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Optimizing Customer Flow through Simulation: A Case Study of Tiranga Bhuvan Restaurant, Pune

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Abstract: ***Small and medium-sized restaurants in high-density urban areas often face operational bottlenecks during peak hours, leading to long queues, extended wait times, and lower customer satisfaction. This study presents a simulation-based approach to diagnose and optimize customer flow in Tiranga Bhuvan, a popular restaurant in Pune, India. Primary data was collected through direct observation, interviews, and time tracking of service stages, then modeled in Excel/Google Sheets to replicate real-world peak-hour dynamics. The model enables what-if" scenario testing-such as adding tables, increasing staff, or adjusting arrival patterns-without disrupting ongoing operations. Results show that minor interventions, like adding one table or an extra server, can reduce peak wait times by over a minute and significantly boost monthly revenue. The research highlights that even simple spreadsheet-based simulations can provide actionable insights for small businesses, bridging the gap between observational knowledge and data-driven decision-making. This methodology offers a low-cost, replicable framework for other service-oriented businesses seeking to balance tradition with efficiency.***

Keywords: Customer flow, Queue simulation, Restaurant efficiency, Operational optimization, Service management

1. Introduction

In today's rapidly evolving service economy, the efficiency of customer flow and time management plays a critical role in shaping the success of small businesses. From food stalls to full-service restaurants, the ability to handle high customer volume during peak hours determines not only operational sustainability but also customer satisfaction and loyalty. Long queues, disorganized service structures, and unpredictable wait timecontinue to plague many local establishments—yet few possess the tools or data-driven insights needed to systematically identify and resolve such issues.

This research paper presents a simulation-based approach to diagnosing and improving customer service efficiency in small, high-traffic businesses—specifically focusing on the case of Tiranga Bhuvan, a popular local restaurant in Pune, India. Using first-hand observational data, stakeholder interviews, and structured time tracking of customer movement through the restaurant's service stages, the study constructs a digital model that replicates the dynamics of a typical rush hour. Through the model is used to explore multiple improvement strategies—from staff reallocation and order scheduling to customer arrival control—and evaluates their projected impact on wait times, throughput, and service efficiency.

The purpose of this paper is twofold: first, to demonstrate how even a simple tool such as a spreadsheet can be used to build an effective simulation of real-world service operations; and second, to provide actionable insights for local businesses like Tiranga Bhuvan seeking to enhance their operational efficiency without requiring costly technology or consultancy. This study lies at the intersection of operations research, service design, and local business strategy, offering a practical methodology that can be replicated by other small establishments facing similar issues.

Unlike traditional case studies or surveys, this project incorporates quantitative modeling, enabling the testing of "what-if" scenarios without interfering with actual business operations. This allows for evidence-based decision-making and informed experimentation—key advantages in environments where downtime, resource waste, or poor customer experience can have immediate financial consequences.

By capturing the flow of customers through each critical phase of the restaurant's service pipeline—arrival, seating, ordering, kitchen processing, eating, billing, and table exit—this study provides a holistic picture of where time is lost and how systems can be refined. Ultimately, it advocates for the use of accessible, affordable modeling tools to bridge the gap between observational knowledge and operational intelligence in small-scale service businesses.

Awareness: The Problem of Wait Times in Small Restaurants

In many growing urban centers in India, small and medium-sized restaurants serve as vital cultural and economic spaces—offering fast, affordable, and flavorful meals to a steady stream of loyal customers. However, in high-demand settings, especially during breakfast and dinner rush hours, these businesses often struggle with a persistent issue: long queues and customer waiting times. While often overlooked as an operational inconvenience, this problem directly impacts customer satisfaction, staff stress levels, revenue generation, and the overall reputation of the business.

Tiranga Bhuvan, a popular and widely trusted restaurant in Pune, serves as a prime example of this dynamic. Renowned for its flavorful Maharashtrian dishes and fast-paced service model, Tiranga Bhuvan regularly draws large crowds, especially during peak hours. However, the very popularity that drives its success also contributes to service bottlenecks—manifesting as congestion at entry, delays in order taking, and lengthy table turnover times. Customers often queue outside the restaurant, wait to be seated, and experience delays between placing an order and receiving their meal. Despite a skilled kitchen and experienced staff, the existing service structure struggles to keep up with peak-time demand.

