A Restaurant Queuing Model to Inform Staffing

DATA 604 Final Project

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Introduction

I have worked in the hospitality industry for the last decade, and am currently the daytime lunch manager at a popular downtown NYC restaurant. The COVID-19 pandemic adversely affected business at the restaurant and resulted in large cuts to staffing. Although business at the restaurant is back up, unfortunately the staffing has not returned to its pre-pandemic "normal," and employees find themselves overworked and unable to gain shift coverage for needed time off.

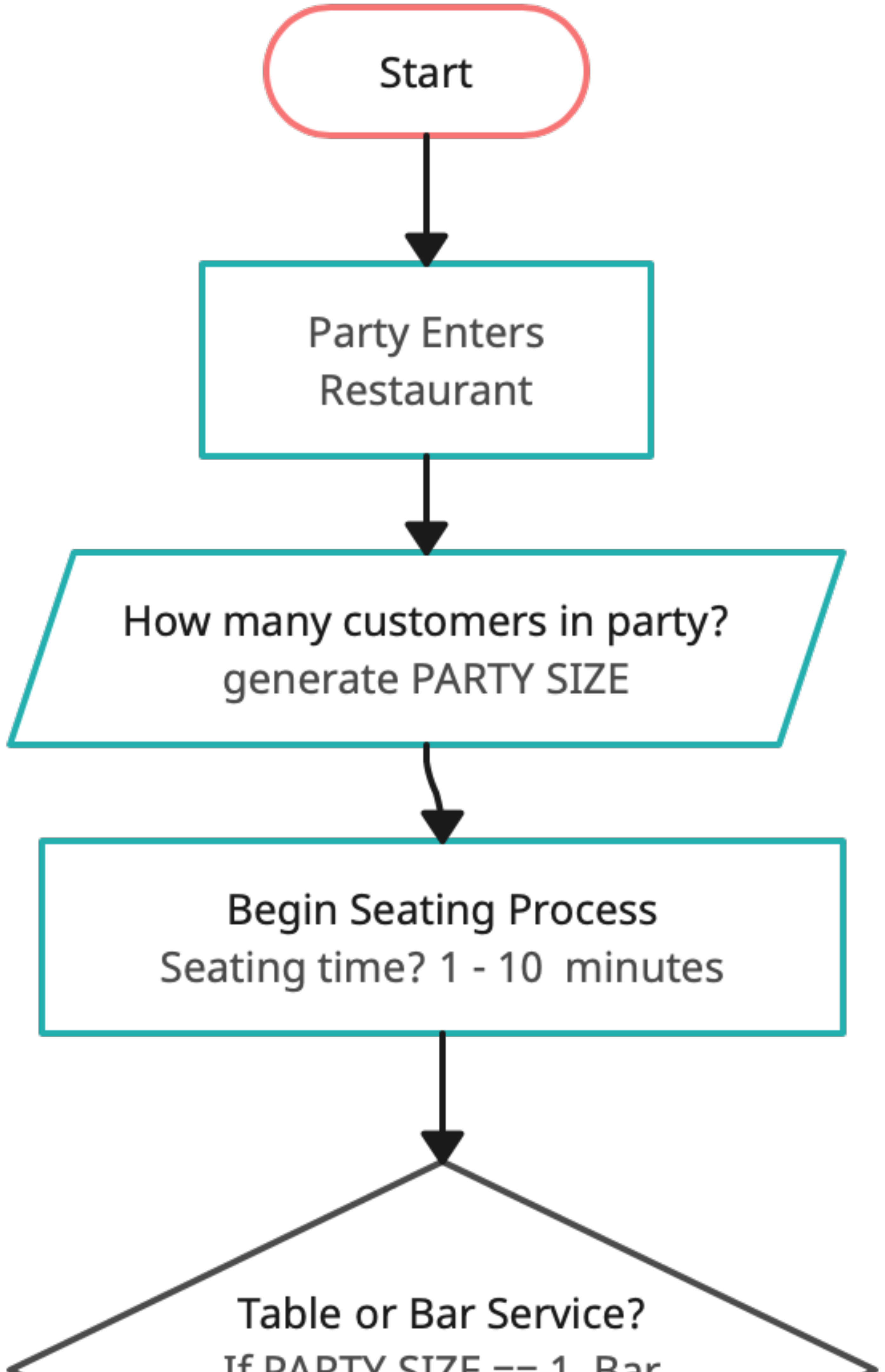
Staffing at a restaurant is highly dependent on business. For a busy shift one needs more staff, and for a slow shift one needs less. Having the appropriate amount of staff per shift is a way to temper wage costs on slower shifts, and being appropriately staffed for busy shifts is important for customer service and sales. Furthermore, in a tipped-wage system, overstaffing can be a detriment to an employee's take-home wages.

