Modeling, Simulation and Analysis of Restaurant Drive-thru Operations to Reduce Roadway Hazards Due to Long Queues

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Abstract

This study models and simulates the operations of a local restaurant located near a busy intersection to address the frequent congestion in its drive-thru lanes. Throughout the day, particularly during peak hours, the queues extend into traffic lanes, posing risks of vehicle and pedestrian accidents and contributing to increased CO2 emissions. The simulation uses ARENA software to evaluate staffing enhancements to reduce queue times and the likelihood of drive-thru queues impacting adjacent traffic lanes. Preliminary data collection was performed using synchronized video recordings to capture real-time traffic flow and vehicle wait times at different stages of the drive-thru. The study finds that strategic staffing adjustments can significantly decrease queue times and prevent overflow into traffic lanes, offering a low-cost, effective solution to enhance safety. The findings are supported by goodness-of-fit tests, such as the Kolmogorov-Smirnov and Anderson-Darling tests, confirming the empirical data's adherence to theoretical exponential distributions. This approach mitigates potential traffic concerns and serves as a methodology for assessing the safety impacts of drive-thru operations in suburban/urban settings.

Keywords – queuing, simulation, restaurant operations, drive-thru.

I. Background & Problem Description

I'll be modeling and simulating the restaurant operations of a local quick service restaurant located near a busy intersection with significant variability in traffic flow throughout the day.

Several times during each weekday, the line/queue into the two drive-thru lanes becomes significantly congested, often causing vehicles to extend into the traffic lanes in front of the restaurant. During these times, customers face a long queue and higher wait times before completing their order, and the risk of a vehicle or pedestrian accident increases.

Beyond the risk of accidents, communities across the US are also asking about the impact of drive-thru lines on CO2 emissions, biking and walking routes within the community and even how drive-thru lanes impact public transit and congestion in their communities.

There are many approaches to addressing this queueing problem, including:

1. Razing and rebuilding restaurant facilities while redesigning the layout and operation of the restaurant, including dine-in and drive-thru facilities,
2. Redesigning lot layouts to accommodate additional drive-thru lanes and longer queues. Additionally, restaurant operators can modify food preparation and delivery processes so they are optimized for drive-thru customers,
3. When possible, simply adding additional drive-thru lanes or optimizing the configuration of order, payment and pick-up zones to accommodate additional drive-thru traffic and
4. Optimizing staffing at existing facilities to better reflect demand during both low- and high-traffic dayparts.

Optimizing staffing is among the easiest and lowest-cost solutions to implement.

The goals of this simulation are to understand and describe the system's behavior using ARENA simulation software, to provide recommendations that might shorten the queue during high-traffic day-parts, increase customer satisfaction while significantly reducing the likelihood of a vehicle or pedestrian accident, and provide a methodology for analyzing the impact of staffing changes on drive-thru queues.

II. Map of Study Area

A street map of the study area and surrounding traffic patterns is shown in Figure 1. The red arrow indicates where an excessive order queue can spill into the roadway. When this occurs, ingress and egress from the study area are significantly impacted, and vehicles traveling on East Butterfield Road may temporarily stop in the roadway. This can create problems for drivers and pedestrians; several cities/towns have recognized the safety issues and passed laws or regulations restricting the use and build-out of new drive-thru facilities. Improper management of queues may also open the facility operator to lawsuits.

Figure 1 Street map showing the location of the study area highlighted in green. Note the proximity of a major four-way intersection controlled by traffic lights in all directions. The simulation intends to mitigate the potential for overflow from the order queue to spill onto East Butterfield Road (red arrow) and cause traffic backups or accidents.

