EXPANSION ON THE COFFEE SHOP PROBLEM: A PYTHON DISCRETE EVENT SIMULATION

Group 3

Griffin Arnone
Anhua Cheng
Bailey Scoville

Northwestern University, MSDS 460

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Abstract

This research conducts a discrete event simulation (DES) of coffee shop operations in a tourism-heavy area. The coffee shop owners aim to maximize revenue while minimizing labor costs and lost revenue due to customers balking and reneging. Using Python, we conduct several simulation experiments to determine optimal staffing levels during three dayparts: morning, afternoon, and evening. We adjust customer behaviors, such as wait time tolerance and average check, to recreate the typical conditions of each daypart. Based on the objective of maximizing revenues, the simulations indicate three baristas should work the morning shift and one barista should work the afternoon and evening shifts.

Introduction

DES, one of the most popular modeling techniques in operations research (OR), is a tool for management to replicate business processes to identify bottlenecks, troubleshoot issues, and optimize procedures (Dagkakis and Heavey 2017). Simulations permit researchers to conduct rapid experiments, manipulate variables, and collect process insights without impacting business operations.

To that aim, we conduct a series of DES experiments to maximize profits at a coffee shop. These simulations include conditions for pain points the coffee shop owners wish to address, including balking and reneging. An event graph of the simulation is in Appendix A.

Problem Definition

The coffee shop owners wish to maximize profits. They recently eliminated tipping due to changes in customer attitudes toward optional gratuity (Helfand 2023). Consequently, barista pay has increased to $18 per hour, emphasizing the importance of managing labor costs.

Additionally, the owners have identified two pain points particular to their customer base. The shop is located in a tourism-heavy area, which creates two distinct customer groups: rushed working professionals and relaxed retirees and vacationers. The different tolerance levels for wait time and queue length of each customer group have caused a noticeable increase in balking and reneging. Both pain points negatively impact immediate and long-term revenues.

DES is the optimal tool to address the labor cost, balking, and reneging concerns. In this DES, we simulate customer arrivals and service during three dayparts: morning, afternoon, and evening. The simulations will provide data essential to determining the staffing requirements for each shift that will maximize revenue without negatively impacting customer service.

This simulation employs the Python programming language. Python is the optimal modeling tool for a simulation of this scope due to its ease of use, quick computational time, low computational cost, and powerful SimPy library. Additionally, Python enables the team to conduct further analysis of the simulation data.

Literature Review

Python is frequently used to create DES models in the OR field and is utilized in a variety of DES software. Python's popularity in simulations is due to its open-source nature, accessibility for beginner programmers, variety of analytical packages, such as scikit-learn and SciPy, and robust SimPy library (Dagkakis and Heavey 2017).

Though a variety of dedicated DES software exists, some fall short in advanced analytical analysis functionality. There are multiple benefits to connecting Python to DES software to build on the software's capabilities and enhance researchers' ability to optimize the simulation with simheuristics, create advanced visualizations, and conduct in-depth scientific analysis (Peyman et al. 2021).

Research Design and Modeling Methods

We completed the simulation code using Python's SimPy and Random libraries, among others. In the test simulation, we defined the number of baristas on shift, range of wait times, rate of customer arrivals, wait time tolerance, and queue length tolerance. We defined functions to randomize customer arrivals, calculate barista service times, and create the event logs in data frames and various file formats for further analysis.

The arrivals function includes the logic to simulate balking. This code specifies a queue length tolerance that applies to all customers. The service process function includes the reneging logic. This applies to the rushed working professionals, roughly 30% of customers, when the wait time exceeds their maximum tolerance. The service process function also adjusts service times by the number of baristas on staff.

We attempted to create a queuing function to occur after customer arrival and before the customer proceeds to barista service. This queuing function was meant to include the reneging logic. However, more troubleshooting is needed before that function can be included in the DES.

After fine-tuning the test simulation, we separated the simulation into three separate four-hour dayparts to replicate the fluctuations in wait time tolerance, customer arrival rate, and average ticket throughout the day. We kept the tolerance for wait time and queue length between six and 10 minutes based on research from the University of Central London. In the study, researchers found customers are likely to abandon a queue after waiting six minutes. The research also indicated customers are hesitant to join queues of more than six people (BBC 2017). We ran each daypart simulation three times to compare outcomes with one, two, and three baristas working the shift. The parameters and results for each shift are displayed in Appendix B.

