Team 05: Emma Cortez, Mahima Korad
Siddalinga Prasad and Maria Laura Farias

ISE 167 System simulation

Lion's Den Pizza Simulation Optimization

Summary of Project & Recommendations

This project focuses on analyzing and simulating the service production process at Lion's Den Pizza to identify bottlenecks and optimize facility layout, staffing, and workflow. The restaurant serves a high volume of both dine-in and takeout customers, each with different expectations for service speed, food quality, and seating availability. By creating a detailed simulation model in ProModel, we were able to replicate the customer journey from entry to exit, including food ordering, kitchen operations, seating, and final departure.

The model captured both the dine-in and takeout flows, as well as the parallel food preparation processes for sandwiches and pizzas. Customer arrival rates were based on time-of-day data while group sizes, seating times, and order preferences were built into the simulation based on provided project data.

We also incorporated equipment limitations such as pizza oven capacity and sandwich warmer throughput to make sure the simulation accurately reflected real-world constraints.

Our goal was to understand how Lion's Den Pizza functions under current demand and how it would perform with increases in customer volume. Using ProModel, we simulated seven different scenarios: one base case, two scenarios with increased customer traffic (+10% and +25%), and four additional experiments that adjusted variables such as seating, staffing, and number of hosts at the front counter. Each configuration was tested using 100 replications to ensure that results were stable and not influenced by randomness.

The simulation results showed that the most important factors impacting performance were the number of resources given to the model such as front counter hosts, kitchen staff, and available tables. Under the base case, the restaurant performed well with three hosts, six pizza makers, and three sandwich makers, serving over three hundred customers per day with reasonable wait times. However, when volume increased by 25%, performance began to decline, particularly in food preparation and customer service wait times, showing the need to scale resources appropriately.

These recommendations are supported by quantitative results and are meant to help Lion's Den Pizza maintain consistent service quality across locations, even as demand shifts. A detailed breakdown of scenario performance and output metrics can be found in the appendix section. With these improvements, the restaurant will be better equipped to reduce wait times, improve customer satisfaction, and operate more

efficiently under both current and future demand conditions.

To reduce the average wait time at the customer registration point (Cust_Reg), one effective strategy implemented was reducing the variability in service time. Originally, the service time followed a Gaussian distribution G(2, 1.75), meaning it had a mean of 2 minutes but a high standard deviation of 1.75 minutes. This introduced considerable variability, with some customers being served quickly and others experiencing much longer delays. Even though the average time was 2 minutes, occasional long service times would lead to congestion and longer queues. To address this, the distribution was changed to either a uniform distribution U(1.5, 2.5) or a Gaussian distribution with reduced standard deviation G(2, 0.75). While these new distributions have maximum values that differ only slightly (2.5 and 2.75 minutes, respectively), the key difference lies in their variance. The uniform distribution has a much lower variance (approximately 0.083) compared to even the reduced Gaussian (0.5625), resulting in more consistent and predictable service times. In queuing systems, even small reductions in variability can significantly improve flow and reduce waiting, particularly during peak periods when the system is near capacity. By smoothing out the service process and minimizing the chances of extreme delays, this change contributed directly to lowering the average wait time at Cust_Reg.

Experimentation & Analysis Performed

2.1 Model Design Summary

The simulation model was constructed to reflect both dine-in and takeout customer flows, as well as parallel food preparation streams for sandwiches and pizzas. The customer journey includes entering the restaurant, placing an order at the front counter, processing to either the seating area or a waiting area for takeout, and exiting after receiving or finishing their food. The kitchen processes are handled separately, with different workflows ensuring efficient resource usage between sandwich making and pizza making.

The model includes important details like customers waiting in line to order, being seated if a table is available, and handling delays for takeout customers who need travel time. We also set capacity limits for kitchen equipment, such as the sandwich warmers and pizza oven, to ensure they could only handle a certain number of items at a time.

The information we used to build the model was taken directly from the project instructions. Customer arrival rates with busy lunch and dinner hours. Group sizes range from two to eight customers, and each group has a specific pattern of sandwich and pizza orders. Sit-down times vary between 20 and 90 minutes depending on the group. Detailed tables containing arrival rates, group sizes and orders, sit-down times, and food preparation steps are provided in the Appendix for reference.

