SINGAPORE UNIVERSITY OF
TECHNOLOGY AND DESIGN

(*Singapore Airlines A380-841* 2017)[1]

Simulation Model for Mobile Cleaning Teams at Changi Airside to Aid Manpower Optimization

<u>40.011 Data and Business Analytics</u>

Client: Changi Airport Group

Group 13

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[1] https://commons.wikimedia.org/wiki/File:Singapore_Airlines_A380-841_parked_at_Singapore_Changi_Airport.jpg

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Executive Summary

Changi Airport Group (CAG) is the team behind Singapore Changi Airport, a leading air hub in Asia and one of the world's most awarded airports. CAG outsources mobile cleaning teams to daily tasks such as (1) Checking and clearing of foreign object debris (FOD) bins, and (2) Manual sweeping and litter picking at aircraft stands and roadways. The cleaning teams work in pairs and are deployed daily to ensure that FOD bins are not overflowing and to upkeep the general cleanliness at the airside. The workers currently perform manual work, which is labour intensive, and by leveraging technology, CAG hopes to increase productivity in airside cleaning operations (ideally, increase by 50% manpower to service 200% area). The type of technology CAG wants to implement is the use of smart bins which can detect bin fullness from IoT sensors.

Flight volume today has fallen drastically due to COVID-19, but as travel restrictions begin to lift, a gradual ramp-up of flights is expected. Hence, there is a need to create a model to optimize the amount of manpower resources needed to clean the airside. Our model was built in two phases: (1) based on flight volume, without the use of smart bin technology, and (2) based on flight volume and bin fullness using data from the smart bin trial.

Firstly, the data we received were past flight volume data, the current deployment of teams and their area allocation, and coordinates of the aircraft stands. We pre-processed the flight volume data in SQLite and grouped them according to their respective areas and by months. Following which, we input coordinates of aircraft stands into QGIS and used Distance Matrix function to calculate the linear distances between stands so that we could calculate the travelling time between stands in each area. For the second phase, we received additional data from the smart bin trial where smart bins were placed at selected aircraft stands and detected the number of days for the bin to reach fullness. Through regression modelling, we plotted the best relationship between the fraction of bin filled per day and the average total flights per day. The best regression model was a linear model.

Secondly, Microsoft Excel was used to build our optimization model. After setting up the decision variables, objective function, parameters (fixed and adjustable), and constraints, we inputted the relevant data into our model. We ran the Solver using the GRG Non-linear method to solve for the optimal number of teams required each day. For example, we ran our model based on November 2019 flight volume and discovered that the total number of teams each day could have been reduced from 12 to 10 teams.

Some limitations of the model include the Distance Matrix function, which is linear distances; hence the travelling time calculated is an understatement of real-life context. Additionally, the model does not account for the possibility that the number of pairs of workers required could be more than the current number should the flight volume be much higher than pre-COVID. Summing up, reducing the number of cleaning teams required helps to minimize the manpower costs for the company.

1. Company Introduction

Changi Airport Group (CAG) is the manager of Singapore Changi Airport, a leading air hub in Asia and one of the world's most awarded airports. CAG performs the critical functions of airport operations, air hub development, retail and commercial activities, infrastructure development and airport emergency services.

CAG operates with the vision "Exceptional people, connecting lives" and mission of becoming the world's leading airport company, growing a safe, secure and vibrant air hub in Singapore and enhancing the communities they serve worldwide.

Today, Changi Airport is known for its highly efficient, technology-driven airport systems and services that provide unrivalled passenger experiences. CAG continues to challenge themselves to implement further creative solutions and signature experiences that will redefine air travel for generations to come.[2]

2. Problem Statement

Changi Airport currently has around 230 parking stands for aircraft. Each of these individual parking stands consists of one Foreign Object Debris (FOD) bin which collects the garbage around the specific parking stand and particular waste from aircraft. Changi Airport has currently executed a system of cleaning where for each shift, a team that consists of two cleaning staff would be assigned a fixed area of the airport. The workers will check and clear FOD bins and perform sweeping and litter picking at aircraft stands and roadways.