Results and Interpretation

The busy morning shift had the highest revenue potential but also experienced the highest customer loss. Between the three simulations, 216-232 unique customers visited the shop, 15-146 balked and 21-54 reneged. The average wait times were 2.62-15.46 minutes, with a maximum wait time of 9.88-29.73 minutes. The maximum profit of $1334 was achieved when three baristas worked this shift. With three baristas working, revenue totaled $1550.00, but $590.00 was lost due to reneging, emphasizing the significance of optimizing service to reduce customer loss.

The afternoon shift demonstrated the most inefficient service and much lower revenue compared to the morning. Between the three simulations, 38-45 unique customers visited the shop. Though the queue length tolerance was reduced to six people, no customers balked, likely due to the higher arrival time variance of 5 minutes on average. 13-14 customers reneged, likely due to the maximum wait time range of 0-39.67 minutes. The mean wait time ranged from 0-6.27 minutes, suggesting very convenient service on average. The maximum profit, reached with one barista on shift, was $43.00, with $115 in revenue and $65.00 lost to reneging.

The evening shift, while having the lowest customer activity, still experienced some customer loss due to reneging, indicating potential areas for improvement in service efficiency. 26-32 unique customers visited the shop, no customers balked, and 7-9 customers reneged. The average wait time was negligible at 0-0.25 seconds, suggesting very efficient service. The maximum profit, reached with one barista on shift, was $13.00, with $85 in revenue and $45.00 lost to reneging, exposing an issue with the evening shift service.

Management Recommendations

We recommend adjusting staff based on expected customer traffic during the three dayparts. Increase staffing during peak hours, especially in the morning, to handle higher volumes. Secondly, implement strategies to improve service efficiency, such as optimizing barista workflows, investing in training, and streamlining processes to minimize wait times and customer loss. The shop can implement measures to prevent long queues, such as offering pre-order options, incentivizing off-peak visits, and adjusting staffing levels dynamically based on expected queue length. Additionally, the shop can be proactive by informing customers about expected wait times and encouraging them to stay in line by providing incentives and updates on their orders. Finally, the shop could explore opportunities to increase revenue, such as upselling strategies, offering specials during slower shifts, and diversifying the menu. By considering these recommendations, the coffee shop can optimize staffing, improve efficiency, minimize customer loss in the short and long term, and maximize profits.

References

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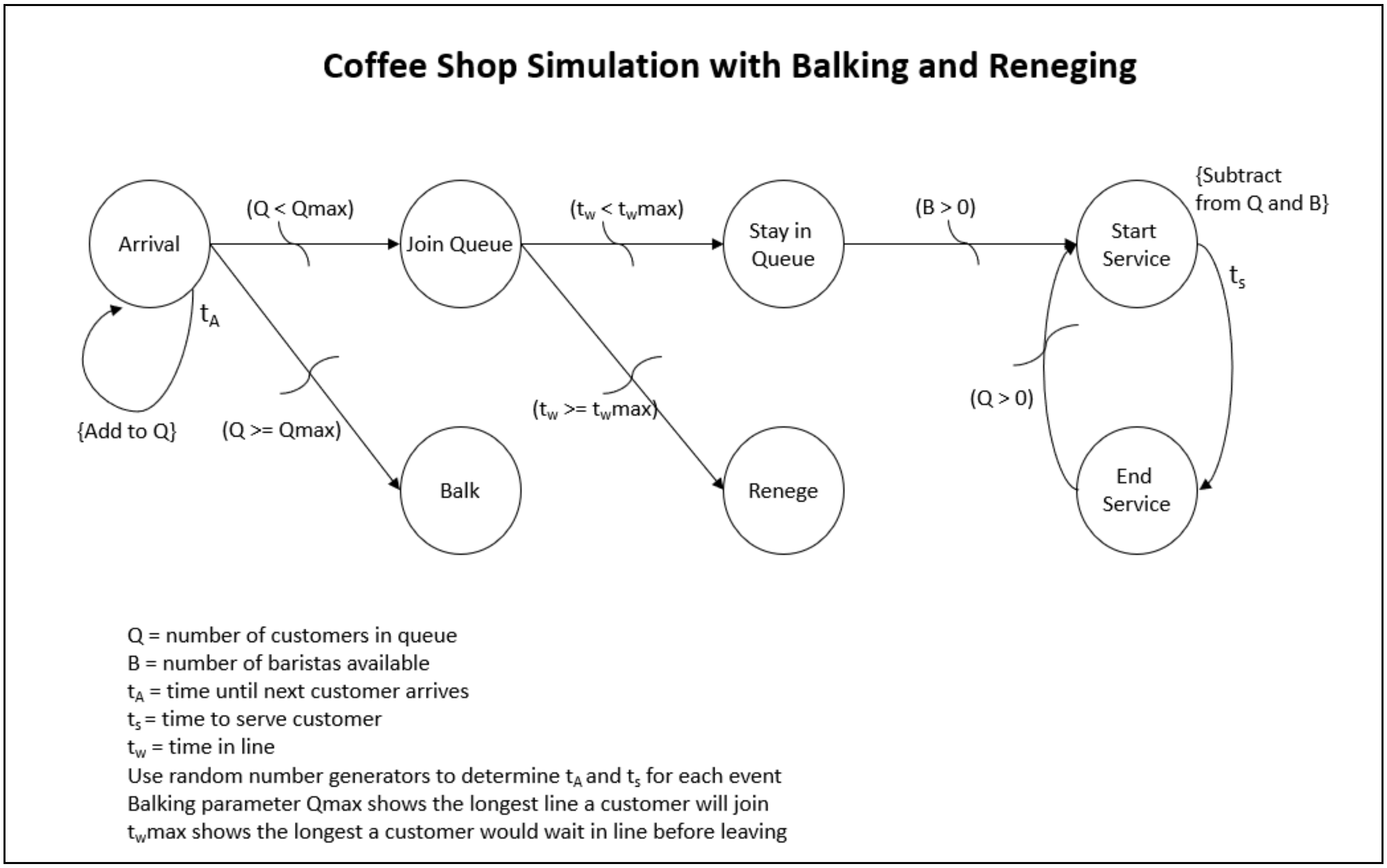
Appendix A