We made some assumptions to keep the model straightforward but realistic. These include making all food fresh to order, following equipment limits, making sure customers stay in either dine-in or takeout paths, and assuming food reaches tables right after being prepared.

2.2 Run-Time Parameters and Verification

In order to ensure realistic and statistically stable results, setting the right run-time parameters was critical. After experimenting with different settings, it was determined that a warm-up period was not needed for the model. This is because Lion's Den Pizza operates on a daily reset cycle, it opens at 11AM, and closes at 11PM, and does not carry over customers or food preparation across days. Since there is no buildup of customers from the previous day and the system begins "fresh" every morning, we found no start-up bias that would require our model to have a warm-up. For peak times or in preparation for increased demand, it is recommended to increase to four front counter hosts, seven pizza

Run length for simulation was set at 12 hours to match the restaurant's business hours. This run time allows us to capture key operational differences between lunch and dinner rushes and quieter periods during the afternoon and late evening. Capturing these time-based fluctuations was important to fully understand resource utilization and customer service performance across different parts of the day.

Deciding how many times to run the model was another important requirement. It was found that doing only a few runs caused our model results to vary significantly, especially for customer wait times and table utilization. Through testing, our team found that running the simulation 100 times gave us much more stable averages for the critical performance measures we were tracking. The number of relocations of 100 helped ensure that random variation was evened out, giving us results we could trust to make final recommendations.

Our team also took the time to verify that the model was working properly. First, we used animation playback inside ProModel to visually follow customers as they moved through the restaurant. This helped us confirm that the process flows were correct, including customer arrivals, ordering, seating, eating, and exiting. To validate kitchen operations, we used the Output Viewer to examine resource logs and processing times for both sandwich and pizza preparation steps. This allowed us to ensure that all kitchen resources such as makers, warmers, and ovens were being seized, used, and released correctly, and that no steps were skipped or overloaded.

Entity tracking was another vital verification step. We used Output Viewer to monitor the status of all customer entities and ensure that each group progressed through all process stages, from arrival and ordering to seating, eating, and exiting. We confirmed that the number of completed exits matched the number of arrivals, and that no entities remained idle or stuck in any part of the model at the end of the simulation. This confirmed that customers were not getting stuck, which gave us confidence that the model logic is functioning correctly.

Resource usage was monitored as well, to make sure that tables, sandwich makers, pizza makers, ovens, and warmers were being used the right way. We used both the animation playback and the Output Viewer to track when each resource was seized, how long it was held, and when it was released. This helped us verify that all resources were operating as intended, with no overlaps, overuse, or missed steps. We also confirmed that no resources were held indefinitely or blocked from being reused, which indicated that there were no stuck resources or broken workflows.

Finally, our team conducted a full walkthrough of the model logic. Each member of the team reviewed the flow charts, ProModel process logic, and key inputs and outputs to make sure we agreed the model was behaving properly. By doing multiple levels of verification, for example, logic checks, animation playback, entity checking, and team walkthrough, we were able to conclude that the model was both technically correct and a good reflection of how Lion's Den Pizza operates.

2.3 Experiments Conducted

To optimize staffing, layout, and resource usage at Lion's Den Pizza, our team conducted multiple simulation experiments. These experiments included a base model representing current customer volume, followed by additional scenarios with increased demand and modified capacity constraints. Each model configuration was run 100 times to ensure that the results were statistically stable and reflective of real operating conditions.

As mentioned before, we also explored variations in runtime settings, such as different warm-up periods and replication counts, as documented in our warm-up analysis table Appendix Table 5: Replication Count Analysis and Confidence Interval.

Analysis confirmed that increasing the number of replications helped stabilize average values for key performance indicators such as customer arrivals, pizza and sandwich orders, and overall system throughput. This validated our decision to use 100 replications per scenario to ensure consistent and reliable results. Additionally, to further reduce variability in simulation outcomes, it is important to assign a separate random number stream for each probability distribution used in the model. This ensures independence across different stochastic processes like arrivals, service times, and food preparation. If confidence intervals are observed to be too wide, two practical steps are to increase the number of replications or to reconsider the choice of distribution used, selecting one that better fits the real-world data and reduces statistical noise.