The issue at hand is not one of food quality or customer interest—it is a logistical and operational challenge rooted in service flow design. Small service businesses rarely use structured data or modeling to understand their systems. While large chains employ queueing theory, demand forecasting, and digital order systems, local restaurants typically depend on the intuition of experienced staff and "trial and error" methods to make service adjustments. As customer expectations rise and urban lifestyles demand faster service, relying solely on instinct is no longer enough.

Addressing this issue requires a deeper awareness of how customers move through the restaurant system—from arrival to exit—and where inefficiencies lie. Without such insight, potential improvements remain either speculative or invisible. Thus, the first step toward operational enhancement is visualizing and analyzing the current customer flow in a structured, data-driven manner.
Correlation

A relevant study that strongly complements our research is the Blue Meadows Restaurant case study conducted by Gumus et al. (2017), which applied queuing theory to assess and improve service delivery in a fast-food outlet. The researchers collected real-time data on customer arrival rates and service durations, finding that arrivals followed a Poisson distribution while service times adhered to an exponential distribution—assumptions similarly adopted in our simulation of Tiranga Bhuvan. Using an M/M/s multi-server queue model, they were able to calculate performance indicators such as system utilization, average queue length, and customer waiting time. At peak times, the Blue Meadows restaurant operated with a utilization of 0.909, resulting in prolonged wait times and reduced customer satisfaction—an issue that closely parallels the conditions observed at Tiranga Bhuvan during peak hours. Our findings echo theirs: with a high inflow of around 80–100 customers per hour, utilization levels in our system regularly exceeded 85%, pushing average wait times beyond 12–15 minutes. By comparing both contexts, we identify a shared challenge in fast-service dining—balancing limited physical and human resources with customer flow to optimize service delivery. Furthermore, while the Blue Meadows team focused on theoretical queue modeling, our study extends this by incorporating real-world timing data into a dynamic Excel-based simulation, allowing for scenario testing such as the impact of increasing table count, adding waitstaff, or modifying customer seating cycles. This practical layer not only validates classical queuing assumptions but also makes our model highly adaptable to small-business operations in high-density urban settings like Pune.

2. Literature Review

1) Worth the Wait? How Restaurant Waiting Time Influences Customer Behavior and Revenue
   This research paper analyzes customer behavior using data from nearly 94,000 diners at an Indian restaurant, aiming to understand how wait times impact customer decisions and overall revenue. The problem identified is that long waiting times lead to higher customer abandonment rates, shorter dining durations, and reduced likelihood of return visits, all of which negatively affect revenue. To address this, the study proposes implementing a reservation system, optimizing table allocation flexibility, and expanding seating capacity by around 20%. Simulations indicate these measures could lead to revenue increases of up to 15%. While reservation and table flexibility are low-cost and feasible interventions, expanding capacity may be limited by spatial and financial constraints, making it a less universally applicable solution.
   https://www.sciencedirect.com/science/article/abs/pii/S0272696318300214?utm
2) A Simulation Model for Managing Customer Waiting Time in Restaurants
   This study uses a simulation approach to examine how customer wait times influence satisfaction and service effectiveness in an upscale restaurant setting. The core issue addressed is the emotional discomfort and loss of customers caused by delays at various service points, such as entry and food preparation. To solve this, the researchers suggest adding additional chefs and service staff during peak hours and inserting extra tables in high-demand zones. Results show that even one extra chef significantly reduces customer anxiety and slightly improves service throughput. Although effective in theory, these strategies might be constrained by factors such as space, staffing budgets, and overall service quality, especially if the restaurant is already operating near full capacity.
   https://www.emerald.com/insight/content/doi/10.1108/bfj-09-2019-0685/full/html?utm
3) Lined Up? Examining a 'Waiting Line 'Effect in Technology-Enabled Restaurant Menu Ordering
   This experimental paper explores how visible queues behind customers using self-service kiosks influence ordering behavior. The central issue is that the presence of a line causes customers to feel rushed, which leads to less exploratory, more habitual, and lower-value purchases. As a solution, the authors suggest redesigning queuing systems, such as introducing a single line feeding multiple kiosks, and incorporating intervention messages that reduce social pressure by reframing customer responsibility. These changes are promising for digital ordering environments and can ease stress while potentially increasing sales. However, the effectiveness of such solutions is context-dependent and may not apply to human-staffed ordering environments or in settings with deeply ingrained social behaviors.
   https://www.researchgate.net/publication/375773228_Lined_Up_Examining_a_Waiting_Line_Effect_in_Technology-Enabled_Restaurant_Menu_Ordering
4) How Much Is a Reduction of Your Customers 'Wait Worth? An Empirical Study of the Fast-Food Drive-Thru Industry
   This paper uses structural estimation methods to evaluate how wait times affect consumer behavior in the drive-thru fast-food industry, with data drawn from Cook County, USA. The problem discussed is the trade-off between customer time sensitivity and price competitiveness, where longer wait times drive customers to competitors regardless of pricing. The proposed solutions include enhancing operational efficiency to reduce wait times and aligning pricing strategies with customer time valuation. The study finds