Event Graph



Appendix B

Daypart Parameters

Red highlight indicates optimal staffing for the shift

Morning Shift			
Assumptions			
Average Revenue per Customer (drink + food)	10	10	10
Baristas Hourly Wage	18	18	18
Variables			
# of Baristas Working	1	2	3
Mean Interval Arrival Time (min)	1	1	1
Min Service Time (min)	1	1	1
Mean Service Time (min)	4	4	4
Max Service Time (min)	8	8	8
Balking Queue Length	6	6	6
Max Wait Time (min)	6	6	6
Simulation Outputs			
# of Customers Arrived	232	232	216
# of Customers Serviced	58	115	155
Min Wait Time (min)	0	0.02	0
Mean Wait Time (min)	15.46	4.96	2.62
Max Wait Time (min)	29.73	13.45	9.88
# of Customer Balked	146	56	15
# of Customer Left the Queue	21	54	44
Estimated Gross Revenue	580	1150	1550
Estimated Cost	72	144	216
Estimated Income	**508**	**1006**	**1334**
Estimated Lost Revenue	1670	1100	590

Afternoon Shift			
Assumptions			
Aerage Revenue per Customer (drink)	5	5	5
Baristas Hourly Wage	18	18	18
Variables			
# of Baristas Working	1	2	3
Mean Interval Arrival Time (min)	5	5	5
Min Service Time (min)	1	1	1
Mean Service Time (min)	2	2	2
Max Service Time (min)	5	5	5
Balking Queue Length	10	10	10
Max Wait Time (min)	10	10	10
Simulation Outputs			
# of Customers Arrived	38	45	41
# of Customers Serviced	23	31	28
Min Wait Time	0	0	0
Mean Wait Time	6.27	0.03	0
Max Wait Time	39.67	0.9	0
# of Customer Balked	0	0	0
# of Customer Left the Queue	13	14	13
Estimated Gross Revenue	115	155	140
Estimated Cost	72	144	216
Estimated Income	**43**	**11**	**-76**
Estimated Lost Revenue	65	70	65

Evening Shift			
Assumptions			
Aerage Revenue per Customer (drink)	5	5	5
Baristas Hourly Wage	18	18	18
Variables			
# of Baristas Working	1	2	3
Mean Interval Arrival Time (min)	7	7	7
Min Service Time (min)	1	1	1
Mean Service Time (min)	2	2	2
Max Service Time (min)	5	5	5
Balking Queue Length	10	10	10
Max Wait Time (min)	10	10	10
Simulation Outputs			
# of Customers Arrived	26	32	27
# of Customers Serviced	17	24	19
Min Wait Time	0	0	0
Mean Wait Time	0.25	0	0
Max Wait Time	3.97	0	0
# of Customer Balked	0	0	0
# of Customer Left the Queue	9	8	7
Estimated Gross Revenue	85	120	95
Estimated Cost	72	144	216
Estimated Income	**13**	**-24**	**-121**
Estimated Lost Revenue	45	40	35