London Fire Brigade Simulation

By

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1.Model Overview and Objectives

1.1 Overview

The London Fire Brigade (LFB) is a London's fire and rescue service. Its reach is expansive, covering the entirety of Greater London. This area is home to over nine million people, and 1,569 square kilometres of property to protect. This immense coverage leads to immense demand for LFB's services. The effects of climate change are adding to this demand. In July of 2022, during England's second heatwave of the summer, LFB saw its busiest day since the blitz.[i] This can be attributed to increasingly arid conditions exasperated by rising temperatures. The organization's efficiency is, and will continue to be, paramount in meeting this increasing demand, and ensuring the safety of all it serves.

1.2 Objectives

- To determine the optimal allocation of Dual Pump Ladder (DPL) trucks between the five busiest fire stations of the LFB during their peak call volume
- To accurately model the five busiest stations of the LFB over a three day period of receiving their highest call volume

2. Data Exploration and Analysis

2.1 Data Integrity and Collection Methods

The data used is available on London Datastore, a platform that is free and publicly accessible. Two different datasets relating to the LFB were downloaded from this source, one titled 'LFB Mobilization Data,[ii]' and the other 'LFB Incident Data'[iii]. Both contained data pertaining to every incident the LFB tended to over the last three years. These datasets are updated monthly. ***Hence, the data is current, licensed, and reliable.***

2.2 Data Exploration, Filtering, and Cleaning

2.2.1 Exploration

Data exploration is done using R and Excel. Most of the data exploration consisted of deciding which columns were needed, figuring out what each column meant by looking at the dates and times, and looking for any correlations between the number of trucks needed, incident type, time it took to tend to the incident, and truck preparation (turnout) time. These boxplots can be seen as Figure B in the appendix. Due to the amount of outliers, removing them was decided against, and individual distributions would be used instead to account for these outliers.

2.2.2 Filtering

After getting a final dataset, we filtered it for summer months (May, June, and July), then extracted data relevant to only the top five busiest stations (Soho, Paddington, Lambeth, North Kensington, and Euston). See Figure 1 for the script that was used.

```
install.packages('readxl')
library(readxl)
df=read_excel(file.choose())
df$date=as.Date(df$DateAndTimeMobilised,format = "%d/%m/%Y")
df1=df
df1$month=months(df1$date)
df2=df1[df1[,"month"]=="May"| df1[,"month"]== "June" | df1[,"month"]== "July",]
sort(table(df2$DeployedFromStation_Name))
df3=df2[df2[,"DeployedFromStation_Name"]=="Soho"| df2[,"DeployedFromStation_Name"]== "Paddington" |
          df2[,"DeployedFromStation_Name"]== "Lambeth"|
          df2[,"DeployedFromStation_Name"]=="North Kensington"| df2[,"DeployedFromStation_Name"]=="Euston",]
```

Figure 1. Filtering Script

2.2.3 Cleaning and Merging

Table 1 shows the main columns that were taken into consideration, as well as a brief description of each. Afterwards, null values were located. If an incident contained a null value in any of the resulting columns, the entire incident was removed from the dataset. Both datasets are matched with primary key 'incident number,' a unique identifier for each incident that LFB serviced. The two datasets were merged into one using this primary key to avoid repeated incidents and to ensure that the resulting dataset only contained incidents that were present in both initial datasets (Figure 2).

```
t1=read.csv(file='C:/021/mob_filtered.csv')
t2=read.csv(file='C:/021/inc_filtered.csv')
one_data=merge(t1,t2,by='IncidentNumber')
write.csv(one_data,"C:\\021\\one_data.csv",row.names = FALSE)
table(one_data[1,53])
z=one_data[1:15698,16]==one_data[1:15698,53]
table(z)
f=read.csv(file='C:/021/project/filtered_data/joined_uncleaned.csv')
f1=f[c(-6,-19,-20,-21,-22,-26,-28,-29,-30,-35,-38,-39,-40,-41,-42,-43,-45,-46,-47,-48,-49,-50)]
sum(is.na(f$DelayCode_Description))
f2=f1[c(-28,-29,-30,-42,-43)]
sum(is.na(f$IncidentNumber))
sum(is.na(f$DeployedFromStation_Name))
sum(is.na(f$IncidentStationGround))
sum(is.na(f$DateAndTimeMobilised))
sum(is.na(f$DelayCode_Description))
```

Figure 2. Cleaning and Merging Script

Table 1. Column Descriptions

LFB Combined Dataset Columns	
Incident Number	Unique incident identifier
CallYear	Year call was placed
Resource_code	Unique truck IDs
Time_of_call	Time call reached the station
Truck_mobilized	Time truck was deployed from station
Time_Arrived	Time truck reached the incident location
TurnoutTimeSeconds	Time between call reaching the station and the truck being deployed
TravelTimeSeconds	Time took to reach incident from fire station
AttendanceTimeSeconds	Total time the truck(s) took to tend to the incident once it/they arrived

TimeLeft	Time the truck left the incident location
DeployedFromStation	Station that sent fire truck to incident location
Date	Date of incident
StopCodeDescription	Incident type (1,2,3,4, or 5)
IncidentStationGround	Station that is nearest to incident

2.4 Deriving Parameters

The parameters needed to create the simulation include:

- Turnout time (for each station)
- Travel time (both to and from the incident)
- Attendance time (for each incident type)
- Interarrival rate of calls

A few different approaches were used to find these parameters. This was purely due to different members of the group preferring different methods.