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that time often holds greater value to customers than pricing, suggesting that reducing wait times can significantly boost market share. However, such improvements require investment and are highly dependent on local labor, infrastructure, and the intensity of competition.
https://www.researchgate.net/publication/228380742_How_Much_Is_a_Reduction_of_Your_Customers'_Wait_Worth_An_Empirical_Study_of_the_Fast-Food_Drive-Thru_Industry_Based_on_Structural_Estimation_Methods

5) Analysis of a Queuing System in a Restaurant: A Case Study
This case study applies a standard M/M/1 queue model at a busy Taco Bell outlet in Chandigarh, India, to understand arrival and service behavior. The main problem is the inefficiency in predicting wait times, service utilization, and customer loss due to delayed service. The study proposes using real-time arrival and service data to calculate metrics like utilization rate (≈0.987) and average wait time (around 13 minutes), then adjusting staff or service stations accordingly. While the model offers helpful baseline insights, real-world applications are limited due to the complexity of actual restaurant environments, which often feature multiple servers, varying peak times, and unpredictable customer behavior. Therefore, practical implementation would require more advanced, adaptive modeling and regular data input.
https://www.iosrjournals.org/iosr-jm/papers/Vol19-issue4/Ser-2/H2004025356.pdf

Assessment: Modeling & Simulating Customer Flow at Tiranga Bhuvan

To move beyond anecdotal observations and gut-based solutions, this research undertakes a structured assessment of customer flow at Tiranga Bhuvan using simulation techniques. The study is based on real-time observation, interviews with staff and management, and the collection of time-stamped data tracking each stage of the customer journey. The focus is not merely on counting customers or tracking revenue but on breaking down service into distinct stages: arrival, wait for seating, ordering, food preparation, dining, billing, and table clearing.

Each of these stages contributes to the customer's total time spent in the restaurant system, and each has the potential to become a bottleneck. For instance, delays in order-taking delays caused by understaffed floor service, or a backlog in the kitchen due to too many simultaneous orders, can have cascading effects across the entire system. By identifying these pain points and measuring their typical durations, the paper constructs a digital model that simulates how the restaurant functions during real-life rush hours.

The simulation is built in Google Sheets/Excel and functions as a simplified yet powerful representation of restaurant operations. Using this model, various 'what-if' scenarios can be tested without affecting actual restaurant functioning. For example:
What if a second billing point is added?
What happens if a token or reservation system is used to control arrivals?
Can orders be taken earlier while customers are waiting to be seated?
What's the effect of limiting table occupancy time during peak periods?

Each of these interventions is simulated using data from Tiranga Bhuvan's actual operations. By comparing metrics such as average wait time, total customer cycle time, staff utilization, and seating efficiency across scenarios, the model reveals which small adjustments could produce significant improvements. This allows Tiranga Bhuvan—and businesses like it—to experiment with innovation without risk, guiding future decisions based on data rather than guesswork.

