MAT 021 SIMULATION COURSEWORK

SIMULATION OF A TELECOMMUNICATION SHOP

GROUP 9

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Introduction

The domino effect of Covid-19 has had a lasting effect in the world, especially on businesses. The change in environment has made businesses more accessible virtually, therefore a lot of people opting to fulfil these tasks at the comfort of their own homes. From the perspectives of the end users this has greatly improved their quality of life due to the convenience, however for businesses that solely rely on customers physically visiting their shops, it has had a detrimental impact. Price digital is a franchise within the telecommunications industry of such infrastructure. Price digital makes profits by selling products and services in their shops. The customers are able to get the same products and services through the company website, however the company website profits are all taken by the parent company that is in partnership with the franchise. Price digital aims to make the most out of the customers who go to their shops so that they can maximise their profits from every customer they get.

Aims and Objectives

The purpose of this research is to look into the shop's current queuing system and experiment with their resources to maximise the number of customers seen by the advisors consequently maximising their profit. The current business model has a number of advisors working in the shop floor. The customer walks into the store and waits until an advisor is free to help them. There are the same number of advisors working every day. If an advisor is not available immediately then some customers decide to leave, therefore the business loses out on its profit. Not all of the customers that come into the store buy merchandise or services, some of the customers may want to speak to a customer regarding a query.

Stakeholders

Price digital:

The main goal for price digital is to maximise their profit. This can be the measured by the quantity of customers that leave the store without being seen by the advisors and the number of advisors who are available to work. Less customers leaving means more profit and less advisors present means less wages to pay. Both attributes contribute to the business profit.

Advisors:

The advisors are not affected by the profit of the business. They are more concerned with the environment of their workplace. The number of advisors needs to be kept at a manageable amount so that they are not being overworked due to the lack of staffing or have a lack of work to do due to overstaffing.

Parent company:

The parent company that is in partnership with the franchise would have a very similar aims and objectives to price digital. This is due to the parent company taking a fraction of profit that Price digital makes. If Price digital is not performing to the parent company's standard, then that can ruin the relationship between the two and possibly losing the partnership. Unlike Price Digital the parent company does not face a detrimental effect if the performance isn't as it has other means of gaining that profit such as the online website.

Customers:

The customer experience has a great effect on the business due to many factors. In the surface level if a customer is likely to have less wait time and able to see an advisor, the more likely they are to spend money in the shop. More effectively if the customer has a good experience, they are likely to spread the word and therefore more likely to bring more customers into the store assisting the business in its aims.

Performance Measures

The main performance measure will be the number of customers that leave the store without being seen by an advisor. The higher the number of customers leaving the less profit the business will make. Price digital can ensure that all customers are seen by advisors by maximising the number of advisors working every day, however in a business perspective the more advisors working equates to more wages to be paid and therefore not beneficial. The experiment must maximise the number of customers seen while minimising the number of advisors working to be beneficial to Price Digital.

Secondary Performance measures:

- Number of advisors working (min)
- Average time a customer spends in the shop
- Number of sales made

Experiment parameters

The main parameter will be the number of advisors working in the shop floor during the day.

Data Collection and Analysis

The data available to carry out this experiment has been provided by price digital. The collection of data was automated by a sensor at the entrance of the shop floor. While this was conducted there was a manual collection for an hour carried out as well to better understand the flow of the work item in the workspace. The table below presents the footfall data.

Location	Total Footfall (30 days)	Day 1 (Sat)	Day 2 (Sun)	Day 3 (Mon)	Day 4 (Tue)	Day 5 (Wed)	Day 6 (Thurs)	Day 7 (Fri)
Cardiff	4316	258	133	253	189	199	202	189

FIGURE 1: FOOTFALL DATA

It can be concluded that Saturdays are the busiest day for the business and therefore will most likely require the highest number of advisors working on that day. Adversely Sundays are the quietest day therefore would require the lease number of advisors.

Long time with advisors (mins)	Type of issues	Short time with advisors (mins)	Type of issues
32	Hardware	18	software
55	software	10	hardware
63	Software	25	software
46	Software	2	hardware
97	software	17	software
62	software	22	software
45	hardware	19	software
37	hardware		
33	software		
42	software		
44	software		
50	hardware		
38	software		
41	hardware		
49	hardware		

FIGURE 2: OBSERVATIONS OF TIME SPENT WITH ADVISOR AND TYPE OF ISSUES

When splitting up the customers into two categories, customers that spend a long time with customers (more than or equal to 30 mins) and short time (less than 30 mins) there was a split of 65%. The mean time a customer who spent longer with an advisor is 49 mins with a standard deviation of 15.66. The mean time a customer that spent shorter time is 17.5 mins with the standard deviation of 7.63. 36.36% of the customers were present for hardware issues and 63.63% had software issues initially. It was also noted that a customer might have to see both a software and hardware advisor for diagnostics.