[2] https://www.changiairport.com/corporate/about-us.html

These mobile cleaning teams currently perform manual work which is labour intensive. By leveraging technology, CAG wishes to increase the productivity of airside cleaning operations. Ideally, by 50% manpower to service 200% of the area. As an initial step towards this goal, CAG hopes to implement smart bins at the airside in place of FOD bins. The main difference between these bins is that FOD bins require constant checking for the staff to know whether it should be cleared whereas the smart bins would provide an indication when the bin is filled so that the staff can clear them directly without having to check them multiple times.

The main task assigned to our team is to build a simulation model that optimizes the number of cleaning teams per shift. The project is split into two main phases. In phase one, we are to assess the current mobile cleaning team allocation per shift and check whether it could be improved further or whether it is already at an optimal. Phase two is where we are required to optimize the number of teams needed per shift by considering the new implementation of smart bins.

Therefore, our task is to build optimization models under these two different phases by considering various factors such as flight volume that contributes mainly to the process and efficiency of cleaning.

3. Pre-processing of Data

From the Changi Aerodrome Map, we can mark the geographic locations of each aircraft stand, colour-coded by their specific sectors given their geographic coordinates. Through this method, we can see which areas have more stands, and ultimately which sectors might have more ground to cover, thus showing which sectors might take a longer time for the cleaning teams to finish tasks. We calculated the linear distance between each stand (bin) represented by the dots on the map in Figure 3.1 using QGIS Distance Matrix function.

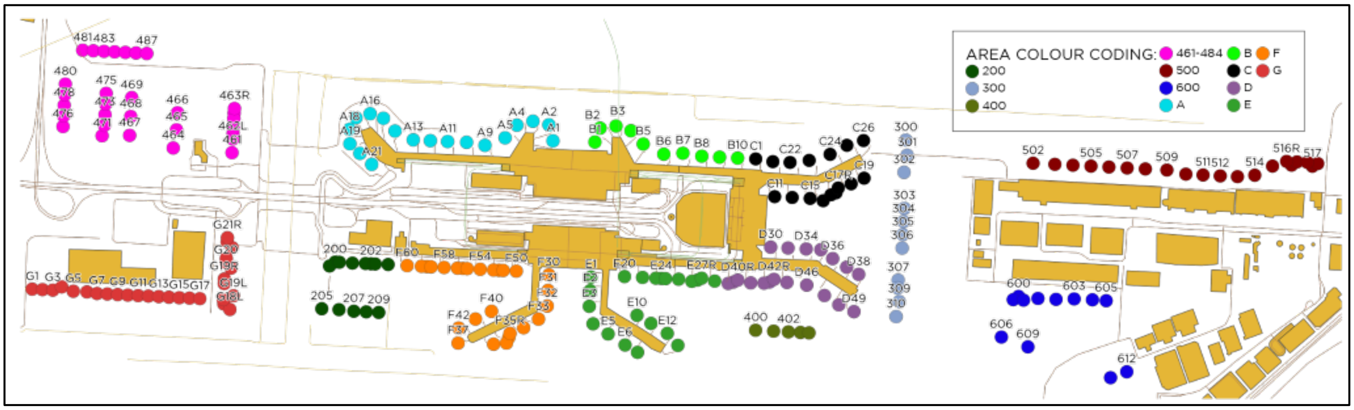

Figure 3.1, Changi Aerodrome Map on QGIS.