Furthermore, the broader goal of this study is to illustrate how simple, low-cost simulation tools can be adopted even by non-digital, traditional businesses to optimize efficiency. The barrier to entry is low—requiring only spreadsheet software and basic training—yet the insights offered can be transformative. In a sector where every extra minute spent waiting can result in customer dissatisfaction or loss of revenue, even marginal improvements in flow can have lasting impact.

3. Methodology of Work

The methodology behind this project followed a systematic and immersive approach designed to capture the operational dynamics of Tiranga Bhuvan — a fine-dining restaurant in Pune — and simulate its performance through Excel-based modeling. The project commenced with extensive primary data collection, where direct conversations were conducted with the restaurant owner and senior staff. Through these dialogues, I was able to gather real-time, situation-specific insights into staffing structures, customer flow, table turnover rates, service bottlenecks, and other nuanced operational details.

Observations were concentrated around peak-demand days, particularly Friday dinners and Sunday lunches and dinners, where traffic was at its highest. During these times, the restaurant hosts two complete table turns across 26 tables, totaling 52 seatings per meal period, each accommodating an average of four customers per table. This results in a maximum hosting capacity of 208–212 people per service period. I recorded and structured timestamps for each key stage in the dining process — from menu delivery and order placement to food wait times, eating duration, billing, and eventual table clearance. Average wait time for a table was observed to be 14 minutes, especially during the 8:30 PM to 10:30 PM peak slot on weekends.

In terms of staffing, I noted a consistent strategy that adapts the workforce to demand intensity. The restaurant operates with a total of 40 staff members on peak days, split equally between kitchen staff and servers. On off-peak days like Monday, staff presence reduces to 70%, approximating 28 individuals. Kitchen operations show strong efficiency, particularly around high-demand non-vegetarian items, such as biryani, which is pre-prepared in bulk (80 kg rice for Sunday). However, dishes like exotic tandoori items require more active preparation and are only half-cooked before service. Even under strain, no additional kitchen expansion is

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deemed necessary due to already-optimized workflows and space usage.

This real-world data was then synthesized into a structured Excel model. I began by creating a base table simulator, factoring in seating capacity, arrival rates, and average duration per table. Each component of the dining timeline — order taking (4 minutes using a tablet), food wait (15 minutes), eating (approximated based on table turn durations of 70–80 minutes), and billing (4 minutes) — was broken into time blocks and simulated using Excel's time functions and logic-based triggers. I also factored in scenarios of congestion, particularly the 25-person queue during high-traffic windows, and modeled their delay impact through simulated wait queues.

Advanced conditional formulas were implemented to reflect changes in staffing (full vs. reduced team), shifts in demand, and seasonal customer inflow (notably around festivals like Ganpati, Navratri, Diwali, and Shravan). While recipe standardization was noted as a significant limitation due to the restaurant's dependence on senior chefs who've crafted signature flavors over decades, this qualitative factor was acknowledged but excluded from quantitative simulation due to its intangible nature.

Moreover, external factors like 40% online delivery load (via Swiggy, Zomato) were acknowledged and their disruptive effects modeled during stress-testing scenarios. However, strategies like pre-billing or high-tech ordering kiosks were consciously excluded due to their incompatibility with the fine-dining experience at Tiranga Bhuvan.

The Excel model not only allowed me to recreate the current service dynamics and provides a powerful tool to simulate hypothetical optimizations — such as increasing staff, reducing billing time, or shifting food prep workflows. The final step was interpreting these simulations by measuring wait time reduction, throughput increase, and customer handling efficiency, which were visually represented using Excel's dashboard features, including pivot charts, time trackers, and conditional formatting indicators.

This layered methodology — blending real-world fieldwork with structured digital simulation — offers a practical framework for analyzing, understanding, and potentially improving the operations of Tiranga Bhuvan. It transforms observational data into a decision-making tool, bridging the gap between traditional business practices and modern optimization techniques.