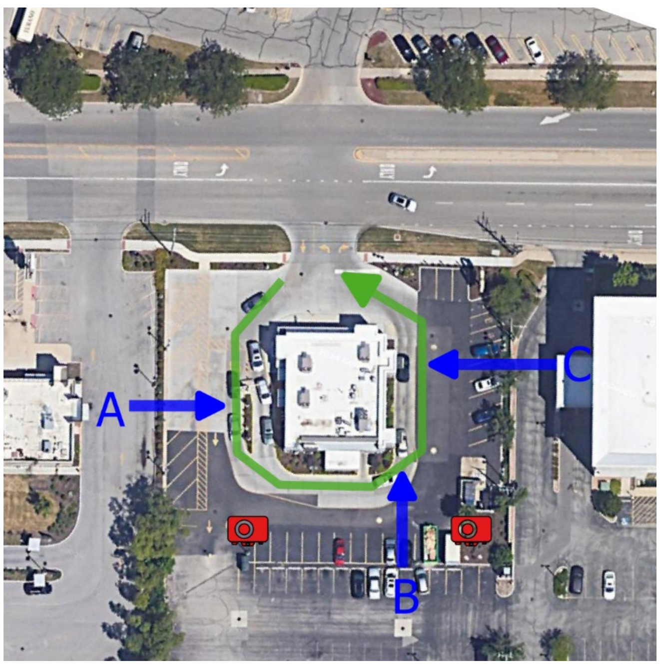

Figure 2 Satellite image of study location showing traffic flow (green), camera locations (red) and process areas (blue A, B, and C). Process area A is the order station, B is the payment station, and C is the order pick-up station. In this image, it is possible to see vehicles queueing at the order window in two lanes.

III. Data Collection

A. Data Collection

Video recording was utilized to collect real-world data on the traffic flow, queues and characteristics of the order, payment and pick-up processes. The computation of interarrival times and waiting times at each of the process areas required synchronized video feeds and capturing actual time data. Professional-level cameras include timecode, genlock, and wordlock features that allow for the precise synchronization of discrete video feeds, but they can be expensive and more complex to operate.

This simulation study leveraged inexpensive off-the-shelf USB webcams and open-source broadcasting software Open Broadcaster Software (OBS) to record multiple synchronized video feeds showing each vehicle as it moved through the system. Timing data was incorporated into the video capture, allowing for accurate data capture of traffic volume, order lane selection, vehicle movement and arrival and wait times at each step of the process. The output of this setup, a video capture file of the entire drive-thru process, is shown in Figure 3.

Figure 3 Screenshot of live synchronized data capture of ingress and egress drive-thru lanes using OBS. Video feeds are set up to allow the capture of vehicles as they proceed through the entire process.

Video data was captured and written to recoverable mpeg4 files in case of camera or recording failure.

B. Traffic Flow

The satellite image of the facility shown in Figure 2 illustrates the traffic flow in the system. Video cameras were placed to capture vehicles, which ingress, move through, and egress the system. Cameras are identified in Figure 1 as red camera icons.

The green arrow illustrates how vehicles enter the order area, move through the payment window, then to the pick-up window and exit the system.

The specific areas that will be computer-modeled and analyzed include points A, the order area; B, the payment window; and C, the pick-up window on the image.

C. Data Cleansing and Analysis

Initial manual approach

The initial approach was to use manual tracking and timing of vehicles as they moved through the drive-thru lane. While this was not particularly challenging during slow periods, when the lines began to queue, this task became daunting.

Secondary approach - image recognition and regions-of-interest time tracking using CV2, Pytorch, YOLO5 and Sort

Looking for an automated approach, I attempted to use video detection, tracking and analysis software to track and timestamp vehicles as they entered the drive-thru lane and proceeded through the ordering, payment, and pick-up stations. This approach relied on open-source software, including CV2 (for image processing and computer vision), Pytorch (a deep learning framework), YOLO5 (an image recognition toolkit) and the Sort image tracking toolkit along with pre-trained models for object recognition.

Figure 4 Screen capture of real-time image recognition and tracking on video of the drive-thru. Note the regions of interest/zones for ordering, payment and pick-up in blue rectangles and the vehicles being identified and tracked in green rectangles. A primary shortcoming of this approach is that vehicles were often tagged with a new ID (in red text in the image) as they moved between ROIs/zones, making accurate time calculations impossible. Despite its current flaws, this approach holds great promise for simulation studies of this type.

