13 58.370961
28 55.307026

In [8]: np.mean(jfk.mu)

Out[8]: 47.904761904761905

In [9]: np.mean(jfk.lam)

Out[9]: 711.3381924198251

In [10]: dummy_terminal = pd.get_dummies(jfk['Terminal'])
dummy_terminal.columns = ['Terminal1', 'Terminal4', 'Terminal5', 'Terminal7', 'Terminal8']
jfk = pd.concat([jfk, dummy_terminal], 1)

```

```

In [11]: def replace_time(x):
    switcher = {'0000 - 0100': 0 , '0100 - 0200':1 , '0200 - 0300':2,
    '0300 - 0400':3, '0400 - 0500':4, '0500 - 0600':5, '0600 - 0700':6,
    '0700 - 0800':7, '0800 - 0900':8, '0900 - 1000':9, '1000 - 1100':10,
    '1100 - 1200':11, '1200 - 1300':12, '1300 - 1400':13, '1400 - 1500':14,
    '1500 - 1600':15, '1600 - 1700':16, '1700 - 1800':17, '1800 - 1900':18,
    '1900 - 2000':19, '2000 - 2100':20, '2100 - 2200':21, '2200 - 2300':22,
    '2300 - 0000':23
}
    return switcher[x]

In [12]: jfk["time"] = jfk.Hour.apply(lambda x: replace_time(x))

In [13]: jfk_clean = jfk.drop(columns = ["Terminal","Hour","Date"]).reset_index()
        jfk_clean = jfk_clean.drop(columns = "index")
        print(jfk_clean.shape)
        jfk_clean.head()

(2058, 15)

Out[13]:   Avg_Wait_t  Booths  passed_in_one_hour  total_arrival  mu  lam \
0           29      25                  1426       1466  57  1466
1           28      15                  1326       1486  88  1486
2           34      15                  280        352  18  352
3           22      15                  977       1020  65  1020
4           19      19                  780        793  41  793

          P_0          L          W Terminal1 Terminal4 Terminal5 \
0 -2.917354e-12  1423.810694  58.273289       1       0       0
1 -1.054026e-07  1471.148500  59.400343       1       0       0
2 -4.864973e-08  339.699808  57.903376       1       0       0
3 -8.558506e-08  992.306341  58.370961       1       0       0
4 -8.626067e-10  730.974530  55.307026       0       1       0

          Terminal7 Terminal8 time
0            0        0   13
1            0        0   18
2            0        0   19
3            0        0   20
4            0        0   11

In [14]: jfk_clean["booth_in"] = 1/(jfk_clean.Booths )

In [15]: jfk_clean["utility"] = jfk_clean.Avg_Wait_t + jfk_clean.Booths

In [16]: #X = sm.add_constant(jfk_clean[["booth_in"]])
        time = 1
        group = jfk_clean[jfk_clean.time == time]

```

```

est = sm.OLS(group.utility, group[["Booths","booth_in"]])
est2 = est.fit()
print(est2.summary())

# plt.rc('figure', dpi= 200)
# plt.text(0.01, 0.05, str(model.summary()), {'fontsize': 12}) old approach
# plt.text(0.01, 0.05, str(est2.summary()), {'fontsize': 12}, fontproperties = 'monospaced')
# plt.axis('off')
# plt.tight_layout()
# plt.savefig('OLS%s.png'%(time))

OLS Regression Results
=====
Dep. Variable: utility R-squared: 0.962
Model: OLS Adj. R-squared: 0.960
Method: Least Squares F-statistic: 382.6
Date: Wed, 08 May 2019 Prob (F-statistic): 4.47e-22
Time: 13:50:53 Log-Likelihood: -106.40
No. Observations: 32 AIC: 216.8
Df Residuals: 30 BIC: 219.7
Df Model: 2
Covariance Type: nonrobust
=====
            coef    std err          t      P>|t|      [0.025     0.975]
-----
Booths      2.5497    0.230     11.103      0.000     2.081     3.019
booth_in    88.8538   16.361      5.431      0.000    55.440    122.267
-----
Omnibus:           8.281 Durbin-Watson: 1.921
Prob(Omnibus):    0.016 Jarque-Bera (JB): 6.884
Skew:             1.080 Prob(JB): 0.0320
Kurtosis:          3.703 Cond. No. 124.
=====

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [17]: #est2.summary().as_latex()