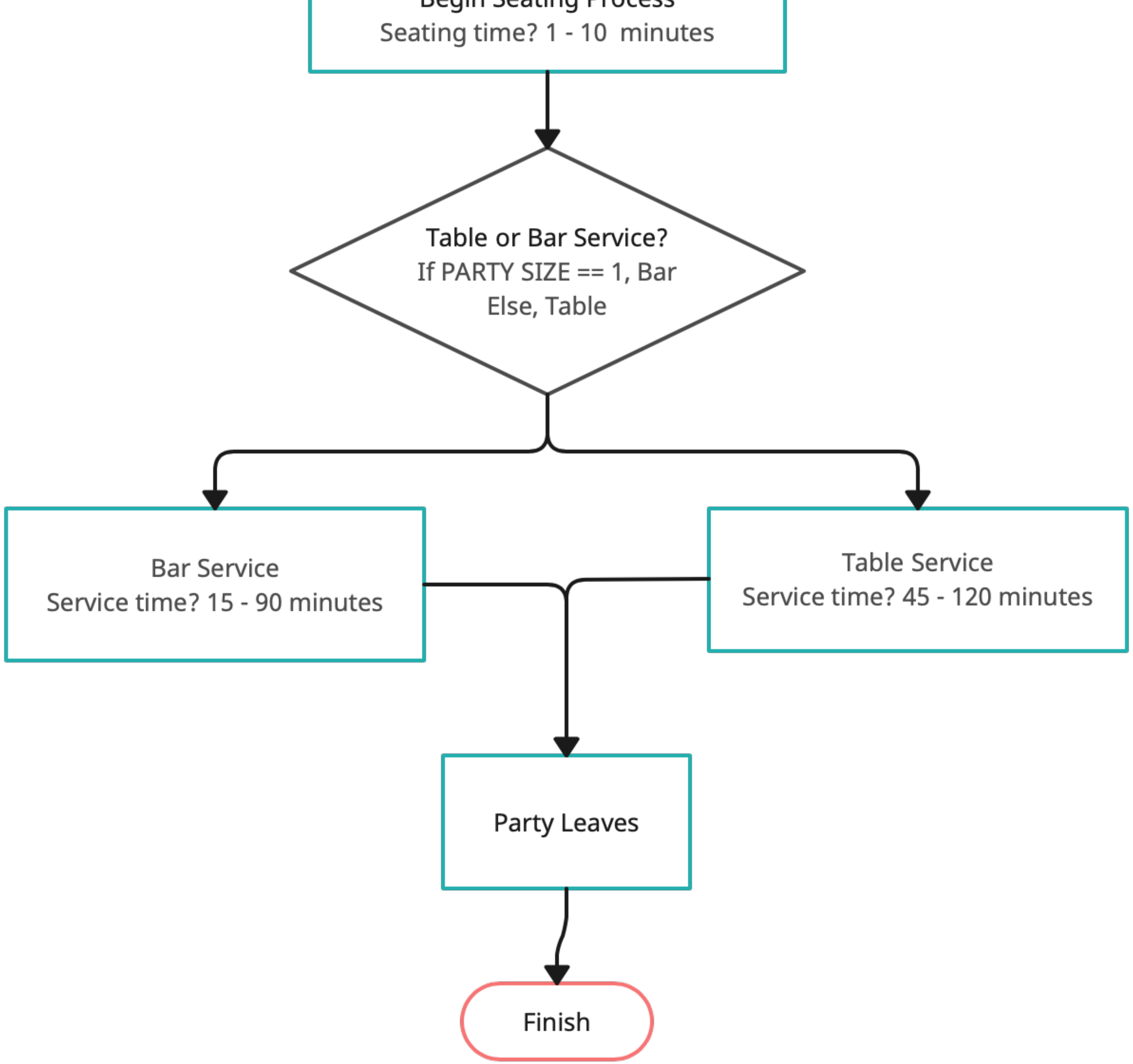
Problem and Significance

It is my attempt with this simulation to model customer flow at a restaurant in order to inform appropriate staffing decisions. At the restaurant where I work, we use a daily "cover count" to predict how busy a shift will be. A "cover count" simply refers to the amount of people you serve within the restaurant. If the restaurant serves 100 people in a day, the restaurant is said to have done "100 covers," and the shift has a "cover count" of 100. I have adapted code for simulating customer flow in a business to return a "cover count" for a typical five hour lunch shift at my restaurant (11 am to 4 pm), and have used my decade of experience to inform the model's logisitics and probabilities.

Having a stochastic model for simulating cover counts and customer flow will allow us to optimize staffing for both employee and employer gain.

Flow Chart


Start
Party Enters Restaurant
How many customers in party?
generate PARTY SIZE
Begin Seating Process
Seating time? 1 - 10 minutes
Table or Bar Service?


Seating time? 1 - 10 minutes
Table or Bar Service?
If PARTY SIZE == 1, Bar
Else, Table
Bar Service
Service time? 15 - 90 minutes
Table Service
Service time? 45 - 120 minutes
Party Leaves
Finish

Simulation

The model simulates a month (30 days) of lunch shifts at a restaurant that offers bar seating to parties of one, and table seating to parties of two to six. There are ten available seats at the bar, and ten available tables on the restaurant floor. The simulation acts as follows:

- Parties enter the restaurant based on a variable arrival rate over a five hour span
- Each party is assigned a customer count based on probablities
- Parties of one are assigned to the bar, and parties of two to six are assigned to tables
- Bar service is timed randomly from 15 to 90 minutes
- Table service is timed randomly from 45 to 120 minutes
- This process iterates 30 times, representing the average amount of lunch shifts in one month

Validity and Verification

I have validated my model by comparing it to my personal experience of working in the restaurant I am simulating. The data output by the model is very comparable to my daily experience with the actual customer flow of the restaurant. I understand that such validation is qualitative, and that the validity of my model would be further bolstered by quantitave or mathematical comparisons.

The report showing the details of individual party outputs for the final iteration of the simulation allows us to verify the model. It shows that the model is behaving in the manner which I intended. Seating and service times are within expected ranges, and parties are correctly sorted to the appropriate service by size.

