# Discrete Event Simulation of a System Using Simul8

## MAT021 Foundations of Operational Research and Analytics

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Data Science and Analytics 2021/22

Cardiff University

November 2021

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# 1 Introduction

The brief for this project required us to use the simulation software Simul8 to model a system of our choice. By collecting primary data first hand, processing it into a usable format and then modelling in Simul8, we aim to reflect real life conditions for our chosen system.

For our system, we have chosen a petrol station. Specifically the RONTEC Esso on Cathedral Road in Cardiff. It has 8 Duel-Fuel pumps with Pay-at-Pump capabilities, 1 payment till, and a small to medium sized food shop. We have focused our data collection and subsequent work on modelling for extreme queueing situations akin to that of the UK fuel crisis of 2021. After a leaked government briefing reporting a shortage of HGV divers, panic buying caused many parts of the UK to run out of fuel. Some analysts blamed the driver shortage to Brexit, some the COVID-19 pandemic and some their combined influence.

## 1.1 Problem Definition and Model Aims

Through this work, we look to simulate the processes observed at the RONTEC Esso on Cathedral Road for normal, busy and extremely busy circumstances. Through adjusting various parameters, we wish to identify the parts of the model that have the greatest impact on the worsening or the betterment of queues within the system, with an overall objective of identifying the optimal settings to ensure extreme queues are reduced and managed to maximum efficiency.

# 2 Data Collection

## 2.1 Data Collection Methods

Two instances of data collection were undertaken at the Rontec Esso on Cathedral Road to assemble data first hand. We obtained permission from the store manager and took timings, rates and extra details for our model over the course of over an hour. Between the 5 team members, we stationed 3 outside in the forecourt, and 2 inside.

The 3 outside measured:

- Pedestrian Rate of Arrival
- Cars Rate of Arrival
- Car Pump Side
- Pump Time
- Pay at Pump Time
- Walk Time to and from the Shop
- Time to Leave the Station after returning to their car

The two inside took measurements of time for two types of users. Till only users, and shoppers. Times started from when the customer entered the shop, until they joined the till for the queue. And then again for their time taken interacting at the till. We didn't measure the time they took in the queue as this was the information that we were going to model. Till only users were only timed for their time interacting at the till.

Therefore, inside we measured:

- Time at the Till
- Time Shopping

We had email conversations with Esso and the company that runs the Cathedral street station, Rontec, but neither were able to help us with requests for company data.

Later on in our process, we used Google Places API data scraping to obtain popularity densities for the petrol station. We discuss that in the section 'Model Building'

All primary data was inputted to Excel where it was cleaned and organised.

| Pump Time (s) | Shop Time (s) | Till Time (s) | Leave Time(s) | Pay at Pump | Pay at Pump (s) |
|---|---|---|---|---|---|
| *28* | *253* | *9* | *14* | *0* | *N/A* |
| *46* | *N/A* | *N/A* | *48* | *1* | *13.5* |
| *61* | *11* | *21* | *26* | *0* | *N/A* |

## 2.2 Assumptions

In our initial set up, we decided to make some assumptions. We did this for the most part to eliminate any unnecessary elements to the model, and to mitigate any irregular variables.

The first assumption we made was that cars with fuel caps on the right had side only visit "Right handed" (RH) pumps. This was based from an observation we made during data collection and we decided would make a difference to our model. In later trials this was disregarded.

The second was to implement a COVID-19 queue. This allowed only 6 customers inside the store at any one time. This was a system that the store implemented during the COVID-19 pandemic but was not being followed at the time of our data collection. We applied this not only because it was an interesting variable to measure, but also to see the impact that such measures had on systems during the pandemic.

While collecting our data we saw that a large number of cars used the petrol station as a turning point, we dismissed these inputs and made the assumption that during extremely busy periods, this would not occur.

In our data collection stage, we noted that whilst we didn't observe it, it would be possible for a pedestrian customer to enter the shop and choose not to purchase anything. We noted that it was a very small set and that would most likely be even less with a social distancing queue implemented. We chose to dismiss it.

Whilst collecting data we noticed that some drivers would pull into the Station and park in a non-pump parking space on the edge of the forecourt to just shop at the store. Others also used a pump-space to do the same. We chose to dismiss these instances and assume that all Drivers entering the station did so to buy fuel first before entering the shop.