In [18]: df_groups = []
         summaries = []
         results = pd.DataFrame(columns = ["Booths_params","booth_in_params", "R_square", "time"]
         rsquares = []
         for i in range(24):
             group = jfk_clean[jfk_clean.time == i]
             group = group[["utility", "Booths", "booth_in", "time"]]
             df_groups.append(group)

```

```

#X = sm.add_constant(group[["booth_in"]])
est = sm.OLS(group.utility, group[["Booths", "booth_in"]])
est2 = est.fit()
Booths_param = est2.params[0]
booth_in_param = est2.params[1]

rsquare = est2.rsquared
# results.iloc[i,"Booths"] = Booths_param
# results.iloc[i,"booth_in"] = booth_in_param
# results.iloc[i,"R_square"] = rsquare
results["Booths_params"][i] = Booths_param
results["booth_in_params"][i] = booth_in_param

results["R_square"][i] = rsquare
results["time"][i] = i

summary = est2.summary()
summaries.append(summary)

rsquares.append(rsquare)

print(len(df_groups))

```

24

```

/Users/mac/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1416: UserWarning: kurtosi
    "anyway, n=%i" % int(n))
/Users/mac/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1416: UserWarning: kurtosi
    "anyway, n=%i" % int(n))

In [19]: results["max_c"] = jfk_clean.groupby(by = "time").max()["Booths"]
         results["time"] = results["time"] + 1
         results

Out[19]:
   Booths_params  booth_in_params  R_square  time  max_c
0        2.38452          110.294  0.921876    1     16
1        2.54965          88.8538  0.962271    2     17
2        2.77804          88.5761  0.942388    3     14
3        2.65307          53.4147  0.95566    4     17
4        1.91944          93.5562  0.981156    5     21
5        1.98047          105.11   0.953806    6     20
6        2.6546           63.9199  0.964709    7     15
7        2.96579          77.4236  0.927836    8     18
8        3.13254          88.9573  0.928013    9     14
9        2.87069          101.269  0.919259   10     16

```

6

| | | | | | |
|----|---------|---------|----------|----|----|
| 10 | 2.73734 | 99.9679 | 0.933754 | 11 | 19 |
| 11 | 2.41814 | 99.377 | 0.966189 | 12 | 24 |
| 12 | 2.28977 | 105.725 | 0.963803 | 13 | 31 |
| 13 | 2.37313 | 134.09 | 0.942585 | 14 | 34 |
| 14 | 2.12654 | 175.246 | 0.941537 | 15 | 32 |
| 15 | 2.10257 | 188.151 | 0.941453 | 16 | 32 |
| 16 | 2.24244 | 214.409 | 0.93327 | 17 | 32 |
| 17 | 1.71045 | 219.73 | 0.913348 | 18 | 30 |
| 18 | 2.36134 | 107.525 | 0.942327 | 19 | 24 |
| 19 | 2.48574 | 107.436 | 0.902682 | 20 | 24 |
| 20 | 2.47652 | 114.653 | 0.908519 | 21 | 20 |
| 21 | 2.23202 | 178 | 0.921931 | 22 | 18 |
| 22 | 2.64025 | 147.771 | 0.933482 | 23 | 17 |
| 23 | 1.89465 | 135.824 | 0.950789 | 24 | 22 |

```
In [20]: from tabulate import tabulate
results = results.set_index('time')
print(tabulate(results, headers='keys', tablefmt='psql'))
```

| time | Booths_params | booth_in_params | R_square | max_c |
|------|---------------|-----------------|----------|-------|
| 1 | 2.38452 | 110.294 | 0.921876 | 16 |
| 2 | 2.54965 | 88.8538 | 0.962271 | 17 |
| 3 | 2.77804 | 88.5761 | 0.942388 | 14 |
| 4 | 2.65307 | 53.4147 | 0.95566 | 17 |
| 5 | 1.91944 | 93.5562 | 0.981156 | 21 |
| 6 | 1.98047 | 105.11 | 0.953806 | 20 |
| 7 | 2.6546 | 63.9199 | 0.964709 | 15 |
| 8 | 2.96579 | 77.4236 | 0.927836 | 18 |
| 9 | 3.13254 | 88.9573 | 0.928013 | 14 |
| 10 | 2.87069 | 101.269 | 0.919259 | 16 |
| 11 | 2.73734 | 99.9679 | 0.933754 | 19 |
| 12 | 2.41814 | 99.377 | 0.966189 | 24 |
| 13 | 2.28977 | 105.725 | 0.963803 | 31 |
| 14 | 2.37313 | 134.09 | 0.942585 | 34 |
| 15 | 2.12654 | 175.246 | 0.941537 | 32 |
| 16 | 2.10257 | 188.151 | 0.941453 | 32 |
| 17 | 2.24244 | 214.409 | 0.93327 | 32 |
| 18 | 1.71045 | 219.73 | 0.913348 | 30 |
| 19 | 2.36134 | 107.525 | 0.942327 | 24 |
| 20 | 2.48574 | 107.436 | 0.902682 | 24 |
| 21 | 2.47652 | 114.653 | 0.908519 | 20 |
| 22 | 2.23202 | 178 | 0.921931 | 18 |
| 23 | 2.64025 | 147.771 | 0.933482 | 17 |
| 24 | 1.89465 | 135.824 | 0.950789 | 22 |