	Party Id	Party Size	Service	Arrival Time	Seating Time	Service Start Time	Service Stop Time	Seating Time (Min)	Service Time (Mins)
0	Party_1	1	Bar	0.961451	4.961451	4.961451	35.961451	4.0	31.0
1	Party_2	1	Bar	6.149206	13.149206	13.149206	61.149206	7.0	48.0
2	Party_5	4	Table	12.800125	14.800125	14.800125	81.800125	2.0	67.0
3	Party_8	3	Table	33.830305	34.830305	34.830305	85.830305	1.0	51.0
4	Party_6	3	Table	21.796720	27.796720	27.796720	100.796720	6.0	73.0
5	Party_7	3	Table	22.518668	29.518668	29.518668	114.518668	7.0	85.0
6	Party_11	2	Table	67.625603	68.625603	68.625603	117.625603	1.0	49.0
7	Party_4	2	Table	12.005066	15.005066	15.005066	131.005066	3.0	116.0
8	Party_3	3	Table	8.885411	17.885411	17.885411	132.885411	9.0	115.0
9	Party_15	1	Bar	101.789906	105.789906	105.789906	142.789906	4.0	37.0
10	Party_10	4	Table	67.015593	73.015593	73.015593	152.015593	6.0	79.0
11	Party_12	4	Table	75.743429	76.743429	76.743429	161.743429	1.0	85.0
12	Party_9	2	Table	40.871964	48.871964	48.871964	166.871964	8.0	118.0
13	Party_13	4	Table	91.607078	97.607078	97.607078	168.607078	6.0	71.0
14	Party_16	3	Table	109.755559	110.755559	114.518668	190.518668	1.0	76.0
15	Party_19	2	Table	120.660215	127.660215	132.885411	204.885411	7.0	72.0
16	Party_21	1	Bar	140.526995	148.526995	152.015593	205.015593	8.0	53.0
17	Party_14	3	Table	93.698938	94.698938	94.698938	208.698938	1.0	114.0
18	Party_17	3	Table	113.810593	114.810593	117.625603	210.625603	1.0	93.0
19	Party_20	3	Table	127.025213	133.025213	142.789906	229.789906	6.0	87.0
20	Party_18	5	Table	117.154785	126.154785	131.005066	231.005066	9.0	100.0
21	Party_23	2	Table	149.298871	158.298871	166.871964	235.871964	9.0	69.0
22	Party_25	6	Table	168.278805	177.278805	190.518668	247.518668	9.0	57.0
23	Party_22	2	Table	142.606873	144.606873	161.743429	251.743429	2.0	90.0
24	Party_27	2	Table	186.197687	190.197687	205.015593	259.015593	4.0	54.0
25	Party_28	2	Table	187.964847	188.964847	208.698938	262.698938	1.0	54.0
26	Party_24	4	Table	152.389631	157.389631	168.607078	273.607078	5.0	105.0
27	Party_26	4	Table	181.604419	183.604419	204.885411	290.885411	2.0	86.0
28	Party_29	2	Table	197.317396	202.317396	210.625603	297.625603	5.0	87.0