Data Characteristics

Accuracy

The data is collected by a sensor that counts the number of people that come in and go out from the entrance to the store. This method of collecting data is automated making it less exhaustive, however there are several assumptions made about the data. The sensor assumes that everyone that walks in and out of the door is a customer. If an advisor that works at the store decides to step in or out through the entrance, then the sensor counts them as a customer.

Completeness

The data is complete as it does not contain any missing values. The dataset contains the footfall data for all 7 days of the week. The completeness of the data could be improved by increasing the timeframe that the data is collected over. The size of the dataset determines the scope of understanding therefore having a dataset that spans over a month would be significantly better than 7 days, however having a larger dataset would require more computing power.

Reliability

The data is reliable as if different method of collecting the data were to be used, it would not contradict the information. There might be a slight variance in the exact figures provided due to different assumptions being made for different methods, but the overall trend would be the same.

Relevance

The aim of this research is to optimise the number of customers that are seen by the advisors and minimise the number of customers that leave without being seen. The data that was collected is very relevant to the study as it presents the number of customers coming into the store.

Timeliness

The data was collected in October 2022 meaning that it was very recently collected. This means that the trend of the number of customers coming into the store will most likely stay consistent in the near future.

Assumptions

The data provided only covers a small fraction of elements that could affect the results of the experiment. In order to get the bigger picture, there have been some assumptions made. The data available only shows the day-to-day figures for first 7 days of the month, therefore the model will assume that the whole month carries the same pattern as presented in the data above. In real life this would not necessarily be true. There is also no data that presents. An example of this is that consumers are more likely to spend during the first week after they get paid. There is a 32% decrease in the number of quantities purchased by a benefit household from week 1 to week 4, (Hastings & Washington, 2010). There was no data collected regarding how much time the customers spend in the front desk. It is assumed with background knowledge that the amount of time spent in the front desk is about 3 mins.

Conclusion on data analysis

From the data we can conclude that the number of hardware and software assistants directly affect the waiting time that customers have to queue. It can be seen that, when the number of technical assistants is 4, less customers leave after waiting for 15mins or more without being attended to. Increasing the number of assistants will increase their efficiency and more customers will have their technical issues attended to without a long waiting time.

From the analysis of the data, it can be concluded that the data is quite reliable, however there is a lack of quantity.

Implementation Model

The development of the model itself was thought of after the data had been gathered and the activity flow diagram was finished. The model was created using Simul8 simulation software. This programme is process-based; thus, entities move through the model until they are stopped by a time-based barrier or a condition that has to be fulfilled.