At the station, there were utilities such as an amazon delivery locker and a vacuum and air machine. We chose not to include these in our model as they had their own parking spaces to access them away from the forecourt.

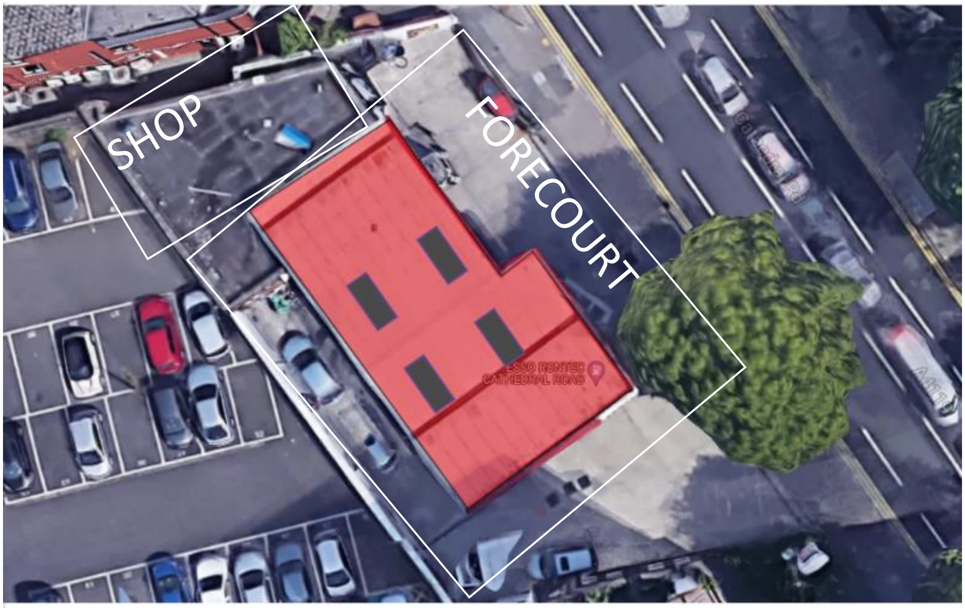


*Figure 1 This image shows a birds eye view of the Esso Rontec with pump stalls marked.*

## 2.3 AFD Generation.

*Figure 2* is an activity flow diagram describing the system we witnessed, discounting assumptions we had made.

We have assigned 3 start points for Left handed pump users, Right handed pump users and pedestrians using the shop without buying fuel. These were important to model as they were a significant proportion of the shop users and so will make an impact on our till queue. We have modelled Left and right handed pump users independently as for the data we recorded, no users chose the opposite side to their cars set up. We are aware that we may need to run iterations later on in our process that brought these two sets together as in extreme queueing, users will be more likely to choose any available space.

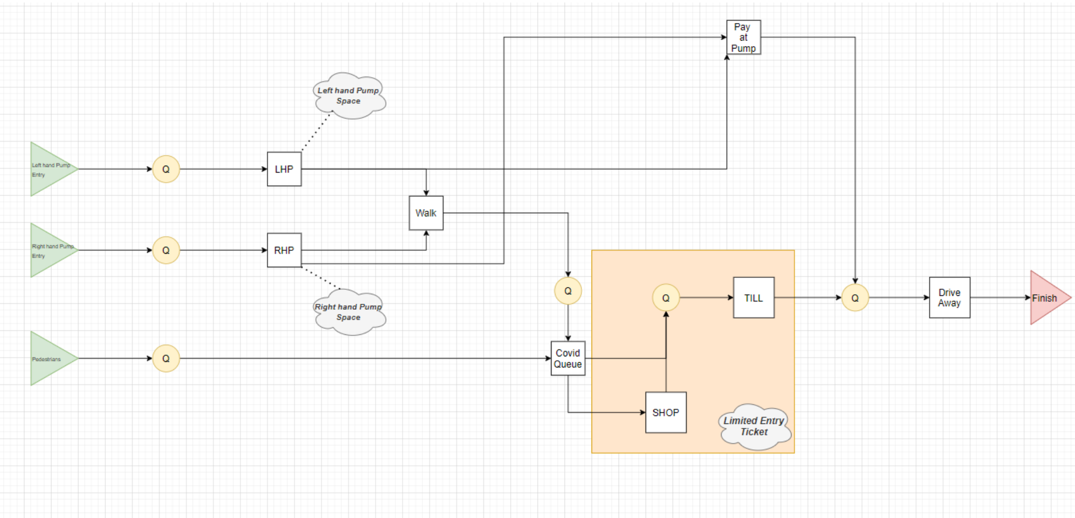


*Figure 2: Activity-Work flow diagram for the observed process at the RONTEC Esso on Cathedral Road*