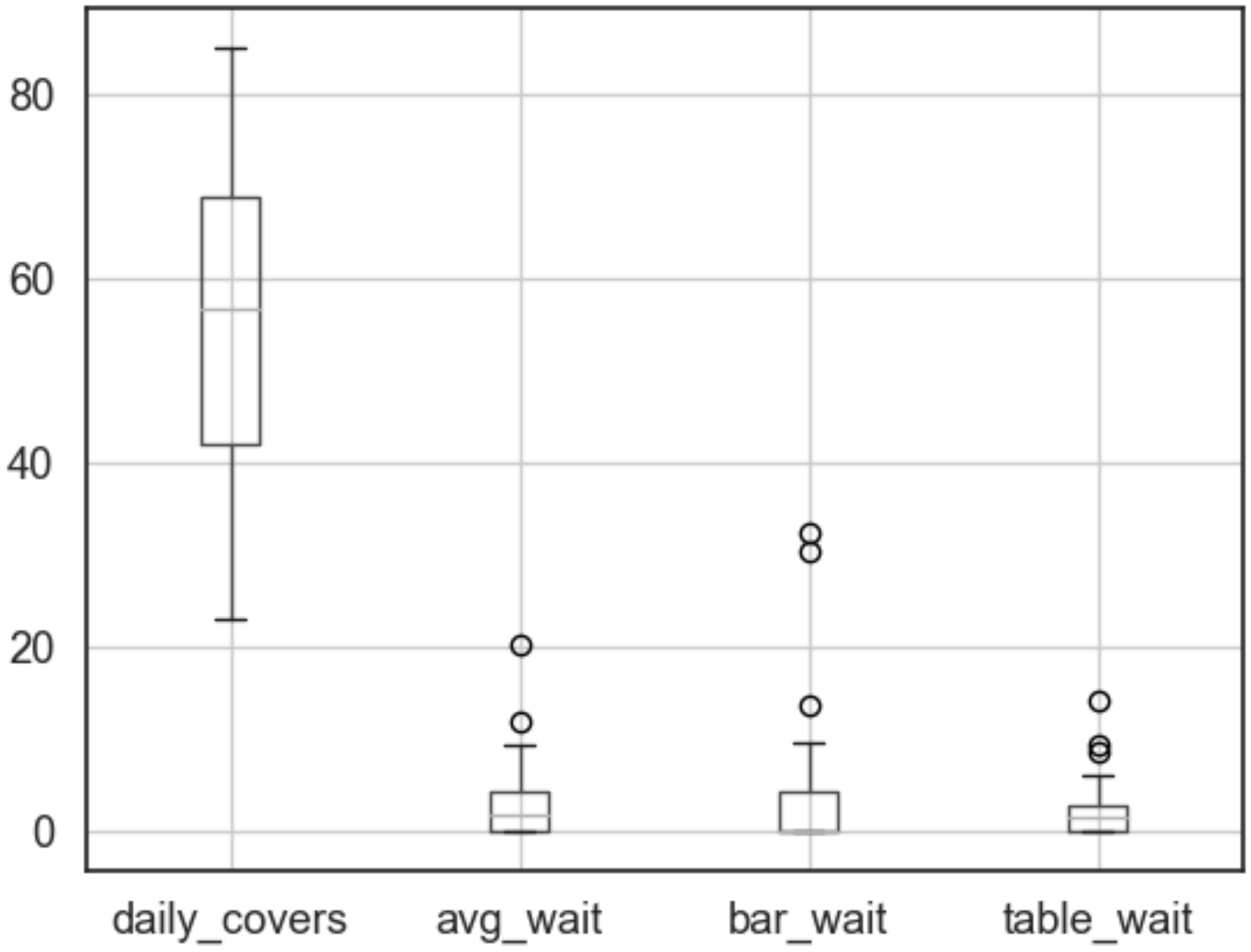
Conclusions

Perhaps the most important metric for our simulation is the mean daily covers calculated over the course of our simulated month. Using the daily cover numbers from our data frame, we see that the mean daily covers for our simulated month is 55.4. This is the metric we would use to determine staffing policy at our restaurant. In my experience, for the restaurant shifts I am attempting to simulate, one server can handle about 70 covers in a day. When we see our cover count increasing to over 70, we may wish to add a second server to the shift.

Obviously the mean cover count is directly related to the frequency of arrivals that was set for the simulation. This simulation has the frequency set for an arrival rate of 1 to 16 parties per hour. The main benefit of this model is that one can vary this arrival rate based upon lived observation to determine a mean cover count for a set span of time (iterations). One can then inform staffing decisions based upon this mean. Perhaps one has observed that during the week, Monday through Thursday, this is an apt arrival rate, but that on the weekends, Saturday and Sunday, one observes that ten to 20 parties arrive per hour. One can re-run the simulation with an arrival rate of ten to 20 parties per hour to output a mean cover count to inform a staffing model for those days that differs from the weekday staffing model.