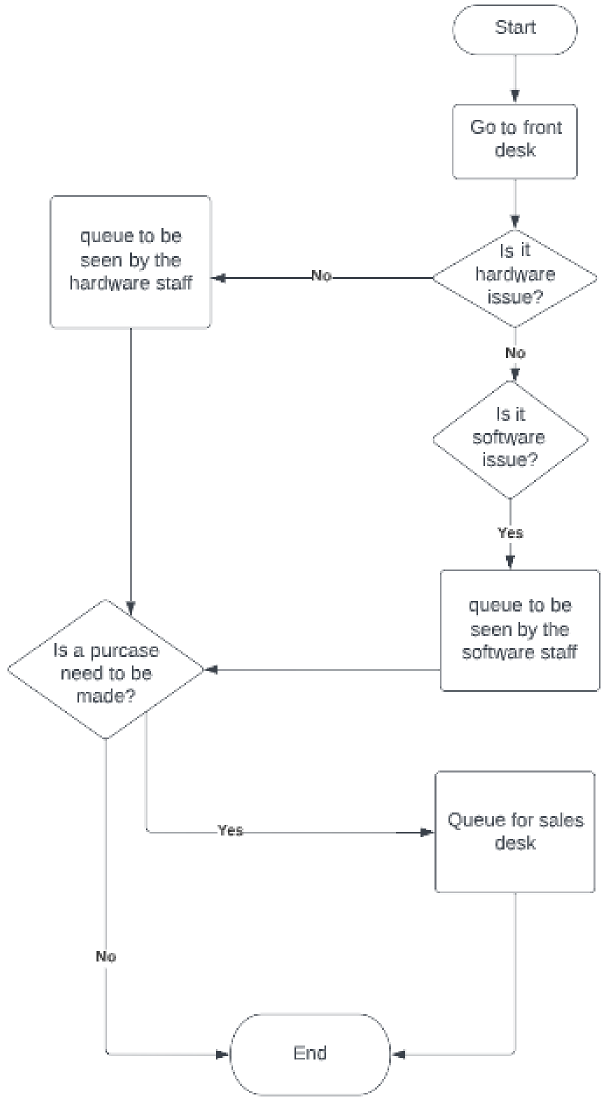

FIGURE 3: THE FLOW DIAGRAM OF WORK ITEM

The amount of time spent waiting to see the technical assistant, the length of time spent with the assistant, and long-time versus short-time arrivals were determined to be the three main areas that the model should address based on the data. The data collected allowed probability distributions to be applied to these occurrences, incorporating randomness into the model. The lengths of the queues for the technical assistants would be the key measure obtained from the model to evaluate its functionality.

In essence, the model operates by introducing every customer in accordance with the probable level of service they require, making some customers wait a little longer and others a little less, and then simulating the length of time spent in queue and with the technical assistant.

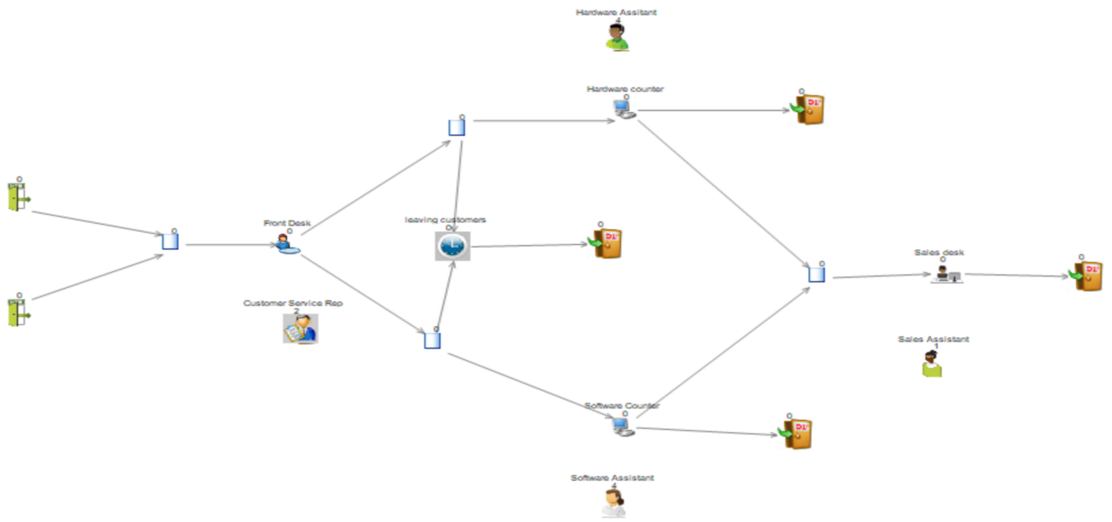

FIGURE 4: SIMUL8 STAGE

The starting point of the model assumes that every customer that enters the store they will queue to get guidance from the front desk where they will be advised on which counter to go to depending on the issue they want resolved. We assume that each customer either has a software issue that needs to be resolved or a hardware issue that needs to be fixed. Some customers can also have both hardware and software issues. These work items are split into two work items that so that they can be seen by both a hardware and software advisors. Additionally, some people are willing to wait for a longer time (but no longer than 15 minutes), whilst others are only willing to wait for a shorter time. This was done in Simul8 using a feature called ‘Expiry’ that had a 15-minute time limit; if the customer had to wait longer, they will automatically leave the store.

The model then classifies the clients according to the service they need, and after that, it moves them to a different workstation and labels them with either a hardware counter or a software counter. After that, the consumers are directed to another workstation where each one is given a label depending on whether they want to buy an item or not. The "branching out" procedure in Simul 8 was used to accomplish this. Depending on the probability profil randomly picked, a label of "Hardware" or "Software" was assigned.

After this, consumers that stayed longer than 15 minutes are routed out of the system via the "Leaving customers" workstation.

Moving on to the following section of the model are the remaining entities.