## 2.4 Distribution Fitting

For the work times, the times taken for each activity were collated within an Excel spreadsheet before using the Excel Add-On '@RISK' to evaluate the shape of each ones distribution. Specifically, this was done for Pump Time, Pay at Pump Time, Shop Time, Till Time and Leave Time. @RISK performs a chi-squared statistical test to give a value representing the goodness of fit alongside the general parameters of the distribution and P-P plots.

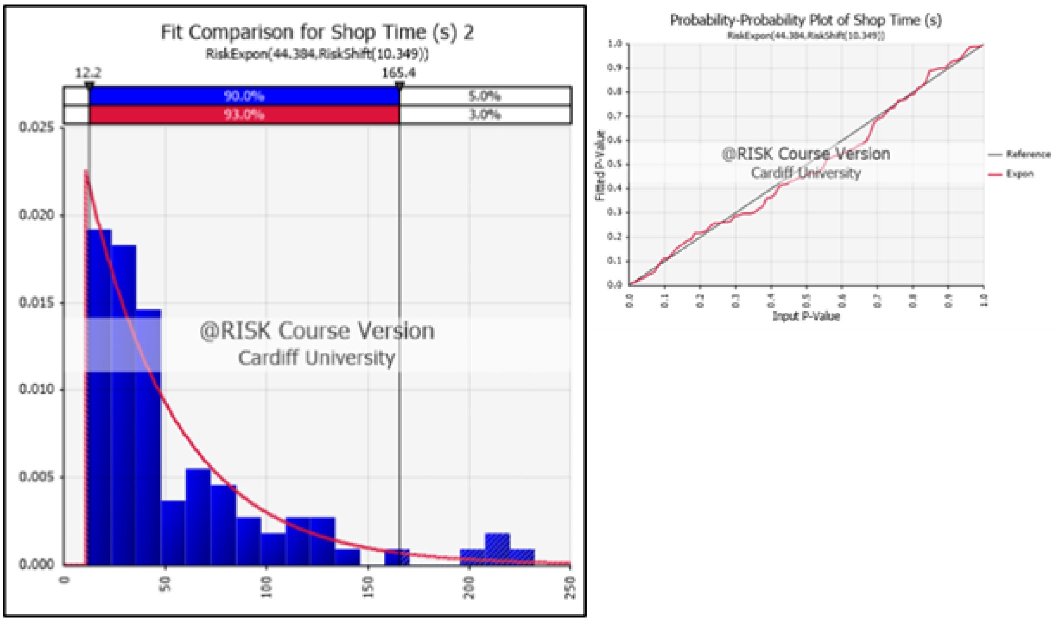


*Figure 3: Fit comparison plot and accompanying P-P Plot for our data Shop Time created by @RIK*

Shop Time is used as example above. Although not perfect, the fit comparison plot shows that the general fit is a fair assumption. The accompanying P-P plot gives a better idea of how closely our data varies from that of an ideal exponential, in this case.

The distributions found were:

| **"Pump time"** | **"Pay at Pump time"** | **"Shop time"** | **"Till time"** | **"Leave time"** |
|---|---|---|---|---|
| *Triangular* | *Exponential* | *Exponential* | *Triangular* | *Exponential* |

Using this and the parameters given by the test, such as the mode and mean of the data, the distribution can easily be replicated in Simul8. For our data however, further steps were taken in creating a lower-bounded exponential to create a minimum time of 10 seconds to pay at the pump, ensuring realism.

# 3 Model and Simulation

## 3.1 Model Components

Entities:

1. Customers

Activities:

1. Pumping Fuel
2. Pay at pump
3. Walk to the shop
4. Shopping
5. Paying
6. Walking out of the Shop
7. Driving Away

Resources:

1. Parking Space at the Pump,
2. COVID Entry Ticket
3. Clerk

Inputs:

1. Arrival Rate of LH and RH Drivers
2. Arrival Rate of Pedestrians
3. Percentage of Pay at Pump users
4. Pump Time Distribution
5. Pay at Pump Time Distribution
6. Shop Time Distribution
7. Till Time Distribution
8. Leave Time Distribution

Outputs:

1. Average Total time in system
2. Max Total time in system
3. Average LH and RH pump queue times
4. Max LH and RH pump queue times
5. Space Utilisation
6. Average Time in Queue for Till

## 3.2 Model Building

When building our model, we used a blend of labels and hold and release resources. We learned that the length of routing arrows dictates the time taken to travel between activities. We decided to turn this feature off and use our collected travel time data to model this instead.