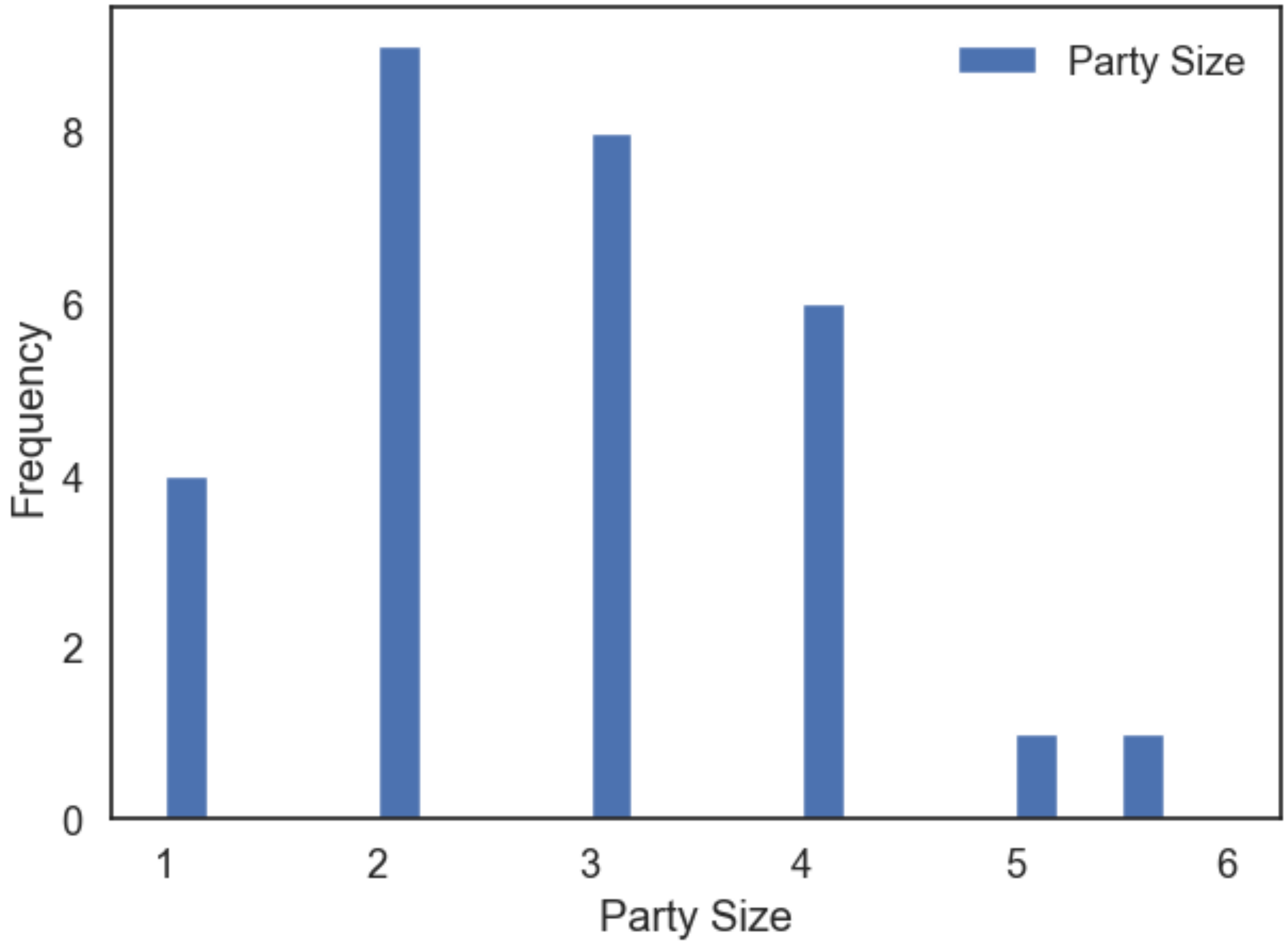
Boxplot

A boxplot shows the mean and distribution of our daily covers as well as wait times for bar and table service.