However, this approach to tracking and timing the vehicles as they moved through the U-shaped drive-thru lane did not work as anticipated. There are several reasons for this, including:

1. The positioning of the camera was not optimal, in that position 1 captured a front-view of each vehicle and position two captured a side- and rear-view image of the vehicles. This makes image recognition and tracking more challenging. An example of this can be seen in the video file, where individual vehicles are recognized and labeled multiple times.
2. Current tracking algorithms, such as the Sort (simple online and real-time tracking) algorithm, are insufficient at tracking vehicles from different perspectives as they move through a curved drive-thru lane, as shown by the green arrow in Figure 4.

While this approach was not successful in providing a fully automated method to track and timestamp vehicles moving along the drive-thru path with specific ROIs (regions of interest), with additional time and model tuning this approach might yield great results.

Third approach – manual tracking of vehicle movement to develop lambda estimates for synthetic data

The third approach was to select a shorter video length and manually notate the arrival times of vehicles at each window to arrive at a reasonable estimate of lambda arrival rates for each window independently.

Drive-thru Zone	Computed λ (lambda)
Entering the restaurant lot	2.46 vehicles/minute
Order window (outer lane)	1.13 vehicles/minute
Order window (inner lane)	1.33 vehicles/minute
Payment window	2.06 vehicles/minute
Pick-up window	1.87 vehicles/minute

Figure 5 Manually observed and calculated lambda for each window in the drive-thru lane. Lambda was calculated by observing a video capture of vehicles as they arrived and moved through the drive-thru.

IV. Selecting & Validating Input Distributions

D. Random Number Generation

The real-world λ (lambda) estimates computed from analyzing a shorter snippet of the drive-thru video and shown in Figure 5 were used to develop synthetic exponential random variates.

Using Excel, 2000 unif(0,1) uniform random variates were derived using the RAND() function and transformed using the inverse transform method into 2000 exp(λ) variates for each of the Computed λ (Lambda) values in Figure 4 using the form:

$$X = -\frac{1}{\lambda}\ \ln(U)$$

All of the unif() random variates and each of the exp() random variates are shown in the SimulationCalculation.xlsx Excel file in the RandomVariates worksheet. Histograms of each synthetic expo(λ) distribution were generated and are shown in the worksheet to verify all distributions visually.

Estimates for λ for the order-window, payment-window and pickup-window were developed using the same process, and resulting in four random exponential random variate distributions. All of the computed exp(λ) random variates are shown in the SimulationCalculations.xlsx file, in the RandomVariates worksheet in the columns LotEntryExp(2.47), InnerOrderWindowExp(1.33), OuterOrderWindowExp(1.31) PaymentWindowsExp(2.06) and PickupWindowExp(1.87).

V. Input Analysis

E. Distribution Fitting

While the exponential random variates for the drive-thru entry, order windows #1 and #2, the payment window and the pick-up window were mathematically generated from unif(0,1) random variates and should fit a theoretical exponential distribution, it is nonetheless essential to statistically confirm this.

Each of the simulated/synthetic exponential distributions was validated for goodness-of-fit to the theoretical exponential distribution using four methods: the Kolomogorov-Smirnov test, the Anderson-Darling test at the 1% significance level, a visual comparison of the histogram of synthetic exponential values versus the theoretical curve at the given lambda, and by comparison of the actual mean and variance of the synthetic data to the theoretical mean and variance at the given lambda value. Recall that lambda values were computed based on the actual count of vehicles arriving at each ROI (region of interest)

Entry Lane

The Kolmogorov-Smirnov test statistic for the entry lane is 0.0107, indicating the sample distribution aligns closely with the theoretical distribution. The high p-value of 0.9747 does not reject the null hypothesis that the empirical data follow the exponential distribution.

The Anderson-Darling test statistic of 0.3202 supports this finding, and a critical value of 1.9560 at the 1.0% significance level further confirms our results. Examination of Figure 6 reveals that the empirical data, depicted in gold, closely mirrors the theoretical curve in red.