Following the queueing stage, the customers are sent through to the technical assistant to be seen for their appointments. The amount of time spent with the assistant is determined using the randomly using the labels. Each technical advisor had their own average time taken to see their customers, or 'service time', as listed in the data collection section, thus the model had to include 2 separate workstations to represent hardware and software with each 4 technical assistants as resources. These times were built into the model using the 'normal' distribution. This distribution was used due to the fact that we had the number of customers seen by an advisor hence there was sufficient data to justify using a parameterised statistical distribution. Once the customer has been seen by technical, they leave the system or proceed to the sales desk. To make a purchase.

Following the stage of queuing, the clients are directed to the technical assistance to be seen. Using the labels, a random number generator determines how much time is spent with the helper. According to the data collection section, each technical advisor had their own average "service time," or the amount of time it took for them to see a client. As a result, the model needed to have 2 different workstations to represent the hardware and software, as well as 4 assistants for each workstation. Utilizing the "normal" distribution, these times were incorporated into the model. Because we have the number of clients seen by an advisor and there was enough data to support applying a parameterized statistical distribution, this distribution was applied. After the customer has been seen by the assistant, they either exit the system or go to the sales counter to make a purchase. Finally, the customers who went to buy something from the sales desk they exit the system after the purchase.

Now that the model is finished, a trial is conducted to get results, with 7 iterations of the model running in the trial to reflect the 7 working days. The queue lengths for the eight assistants serve as the model's primary outputs. Along with the maximums of these, the average queue lengths and average queueing times are taken into account. The proportion of clients that waited less than the desired 15 minutes or less in line was also noted. Each user's average time in the system is provided, along with their maximum and minimum times.

SIMUL8 Features used: -

Resources

There are 11 resources in our model who are as assigned duties as follows: - 2 customer service representatives, 4 hardware assistants,4 software assistants,1 sales assistant.

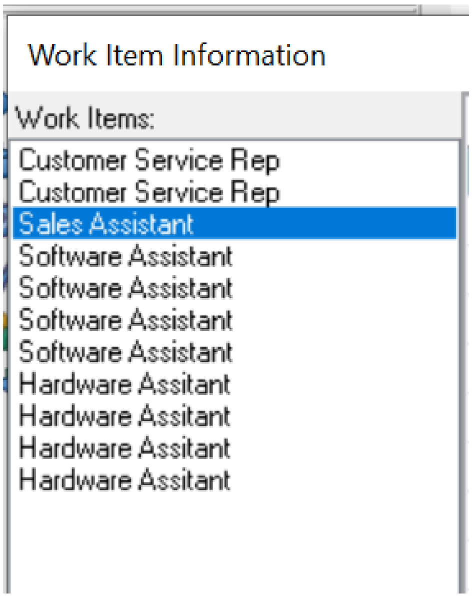

FIGURE 5: RESOURCES

Timing/clock

The Price Digital shop has 8 technical assistants who assist the customers from 9am to 8pm. However, the times at which customers come to the shop varies significantly. Since the primary interest of this report is to look into how to customers waiting time and the number of the assistants needed during the peak time. The proportion of customers willing to wait longer for their appointments to be 64% and those who want to wait for a shorter period is 36%.

Interarrival times

Intuitively, there should be one customer arriving every 3.5 minutes. However, the times at which customers come to the shop varies significantly. The interarrival rate was calculated by looking at the number of customers that arrive in an hour.

Service Times

Given the fact that the consultations are only supposed to last for 30 minutes, this is not usually the case. Factors like the complexity of the customer's issue or the customer's or assistant's gregariousness can all determine how long they last. The average "service time" for every technical assistant is determined by averaging the lengths of services provided to each client. The average distributions of these service periods, with average times of 30 minutes, will be entered into the Simul8 model.

Day planner

The amount of work that will be completed within the designated intervals for each workstation is what is entered into the day planner. The data below shows the day planners.

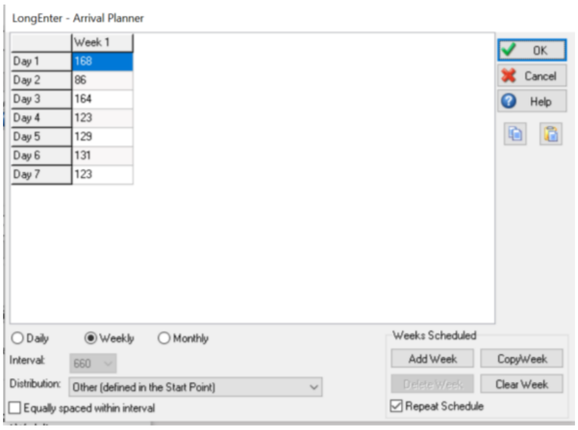

FIGURE 6: LONGENTER DAY PLANNER

Labels

Label based routing out is one of the fundamental features of this simul8 model. The labels that each work items are assigned determine the route within the system.