Tiranga Bhuvan – Operational Data, Cost Estimates & Impact Analysis

Parameter	Value / Description	Approx. Cost (Monthly/One-Time)	Impact of +1 / –1 (throughput & wait time ±)
Tables (4-seat, 26 units)	2 turns ⇒ 52 seatings per peak period	₹ 30,000	+1 Table → +4 seats, ~8 extra peak customers, –4–5 min wait; –1 Table → opposite
Chefs (20 staff)	Highly experienced; prep time ~20 min per exotic dish	₹46,174/month average	+1 Chef → ~10% faster prep, –3–4 min total time; –1 Chef → prep delays, +3–5 min
Servers (20 staff)	Average salary ₹14,623–₹17,000/month		+1 Waiter → 1-2 min faster service, –2 min wait; –1 Waiter → backlog, +2 min wait
Biryani (pre-made batches)	Prepares approximately 80 kg of rice for Sundays	Ingredient cost built-in; no extra staff/equipment needed	Not staff-sensitive
Tandoori products (4 tandoors)	Half-cooked and ready-to-grade prep	Already optimized; no cost impact	Not applicable
Delivery staff load	~40% online sales (Swiggy/Zomato) — staff/pick issues on peak	Staff overtime cost hidden in existing labor (~40 people)	Not adjustable in model
Peak group queue	~25 waiting; avg wait time ~14 min	Potential revenue loss: ~25 × ₹475 = ₹11,875 per peak	Longer per-guest wait possibly leads to drop-off
Avg ticket per person	₹475 per diner	-	
Fine-dining setup	Not a QSR—pre-billing not feasible; menu experience is table-centric	Higher initial CAPEX (₹1 Cr+ setup)	Pre-billing inapplicable
Festival surges	Before/after Shravan, Navratri, Diwali—60-80% volume spikes	Temporary cost: +10–20% staff/additional inventory	Can cause short-term queue increase

Tiranga Bhuvan Operational & Modeling Data

Metric	Value / Description
Seating capacity per table	4 persons
Total tables	26
Table turns per peak period	2 turns (peak length ~70–80 mins each)
Max people served per peak service	~208–212 (~4 × 26 × 2)
Peak hours: Friday and Sunday	8:30 PM to10:30 PM
Average wait queue size at peak	~25 customers
Average wait time (overall)	~14 minutes
Average durations: menu, order, food, billing	Menu: 2 mins; Order: 4 mins; Food wait: 15 mins; Billing: 4 mins (after order)
Staff on rush days	40 (20 in kitchen; 20 servers)
Staff on Monday (off-peak)	70% strength = 28 staff
Biryani prep	Pre-made (rice ready), prep load minimal; exotic dishes take ~20 mins
Revenue per person	₹475 pp average ticket size

Delivery load	~40% sales come through Swiggy/Zomato
Veg / Non-veg mix	~15% vegetarian; 85% non-veg
Peak crowd type	Families & working professionals after office hours
Tandoori capacity	4 tandoors, half-cooked prep system
Demand peak events	Festivals (Shravan, Ganpati, Navratri, Diwali)
Staff risk factors	Aging chefs (~35% >25 years tenure), recipe-dependent taste sustainability

4. Discussion of Results

The simulation conducted using Excel models, built upon field data collected directly from the restaurant owner and observed operations, yielded significant insights into how Tiranga Bhuvan functions under varying conditions. A close analysis of weekend operations—specifically on Friday evenings and Sundays during lunch and dinner—revealed that the restaurant operates at near-maximum efficiency during peak hours, with full table turnover occurring twice, accommodating 212 guests in a 3-hour period. Each table averages 4 guests, and there are 26 physical tables resulting in 52 table turns across a rush session.

During peak times, average wait time for customers reaches approximately 14 minutes, with a maximum observed rush involving 25 people waiting for a table. Process decomposition suggests that the order-taking process consumes about 4 minutes via a tablet-based system, followed by an average food preparation time of 15 minutes. Billing is completed within 4 minutes after the check is requested. The total cycle time from seating to departure averages around 70–80 minutes, which aligns with a reasonable turnover target.

The staffing distribution was found to be critical. On high-traffic days, 40 total staff are employed—20 in the kitchen and 20 as service staff. This number drops to 70% (approximately 28 staff) on lean days such as Mondays. Simulation models indicated that any reduction of service staff by even 1 member (from 20 to 19) could increase the wait time per table by nearly 1.8 minutes on average due to delays in order-taking, seating coordination, and billing.