The computed lambda (λ) from the actual data is 2.47, closely matching the estimated λ from the exponential distribution of 2.46. Finally, the estimated mean and variance of our exponential distribution, at 0.4059 and 0.1648, respectively, are comparable to the theoretical values of 0.4048 and 0.16396

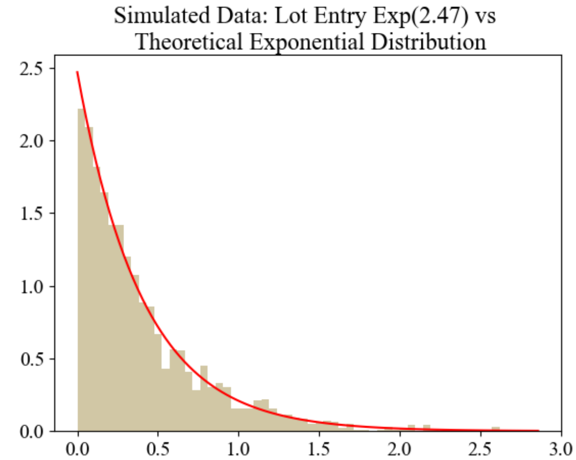

Figure 6 Graph of exp(2.47) for the entry lane versus theoretical exponential distribution

Inner Order Lane

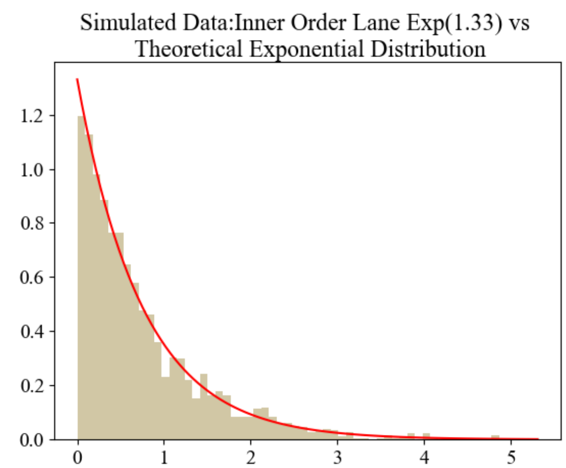

Figure 7 Graph of exp(1.33) for the inner order lane versus theoretical exponential distribution

The Kolmogorov-Smirnov test statistic for the inside order lane is 0.0107, indicating the sample distribution aligns closely with the theoretical distribution. The high p-value of 0.9747 does not reject the null hypothesis that the empirical data follow the exponential distribution.

The Anderson-Darling test statistic of 0.3202 supports this finding, and a critical value of 1.9560 at the 1.0% significance level further confirms our results. Examination of Figure 7 reveals that the empirical data, depicted in gold, closely mirrors the theoretical curve in red.

The computed lambda (λ) from the actual data is 1.33, closely matching the estimated λ from the exponential distribution of 1.34. Finally, the estimated mean and variance of our exponential distribution, at 0.7455 and 0.5558, respectively, are comparable to the theoretical values of 0.7518 and 0.5653.

Outer Order Lane

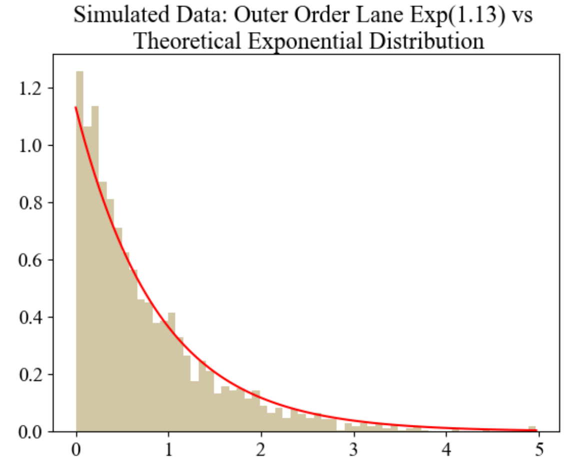

Figure 8 Graph of exp(1.31) for the outer order lane versus theoretical exponential distribution

The Kolmogorov-Smirnov test statistic for the outside order lane is 0.0600, indicating the sample distribution aligns closely with the theoretical distribution. The high p-value of 0.9747 does not reject the null hypothesis that the empirical data follow the exponential distribution.

The Anderson-Darling test statistic of 0.3202 supports this finding, and a critical value of 1.9560 at the 1.0% significance level further confirms our results. Examining Figure 8 reveals that the empirical data, depicted in gold, closely mirrors the theoretical curve in red.