After obtaining the linear distances from QGIS, we then totaled up the total distance and respective travel time within each area based on our assumption of a reasonable path the workers might take. For example, that workers will travel from A1 to A2, from A2 to A3, etc. and not from A1 to A10 and then back to A2. To calculate the travelling time, we assumed that the truck travels at a speed of 30km/h on average.

	start	end	dist (m)	area		area	dist (m)	time (min)
0	A1	A2	69.8962	A		A	1198.36	2.3967273
1	A2	A3	69.0425	A		B	681.746	1.3634913
2	A3	A4	69.5233	A		C	1038.23	2.0764622
3	A4	A5	72.8857	A		D	1130.47	2.2609301
4	A5	A9	90.2857	A		E	1368.08	2.7361645
5	A9	A10	78.3569	A		F	1457.84	2.9156812
6	A10	A11	80.0815	A		200-209	699.267	1.3985343
7	A11	A12	72.4488	A		300	751.779	1.5035587
8	A12	A13	72.328	A		400-404	224.813	0.4496256
9	A13	A14	85.4114	A		500	1230.76	2.4615261
10	A14	A15	72.7073	A		600	1128.68	2.2573611
11	A15	A16	59.3311	A		461-484	1998.93	3.9978582
12	A16	A17	62.1806	A		G	1235.94	2.4718835

Figure 3.2, Distance between Stands and Travelling Time within Areas.

Next, using SQLite, we pre-processed flight volume data by extracting the relevant fields such as date, time and parking stand of each flight. We counted the varying flight volume of each area according to the different shifts which will be used in our regression and optimization models.

	DATE	TIME	AIBT_FINAL	SHIFT	SIBT	FLIGHTO	NATURE	FLIGHT_I	AIRCRAF	AIRCRAFT	TERMINA	PARKING	GATE
319	2019-06-07	14:55	2019-06-07 14:55	1	6/7/2019 15:00	O	PAX			B8338	1	C17L	C17L
320	2019-06-07	15:17	2019-06-07 15:17	1	6/7/2019 15:30	O	PAX			9VJSQ	1	D49	D49
321	2019-06-07	15:32	2019-06-07 15:32	1	6/7/2019 15:50	O	PAX			9VJSV	1	C25	C25
322	2019-06-07	15:42	2019-06-07 15:42	1	6/7/2019 15:35	O	PAX			PHBVO	1	D42	D42
323	2019-06-07	15:49	2019-06-07 15:49	1	6/7/2019 15:45	O	PAX			9VJSB	1	D35	D35
324	2019-06-07	15:56	2019-06-07 15:56	1	6/7/2019 15:45	O	PAX			FGZNE	1	C15	C15
325	2019-06-07	15:59	2019-06-07 15:59	1	6/7/2019 16:25	O	PAX			B5948	1	D36	D36
326	2019-06-07	16:01	2019-06-07 16:01	1	6/7/2019 15:45	O	PAX				1	D32	D32

Figure 3.3, Flight Volume Data provided by CAG in SQLite.

DATE	SHIFT	TotalArea_A	TotalArea_B	TotalArea_C	TotalArea_D	TotalArea_E	TotalArea_F	TotalArea_T4G	TotalArea_T4	TotalArea_200	TotalArea_200_2	TotalArea_300	TotalArea_500	TotalArea_600	TotalArea_461_4
1/6/2019	1	51	27	49	35	53	54	51	54	0	5	0	0	1	2
2/6/2019	1	53	29	53	35	50	50	49	52	0	5	0	0	3	2
3/6/2019	1	53	28	45	39	58	57	49	52	0	4	0	0	1	2
4/6/2019	1	49	28	49	43	52	49	51	54	0	4	0	0	2	2
5/6/2019	1	48	27	50	41	47	55	50	54	0	6	0	0	1	3
6/6/2019	1	55	28	47	39	48	58	52	56	0	5	0	0	1	3

Figure 3.4, Daily Number of Flights for each Area Allocation.

4. Regression Modelling

After pre-processing the data, we were able to obtain the number of flights per month for each stand. We combined this with the smart bin trial data that is given to us by CAG to do regression modelling. We took the fraction of bin filled per day to be the reciprocal of the average number of the days it takes to fill the bin: $Fraction\ of\ bin\ filled\ per\ day = \frac{1}{Average\ Days\ to\ Fullness}$.

Serial	Description	Stream Type	Capacity	Avg. Days to Fu
1517799	A9		HC	5.0 days
1517800	A11		HC	3.2 days
1517801	A10		HC	2.8 days
1519110	A12		HC	3.0 days
8520062	A13		SC	2.4 days

Figure 4.1, An example of the Smart Bin Trial Data (5 stands) provided by CAG.