The base model simulated an average of 345 customers per day. Under these conditions, the restaurant was able to serve an average of 303.6 customers with stable wait times and balanced resource utilization. Table usage was consistent, with 2-person and 4-person tables operating at average utilization levels of 38.79% and 39.22%, respectively. This setup showed no major bottlenecks or performance issues and served as a reliable benchmark for further experimentation.

To explore how the restaurant would perform under higher customer volumes, we simulated demand increases of 10% and 25%. For these experiments, all other variables were held constant to assess whether the existing system continued to perform accordingly, serving between 333 and 379 customers on average, with only slight increases in wait times and workload for kitchen staff. However, when demand increased by 25%, wait times increased noticeably, exceeding 50 minutes on average. This suggested that while the current system could accommodate the 25% increase in demand, further increases in demand would require capacity improvements.

We further supported these findings with grouped hourly arrival breakdowns from Appendix Table 6: Customer Group Arrivals and Demand by Time of Day, which outlined the total number of customers expected per hour block across lunch, afternoon, and dinner periods. This allowed us to confirm that our model's logic aligned with real peak traffic patterns.

The analysis also showed that approximately 95% of customers were dine-in and 5% were takeout, which allowed us to verify that the takeout flow was correctly modeled. This confirmed that the majority of system demand was focused on dine-in service, aligning with our decision to prioritize analysis and improvements around dine-in operations.

To address this, we modeled additional scenarios adjusting the number of tables, staff, and front counter hosts. One scenario reduced seating to 35 two-person tables and 25 four-person tables, which led to significantly higher utilization rates, of over 55 percent and longer wait times, indicating that seating was a constraint in this configuration.

An in-depth breakdown of kitchen staff utilization is provided in the Appendix Table 10: Sandwich and Pizza Maker Utilization by Staffing Levels (Baseline, 10%, and 25%). This table shows how utilization changed across different staffing setups under baseline, 10% increase, and 25% increase demand scenarios. It clearly illustrates that increasing staff beyond three sandwich makers or six pizza makers leads to the decline of utilization rates. For instance, with five sandwich makers and seven pizza makers, the utilization dropped to 46.96% and 61.58%, compared to earlier rates of 78.22% and 71.85% with three sandwich makers and six pizza makers. This showed clear signs of excess capacity. These findings helped us identify the optimal staffing levels, balancing efficiency and labor cost.

Another scenario tested an increase in kitchen staff to 10 pizza makers and 10 sandwich makers. This did improve service speed, but adding more workers after a certain point did not make a difference, reaffirming our earlier conclusion that 6 to 8 pizza makers and 3 to 4 sandwich makers are the most efficient range.

An additional test increased seating to 55 tables of each size, which provided minor improvements in flow and wait times but was not critical unless customer volume remained high throughout the day.

Finally, we modeled a setup with only two front counter hosts. This resulted in longer customer wait times at the register compared to the baseline, confirming that at least 3 to 4 hosts are necessary to maintain acceptable service levels.

The impact of different seating layouts was captured in the Appendix Table 11: Table Utilization Across Different Seating Configurations (Baseline, 10%, and 25%), which compared table utilization rates across several combinations of two-person and four-person tables. The results showed a clear pattern: as the number of tables decreased, utilization percentages increased. For example, a configuration of 100 two-person tables and 100 for four-person tables have utilization rates of 21.95% and 21.8%. Now, reducing to 40 two-person tables and 45 four-person tables led to 53.99% and 47.82% utilization.

The complete data from all experiments, including the number of customers served, wait times, table usage, and resource utilization is presented in Appendix Table 8: Input-Output Summary Across Experimental Scenarios.

These results reinforced our staffing and layout recommendations by identifying which changes significantly improved performance and which provided minimal changes.

While our main focus during simulation was on key performance measures such as wait times and how much resources were used, we also looked at how the whole system behaved when we changed capacity levels. In Appendix Table 8:Input-Output Summary Across Experimental Scenarios, we tracked how different capacity setups affected performance in several test cases.

This helped us find the points where the system either started to slow down or stopped improving. Running extra tests gave us more confidence in our final recommendation and helped us better understand how our model works in general and more specifically, how changes in staffing and seating affect the system under different levels of demand.