2.4.1 Turnout Time

First, Python was used to find which distributions fit the turnout time data for each station the best, as well as the parameters for said distributions. However, sometimes the distribution that fit the data best was not included in Simul8(F distribution, Laplace distribution, Rayleigh distribution etc). Consequently, there were instances in which the second or third best distribution was chosen over the first because the first best distribution was not available to use on Simul8. For instance, look at the turnout time distribution for the Soho station (Figure 3). A t-distribution is the closest, but we use a normal distribution since the t-distribution and laplace distribution weren't available on Simul8. Figure 3 shows the top five distributions fit over the Soho turnout time data. This process was repeated for each station's turnout times, see Figure A in the appendix for the other four stations.

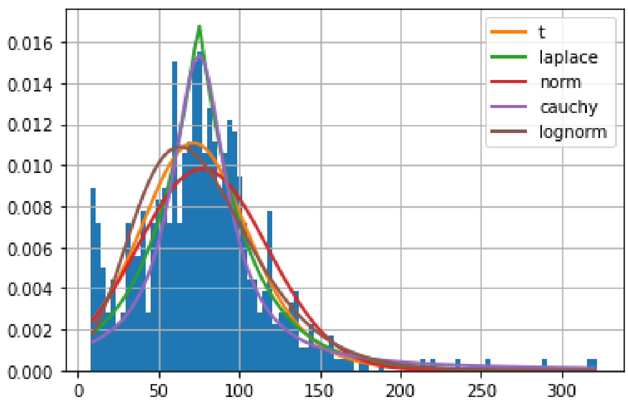
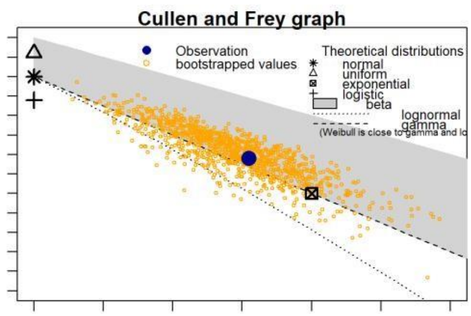


Figure 3. Soho Turnout Time

2.4.2 Attendance Time

R was used to fit the attendance time distributions. First a histogram of each incidence type's attendance times, as well as a CDF were plotted to visualize the data using the command 'plotdist()'. Then the data and 1000 bootstrapped values were plotted onto a Cullen and Frey graph to decide which distribution was the most representative of the data using command 'descdist()'. Figure 5 shows the histogram and CDF of the attendance time for primary fires. Figure 4 shows the Cullen Frey graph. From the graph, we can



see that a lognormal distribution fits the data best. For Figure 4. Primary Fires Attendance Time lognormal distributions, Simul8 takes the mean and standard deviation of the data as the parameters, so these were found in R and put into Simul8. This process was repeated for each incident type.

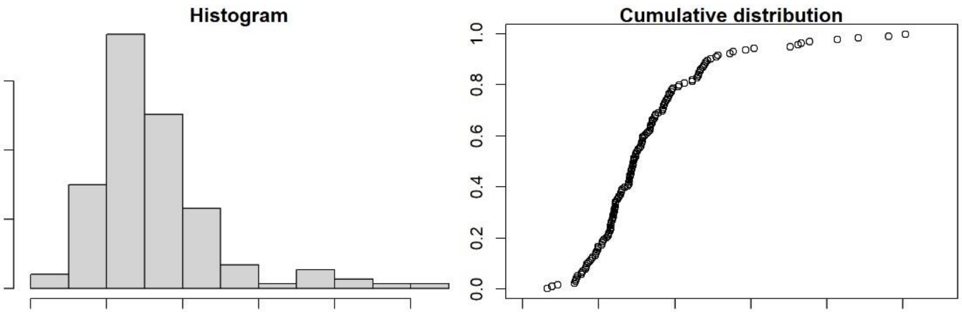


Figure 5. Primary Fires Attendance Time

2.4.3 Call Interarrival Times

The call volume was intended to mimic theirs highest call volume recorded since the blitz, which was 2,600 calls per day. However, this number includes calls sent to all stations of the LFB. There are 106 of them. To find the approximate number of calls to each station, 2,600 was divided by 106. This was multiplied by five since the model includes five stations. This value (123) was the number of calls arriving per day, so the interarrival time was found by dividing the number of seconds in a day (86,400) by 123. This served as the interarrival rate of calls.

2.4.4 Travel Times

The time it takes each truck or set of trucks to reach an incident is equal to the average of all travel times in the final dataset, because the average travel time was roughly the same regardless of the station the truck(s) left from. The return time was a replicate of this metric, since return time data was unavailable.

3. Simulation Development

3.1 Description

The model has the general flow outlined in Figure 6. The model was developed to include calls as the entities that utilize trucks and 999 operators as resources. The model must have the ability to recruit trucks from the second or third closest stations if the trucks at the nearest station are already occupied. The number of trucks needed per incident varies depending on the incident type, so this needed to be implemented into the model as well. There are five types of incidents: primary fire (PF), secondary fire (SF), special services (SS), automatic fire alarm (AFA), false alarm (FA).See Figure 7 for the, a bit more detailed, activity flow diagram.

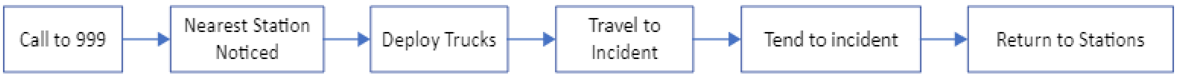


Figure 6. General Flow

3.1.1 Model Inputs and Outputs

Interarrival rates of the 999 calls served as the model inputs, controlling the traffic of entities throughout the model. The outputs included resource utilization for each station's trucks, and the overall time in system. The resource utilization aided in optimizing the allocation/amount of trucks per station, while the time in system served to validate the model.