Similarly, removing just one table from the current capacity (from 26 to 25 tables) could result in a loss of approximately 8 guests per shift (4 per table per turn × 2 turns). This directly translates to a revenue loss of ₹3,800 per day (based on the average ticket size of ₹475 per person), or ₹114,000 per month if extrapolated over 30 days. On the other hand, adding one table could decrease average wait time during peak hours by 1.2 minutes, absorbing excess demand more efficiently and increasing monthly revenue by a similar margin. However, this assumes sufficient floor space and does not account for the cost of restructuring. A summary of sensitivity analysis is shown below:

Change	Impact on Wait Time	Estimated Daily Revenue Impact	Monthly Revenue Impact	Approximate Cost	Additional Notes
+1 Table (Total: 27)	↓ 1.2 minutes	₹ 3,800	₹ 1,14,000	₹15,000–₹25,000 (Table setup)	Space permitting; benefits exceed cost
-1 Table (Total: 25)	↑ 2.0 minutes	₹ -3,800	₹ -1,14,000	-	Crowding and customer dissatisfaction risk
+1 Waiter (Total: 21)	↓ 2.3 minutes	+₹1,900 (via faster table rotation)	₹ 57,000	₹15,000/month (salary)	Helps reduce customer friction
-1 Waiter (Total: 19)	↑ 1.8 minutes	₹ -1,900	₹ -57,000	-	May lead to service breakdown
+1 Chef (Total: 21)	↓ food prep by 2 mins	↑ table turnover rate marginally	+₹25,000–₹30,000	₹18,000/month (salary)	Especially helpful for non-veg demand
Pre-billing implementation	↓ Billing time by 2 mins	↑ 1–2 extra table turnovers/month	+₹19,000–₹30,000	₹10,000–₹15,000 (system setup)	*Currently not feasible* at Tiranga Bhuvan

The cost-benefit ratio here clearly indicates that adding waiters or tables offers the highest marginal returns in peak conditions. Conversely, investing in pre-billing or faster tech solutions offers only partial benefit, especially as the restaurant operates in a semi-traditional style with a personalized touch. Recipe standardization, another possible technological lever, was assessed but found to be non-viable. About 35% of the staff have been part of the restaurant for over 25 years, and the culinary flavour is deeply embedded in their techniques. Standardizing recipes might dilute customer loyalty and compromise the brand identity.

Moreover, Swiggy/Zomato orders, contributing 40% of total sales, were also considered in the simulation. During rush hours, these deliveries exert pressure on kitchen bandwidth. Adding more tandoor setups or temporarily pausing online orders during peak dine-in times could significantly improve service flow.

5. Conclusion / Summary

The simulation study provides empirical clarity into how operational tweaks affect service efficiency at Tiranga Bhuvan. The restaurant's strength lies in its experience-driven staff, well-paced turnover, and high non-veg demand, particularly during weekends and post-festival times. Data modeling in Excel revealed that minor operational changes—such as adding a single table or one more staff member—can dramatically alter wait times and revenue.

Yet, these must be weighed against feasibility and space constraints. Infrastructure limitations, human reliability (especially aging senior chefs), and the nature of traditional cooking restrict radical innovations like recipe standardization or complete tech automation. However, Excel-based simulation can serve as a reliable decision-support tool for assessing such what-if scenarios and forecasting peak-time bottlenecks before they occur.

As Pune's F&B landscape continues to evolve, Tiranga Bhuvan's sustainable growth will likely rely on balancing tradition with selective, data-driven innovations in staffing and seating strategy.

6. Future Scope

While the current simulation focuses on staffing, seating, and order-flow optimization, there is scope to expand the model in several directions. Future work could incorporate:

- Real-time queue monitoring using simple tablet or mobile-based data entry, allowing for continuous updates to predictions.
- Integration with POS (Point of Sale) data to link order complexity with preparation times.
- Seasonal and festival demand forecasting, using historical footfall data to pre-allocate resources.
- Multi-objective optimization to balance in-house dining with online delivery without overloading the kitchen.
- Application to other small businesses such as cafés, street-food vendors, or retail stores, adapting the simulation framework for varied service models.

By extending this approach, local businesses could develop low-cost operational "digital twins" to test strategies before implementation, further improving resilience and customer satisfaction.

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