2.4 Random Number Stream (RNS) - Overview and Application

Although we did not implement distinct Random Number Streams (RNS) in our final simulation experiments, we gained valuable understanding of their significance. In simulation modeling, RNS are essential when multiple sources of randomness such as customer arrivals, service times, and food preparation durations need to be independently and consistently represented. Using different streams for each distribution ensures statistical independence and avoids unintended correlations that could bias the results. For example, if customer arrival times and kitchen processing times shared the same random stream, the simulation might inadvertently create dependencies between these two unrelated processes.

The concept of RNS is often applied using Linear Congruential Generators (LCGs), which are deterministic but designed to approximate true randomness by producing sequences that appear uniform and uncorrelated. While our current ProModel implementation used shared default streams, future versions of the model could be enhanced by assigning separate random number streams to each major stochastic process. This would improve the model’s statistical robustness and align with best practices in discrete-event simulation.

Interpretation of Results and Conclusions

After running all of our simulation experiments, we analyzed the results to understand how our model for Lion’s Den Pizza performs under both current and increased customer volumes. Our goal was to identify where the restaurant’s operations succeed and where they begin to face limitations, specifically looking at customer wait times, worker utilization, and seating availability during peak periods.

Under baseline conditions, the system handled around 345 customers per day with minimal issues. The average customer wait time at the register was approximately

22.9 minutes, while wait times for pizza and sandwich preparation remained reasonable. Worker utilization was balanced, and seating capacity was sufficient to prevent dine-in delays. These results suggest that the current staffing levels and table counts are well suited for normal business days, with smooth service flow and minimal bottlenecks.

However, when we increased demand by 10 percent and then 25 percent, pressure points in the system became clear. The most noticeable issue was the rise in wait times, particularly for sandwich orders. With a 25 percent increase in customer volume, the average wait time for sandwiches exceeded 50 minutes. Front counter wait times also increased when only three hosts were available, suggesting that an additional host is needed to maintain a consistent customer experience during peak or busy periods.

Our group also observed that reducing the number tables caused table utilization rates to increase significantly. It was mentioned before that with 40 two-person tables and 45 four-person tables, utilization went above 50%, meaning customers were likely waiting longer to be seated. These results show that seating becomes a constraint as demand increases and again, supports our recommendations. Similarly, increasing kitchen staffing to 10 sandwich and 10 pizza makers resulted in only small improvements, demonstrating that overstaffing is not a cost-effective solution and that optimal resource levels exist.

From the worker utilization data, we noticed that efficiency decreased when too many staff were added. For instance, pizza maker utilization dropped when staffing increased beyond seven, confirming that simply increasing headcounts does not always lead to faster service. The takeaway here is that scaling operations requires a strategic balance, more resources help up to a point, but eventually could lead to waste or underuse. On the other hand, having too few staff or tables results in long queues, customer dissatisfaction, and potential loss of business.

We also considered the distribution of dine-in versus takeout customers. Approximately 95% of all customers chose to dine in, this confirmed that in-house seating should be a key area of focus when it comes to allocating resources. This influenced our decision to prioritize maintaining a right amount of table counts and keeping the seating process smooth and responsive. If the restaurant sees shifts in customer behavior in the future, such as more takeout orders, it may require a reallocation of staffing or space usage.

To support our conclusions, we reviewed the Location Summary Tables generated by ProModel, which report the average and maximum "content" at each station. In this context, content refers to the number of entities (such as customer orders or items) waiting in a queue or being processed at a given location. A high average content suggests a station is consistently busy, while a high maximum content indicates occasional spikes that may cause delays or overcrowding.

The most significant congestion was found at the Sandwich Matching Station (San Match), which had an average content of 17.52 and a maximum of 30.81. This means that, on average, there were nearly 18 orders waiting at this station, with peaks of over

30. This suggests frequent delays in sandwich completion, making it a likely bottleneck that could benefit from added capacity or process improvements.

On the pizza side, Pizza Bake (Piz Bake) also showed signs of congestion, with a maximum content of 14.65 and a consistently high average. This indicates the oven is a critical part of the process and a potential constraint during busy periods.

Other stations such as Customer Register, Sandwich Gather, and San Plating had moderate content levels, suggesting they are operating close to full capacity but are not immediate bottlenecks. Locations like Pizza Order, Pizza Match, and Sandwich Warm had lower content values and are performing efficiently.