3.2 Activity Flow Diagram

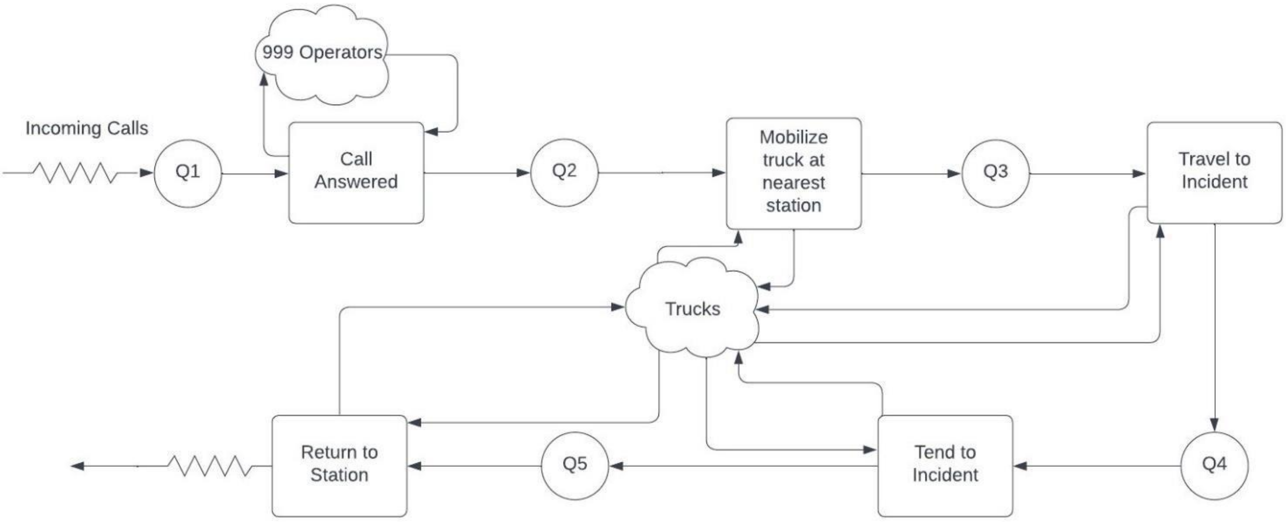


Figure 7. Activity Flow Diagram

3.3 Assumptions

- A 999 call lasts 25 seconds on average before the closest station to the incident is informed
- A truck is a 'dual pump' truck, so two pumps is equivalent to one truck
- Mobilization of truck begins as soon as station is notified
- Each station responds to incidents within approximately the same square area
- One call occupies exactly one 999 operator until the nearest station is informed
- Every truck returns to its home station once the incident has been tended to
- A truck's return time is equivalent to its travel time to the incident

3.3 Overall Functionality

Figure 8 shows the final model's structure. The following list goes through the functionality from left to right.

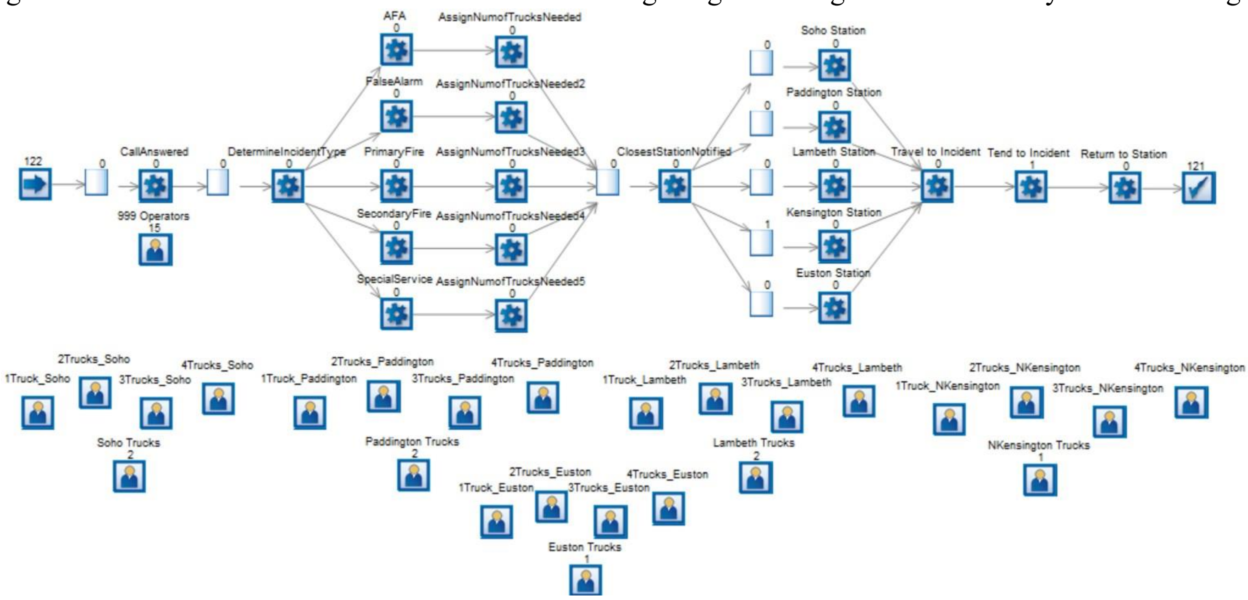


Figure 8. Final Model

I. Calls are input into the system according to their interarrival rate.

II. Calls are answered at ‘CallAnswered’, they require one 999 operator, and last 10 seconds on average.

III. At ‘DetermineIncidentType’, the calls are routed out to five activities in parallel (labelled after the different incident types) according to the probability of each incident type (Figure 9). These probabilities were calculated by finding the proportion of calls that were each incident type during the summer months over the past 4 years.