Our model runs 24 hours a day, 7 days a week. The model is split into 3 main areas for clarity, the Forecourt, Ticketing and Shop.

**Start Points**

Our Model originally has 3 start points, 1 for pedestrians and 2 for LH or RH Drivers. This ensures clarity and gives us the ability to change the arrival rates of each customer type individually. In later trials, the LH/RH drivers are combined to shares the pumps regardless of which side the pump is.

Each start point assigns a label to each work item it produces and these labels are used to change the routing of the work items later in the simulation. The numeric label assigned to all work items is 'Customer Type' and has a value of 1 for all Drivers and 0 for all pedestrians.

**Pumps**

From their start points, RH and LH Drivers move to their respective queues to pump fuel. The 'Pump' activity has 8 replicates (4 RH and 4 LH) and requires its respective resource 'Space' to do work. This resource is collected and carried by the work item until the activity 'Leave' in which it is returned to be used by another work item. This process replicates the real-life scenario of a customer's car occupying a space at the pump throughout the during of pump, shopping and paying, preventing others from using the pump until the customer leaves.

After completing the pump activity, work items move to either 'Pay at Pump' or 'Walk to Shop', initially at a ratio of 20:80 percent as observed at Cathedral Road. This ratio is changed in later trials. 'Walk to Shop' has an average time of 10 seconds and simulates the time taken to walk from the pump to the shop. It is replicated 100 times to signify that almost unlimited people can walk to the station at once. Work items assigned to 'Pay at Pump' avoid entering the COVID ticketing queue and the shop and is fast-tracked to the queue to leave the petrol station.

**COVID Ticketing**

Pedestrians who visit the petrol station do not pump fuel or use a 'Space' resource to do so therefore advance directly to the COVID ticketing queue.

The COVID Ticket activity follows from the Walk to Shop activity for the Drivers. This activity takes zero time but looks to reproduce the system that many businesses employed during the COVID Pandemic to abide by the Law ensuring a maximum of 6 people were allowed in the same confined space at one time. There are 6 COVID ticket resources and these are required to advance beyond the COVID ticket activity. This ensures that no more than 6 people enter the shop at one time. This pertains to both Drivers and Pedestrians. As with the 'Space' resource, this resource is carried by the work item and kept until they leave the shop, at which point the resource is returned.

**Shop and Till**

Because pedestrians only visit the station to shop, they all route into the shopping activity. As observed on Cathedral Road, 80% of Drivers shop, 20% advance directly to the Till to pay for their fuel. The shopping activity does not need a limit as that is the job of the COVID queue. In later trials, when the COVID ticketing system in removed, the limit is made 100.

The till requires the resource 'Clerk' to do work, every work item not routed through Pay at Pump will have to pass through this activity to pay for their fuel, shopping or both. There is a queue before the till to accommodate those waiting to be served by the clerk as the till has a capacity of 1.

**Leaving**

Leaving the shop, Pedestrians are routed directly to the end point by their label value (as mentioned earlier). Drivers are routed to 'Walk Out' which simulate the walk from the shop to their car, identical to 'Walk In'.

Next, the leave activity simulates the Drivers entering their car, starting the engine and driving out of the station. Once complete, the pump is available and therefore the 'Space' resource is returned to be used by another work entity. There is a queue before the 'Leave' activity where Pay at Pump customers re-join the process and accommodate those who cannot leave. As observed, cars can only leave one at a time on Cathedral Road therefore the Leave activity is replicated only once.