Our computed lambda (λ) from the actual data is 1.33, closely matching the estimated λ from the exponential distribution of 1.34. Finally, the estimated mean and variance of our exponential distribution, at 0.7455 and 0.5558, respectively, are comparable to the theoretical values of 0.7518 and 0.5653

Payment Window

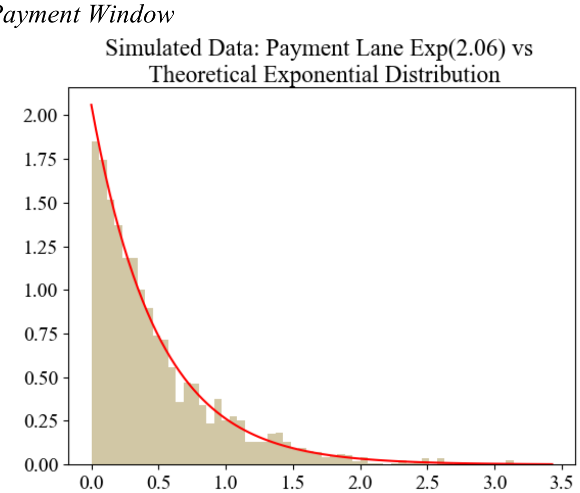

Figure 9 Graph of exp(2.06) for the payment lane versus theoretical exponential distribution

The Kolmogorov-Smirnov test statistic for the payment lane is 0.0107, indicating the sample distribution aligns closely with the theoretical distribution. The high p-value of 0.9747 does not reject the null hypothesis that the empirical data follow the exponential distribution.

The Anderson-Darling test statistic of 0.3202 supports this finding, and a critical value of 1.9560 at the 1.0% significance level further confirms our results. Examination of Figure 9 reveals that the empirical data, depicted in gold, closely mirrors the theoretical curve in red.

Our computed lambda (λ) from the actual data is 2.06, closely matching the estimated λ from the exponential distribution of 2.07. Finally, the estimated mean and variance of our exponential distribution, at 0.4813 and 0.2317, respectively, are comparable to the theoretical values of 0.4854 and 0.2356

Pick-up Window

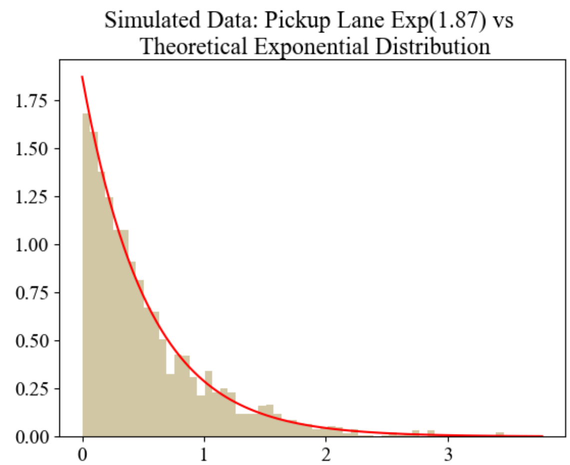

Figure 10 Graph of exp(1.87) for the pick-up lane versus theoretical exponential distribution

The Kolmogorov-Smirnov test statistic for the pick-up lane is 0.0107, indicating the sample distribution aligns closely with the theoretical distribution. The high p-value of 0.9747 does not reject the null hypothesis that the empirical data follow the exponential distribution.

The Anderson-Darling test statistic of 0.3202 supports this finding, and a critical value of 1.9560 at the 1.0% significance level further confirms our results. Examination of Figure 10 reveals that the empirical data, depicted in gold, closely mirrors the theoretical curve in red.

Our computed lambda (λ) from the actual data is 1.87, closely matching the estimated λ from the exponential distribution of 1.88. Finally, the estimated mean and variance of our exponential distribution, at 0.5302 and 0.2811, respectively, are comparable to the theoretical values of 0.53474 and 0.2859.

Given that the exponential distributions used in the simulation were each mathematically derived from the same random uniform distribution, it is unsurprising that results from the Kolmogorov-Smirnov and Anderson-Darling tests were identical.