   a. At each activity labelled after an incident type, the call is labelled as one of the five types using the label ‘Incident Type’ (Figure 10)

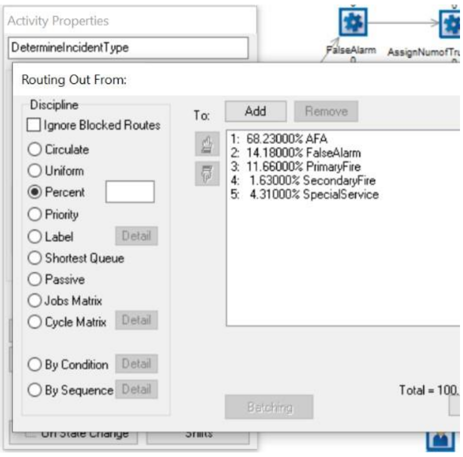


Figure 9. Routing Out from DetermineIncidentType

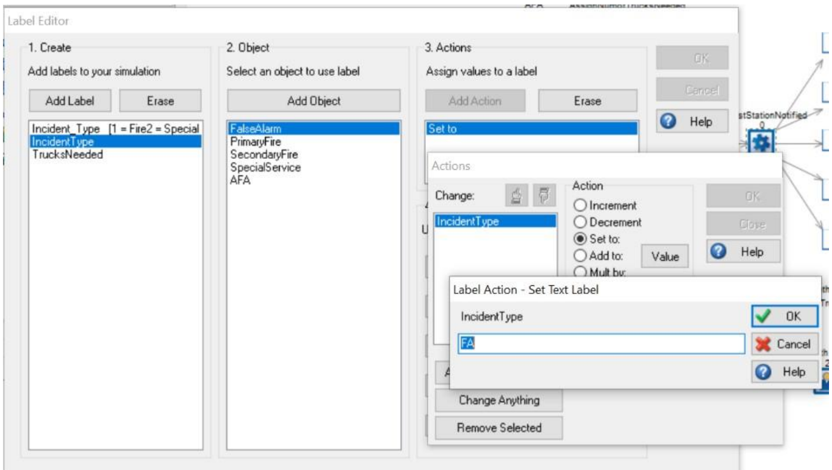


Figure 10. Labelling Incident Type of Call

IV. At the next five activities in parallel, the number of trucks needed per incident was determined by using labels that are set to 1, 2, 3, or 4 (Figure 12) according to a probability profile (Figure 11). Each incident type has a different probability profile regarding the number of trucks needed, so this step was repeated for each incident type.

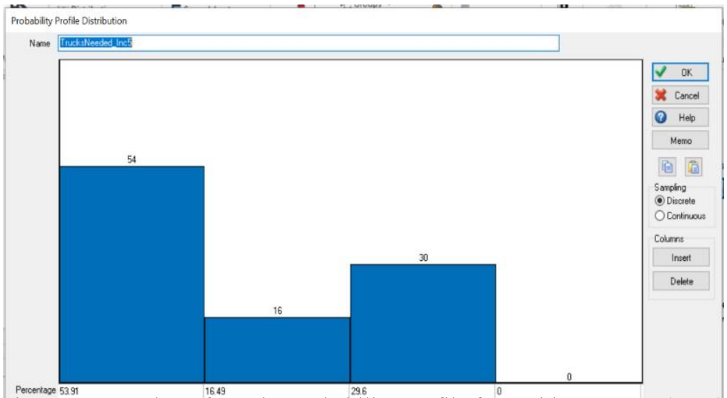


Figure 11. Number of Trucks Probability Profile for Incident Type 5 (AFA)

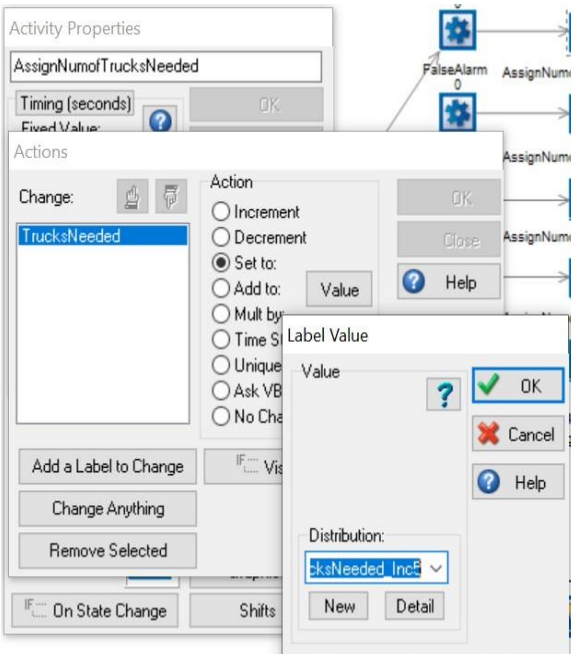


Figure 12. Using Probability Profile to Label

V. 'ClosestStationNotified - Routing out from this activity is proportional to the number of calls that were forwarded to each station in the data set (Figure 13).

VI. At each station, the appropriate number of trucks from designated stations are assigned to the incident (see section 3.3.1). The truck resources are not released until the entity leaves the system. This is also where the trucks are prepped, so the distributions found for each stations time are this activity's duration.