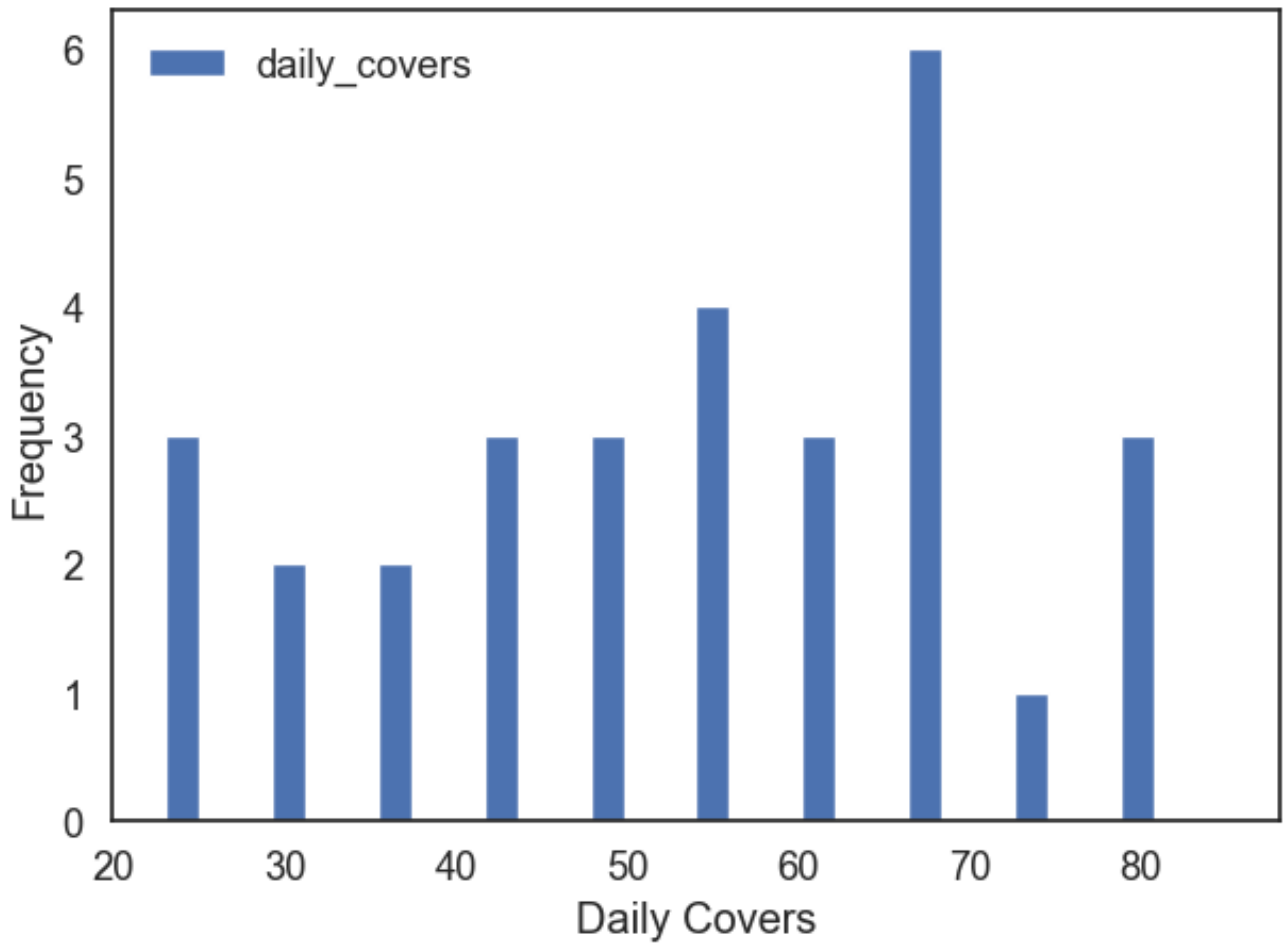
Histogram 1

A histogram of party size frequency over the month directly correlates to the percentages set for party size distribution in the model.



Histogram 2

A second histogram shows daily cover frequency over the month. This histogram would also by a good way to inform staffing decisions. One could decide to staff for the cover count that shows the highest frequency over the simulation, in this case about 68.



Bar Plot

Finally, I have sorted our daily cover numbers in ascending order and plotted them on a bar plot to reveal a linear distribution of daily covers in our simulation.