It should be noted that the point estimates for the means and variances were different, as expected across the distributions, due to the differing lambda parameters. However, within each distribution, the estimated and theoretical values were quite similar.

VI. Arena Simulation

F. Model Building

An Arena simulation model was developed to model the drive-thru zones.

The model, while simple, reflects vehicle movement through the drive-thru during peak drive-thru hours. Important features of the model include:

1. Customers (entities in the model) automatically select the drive-thru order window (of two available) based on queue length. Our real-world observation confirms that customers generally select the order window with the shortest line.
2. Each region-of-interest/zone, such as the order zone, payment zone and pick-up zone, are based upon real-world observations – including traffic flow coming into the restaurant parking lot.
3. The model includes a warning indicator that flashes when individual queues or a combination of queues exceeds the available queue space in the physical restaurant lot. This visual indication makes it easy for users to understand the implications of resource/staffing decisions.
4. The model validates the usefulness of low-cost and easy-to-implement solutions to a potentially serious problem (vehicle queues extending into the roadway) that do not require physical property modifications.

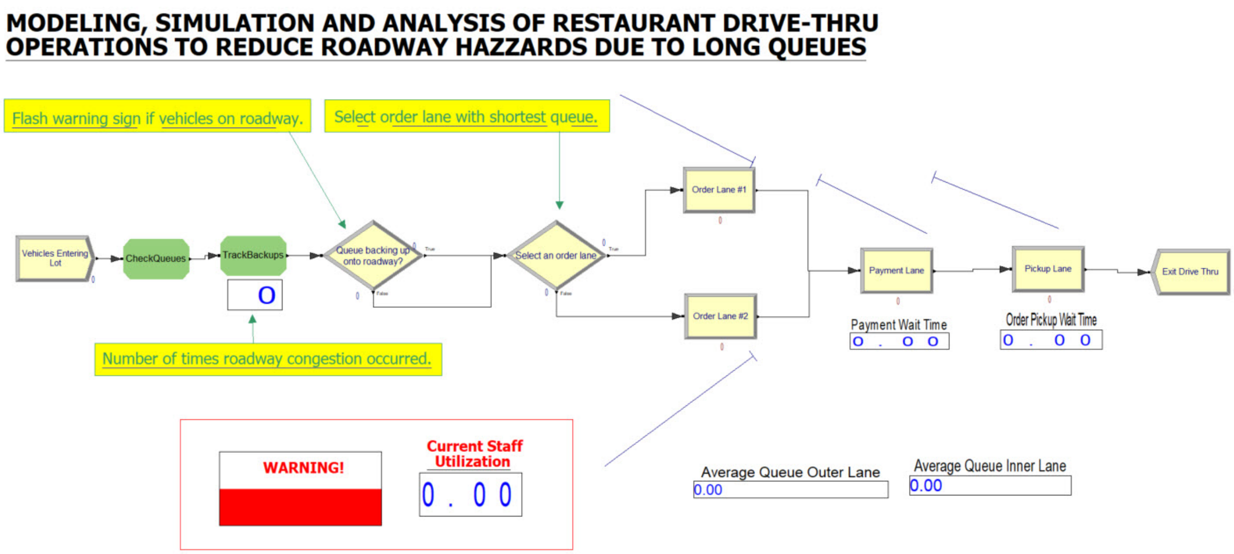

Figure 11 Screen capture of simulation model showing key components of the model. The model is designed to test differing staffing resource allocations and constraints and their impact on the ordering, payment, and pick-up, which can collectively cause vehicles to queue onto the entry roadway, creating a safety hazard for vehicles, bicycles and pedestrians using the roadway. A flashing red warning sign visually alerts users that vehicles are backing onto the roadway when the simulation is running and queues are too long.

VII. Output Analysis

Recall that the goals of this simulation study were to simulate and evaluate statistically how effective staffing modifications to drive-thru zones might impact drive-thru queue lengths and, perhaps more importantly, provide restaurant operators with low-cost recommendations that could remediate queues from causing roadway congestion.