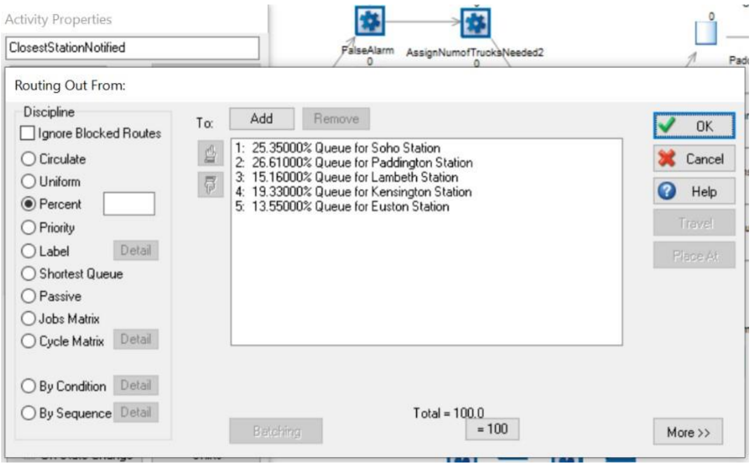


Figure 13. Routing Out From 'ClosestStationNotified' turnout

VII. The truck(s) travel to the incident.

VIII. The incident is tended to.

a. The time it takes the truck(s) to tend to the incident is dependent on the type of incident it is, so the duration of this activity is a label based distribution that uses the label 'IncidentType' IX. The truck(s) return to their home station.

3.3.1 Truck Assignment Using Resource Pooling

Truck assignment takes place once the nearest station is notified (i.e. at the activities named after the stations, 'Soho Station', 'Paddington Station', etc). These activities require resources as seen in Figure 14. Each of these resources is a resource pool tied to a main resource containing all of the station's trucks. The resource pools ensure that 1, 2, 3, or 4 trucks are required simultaneously. This is achieved by making the minimum and maximum number of resources in each resource pool the same. For example, if two of Soho's trucks were required for an incident, the activity would pull two trucks at the same time from the '2Trucks_Soho' pool. Notice that the 'Select resource by label [TrucksNeeded]' box is ticked. This makes sure that the number of trucks needed, denoted by the TrucksNeeded label, corresponds to the pool containing that specific number of trucks.

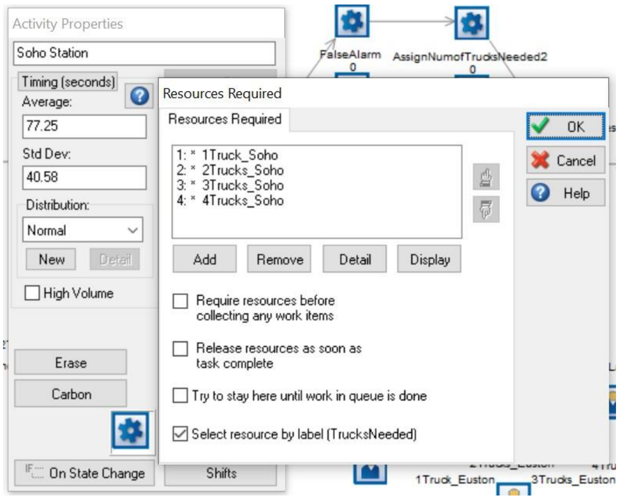


Figure 14. Truck Quantity Assignment

If there are not enough trucks at the nearest station, trucks must be recruited from the next nearest station. To give the model this ability, first the relationships between the stations were ranked from one to three, one being closest. This was done by counting how many times that each stated recruited trucks from each other station. A relationship matrix is shown in Table 2. Note, some stations only ever recruited trucks from one or two other stations. This is reflected in the relationship matrix.

Table 2. Station Relationship Matrix

	Soho	**Euston**	**Paddington**	**N. Kensington**	**Lambeth**
Soho	X	1	2	0	3

Euston	3	X	2	0	0
Paddington	3	2	X	1	0
N. Kensington	0	0	1	X	0
Lambeth	1	0	0	0	X

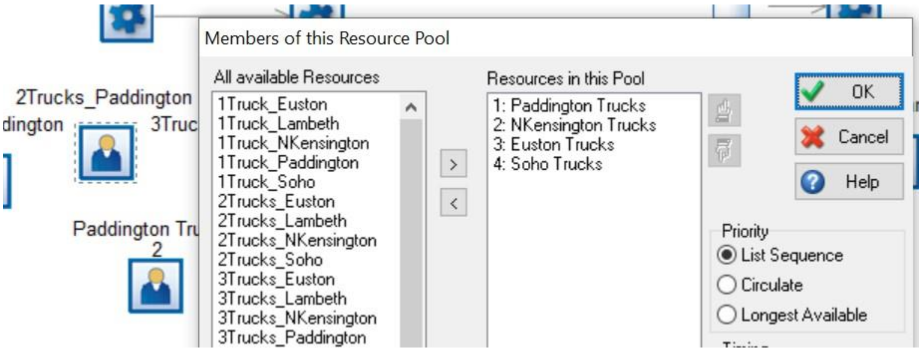


Figure 15. 2Trucks_Paddingon Resource Pool Prioritization

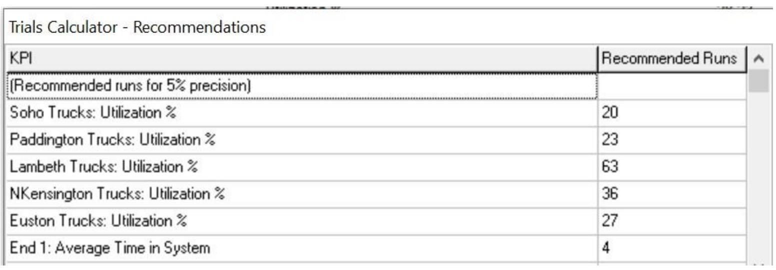
The resources allowed to be drawn from by each pool are then prioritised according to these relationships. For example, look at the '2Trucks_Paddington' resource pool. This pool would be chosen as a resource if there was an incident nearest to Paddington station that required two trucks. First, the model would check if two Paddington trucks were available. If not, the model would first check if any trucks at North Kensington station were available. If not, it would then check if any of Euston station's trucks were available, and so on. It is important to mention that the 'List Sequence' option needs to be selected for this to work. This process was replicated for each resource pool.