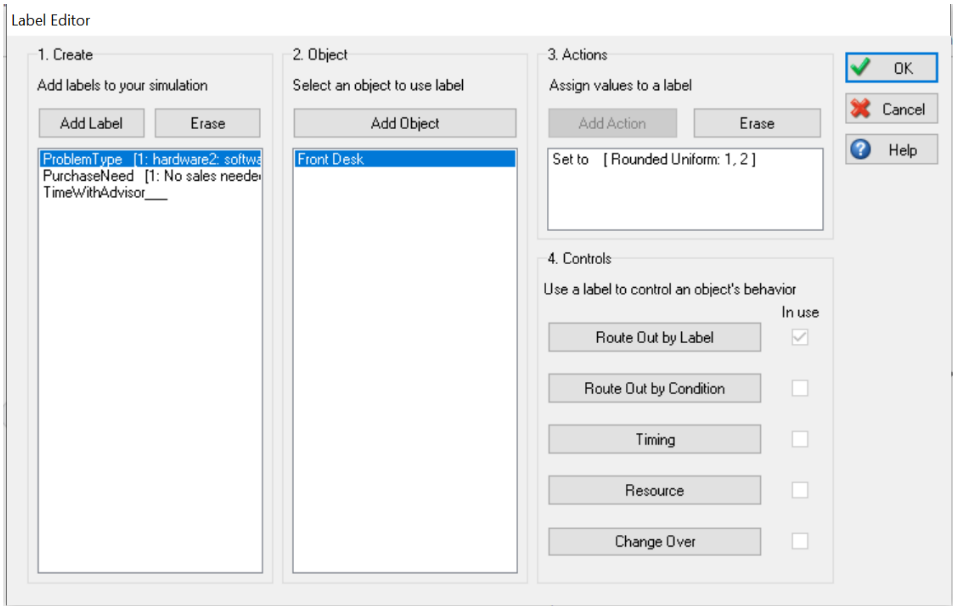

FIGURE 7: LABELS

There are 3 labels that were used in this system. The first one is the problem type. This is a label assigned to each work item. If they are labelled 1 then it determines that they are a hardware issue. If the work item is labelled 2 then it determines that the issue is with the software. This label is assigned at the front desk once they have had their first point of contact with a member of staff. Once the label has been determined it sets the route for the work item to go through.

The second label is the PurchaseNeed label. This label determines if the customer will require to make a purchase. If the customer does not need to make a purchase, then they labelled 1 at the counter will go the end point. If the customer does need to make a purchase, then they will be labelled 2 and will have to queue at the sales counter. The label is determined in either of the hardware and software counters.

The final label used is the timeWithAdvisor. This label is assigned in the longEnter and shortEnter start points. They will then be randomly labelled according to the long or short distribution respectively to determine how long the issue they have will take to solve.

Routing out

The labels used above is used to determine the route that the work item travels within the system. The ProblemType label is used to determine which counter the work item should go to. From the front desk if the item is labelled 1 for hardware, then that item goes to the queue for hardware and if it is labelled 2 for software then it goes to the software.

FIGURE 8: ROUTING OF PROBLEMTYPE

The next routing out is also label based. The routing out from hardware counter and software counter checks for the label to determine whether a purchase is required to be made and then routes the item to the respective stations.

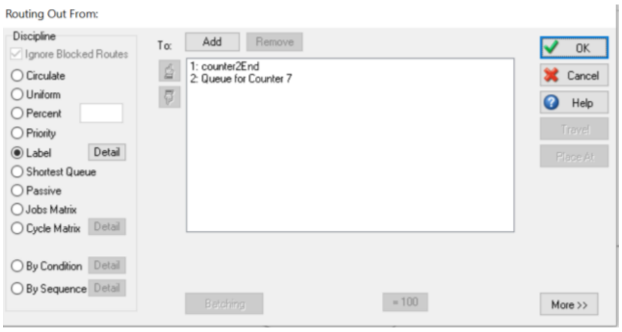

FIGURE 9: ROUTING OUT FROM HARDWARE COUNTER

Batching

Batching is used to show parts within the system where a singular work item may be split into multiple parts. In this specific model this can be present when an issue might initially be thought to be either a software or hardware issue but turn out that it could be both. Batching was used to in the front desk so that a small percentage of the issues get split into two which requires a visit to both the software and hardware counter.