Some values, however, were found to be misleading. The Table Area had an average content of 33.74 and maximum of 67.49, but this reflects a cumulative count of occupied seats across different table sizes, not actual table units or customer groups. Therefore, it does not accurately signal seating bottlenecks. Likewise, the Waiting Togo queue reported an extreme average wait time exceeding 11,000 seconds, which is not realistic. This suggests a flaw in the to-go pickup logic that needs correction.

Overall, the key congestion points identified were San Match and Piz Bake, while other stations showed stable performance. Certain outputs like Table Area and Waiting Togo should be interpreted cautiously due to modeling abstraction or logic gaps.

In conclusion, our simulation results provided a clear, data-backed plan for optimizing operations at Lion's Den Pizza. We recommend configuring the system with 4 customer registers, 4 sandwich makers, and 7 pizza makers to handle both current and increased customer volumes effectively. This setup offers a well-balanced service flow, minimizes wait times, and avoids the pitfalls of over or under utilizing staff. Additionally, maintaining 45-50 tables of each size ensures it does not become a bottleneck, especially during peak hours. These recommendations are supported by consistent results across 100 replications and are detailed further in the appendix. With these changes, Lion's Den Pizza can improve customer satisfaction, increase efficiency, and prepare its operations for future growth.

Appendix

Table 1: Arrival Rate for Customers Groups by Time of Day

Time of Day	# Groups per Hour	Peak/Non-Peak
11 AM - 2 PM	50	Peak
2 PM - 5 PM	10	Non-Peak
5 PM - 8 PM	30	Peak
8 PM - 11 PM	25	Non-Peak

Table 2: Customer Group Size and Corresponding Food Orders

# of Customers	% of Arriving Groups	# of Sandwiches	# of Pizzas
2	40	2	0
		0	1
4	30	0	1
		0	2
		1	2
6	20	0	2
		2	2
8	10	2	2

Table 3: Sit-Down Time for Each Customer Group

Sit-Down Time (min)	Percentage of Groups
20-30	30%
30-50	50%
50-90	20%

Table 4: Sandwich and Pizza Making Process and Time Requirements

Sandwich/Pizza	Process Step	Time (min)	Required Resource
Sandwich	Gather sandwich ingredients	3-5	Sandwich Maker
Sandwich	Warm Sandwich	1-2	Sandwich Warmer
Sandwich	Assemble & Plate	1-2	Sandwich Maker
Pizza	Open Dough	2-5	Pizza Maker
Pizza	Add Sauce & Toppings	1-3	Pizza Maker
Pizza	Bake Pizza	7-13	Pizza Oven
Pizza	Slices & Plates Pizza	1-2	Pizza Maker

Table 5: Replication Count Analysis and Confidence Intervals

	Cust_Arrival		Sandwich		Pizza	
# of Replication	95% of CI of LCL	95% of UCL	95% of CI of LCL	95% of UCL	95% of CI of LC	95% of UCL
10	303.82	308.78	271.9	300.48	413.09	432.51
20	305.42	309.68	274.68	294.22	419.3	430.6
40	305.09	309.26	277.73	291.12	421.76	430.19
60	305.03	308.27	280.28	290.12	424.76	432.51
80	305.36	308.24	278.8	287.7	426.64	433.51
100	305.6	308.18	278.63	286.27	427.28	433.1
120	305.78	308.04	279.77	286.45	427.4	432.5
150	306.3	308.32	280.17	286.11	427.76	432.4

Table 6: Customer Group Arrivals and Demand by Time of Day

Hrs	Groups/hr	Total #	Increase by 10%	Approximately	Increase by 25%	Approximately
3	50	150	165	165	187.5	188
3	10	30	33	33	37.5	38
3	30	90	99	99	112.5	113
3	25	75	82.5	83	93.75	94
Total number of Customers /Day		345	379.5	380	431.25	432
	Output	306.86				

Table 7: Front Counter Host Performance at Varying Staffing Levels

No of Hosts requ	Utilization %	Customer Exits	Sandwich	Pizza	Average Waiting Ti	Average Waiting Time	Average Waiting Time(min)(Pizza)
1	99.77	176.15	162.48	252.81	213.5436667	58.76816667	9.085166667
2	83.64	304.26	282.82	428.71	42.7895	40.90033333	7.5
3	55.83	306.17	286.22	431.01	28.867	46.88016667	8.058
4	41.73	306.89	282.45	430.19	27.97216667	48.71516667	8.099333333
5	33.47	307.02	283.02	432.82	27.733	47.4705	9.526666667
6	27.72	307.8	286.9	431.81	27.985	47.7395	8.640666667