We then tried various regression models to find the best relationship between the average total flights per day (independent variable) and the fraction of bin filled (dependent variable). Our resulting linear model in Figure 4.2 below is the best fit based on R^2 value and distributed residuals. The resulting regression equation is then used in our optimization model.

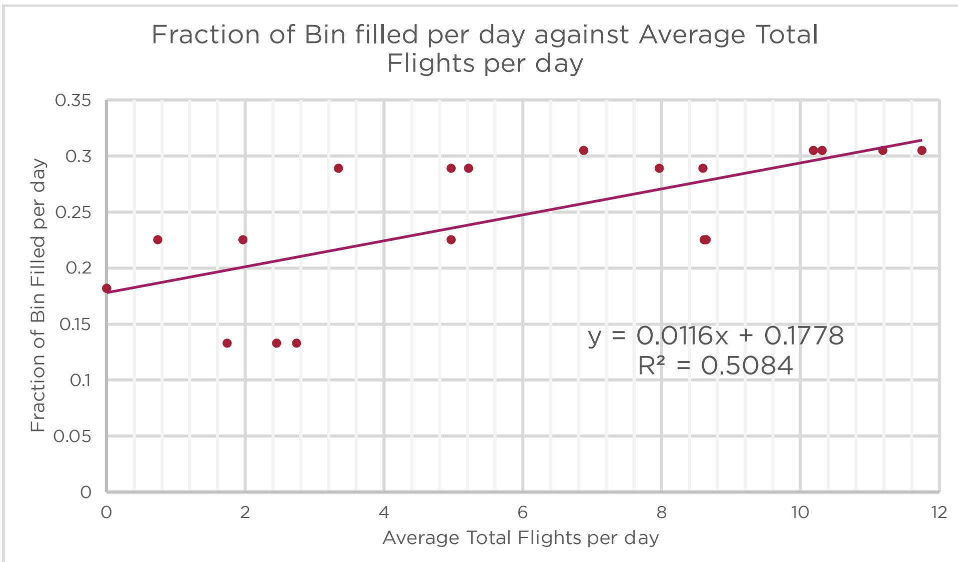

Figure 4.2, Regression Model.

5. Optimization Model

The choice of tool is Microsoft Excel add-in program, Solver. Due to the nature of the Model having non-linear constraints with logical statements, the choice of optimization is GRG Nonlinear in Excel. The objective function of the Model is to minimize the number of pairs of workers needed for each shift such that the excess time left of their working hours per team is minimum. The decision variables are binary variables, where 1 represents the area (column) is allocated to the pair of workers for that shift (row), and 0 represents the area is not assigned to the team of workers for that shift. Example for the optimal number of pairs of workers in the table below, looking at the 4th row: Shift 1 Pair 4, which represents the 4th pair of workers in Shift 1 and the area allocated to them are 400-404, 500, 600 and 461-484. The constraint is each area, if opened, is checked once only for every round during each shift.

Area Allocation & Solver

	A	B	C	D	E	F	200-209	300	400-404	500	600	461-484	G	
Shift 1 Pair 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Shift 1 Pair 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Shift 1 Pair 3	0	0	0	0	0	0	0	0	0	0	0	0	1	1
Shift 1 Pair 4	0	0	0	0	0	0	0	0	1	1	1	1	0	1
Shift 1 Pair 5	0	0	1	1	1	0	0	1	0	0	0	0	0	1
Shift 1 Pair 6	1	1	0	0	0	1	1	0	0	0	0	0	0	1
Shift 2 Pair 1	0	0	0	0	0	0	0	0	0	0	0	1	1	1
Shift 2 Pair 2	0	0	0	0	0	0	0	1	1	1	1	0	0	1
Shift 2 Pair 3	0	0	1	0	1	1	0	0	0	0	0	0	0	1
Shift 2 Pair 4	1	1	0	1	0	0	1	0	0	0	0	0	0	1
Shift 3 Pair 1	0	0	0	0	0	0	0	0	0	0	0	1	1	1
Shift 3 Pair 2	1	1	1	1	1	1	1	1	1	1	1	0	0	1
													Solver	10