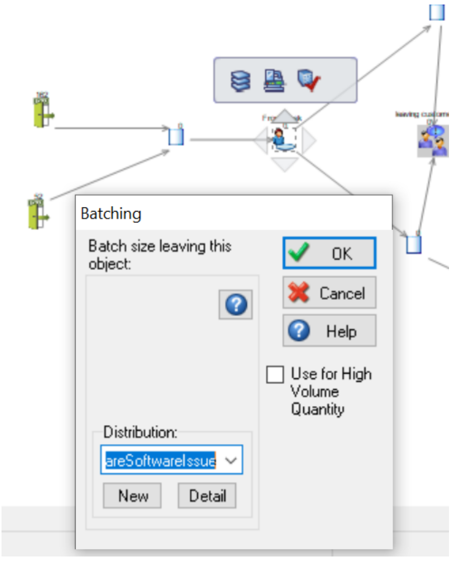

FIGURE 10: BATCHING

Expiry

This represents the maximum waiting time the customer is willing to wait in the queue. Some customers are willing to wait for a longer time (but no longer than 15 minutes), whilst others are only willing to wait for a shorter time. This was done in Simul8 using a feature called 'Expiry' that had a 15-minute time limit; if the customer had to wait longer, they will automatically leave the store. This is guides the model to automatically exit the customers who have waited for more than 15 mins.

Distributions

Distributions describe the values of the data and the likelihood of that value occurring. In this project the distribution is a great tool that can explain certain behaviours within the model.

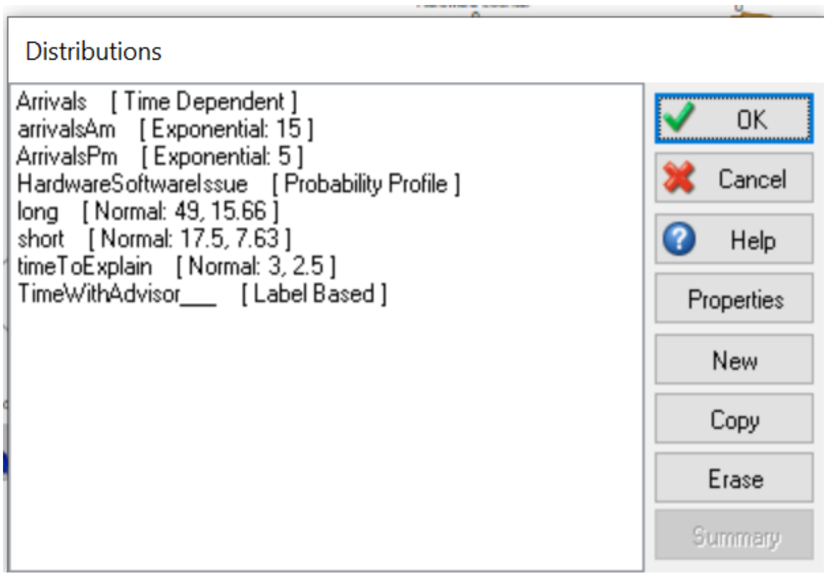

FIGURE 11: DISTRIBUTIONS USED IN MODEL

The arrivals distribution which is a time dependant distribution made up of two distributions. The first distribution is the arrivalsAm distribution that is exponential with an average of 15 and the second in the arrivalsPm distribution that has is exponential with a distribution of 5. The arrivalsAm distribution occurs from 9am to 1pm and the arrivalsPm occurs from 1pm onwards. This distribution is used in the start points longEnter and shortEnter. This distribution will be used to simulate the rate of arrival into the shop floor.

The next distribution used is the hardwareSoftwareIssue distribution. This is the distribution is a probability profile and describes the split between the hardware and software issues. It was previously determined that 63.64% of work items coming in are for hardware issues so this distribution splits the hardware software issues into that percentage.

The next distribution used is the long and short distribution which describes the amount of time the customer would require to spend with the customer. Both of these distributions are normally distributed with a mean and standard deviation calculated from the data collected. These two distributions make up the label-based distribution timeWithAdvisor.

The time to explain distribution describes the time a customer will spend explaining their issues to the front desk. There were no data collected regarding how long a customer would spend in this first station, however we used the background knowledge from observation and concluded that it would take around 3 minutes with a standard deviation 2.5.