Table 8: Input-Output Summary Across Experimental Scenarios

INPUT										
Contraints		Base Model			Customer Group		Capacity Variations			
		01			02	03	04	05	06	07
Total number of Customers		345			10%	25%				
Customer Register		4							2	8
2 Person Table		50						35		
4 Person Table		50						25		
Pizza Makers		7					10			
Sandwich Makers		4					10			
OUTPUT										
		BaseLine (01)			02	03	04	05	06	07
Metrics		Average	CI LL	CI UL	Average	Average	Average	Average	Average	Average
Count	Number of Customers Served	303.60	302.17	305.03	333.96	379.37	304.43	265.71	303.80	302.13
	No of Pizzas	432.34	429.38	435.30	478.28	347.40	429.00	360.43	427.93	276.28
	No of Sandwich	278.79	275.22	282.36	303.38	538.73	280.08	241.33	279.88	432.00
Resource Utilization %	Sandwich Makers	58.94	58.30	59.58	63.68	72.68	23.32	58.51	58.44	58.71
	Pizza Makers	61.75	61.34	62.16	68.06	76.57	43.22	61.59	61.68	61.73
Table Utilization %	Utilization of 2 Person Table	38.79	37.79	39.78	44.58	53.40	34.32	55.30	34.74	38.71
	Utilization of 4 Person Table	39.22	37.46	40.98	46.13	55.21	32.29	80.44	33.88	41.44
Wait Time(min)	Avg Wait time in Min for CustReg	22.90	22.38	23.43	27.75	34.70	16.73	22.23	40.75	47.26
	Avg Wait time in Min for San	49.36	45.66	53.06	50.13	54.78	39.78	80.28	40.32	72.08
	Avg Wait time in Min for Pizza	9.07	8.48	9.66	12.39	17.41	7.83	37.85	7.78	17.20
Orders	Dine-In	295.48	293.95	297.01	323.46	366.10	298.29	257.01	297.46	293.32
	Togo	8.12	7.59	8.65	10.50	13.27	6.14	8.70	6.34	8.81

Table 9: Customer Register Staffing Impact on Wait Times and Output (Baseline, 10%, and 25%)

No of Hosts required at Customer Arrivals	Utilization %	Customer	Sandwich	Pizza	Average Waiting Time(min)(Customer	Average Waiting Time (min)(Sandwich	Average Waiting Time(min)(Pizza)
1	99.77	176.15	162.48	252.81	213.5436667	58.76816667	9.085166667
2	83.64	304.26	282.82	428.71	42.7895	40.90033333	7.5
3	55.83	306.17	286.22	431.01	28.867	46.88016667	8.058
4	41.73	306.89	282.45	430.19	27.97216667	48.71516667	8.099333333
5	33.47	307.02	283.02	432.82	27.733	47.4705	9.526666667
6	27.72	307.8	286.9	431.81	27.985	47.7395	8.640666667

No of Hosts required at Customer Arrivals (10%) INC	Utilization %	Customer	Sandwich	Pizza	Average Waiting Time(min)(Custome	Average Waiting Time (min)(Sandwic	Average Waiting Time(min)(Pizza)
1	99.8	16.93	163.67	253.06	235.5148333	56.0785	26.09333333
2	91.06	332.45	303.51	470.27	50.45116667	44.46716667	7.331166667
3	61.09	338.12	316.53	475.58	34.88116667	49.0305	8.992333333
4	45.96	338.64	314	474.9	33.5	50.55466667	11.8145
5	36.63	337.72	312.96	472.83	33.95666667	54.12766667	12.20266667
6	30.51	337.98	315.08	476.36	34.13333333	52.93333333	12.2035

No of Hosts required at Customer Arrivals (25%) INC	Utilization %	Customer	Sandwich	Pizza	Average Waiting Time(min)(Custome	Average Waiting Time (min)(Sandwic	Average Waiting Time(min)(Pizza)
1	99.82	177.08	162.35	253.75	252.916	58.41283333	8.398
2	99.38	357.64	332.35	508.26	81.0055	41.384	7.112666667
3	69.02	382.4	359.25	538.33	47.865	55.75566667	11.10033333
4	52.06	383.91	358.9	539.39	46.26866667	62.57	17.46866667
5	41.49	384.15	359.33	537.19	45.081	61.44866667	18.398
6	34.77	384.06	356.52	539.28	44.541	62.19583333	18.3175