4. Experiments and Results

4.1 Trials Calculator and Warm Up Period

To begin experimenting, first the trials calculator was used to compute the recommended number of runs needed for 5% precision. These results are shown in Figure 17. From these results, it was determined that 63 runs will be used for the duration of the experimentation process to ensure a 95% confidence interval for all results.

A warm up period of 12 hours was utilized since the system that is being modelled is a continuous one. Results were gathered for a period of three 24-hour days after the warm-up period.


Trials Calculator - Recommendations

KPI	Recommended Runs
(Recommended runs for 5% precision)	
Soho Trucks: Utilization %	20
Paddington Trucks: Utilization %	23
Lambeth Trucks: Utilization %	63
NKensington Trucks: Utilization %	36
Euston Trucks: Utilization %	27
End 1: Average Time in System	4

Figure 17. Recommended Runs per KPI

4.2 Baseline Truck Allocation

Table 3 illustrates the number of DPLs/trucks each station has initially. These values were derived by researching how many Dual-Pump Ladders (DPLs) each station houses currently.

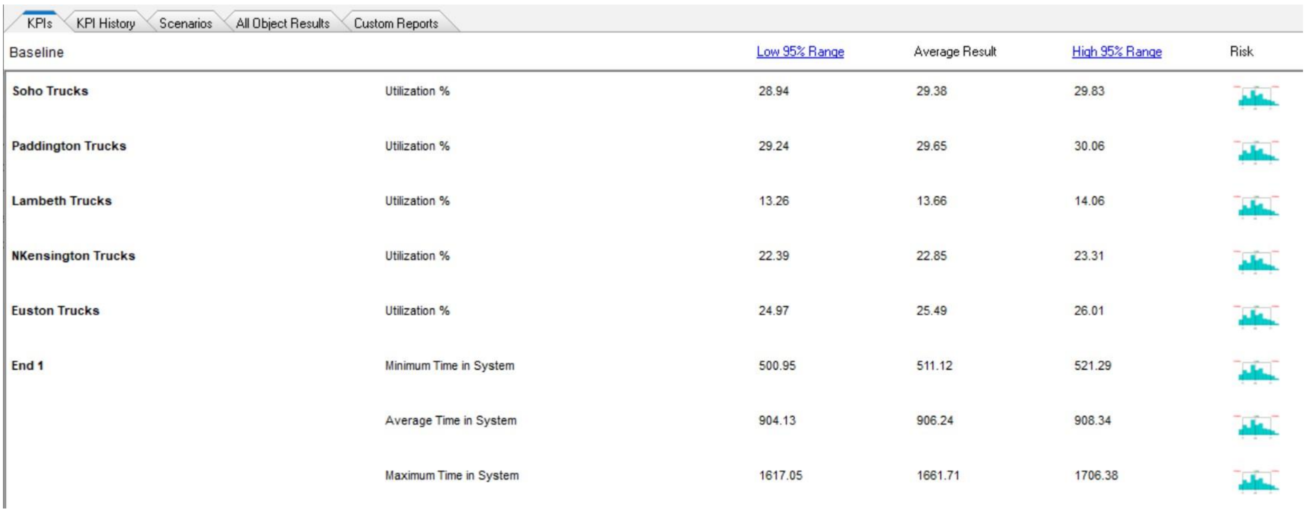
Table 3. DPLs per Station

Station	Current Number of DPLs
Euston	1
Lambeth	2

North Kensington	2
Paddington	2
Soho	2

4.3 Baseline Results

The results of the baseline scenario are shown in Figure 18.



KPIs | KPI History | Scenarios | All Object Results | Custom Reports

Baseline		Low 95% Range	Average Result	High 95% Range	Risk
Soho Trucks	Utilization %	28.94	29.38	29.83	
Paddington Trucks	Utilization %	29.24	29.65	30.06	
Lambeth Trucks	Utilization %	13.26	13.66	14.06	
NKensington Trucks	Utilization %	22.39	22.85	23.31	
Euston Trucks	Utilization %	24.97	25.49	26.01	
End 1	Minimum Time in System	500.95	511.12	521.29	
	Average Time in System	904.13	906.24	908.34	
	Maximum Time in System	1617.05	1661.71	1706.38	

Figure 18. Baseline Results

4.4 Verification and Validation

4.4.1 Verification

To verify our model, and ensure that the model is representative of the system being simulated, the number of trucks was changed to ten at each station. If the model is accurately representing the system, the resource utilization should go down. This was indeed the case, each resource utilization percentage decreasing to 3-5%, proving that this model does in fact represent the truck usage at each station.

4.4.2 Validation

To validate the model, and ensure that the models parameters are correct, the average time in the system generated by the simulation was compared to average time between 999 call receival and the truck's return to its home station.

A sample of 200 observations was taken from the data. The mobilization time, travel time, attendance time, and return time were added together for each observation. Additionally, a 22 second call time was added per observation (since that is the call time assumed in the simulation). Once these sums were calculated, they were all averaged.