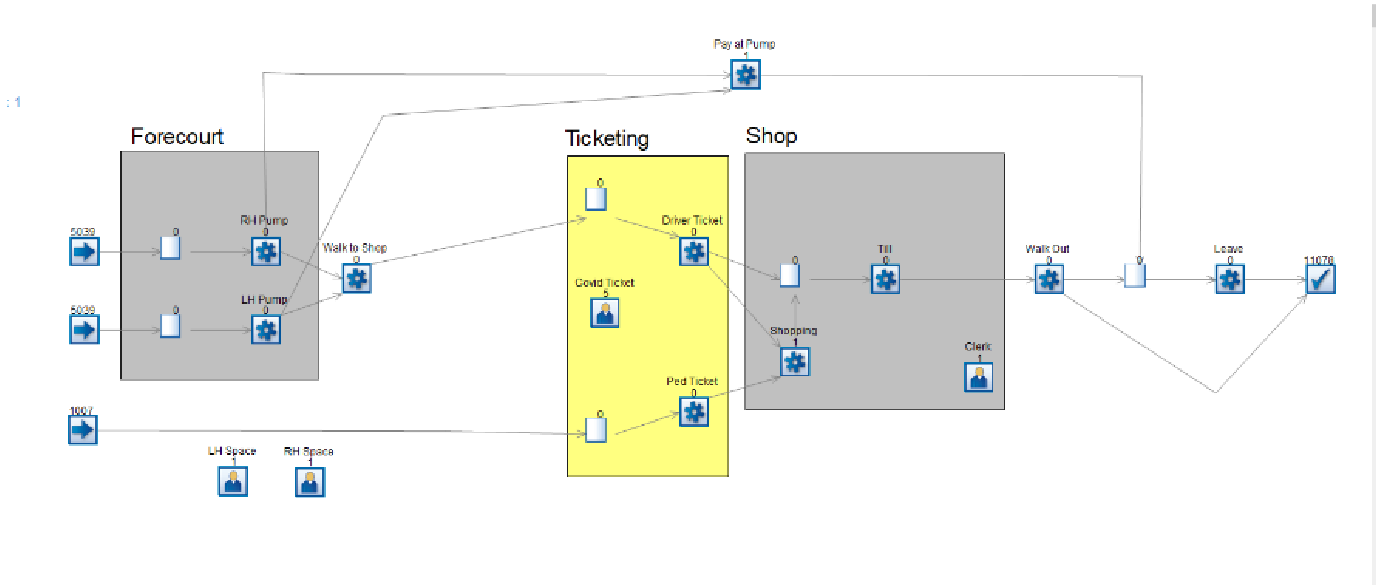


*Figure 4: Screenshot of our Simul8 Model built to replicate the process of our petrol station*

3.3 Python Data scrape using google API.

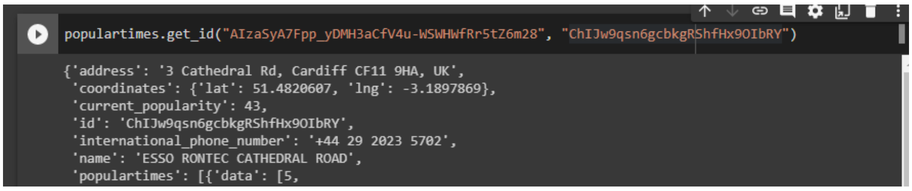


*Figure 5: Screenshot of the Python code used to scrape data using Google API*

To understand a realistic daily distribution of "busyness" or "popularity" we chose to use google location data. Using a python program called popular-times and the companies "place ID" we were able to use python and Google places API services to scrape a popularity density of our chosen location.

Seen here is the daily popularity for each day of the week mapped over 24 hours starting at 1900 hours. We then plotted an average line through the day. By starting at 1900 we can see clearly 2 peaks with a reasonably even breadth, and an almost 2:1 height. This is skewed slightly by high numbers of late night usage on Fridays and Saturdays which we have put down to taxi usage. For our simulation models, we weren't able to plot our input distributions by day of the week, but we were able to split the day into sections using "Time Distributions" function.