```
In [21]: results[:12].to_latex(index=False)

Out[21]: '\\begin{tabular}{lllr}\\n\\toprule\\nBooths\\\_params & booth\\\_in\\\_params & R\\_square

In [22]: results.to_csv("parameters2.csv")

In [23]: np.mean(rsquares)

Out[23]: 0.9396934401078557

In [ ]:
```

C.3 GAMS

```
Sets
  t time /1*24/;

Scalar
  B      "Budget per day"          / 10000 /
  S      "personnel salary per day" / 14  /;

Parameter
  cmax(t)  maximum number of booth opening each hour
/
  1       16
  2       17
  3       14
  4       17
  5       21
  6       20
  7       15
  8       18
  9       14
  10      16
  11      19
  12      24
  13      31
  14      34
  15      32
  16      32
  17      32
  18      30
  19      24
  20      24
  21      20
  22      18
  23      17
  24      22  /

a1(t)  coeff for 1c-lam
```

```
a1(t) coeff for lc-lam
/ 1      110.2937285
  2      88.85381539
  3      88.57607534
  4      53.41473556
  5      93.55620583
  6      105.110452
  7      63.9199022
  8      77.42358587
  9      88.95733983
 10     101.2685795
 11     99.96787133
 12     99.37699035
 13     105.7251411
 14     134.090214
 15     175.2464158
 16     188.1508381
 17     214.4093222
 18     219.7296484
 19     107.5251829
 20     107.435589
 21     114.653227
 22     178.0004176
 23     147.7706578
 24     135.8240409 /
```



```
a2(t) coeff for c
/ 1      2.384518075
  2      2.549650703
  3      2.778041527
  4      2.653074157
  5      1.919444833
  6      1.980472068
  7      2.654595506
  8      2.965786605
```

```
a1(t) coeff for lc-lam
/ 1      110.2937285
  2      88.85381539
  3      88.57607534
  4      53.41473556
  5      93.55620583
  6      105.110452
  7      63.9199022
  8      77.42358587
  9      88.95733983
 10      101.2685795
 11      99.96787133
 12      99.37699035
 13      105.7251411
 14      134.090214
 15      175.2464158
 16      188.1508381
 17      214.4093222
 18      219.7296484
 19      107.5251829
 20      107.435589
 21      114.653227
 22      178.0004176
 23      147.7706578
 24      135.8240409 /

a2(t) coeff for c
/ 1      2.384518075
  2      2.549650703
  3      2.778041527
  4      2.653074157
  5      1.919444833
  6      1.980472068
  7      2.654595506
  8      2.965786605
```

```

9      3.132540828
10     2.870691008
11     2.737337759
12     2.41814318
13     2.289772009
14     2.373127565
15     2.126542186
16     2.10256522
17     2.242444069
18     1.7104446439
19     2.36133916
20     2.485742949
21     2.476521742
22     2.232016961
23     2.640254451
24     1.894645067    /;

Variables
  u   utility function
  c(t)  number of booths to open at hour t;

Integer variable c(t);
c.lo(t) = 1;

Equations
  Utility      objective function
  con(t)       constraints for number of opening booths each hour
  budget       total budget;

Utility ..  u == sum(t,a1(t)/(c(t))+a2(t)*c(t))/24;
con(t) ..   c(t) =l= cmax(t);
budget ..   sum(t,c(t))*2*S =l= B;

Model portfolio /all/;

Option solver=scip;
Solve portfolio using MINLP minimizing u;
Display c.l, u.l;

```

References

- Sundari, S. M. and Srinivasan, S. (2011). M/m/c queueing model for waiting time of customers in bank sectors. *Int. J. of Mathematical Sciences and Applications*, 1(3).
- Taylor, III, B. W. (2007). *Introduction to Management Science*. Prentice-Hall, Inc., Upper Saddle River, NJ, USA.