End

These are the exit points where the customer leaves the system. We have 4 exit points.

a. Exit if the customer has waited for 15 minutes or more.
b. Exit after the customer has seen the hardware assistant
c. Exit after the customer has seen the software assistant
d. Exit after the customer has seen the hardware or software assistant then proceeds to the sales desk

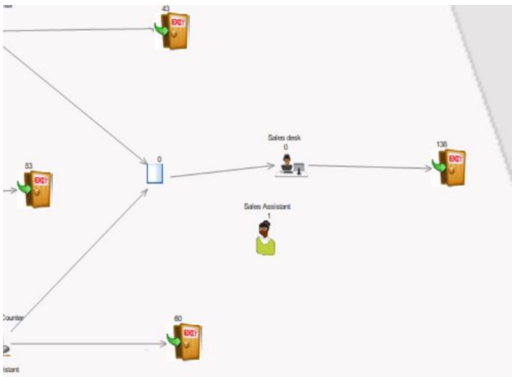

FIGURE 12: ENDS

Queues

Work can wait until the proper Resources or Activities are available in a queue. In the model we have queues for the customer service rep, hardware counter queue, software counter queue and the sales counter.

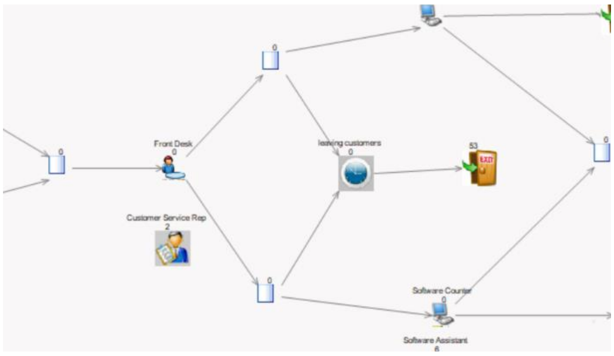

FIGURE 13: QUEUES

Resource Result:

The use of a resource as well as the amount of travel time are shown in resource results, together with the percentage of a resource's availability that has been utilized by the Activities.

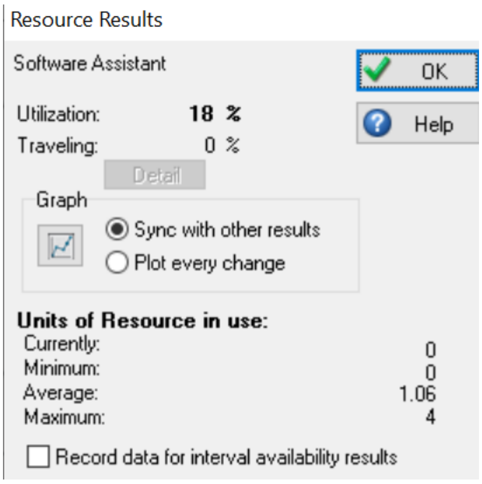

FIGURE 14: RESULTS

Resource Graphics

To customise how each Resource is shown, we used the Resource Graphics for better presentation of the model.

Entities:

These are the customers in our model who come to the shop.

Activities:

These are the actions that are attached to each workstation, we have activities at the hardware technical support, software technical support customer service rep, sales assistant.

Events

The events in our model are the arrival, wait time to see a specialist, hardware repair, software repair, leave.

Verification and Validation

The 'Step' button in Simul8 was used to follow users through the system at each level of the model construction, and numbers were adjusted to run extreme value tests. The results of every test indicated that the model is working as intended. It should be noted that this is not going to be an exact replica of the real-life situation, as is the case with any simulation model. While every effort has been made to guarantee that the major characteristics are as realistic as possible, it is impossible to exactly imitate real-life. This system has been extensively reviewed and debated with Price Digital employees who are the most knowledgeable about the process. As an expansion to this evaluation, a few presumptions could be investigated further. At the entry point of the system, everyone is treated as a customer, even the personnel. However, the overall model accurately captures the shop's queuing system, and the analysis's findings offer useful guidance on how to best manage both the flow of customers and the number of technical assistants at Price Digital.

Experimentation (Scenario Testing)

Following the model's completion, 5 scenarios were created to examine the impact of adjusting the approach to dealing with customer wait times. Each situation was given a random trial. Since the main objective of our model was decreasing the waiting time for the customers waiting to see the technical assistants then we shall mainly consider when the number of technical assistants and how they affect the queuing times.

Scenario 1: Customers wait time when there are 8 technical assistants.