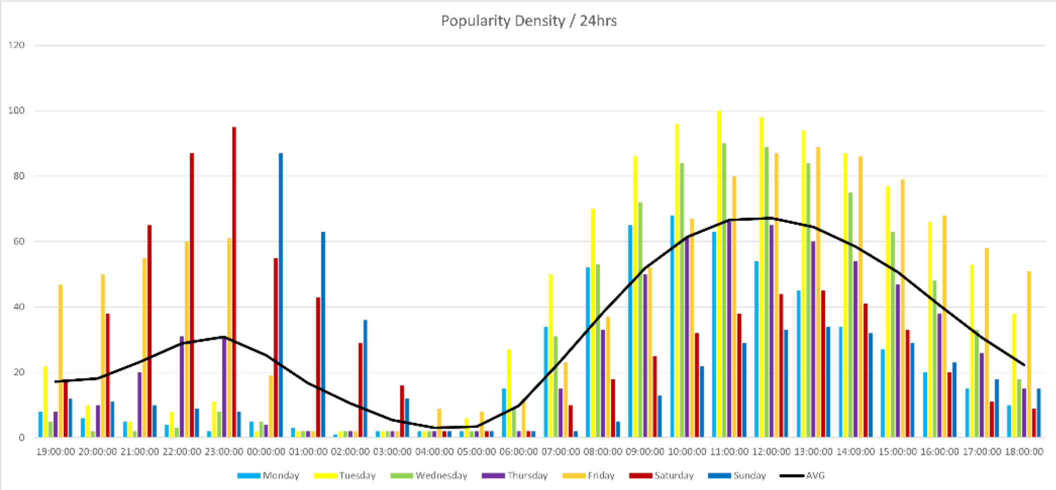


*Figure 6: The average density plot over 24 hours of the footfall at the RONTEC Esso Station, data from Google*

Our data was collected across the busiest periods on our chosen days, 11am through to 1pm. This , and our two clear peaks allowed us allowed us to split our distributions into two.' Busy' from 0500 -1800, and quiet otherwise. The Peak of the 'quiet' section was almost exactly half that of the 'busy' and so we halved the input regularity during these times.

The Data scrape was done so to allow us to gain an accurate representation of the time taken to complete each activity as well as the inter-arrival times of each customer. Arrival times were easy to calculate as we simply divided the number of customers we observed by the time we spent at the station. To include variability, we gave these arrival times a normal distribution with a standard deviation of 10% of the mean

3.4 Model Verification and Validation.

Face Validity. After many iterations of running our initial model builds, we decided that we had a reasonable layout and simulation design.

We could now check the logic of the model. We ran the model very slowly and traced the entities throughout the model. This allowed us to see if the entities followed the correct tracks and if our labels and routing out specifications were working correctly. We then checked the basic results from the activities, this allowed us to see average wait times and throughput rates. By doing this we could confirm that they fit within our set distributions and we didn't have any errors in our simulation. We could use this information to compare with randomly generated activity results.

Finally, we set our inputs to be in an 'on or off' state. This allowed us to check that our inputs could run independently. For example, we set our pedestrian inputs to zero to make sure that we still had reasonable results from our pump users at the shared activities like shop and till.

### 3.5 Testing

#### 3.5.1 KPIs

- Average Total time in system
- Max Total time in system
- Average LH and RH pump queue times
- Max LH and RH pump queue times
- Space Utilisation
- Average Time in Queue for Till

#### 3.5.2 Scenario Iterations

Warm up time - After reviewing some results from our initial runs, we decided that a warm up time was necessary for our model. This would allow our queues to settle into normal conditions. We chose a warm up time of 60 minutes.

Trials Calculation - Once we had a model we were happy with, we ran a trial calculator to obtain a reasonable number of runs that would give us a reasonably confidence level for our trial. We chose 95%. The results told us that 113 runs would obtain us the required confidence.

**Trial 1 Normal**

In trial 1, or our "realistic" simulation. We found that it ran smoothly and reliably. Queues were short and infrequent. Where queues did build up was generally for the pumps as the spaces being taken up by the cars, and the covid queueing system preventing too many people accessing the shop prevented queues at the till.

We would find that this was a common theme across our iterations as when a car takes a space in the forecourt, there is nowhere else for the cars to go, and so when activity times are at the long end of the distribution, the queue builds up behind the cars, not the user themselves.

**2, 200% Input rate increase**

In trial 2 we only changed one thing, we increased our input rate to 200%, leaving pedestrian customers at their standard input distribution. Here we started to see the issue with one of our assumptions. Our average Queue for the Right hand pumps leapt to 38 mins with a 92% utilisation and our LH pump remained at only 0.5 mins with a 65% utilisation.

**2b, 250% Input rate Increase**

At 250% rate increase, our Right hand Pump Average Queue shot up to around 1000mins with a 100% utilisation. Whereas LH remained at 6mins with an 82% utilisation.

**2c, 300% Input rate Increase**

At 300% our queues became unreasonable.

**2ci, 300% Input rate Increase – Reduced 'Leave Time'**

To mitigate these problems of extreme queueing, we decided to start implementing changes.

