MSDS 460 Assignment 4: Monte Carlo Methods - Benchmark Design and Analysis

Abstract

This study intends to optimize staffing levels at a coffee shop using Monte Carlo simulations. Using the SimPy Python library, a discrete event simulation environment is generated to represent the basic processes that take place in the daily operation of a coffee shop: a customer arrives, they wait in line, and eventually their order is taken by a barista. Discrete event simulations using 1, 2, and 3 employees are run, and wait-time benchmarks are compared for each employee count to determine the optimum staffing level for the coffee shop.

Introduction

Small businesses, and especially those in the hospitality industry, can often struggle to maintain an efficient level of operation. It was estimated in 2023 that 87% of restaurants in the United States were operating with insufficient staff. (Mintz) In the current day, it may not be common practice for a coffee shop to run discrete event simulations of their day-to-day operations, but this could be a powerful tool that unlocks a more complete understanding of where inefficiencies lie for small business owners. This study aims to show that discrete event simulations can provide value to a coffee shop in determining their optimum staffing level, and further, to demonstrate that data science can impart a wealth of knowledge to many industries that are not typically associated with data science.

Literature review

There have been several studies that set out to optimize the staffing levels in restaurants, though there are a couple that were of particular interest. David et al. utilized Monte Carlo simulation to gain a complete understanding of a restaurants' service system, then used their learnings to allocate employees to certain work stations at the right time to better meet customer expectations of service and ultimately minimize labor costs. S. Curin et al. analyzed the results of a detailed Monte Carlo simulation of a fast food restaurant to discover high utilization of cash registers, and used this discovery to recommend a change in the server set-up.

This study may use a less detailed simulation than previous studies, but the learnings from even a simple simulation can still be highly valuable, and perhaps more easily digestible for restaurant owners.

Methods

To conduct the Monte Carlo simulation, the SimPy Python library was used to create a discrete simulation environment. Beginning with the user-defined **arrival** function, we create an infinite loop of arrivals, i.e. new customers, to simulate a busy coffee shop. This function also incorporates a 'balking' limit - i.e. the maximum amount of time a customer will wait in line before they will decide to leave the line.

The user-defined **random_service_time** function establishes a random service time per customer to simulate the varying length of time it may take to prepare a beverage. The **service_process** function forces the simulation to wait for a barista to become available for service, and once there is availability, it uses **yield env.timeout** to determine the end of the event service, based on the length of time the service took. To more easily access the data generated by the simulation, user-defined functions **trace** and **event_log_append** were created, using example code provided in the SimPy Monitoring documentation.

Simulation parameters are then defined to allow for running multiple simulations with different employee counts, simulation lengths, service times, balking times, etc. Simulations are then run 100 times for each employee count, utilizing different random seeds to simulate 100 days of varying coffee shop traffic. With each simulation run, an event log is generated and saved in a CSV file, which is then combined into a Pandas dataframe for analysis.

Results

Our study produced some results that were to be expected: the simulations that utilized 3 employees had the fewest average balking customers, with just 0.08% of customers deciding to leave the queue. Correspondingly, the simulation with 3 employees also had the lowest average amount of wait plus service time per customer, with a mean average total time of 2.77 minutes. Fig. 1 shows average total time statistics for each employee count, with the 3-employee simulations represented by sim_tag 3.

001. Pictures > total-time-stats.md

sim_tag	mean	std	min	25%	50%	75%	max
1	20.31	5.36	1	17.08	20.4	23.8	41.27
2	7.06	3.81	1	4.02	6.85	9.82	21.98
3	2.77	1.8	1	1.15	2.25	3.92	14.8

Fig. 1 - Total wait time plus service time statistics table

One of the most interesting findings in this study is the sheer amount of total time saved by increasing the employee count by 1. When going from 1 employee to 2 employees, the average percentage of customers balking decreases from nearly 50% with 1 employee to 7.08% with 2 employees. Fig. 2 highlights this dramatic decrease.

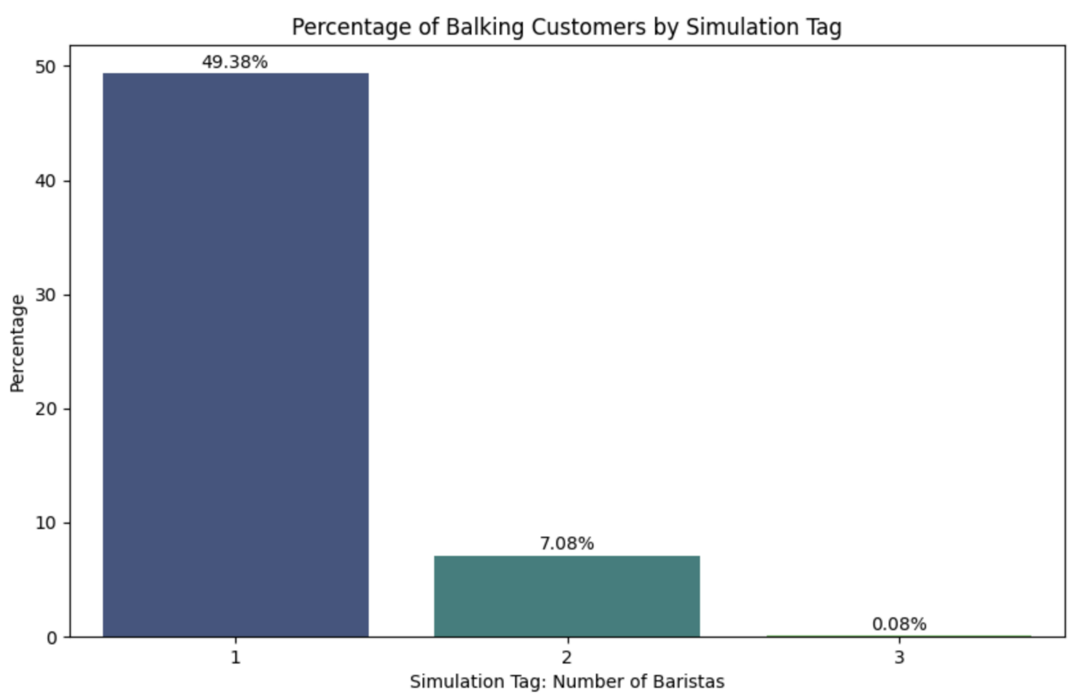

Fig. 2 - Percentage of Balking Customers by Simulation Tag

Ultimately, the results of these simulations indicate that 3 employees is the ideal staffing level, though 2 employees is such a significant improvement over 1 employee that this would also be an acceptable staffing level.

Conclusion

Coffee shops stand to gain significant improvements in efficiency and lowered wait times for customers by utilizing Monte Carlo simulations to better understand their service levels. The results of this study show the powerful impact that adding just 1 employee can have on customer wait times, which directly correlates to increased customer satisfaction. One limitation of this study is the lack of labor cost minimization. The team struggled to incorporate this aspect of staffing optimization within the context of a Monte Carlo simulation. Without having to account for labor costs, this means the highest number of employees will always be the ideal number of employees. In a repeat study, it would be important to incorporate this aspect.

However, the learnings to be gained for a small business from utilizing Monte Carlo simulations can be substantial, even without cost factors incorporated. For data scientists and management, it is important to use simulations when developing new business processes or revamping existing processes. The results of simulations can uncover previously unknown inefficiencies and give business leaders critical process knowledge, leading to data-driven decision-making and an overall increase in staff knowledge.

Bibliography

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