To simulate the variability of drive-thru traffic, we used exponential distributions, then ran 50 replications of 2 hours each using exponentially distributed data representing arrivals at the restaurant and each drive-through zone. Each replication was independent and i.i.d from other replications. Furthermore, I ran replications making small changes in the staffing resources available to operate the two drive-thru order zones, the payment zone and the order pick-up zone. Our baseline for staffing the drive-thru was two employees, determined by conversations with restaurant employees.

G. Metrics of Interest: Queues impacting roadway traffic and duration of drive-thru experience

The primary metrics of interest are the *number of times a vehicle was queued onto the roadway* and the *average time in the drive-thru lane*.

With two staff supporting the entire drive-thru lane, the 95%

confidence interval for the number of times vehicles were queued onto the roadway is 136±22, while the average time in the drive-thru lane is 12.9±1.6 minutes.

Alternatively, adding ½ additional staff supporting the drive-thru lane reduces the likelihood of queues interfering with the roadway and reduces overall wait times for customers. The 95% confidence interval with 2.5 staff dedicated to the drive-thru lane reduces the number of times vehicles were queued onto the roadway at the 95% confidence level is 5.88±4.26, while the average time in the drive-thru lane decreases to 3.57±0.3 minutes.

Comparing these means using paired t-test at the 0.05-level rejects H_0*: true mean difference is zero*, demonstrating that these differences are statistically significant.

But perhaps the question is not if restaurant operators can **reduce** the risk of drive-thru queues extending onto an adjacent roadway but rather if they can **eliminate** the risk of roadway encroachment entirely with staffing adjustments. I ran simulations with staffing levels at 3 and 3.5 employees dedicated to the drive-thru to determine if this is possible.

With three staff supporting the drive-thru lane, the number of times vehicles were queued onto the roadway at the 95% confidence level is 0.88±1.16. The average time in the drive-thru lane in this scenario decreases to 2.48±0.12 minutes. Further additions to staffing, up to 3.5, drove the 99% confidence level for roadway-impacting queues to 0±0.0.

While no strategy can guarantee queues will never extend onto adjacent roadways, the simulation suggests there are simple and inexpensive staffing strategies to mitigate the risk effectively.

H. Model Observations vs Real-world Observations

I spent nearly a day observing and videoing drive-thru traffic at a local quick-service restaurant. During this time, I observed large queues forming at each of the zones during peak times; however, I did not observe the drive-thru queues impacting the adjacent roadway on this particular day. Previously, I have driven by this restaurant location and observed queues spilling into the entry roadway, creating potentially dangerous congestion and traffic stops at the lot entry.

VIII. Conclusions

I. Real-world Data Collection is Challenging

My attempt to capture real-world drive-thru data using two real-time video streams and later using video detection software to capture vehicle movement and timing at each window as they proceeded through the drive-thru lanes was problematic. Problems include inconsistent video capture of front and side views and difficulties identifying and tracking vehicles as they moved through the curved drive-thru lane.

J. Simple Solutions Can Be Effective

Since COVID and the movement restrictions placed on the public, quick-service restaurants have been testing approaches to increasing revenues via drive-thru service. Most have focused on reducing drive-thru queues and service times, often turning to technology such as remote ordering using geographically distributed call centers that adapt on-the-fly to demand and self-service phone apps. Many restaurants have installed additional drive-thru lanes or made facility enhancement. Modeling the drive-thru process in Arena was quite interesting, and seeing how simple changes in staffing at the drive-thru lanes would impact queues was very interesting.

K. Application of Video Analytics to Simulation Models

Within the past year, I worked with a client in my day job whose company has developed an AI-accelerator semiconductor that is optimized for video analytics. When looking for a software tool that could analyze drive-thru video, I was surprised when I could not find a suitable solution. Having completed the analysis, it seems there might be an opportunity for a video analytics solution leveraging YOLO, PyTorch, SORT or DEEPSORT trained and tuned specifically for this task.

L. Model Enhancements

The simulation I developed in Areana is rather simple, focusing only on the movement of vehicles through various drive-thru zones and queues. Future enhancements could include modeling how traffic flow around the restaurant, specifically the impact of traffic lights, impacts drive-thru lane flow, or more accurately modeling employee working within the restaurant.

IX. References

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