The first change we made was to reduce our leave time. On a regular day at the Rontec Esso, there are almost never queues, even at peak times. This means that customers take their time returning to the car and setting off. We believe this has left our data for 'Leave time' somewhat skewed. Because of this, we have assumed that in busier periods customers would be more inclined to leave faster when the queue behind them was long. We did a physical test for how long it took to start a car and pull away. We found it took around 10s and so we implemented this into our model. This could be implemented in real life by a station attendant encouraging customers to leave more swiftly.

By doing this we reduced our Left hand Pump queue times to 30s and our RH to 74 minutes for 300% busyness.

**3, One Pump system – 200% input rate increase**

In iteration 3, we made some fairly major changes to our system but had a vide variance in the average queue times between the pumps. For this, we made another assumption. In busy times, customers would use either side pump, despite it requiring extra effort to get the hose to the far side of the car. This gave us some interesting results.

For a 1 pump system, with the distributions adjusted to include the total of right hand and left hand cars we found that Average queues dropped to 2.5 mins with a max of 22 minutes. Compared to the equivalent 2 sided system in 'Trial 2', this is a reduction of 36 minutes average queue time.

We considered this significant enough to carry through to our other trials.

**3b, 250% Input rate – Original 'Leave times'**

For this iteration, we increased the input rate to 250% and went back to our original 'Leave time' This resulted in an average queue time of 276 mins at the pump and a pump utilisation of 99%

**3c, 200% Input rate – New 'Leave time'**

In this iteration, we had our optimised "One pump" system, and a reduced 'Leave time' This resulted is a close to 0 average wait time, with a max of only 3 minutes. This resulted in a 52% pump utilisation.

**3d, 300% Input rate**

Still using the 1 pump system and the reduced leave time, this iteration resulted in an average pump queue of 1min 30s with 80% Utilisation.

**4a, 300% input rate, 50% Pay at Pump.**

For our next change to our system, we noted that by paying at the pump you avoided two queues, the Covid ticketing queue, and the queue in the shop. The queue in the shop has not just fuel users, but also regular shoppers.

We proposed encouraging customers to use the Pay at Pump feature more regularly. This had exactly the results we wanted. By increasing our pay at pump proportion from 20% to 50%, we were able to reduce the 300% wait times to 1min 10.

**4b, 300% input rate, 100% Pay at Pump.**

Using the same method as above but with an increase to 100%, the Average wait time at the pumps decreased again to 40s with a 56% Utilisation.

**5a, 300% Input rate Shop Closed.**

Next, we trailed closing the shop. The logic behind this was that without pedestrian shoppers, or the possibility for fuel users to waste time using the shop, the resources of a pump space would be freed up quicker. We found that it made little difference and the average queue time to access a pump remained within a few seconds of trial 3d and returned 1 minute and 25 seconds. We decided that this was not a significant difference.

**6a, 300% input rate, Close the Covid Queue**

For our final iteration, we chose to close the covid queue. I we saw results similar to that of 5a with an average pump queue of 1 minute 10. We noted that due to the nature of a petrol station, only 8 pump users can be in the shop at any one time anyway while occupying a space. So the increase from 6 to 8 made little difference. We noted a small increase in our till queue times but it was negligible.

## 4 Findings

The first 5 Trials conducted were focused on increasing busyness under the current conditions observed at the Esso Rontec on Cathedral Road. It was found that with increasing busyness, the queues worsened, as expected. However, it was evident that the RH pump's greater arrival rate caused a disparity between its queue and that of the LH Pump. At 200% busyness, the RH pump had an average queue time of 38 minutes compared to the LH's 24 second and a utilization of 91% compared to the LH's 62%. These queues were worsened at 300% to an average queue time of 1820 minutes and 141 minutes for the RH and LH pumps respectively. Both queue times would obviously be disastrous in a real-life setting, but for the model the discrepancy between the two pump queues caused need for evaluation and remodelling. It should be noted that the queue's times were due to a lack of spaces at the pumps. Little to no queuing was observed in the shop itself with an average till queue time of 0.03.