The average time in system generated by the simulation was 906.24 seconds at a 95% confidence level. The average 'time in system' calculated from the actual data was 903.07 seconds. Since these two values are only 3 seconds apart, it was validated that the model's parameters do – very accurately – reflect the actual system's behaviour. Therefore, it can be assumed that the resource utilization is also as accurately reflective of London Fire Brigade's DPL utilization at their top five busiest stations.

4.5 Experimentation

The goal of this simulation is to optimally allocate DPLs across the five stations. Typically, in multivariate systems such as this, the balance of resource utilization is indicative of the system's efficiency and robustness.

Therefore, in these experiments, the goal will be to get the resource utilization for each station's DPLs as balanced as possible.

4.5.1 Scenarios

Considering the initial results, Soho and Paddington's trucks are utilized 15.72% and 13.99% more than Lambeth's trucks respectively. Therefore, the following scenarios will be tested:

- Adding an additional DPL to Soho station's fleet o Adding an additional DPL to Paddington station's fleet
- Adding an additional DPL to both Soho's and Paddington's fleets simultaneously

4.5.2 Results

Additional DPL at Soho		Low 95% Range	Average Result	High 95% Range	Risk
Soho Trucks	Utilization %	23.15	23.54	23.94	
Paddington Trucks	Utilization %	26.89	27.29	27.69	
Lambeth Trucks	Utilization %	12.73	13.12	13.51	
NKensington Trucks	Utilization %	22.20	22.66	23.12	
Euston Trucks	Utilization %	19.31	19.82	20.32	
End 1	Minimum Time in System	499.94	509.94	519.94	
	Average Time in System	901.87	903.96	906.04	
	Maximum Time in System	1583.40	1628.84	1674.28	

Figure 19. Additional DPL at Soho Results

Additional DPL at Paddington		Low 95% Range	Average Result	High 95% Range	Risk
Soho Trucks	Utilization %	28.19	28.63	29.06	
Paddington Trucks	Utilization %	23.57	23.94	24.31	
Lambeth Trucks	Utilization %	12.84	13.23	13.62	
NKensington Trucks	Utilization %	17.95	18.40	18.85	
Euston Trucks	Utilization %	23.70	24.23	24.76	
End 1	Minimum Time in System	500.95	511.12	521.29	
	Average Time in System	900.82	902.91	905.00	
	Maximum Time in System	1574.03	1618.51	1662.99	

Figure 20. Additional DPL at Paddington Results

Additional DPL at Paddington and Soho		Low 95% Range	Average Result	High 95% Range	Risk
Soho Trucks	Utilization %	22.76	23.15	23.55	
Paddington Trucks	Utilization %	21.54	21.90	22.27	
Lambeth Trucks	Utilization %	12.70	13.09	13.48	
NKensington Trucks	Utilization %	17.77	18.22	18.67	
Euston Trucks	Utilization %	18.27	18.79	19.32	
End 1	Minimum Time in System	499.94	509.94	519.94	
	Average Time in System	899.57	901.59	903.60	
	Maximum Time in System	1547.58	1589.99	1632.41	

Figure 21. Additional DPL at Paddington and Soho Results

- Upon adding an additional DPL at Soho, Soho's DPL utilization decreased by 5.84% at 95% confidence. Paddington's DPL utilization also decreased, but by 2.36% at 95% confidence. Euston's DPL utilization dropped by 5.67% at 95% confidence as well, due to Soho and Euston's level 1 relationship.
- After adding an additional DPL to Paddington's fleet, Paddington's DPL utilization decreased 5.71%, North Kensington's by 4.45%, and the other's negligibly, all at a 95% confidence level.
- Adding an additional DPL to both Soho and Paddington's fleet dropped Soho's DPL utilization by 6.23%, Paddington's by 7.75%, North Kensington's by 4.63%, and Euston's by 6.7% all at 95% confidence.

4.6 Interpretation and Potential Insights

Overall, the results show that none of the DPL trucks belonging to the top five busiest stations of the LFB are overworked. Instead, the results show the contrary. However, with increasing demand due to climate change along with the importance of timely service, decreasing the number of trucks is not a viable option.

It is interesting to note that the average time spent in the system essentially stayed the same. This shows that resources are not being waited for. It also demonstrates that maximizing robustness of a system and maximizing efficiency of a system are not the same thing.

If money is no object, it would be best to add a DPL to both Soho and Paddington's station. This would balance the truck utilization the most, making the system the most robust, able to take on the most increase in demand without risking bottlenecks.

Since money is always an object, the most viable option would be to add one DPL to Soho's station, as this scenario balanced the system's truck use more than adding an additional DPL to Paddington's fleet did.