Constraint

	A	B	C	D	E	F	200-209	300	400-404	500	600	461-484	G
Shift 1 Area	1	1	1	1	1	1	1	1	1	1	1	1	1
Open/Close	1	1	1	1	1	1	1	1	1	1	1	1	1
Shift 2 Area	1	1	1	1	1	1	1	1	1	1	1	1	1
Open/Close	1	1	1	1	1	1	1	1	1	1	1	1	1
Shift 3 Area	1	1	1	1	1	1	1	1	1	1	1	1	1
Open/Close	1	1	1	1	1	1	1	1	1	1	1	1	1

Figure 5.1, Objective Function, Decision Variables and Constraints.

The parameters of the Model built can be split into two main categories: Mainly fixed parameters and adjustable parameters. The adjustable parameters are essentially variables that the client has requested to be adjustable before each round of optimization.

Adjustable parameters (Purple coloured cells in Figure A of the appendix) include:

1. The number of stands or bins opened per area (airport can be closed for specific areas).
2. The number of rounds around their allocated area per shift for the pairs of workers.
3. Checking and Clearing Timings of each bin, current assumption: 2 minutes and 4 minutes (if the bin is fully filled) respectively.
4. Total (Includes non-working) hours per shift.
5. Total working hours per shift.
6. Average Flight Volume per day for the month.

Fixed parameters (White coloured cells in Figure A of the appendix) include but not limited to:

1. Travel time between each bin.
2. The fraction of bin filled per day for each area.

From the above parameters, we sum up the clearing time per bin based on the fullness of the bin, the checking time per bin and the travel time between each bin for the allocated area for a round of check. Then, we sum up for all rounds of a check, resulting in the Consolidated Timings shown below in Figure 5.2. Finally, the different allocation of areas for each team in each shift will affect the timing needed for each pair of workers and hence affect the excess time remaining of their working hours. Besides, another constraint is that the total working time we calculated must be within the shift timings.

Consolidated Timings (All Rounds)

	Shift 1	Shift 2	Shift 3
A	129.6865638	86.45770917	48.09965459
B	72.41394798	48.27596532	26.95998266
C	115.509973	77.00664865	43.20412433
D	134.9470803	89.9647202	49.9033601
E	150.2100872	100.1400581	55.26542906
F	182.6902874	121.7935249	67.02756246
200-209	90.31070602	60.20713735	32.71656867
300	78.33785213	52.22523476	28.32361738
400-404	27.8341533	18.5561022	10.0356511
500	146.7352566	97.82350442	52.88915221
600	89.16216681	59.44144454	32.13272227
461-484	212.5101489	141.6734326	76.5187163
G	198.5840008	132.3893339	72.69646695

Excess Timings (For Cleaning Tasks + Travel between Areas)

	Timings needed per shift	Shift Working Hc	Excess(min)
x11	0	480	480
x12	0	480	480
x13	198.5840008	480	281.4159992
x14	476.2417256	480	3.758274356
x15	479.0049926	480	0.995007398
x16	475.1015051	480	4.898494864
x21	274.0627665	300	25.93723351
x22	228.0462859	300	71.95371408
x23	298.9402317	300	1.059768307
x24	284.905532	300	15.09446796
x31	149.2151832	480	330.7848168
x32	446.5578248	480	33.44217517

Figure 5.2, Consolidated Timings and Excess Timings.

After running the Solver, Excel will choose the optimal/minimum number of teams for each shift, such that the above excess time for each chosen pair of workers with their specific area allocation is the minimum. Then we collate the number of teams of workers needed per shift into a table shown below in Figure 5.3 for the client to view.