Resources			Queuing time for the Customers		Percentage within the 15 mins time limit
	Number	Utilisation	Average	Maximum	
Hardware	4	27%	9.41	36.46	63%
Software	4	27%	9.21	54.65	70%

FIGURE 15: SCENARIO 1 RESULTS

Scenario 2: Customers wait time when there are 2 technical assistants.

Resources			Queuing time for the Customers		Percentage within the 15 mins time limit
	Number	Utilisation	Average	Maximum	
Hardware	1	43%	53.43	163.35	21%
Software	1	58%	292.48	683.91	25%

FIGURE 16: SCENARIO 2 RESULTS

Scenario 3: Customers wait time when there are 4 technical assistants.

Resources			Queuing time for the Customers		Percentage within the 15 mins time limit
	Number	Utilisation	Average	Maximum	
Hardware	1	45%	53.37	163.35	21%

Software	3	37%	100.46	281.39	46%

FIGURE 17: SCENARIO 3 RESULTS

Scenario 4: Customers wait time when there are 7 technical assistants.

Resources			Queuing time for the Customers		Percentage within the 15 mins time limit
	Number	Utilisation	Average	Maximum	
Hardware	2	36%	21.16	66.87	36%
Software	5	24%	33.84	131.79	52%

FIGURE 18: SCENARIO 4 RESULTS

Scenario 5: Customers wait time when there are 10 technical assistants.

Resources			Queuing time for the Customers		Percentage within the 15 mins time limit
	Number	Utilisation	Average	Maximum	
Hardware	4	27%	9.41	36.46	63%
Software	6	18%	9.21	54.65	70%

FIGURE 19: SCENARIO 5 RESULTS

Results and Analysis

From the above scenarios, we find that the number of assistants directly affects the waiting time of the customers. Hence, we could conclude that the optimal number of technical assistants needed is 10. The hardware counter with 4 while the software counter with 6 assistants. This is made sure that the average customer waiting time is below 15 minutes.

The shortcoming of the data is that we have assumed that all the people coming into the shop are customers. Hence, from the data we had no provision for excluding the staff.

In real life situations there are many attributes that come into play. Not all of these attributes can be accounted for. Environmental effects e.g., cost of living and holidays such as Christmas can also have an effect on the consumers spending habits. The figure above shows the recent financial climate caused by the cost of living. Households that have lower incomes are less likely to make expenditures on nonessentials such as the telecommunication industry during this period. Due to the lack of data availability environmental factors as such has not been put into consideration.

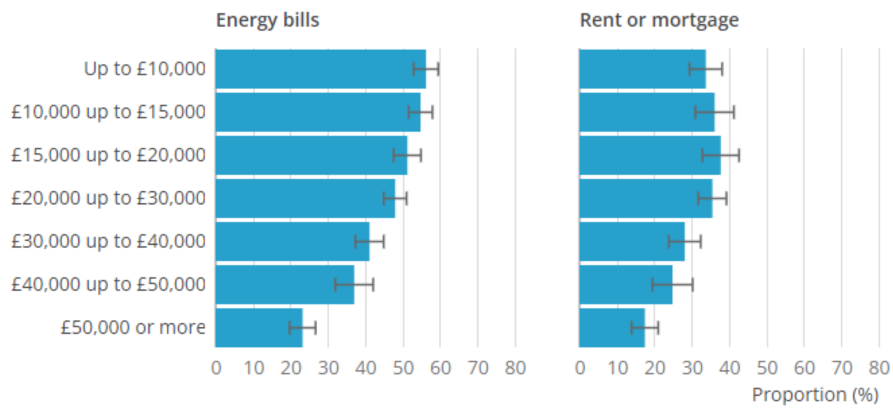

FIGURE 20: THE PROPORTION OF DIFFICULTY REPORTED IN AFFORDING ENERGY, RENT OR MORTGAGE PAYMENTS AMONG ADULTS, (CALEB OGWURU, 2022)

Conclusion

The implementation of this model and the experimentation has suggested that in order to optimise the system in place there should be 10 technical assistants' hardware with 4 and software counters with 6. The results produced are highly dependable on the data availability meaning that the quality of the results is as good as the data. The data does not cover the full scope of the situation such as environmental factors and therefore having a more detailed data could help tune the model even further. The increase of data can improve the quality of the results produced such as having a yearly figure as opposed to a weeks' figure. Increasing the number of resources such as staff may reduce the number of customers that leave without being seen as they have shorter waiting times, however from a business perspective more staff equates to more wages to be paid. The results of this research will be presented to Price digital where they can make executive decisions with additional background information.

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