Appendix

Figure A. Turnout Time Distributions for Other Four Stations

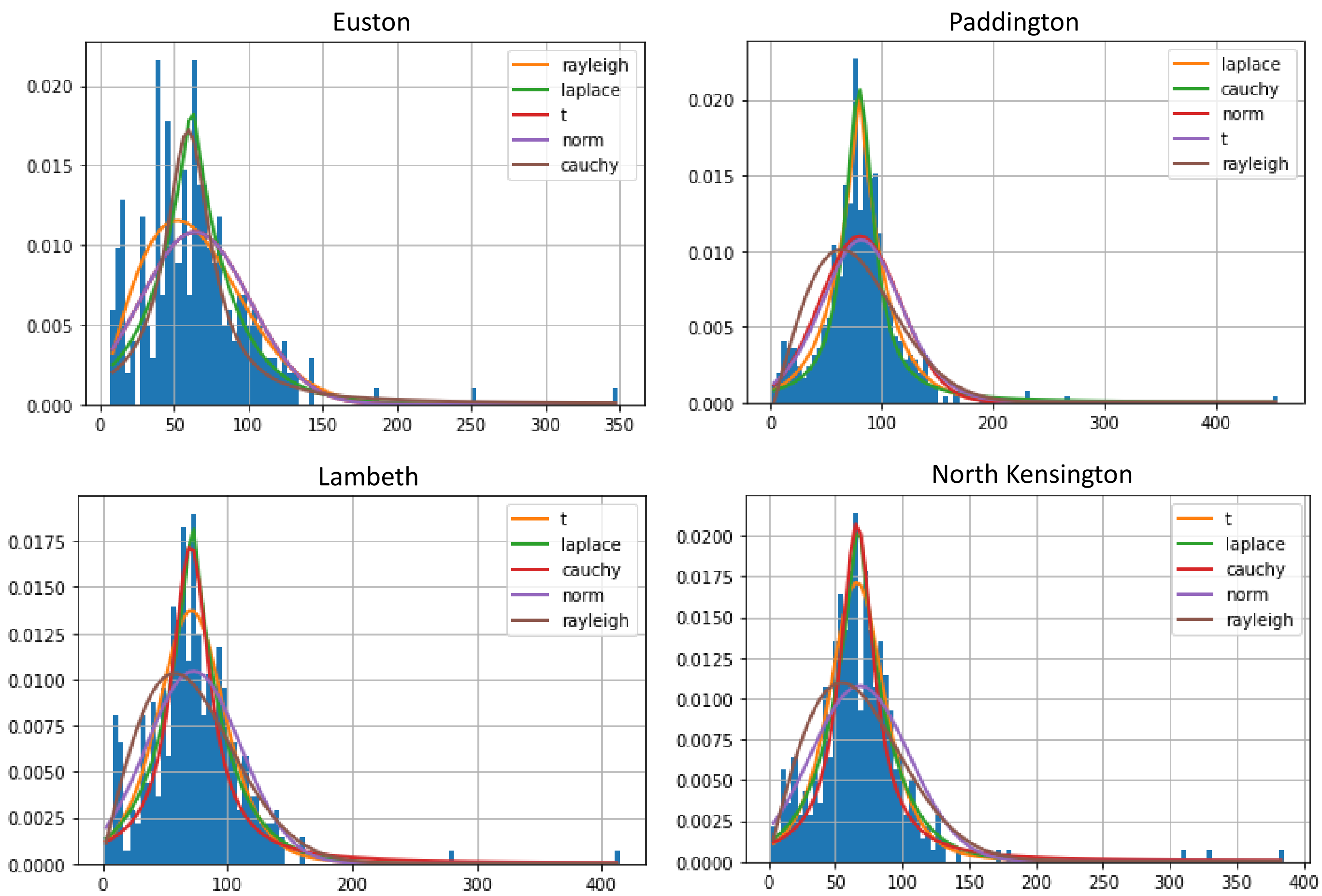
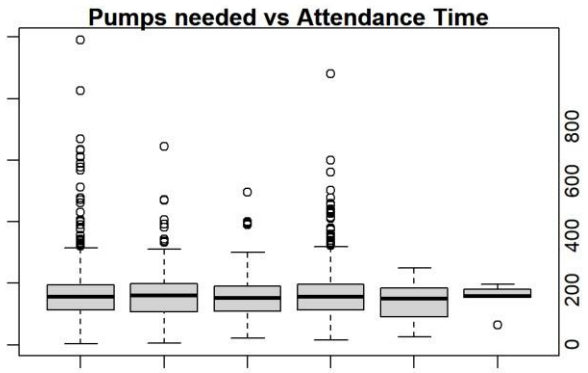
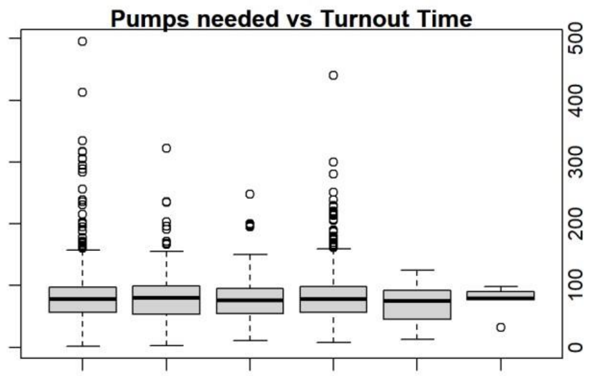
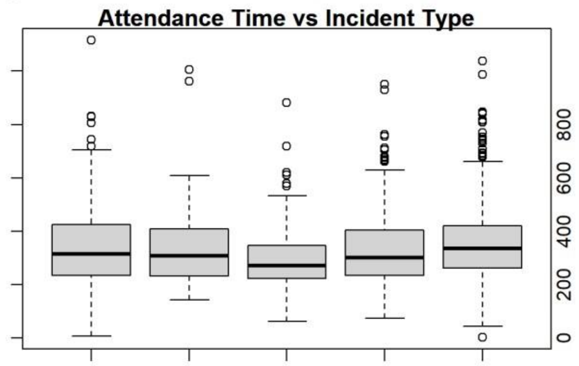


Figure B. Data Exploration Boxplots







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i https://www.huffingtonpost.co.uk/entry/london-fires-busiest-day-second-world-war_uk_62d83da1e4b081f3a8fa7108)

ii https://data.london.gov.uk/dataset/london-fire-brigade-mobilisation-records

iii https://data.london.gov.uk/dataset/london-fire-brigade-incident-records