Result

Optimal No. of Teams	
Shift 1	4
Shift 2	4
Shift 3	2

Figure 5.3, Result of the number of teams needed (for November 2019)

6. Main Results

To visualize the results of our model, we use the flight data for the month of November 2019 and input that data into our optimization model. Looking at Figure 6.1 below, we see that only 4 teams are needed for Shift 1 as compared to 6 teams, while the number of teams for Shift 2 and Shift 3 remained the same, at 4 teams and 2 teams respectively. We can also examine what the excess timings are like from each shift. The reduction of 2 teams for shift 1 represents a reduction in manpower costs for our client.

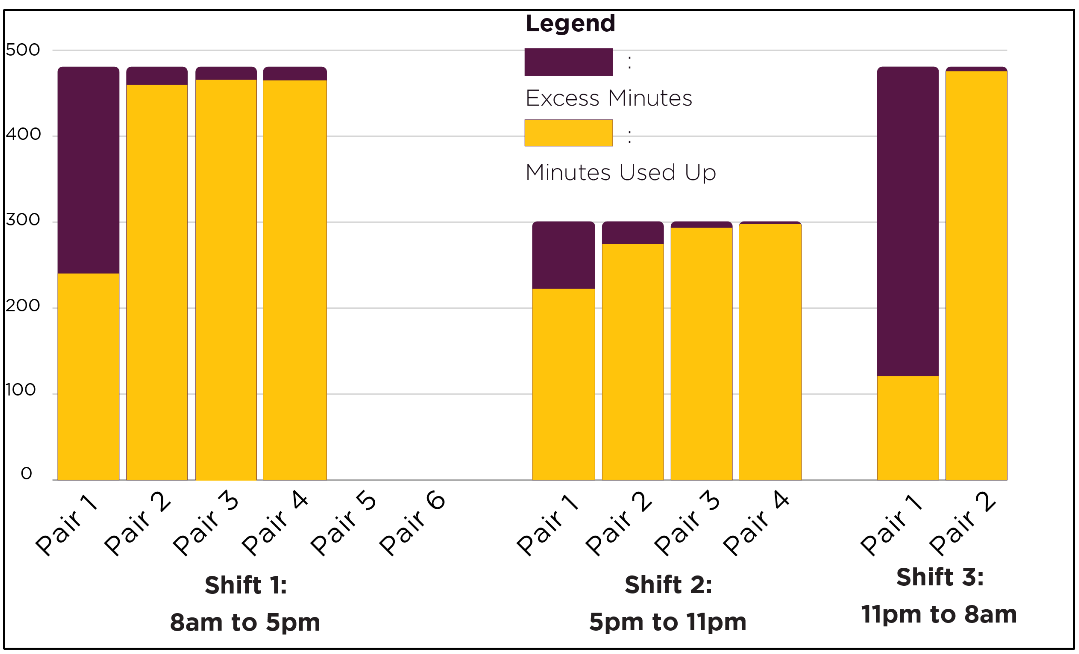

Figure 6.1, Results for November 2019.

7. Assumptions and Limitations

Firstly, due to the limited number of smart bin trials, we had insufficient data points to plot an accurate regression model to model the relationship between flight volume and rate of bins filling up. We were only given 20 data points to work with, but having 30 or more data points might have helped us build a more accurate regression model. To overcome this, we had to classify and artificially inflate the number of data points to improve the precision of our regression modelling.

Secondly, by calculating the linear distances between stands, we assumed that the travelling path is a straight line, which does not hold in reality as the path taken is non-linear. Therefore, the linear distances would be an underestimation of the actual travelling path distance between the stands, and hence an underestimation of the travelling time that we had used in our optimization model.

Lastly, the travelling time calculated is also measured within each area and does not factor in the travelling time between areas. The reason is due to the numerous permutations of the possible ways to from one area to the other, for example, one could travel directly to it or loop through other areas (if those areas are also allocated to them to check and clear).

8. Possible Improvements

One possible improvement to the current optimization model would be to add in the entire distance matrix from QGIS into a separate sheet in Excel. The distance matrix includes the linear distance from every stand in the airport to every other stand. Then for every permutation of the area allocation, given a set of stands, we can use the lookup function to find out the linear distance between every stand for the allocated area. Then following the travelling salesman problem, for every permutation, we need to find the shortest distance to travel each stand once and back to the initial stand.