Reflecting on these results and considering real-to-life behaviours of drivers should they be in a high demand scenario, we made two adjustments going forward. We merged the LH and RH pumps together. 8 Pumps and spaces would still be available however not only LH or RH drivers would go to LH or RH pumps, instead they would go to any pump available and, (in real-life) pull the pump around their car if necessary. Secondly, we set the Leave Time to 10 seconds from 44 seconds. We felt that people would leave faster in a high demand scenario rather than behaving unhurried as we observed on Cathedral Road.

Re-running the 300% busyness trial but with a reduced leave time brought down the average queuing time for RH pump from 1820 minutes to 74 minutes and had a similar effect on the LH pump. This reduction of 30 seconds in the forecourt for each car occupying a pump space proved to be a catalyst in reducing queue times, although an average 74 minute queue time would still be far from ideal in reality.

Following this, the universal-sided pumps were introduced for the same driver arrival rates. The queues fared much better and overall space utilization was reduced. At 200% busyness, the universal-sided pump had an average queue time of 2.5 minutes compared to 38 minutes for the RH pump previously, a great improvement. The maximum queue time experienced by a work item here was 22 minutes compared to 120 minutes without the universal pump. Reducing the leave time to 10 seconds once more further compounded this reduction in queue time to an average of 0.7 seconds and a maximum experienced over 113 weeks of 3 minutes.

These conditions were tested against 300% busyness with results of 1.5 minutes average queue time and maximum 13 minutes. Appropriate utilisation of all the available pumps combined with less customers lingering after fuelling greatly improved the performance of the petrol station.

Next, we looked to explore consequences of increasing the percentage of customers who paid at pump. For all of the previous iterations, 20% of fuel buyers paid at pump – as observed on Cathedral Road. We tested for 50% and 100% of buyers paying at pump, expecting a reduction in queue times. This was expected as it would take less time to Pay at Pump than to walk to the shop, more than likely engage in shopping, pay and walk back to the car. This means that pump spaces would be freed at a greater rate, allowing new customers to pump fuel. 50% of customers paying at the pump saw a 22% decrease in queue times from 90 seconds to 70 seconds. 100% of people paying at pump saw average queue times fall to just 40 seconds and space utilisation become 56% compared to 80% and 70% for 20% and 50% pay at pump customers, respectively.

We wondered if pay at pump had such an impact on the system due to the fact that it caused customers to spend no time shopping, the most time costly activity in our system. Therefore, we observed the effect of closing the shop. This meant no pedestrians entered the shop. 80% of drivers still entered to pay for their fuel but zero shopped. This trial saw just a 6% reduction in the average queue time compared to the same conditions with the shop available.

Lastly, we took away the COVID ticketing system, this system ensured no more than 6 customers entered the shop at one time. Without it, there was no limit. However, the combination of a relatively low pedestrians rate of arrival and only 8 spaces for drivers to park meant that more than 6 people occupying the shop at one time was unlikely anyway, therefore it was expected little would change. Again at 300% busyness, we saw an average pump queue time of 1 minute 10 seconds. The shopping activity had a maximum one-time occupation of 6 customers but an average of just 0.97.

OpQuest is a Simul8 plug in that finds the best possible parameter settings for a solution, much likely linear programming. Only available in Simul8 Professional, this could be used to find the optimum parameter settings for minimising queue times. It would also be useful to use this as a tool to find the maximum rate of customers the system could handle before forming queues longer than, say, 5 minutes.

## 5 Conclusion

We learned a lot in this project, in particular the impact of seemingly insignificant variables on the system as a whole.

Some honourable mentions. Should we have had more time it would have been interesting to observe the effect of a time allocated ticketing system for the purchase of fuel. Simulating this would involve changing the arrival rate distributions to a fixed interval time or batching say 5 work items into the system every 5 minutes to replicate the customers having allotted times they arrived at. Many businesses employed this system during the pandemic so would be a realistic and feasible order. Another might be a parking bay which could accommodate cars after they had pumped fuel could help alleviate congestion by freeing the pump space while the customer pays/shops. But its possible that this would have just moved the problem further down the line. Ultimately a petrol station as a small footprint business with physical infrastructure, it is hard to make changes on the fly. This is also made worse by the nature of the system with cars utilising resources for a long time.

If we were able to do this project again, we would have pushed a little harder to obtain company data from Esso. This would have allowed us to do better data analysis with a greater quantity of more reliable data.

We hope that should the UK be faced with a similar fuel crisis in the future that companies and councils will have used the experience from this year to enact systems like we discussed in this report to ease and mitigate the problems caused by a surge in requirement for fuel.