Table 10: Sandwich and Pizza Maker Utilization by Staffing Levels (Baseline, 10%, and 25%)

Sandwich Maker	Pizza maker	Utilization % of Sandwich	Utilization % of Pizza	Total Sandwich	Total Pizza	Customer Exits
2	4	99.1	99.12	245.8	399.8	272.08
3	5	78.34	85.93	276.15	433.23	302.08
3	6	78.22	71.85	281.37	432.79	305.2
4	6	59.07	71.77	279.29	432.12	303.08
5	7	46.96	61.58	277.33	431.89	302.77
4	7	58.45	61.67	276.71	431.8	303.53
3	7	77.84	61.32	282.45	430.19	306.89
6	8	38.95	53.45	278.21	426.38	304.38

10%

Sandwich Maker	Pizza maker	Utilization % of Sandwich	Utilization % of Pizza	Total Sandwich	Total Pizza	Customer Exits
2	4	99.13	99.11	245.16	400.55	270.61
3	5	85.88	94.1	305.43	475.29	332.28
3	6	85.39	78.88	311.51	476.3	337.42
4	6	64.47	78.67	303.13	474.9	333.15
5	7	51.36	67.55	303.24	474.28	333.15
4	7	64.03	67.45	306.44	471.74	334.52
3	7	86.27	67.67	316.53	475.58	338.12
6	8	43.11	59.21	308.02	471.91	334.56

25%

Sandwich Maker	Pizza maker	Utilization % of Sandwich	Utilization % of Pizza	Total Sandwich	Total Pizza	Customer Exits
2	4	99.2	99.19	245	399.86	274.33
3	5	95.49	99.09	326.83	345.84	496.89
3	6	95.59	89.14	352.48	539.59	380.82
4	6	72.41	89.5	340.91	540.17	376.68
5	7	58..92	76.46	342.57	535.06	374.08
4	7	72.68	76.57	538.73	347.4	379.37
3	7	95.7	76.66	539.39	358.9	383.91
6	8	48.74	67.01	343.26	533.95	374.51
4	8	73.18	67.16	353.99	537.63	381.57

Table 11: Table Utilization Across Different Seating Configurations (Baseline, 10%, and 25%)

Table 2	Table 4	Utilization % of Table 2	Utilization % of Table 4	Total Sandwich	Total Pizza	Customer Exits
100	100	21.95	21.8	281.37	432.79	305.2
75	75	29.26	29.06	281.37	432.79	305.2
50	50	43.57	43.59	281	432.79	305.52
45	45	48.8	47.83	277.07	433	305.14
40	45	53.99	47.82	274.95	433.63	305.22
35	45	60.66	48.03	276.46	432.39	304.56
45	40	47.9	54.61	280.17	429.33	303.91
35	35	60.96	60.93	276.78	429.93	302.12
35	38	62.03	57.91	276.08	430.5	301.86
43	43	51.15	49.5	282.83	433.34	304.68

10%						
Table 2	Table 4	Utilization % of Table 2	Utilization % of Table 4	Total Sandwich	Total Pizza	Customer Exits
100	100	21.25	21.34	306.84	473.38	334.63
75	75	28.55	28.46	306.84	473.38	334.63
50	50	42.64	41.39	306.84	471.74	334.52
45	45	46.93	46.04	303.33	476.91	335.93
40	45	52.84	46.89	309.01	471.28	334.17
35	45	62.36	45.84	295.1	470.29	326.95
45	40	47.54	54.95	305.1	476.11	332.68

25%						
Table 2	Table 4	Utilization % of Table 2	Utilization % of Table 4	Total Sandwich	Total Pizza	Customer Exits
100	100	24.55	24.99	346.18	539.21	379.28
75	75	32.74	33.31	346.18	539.21	379.28
50	50	49.86	49.41	348.8	540.19	379.11
45	45	55.26	57.02	348.07	537.53	378.07
40	45	62.1	55.7	345.71	534.2	376.07
35	45	73.8	54.97	317.87	522.19	358.39
45	40	54.47	63.45	342.91	531.33	375.38

Table 12: Process Flow