Appendix

Parameters of the Model:

Calculations

y = 0.0116x + 0.1778
Equation of regression

** MUST copy paste
Month = Nov

Timings per round of clearing

SHIFT 1 areas	Open=1/Closed=0	no. of stands/bins	Fraction of Bin per stand Filled per day	Avg flights per stand per day	Clear time (With Flight Volume) per area/min
A	1	18	0.2706	8	2.4354
B	1	10	0.2822	9	1.411
C	1	16	0.2938	10	2.3504
D	1	19	0.259	7	2.4605
E	1	21	0.2474	6	2.5977
F	1	26	0.2358	5	3.0654
200-209	1	13	0.201	2	1.3065
300	1	11	0.201	2	1.1055
400-404	1	4	0.1894	1	0.3788
500	1	21	0.1894	1	1.9887
600	1	12	0.201	2	1.206
461-484	1	30	0.1894	1	2.841
G	1	29	0.2242	4	3.2509

Clear time (All bins full) per area/min	Check time per area/min	Travel Time (within area) per area/min
72	36	4.793454586
40	20	2.726982659
64	32	4.152924326
76	38	4.521860102
84	42	5.47232906
104	52	5.83136246
52	26	2.797068674
44	22	3.007117378
16	8	0.899251101
84	42	4.923052209
48	24	4.514722271
120	60	7.995716301
116	58	4.943766946

Assumptions

Number of Rounds per day	
Shift 1	3
Shift 2	2
Shift 3	1

Check and Clear Timings	
check time (mins)	2
clear time (mins)	4

Hours per shift	
Shift 1	9
Shift 2	6
Shift 3	9

Sum should be 24 hours. Assumption that there are always workers 24 hours

Working Hours per shift	
Shift 1	8
Shift 2	5
Shift 3	8

Flight Volume Data

Total Flights per area per month	A	B	C	D	E	F	200-209	300	400-404	500	600	461-484	T4G
Jan													
Feb													
Mar													
Apr													
May													
Jun	4345	2438	4117	3126	4030	4422	493	331	11	593	522	249	3213
Jul	4501	2522	4198	3242	4184	4596	477	402	4	604	538	242	3299
Aug	4482	2533	4162	3268	4131	4643	524	401	7	611	574	245	3253
Sep	4247	2523	4114	3015	4047	4429	492	433	3	596	536	238	3172
Oct	4382	2571	4409	3371	3952	4243	533	540	31	617	546	266	3251
Nov	4078	2488	4738	3839	3468	3722	524	627	34	630	565	238	3219
Dec	4246	2613	5000	4072	3640	3869	524	555	43	525	587	273	3383

Avg flights per stand per day	A	B	C	D	E	F	200-209	300	400-404	500	600	461-484	T4G
Jan	0	0	0	0	0	0	0	0	0	0	0	0	0
Feb, If Leap year: 29 days	0	0	0	0	0	0	0	0	0	0	0	0	0
Mar	0	0	0	0	0	0	0	0	0	0	0	0	0
Apr	0	0	0	0	0	0	0	0	0	0	0	0	0
May	0	0	0	0	0	0	0	0	0	0	0	0	0
Jun	9	9	9	6	7	6	2	2	1	1	2	1	4
Jul	9	9	9	6	7	6	2	2	1	1	2	1	4
Aug	9	9	9	6	7	6	2	2	1	1	2	1	4
Sep	8	9	9	6	7	6	2	2	1	1	2	1	4
Oct	8	9	9	6	7	6	2	2	1	1	2	1	4
Nov	8	9	10	7	6	5	2	2	1	1	2	1	4
Dec	8	9	11	7	6	5	2	2	1	1	2	1	4

** To paste each row (month) as a col in the calulcations tables: Copy the row, then use paste special: pick values and transpose to enter as a column in Column T