From Congestion to Flow: Optimizing Entry Systems at Pardee Way

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I. Introduction

ID queuing systems have become a common form of identity validation for businesses, small and large. Different in their own ways, the organization of these queuing systems gives way to various advantages and disadvantages for the audience they serve.

USC's recent developments, following their priority to increase institutional safety, have included the implementation of these ID queuing systems spread across campus entry points. The Pardee Way security checkpoint is particularly interesting because of the unique physical constraints it is subjected to—that being the narrow arches—which limit the options to optimize its layout. In this paper, we will explore how to simulate Pardee Way in an accurate manner as well as methods to optimize its operational processes.

II. Data Collection

Our dataset for this project consists of 1018 data points including students, faculty, and visitors who entered through Pardee Way. We collected this data over the course of 5 days—Tuesday through Saturday—with three shifts per day. Our rationale for observing these specific days was to collect data that would reflect the variations in foot traffic of people entering on weekdays versus on weekends. In this case we categorized Friday as a weekend, due to students' typical low attendance rate, especially at Marshall Business School which is closest to Pardee Way. As for the timing of shifts, we observed the gates for 30-minute periods at 7:40AM, 11:40AM, and 3:40PM. Understanding that usual class schedules start on the hour, we strategically chose this specific setup to capture the peak flow of arrivals right before classes begin while also observing any latecomers. It also captures different sections of the day—morning, afternoon, and late afternoon—offering a more comprehensive representation of daily foot traffic.

At this point, we also recognize the limitations of this data collection. Due to the quick nature of scanning and the influx of large groups that happen periodically, we estimate that our recorded service time data has a margin of error of ± 1 seconds. For the same reason, we estimate that our headcount may have a margin of error of ± 10 people per shift taken. Additionally, due to limited time constraints, there could be more data collected to make our following calculations even more substantial. All of this was and should be taken into account when using our results for appropriate mandated changes.

III. Layout

The layout of the Pardee Way entrance is as follows: There are 2 lanes for individuals to enter. We will refer to Lane 1 as the lane closest to Popovich Hall and Lane 2 as the lane adjacent to the car entrance. Directly next to Lane 1 is a designated path for exiting (see Appendix D).

Each lane has 3 scanners linked to a computer where individuals can either swipe or tap their USC ID. Scanner 1 is positioned nearest to the road, Exposition Blvd, with each subsequent scanner further down the lane. Occasionally, workers will use handheld scanners and iPads, especially when visitors arrive in groups and require their Visitor Pass or state ID to be scanned. Due to the infrequent appearance of these handheld scanners and iPads, we have chosen against including these characteristics in our simulation.

IV. Assumptions

For this simulation we have employed various assumptions not only because of the limited number of data points, but also to maintain the simplicity of the model. Firstly, we are assuming that when there is an available scanner, individuals proceed to said scanner rather than queuing behind occupied ones. Only when all three scanners are in use will we record the wait time of people in the queue.

During our data collection we also observed individuals exiting through the wrong lane specifically in Lane 2. Wrong exiters would impact the service time for individuals already scanning in as it interferes with the flow of traffic while also diverting workers' attention. These workers now have to redirect individuals. We assume the impact of wrong existers on the service time is an additional 3 seconds on all people scanning in if the system is full. In reality, this impact varies based on how busy the entrance is such as if the wrong exiters are traveling in a group or if workers choose to intervene.

Finally, we will not be considering batching in this model. In other words, we are assuming that every person entering the gate is entering independently and not as a group because we could not accurately assume who was in a group.

V. Base Model

Our base model provides a high-level framework to depict the process by which a typical student enters USC security checkpoints, particularly Pardee Way. The base model accounts for individuals entering, with both fast and slow service time, but it does not incorporate the complexities of a multi-service system (two lanes). Before observing Pardee Way, this approach may overgeneralize the types of people walking through the system. It does not account for different types of disruption or obstacles, causing the process to be slow or congested for individuals.

Overall, the average waiting time that the base model produced, whether mixed service time was taken in to account or not, was around 0.50 seconds. This means that, on average, a typical person walking in to USC through Pardee Way does not have to wait very long—if at all—in the queue. This brought up questions whether the base simulation was accurately reflecting all the nuances that actually went into the Pardee Way queuing system. We ask ourselves how this would change during different rush hours of the day, for a "non-typical" person, or for additional obstacles through the system.

VI. Enriched Model

A. Approach

Developing our base simulation to represent the flow of traffic into USC through Pardee Way models what this system would look like in a broad context. However, when considering the alterations needed for an enriched simulation model, it was necessary to incorporate some of the nuanced observations that wouldn't be so obvious when thinking about the system at large. During the data collection process, a few of these unobvious subtleties stood out to us.

Firstly, the amount of time to be "serviced" (scanned in) was highly dependent on characteristics of the individual scanning in. We specifically noticed 4 different categories of incoming persons:

1. Individuals who are ready and do not contribute to any potential blockage = "normal"
2. Individuals who need extra time to find their required materials to scan in such as USC IDs, Visitor Passes, or state IDs = "unprepared"
3. Individuals who are entering with wheeled or personal transport such as bikes, scooters, or skateboards = "mobilized"
4. Individuals who require assistance to scan in such as people who forgot their IDs or do not have Visitor Passes = "assisted"

The frequency of each of these persons is used to compute the proportions of each categorical group which is used to predict the next person in the queue belonging to a specific category. This categorization is used to find the service time for the random person entering our simulated queue which varies based on the group they belong to. Essentially, the service distribution is a **mixture distribution**.

Secondly, the usage of scanners is based on a **sequential prioritization**. We notice that the most frequently used scanner was scanner 1, then scanner 2, then scanner 3 (not particularly based on one category of people). When determining the placement of the next person in the simulation, and consequently the availability of scanners for each lane, scanner selection is based on this scanner priority.

Thirdly, we observe that people who are exiting at Pardee Way tend to use unmarked exit spaces, mainly in Lane 2. These exiters would cause confusion, redirection from workers, or collisions that would cause a delay in the system and ultimately affect the service time of persons entering the gate. We decided to leverage a "**wrong exiter**" variable, which evenly spreads wrong exiter's throughout the shifts and would add approximately 3 seconds for anyone being serviced in the queue in Lane 2.

Based on these observations, we extend our base model to incorporate all three considerations in an enriched simulation model. Given a person entering the queue, we predict their "type" based on the categorization proportions, and we predict which lane they choose based on lane probabilities computed from our data. Their average service time is computed from the distribution of service time for each categorical group, also collected from the data. They choose a scanner using scanner prioritization, and the scanner that is currently available. If no scanners are available in that lane, we record their wait time as the time it takes until the next scanner opens up. Otherwise, this person has no wait time. The model also determines when wrong exiters are present, and adds 3 seconds to the service time of every person currently using a scanner. Our main computations from this simulation focused on the overall average wait times per lane for every shift.

B. Analysis

By averaging the wait times of every person through our queue for each lane, regardless of their type, we can interpret the result to represent the length of time it would take for a typical person walking into USC through Pardee Way. We chose this output because it models how long a random person, unknowingly of the type of disruptor they would be (if at all), should expect to wait to get through these gates.

To ensure our model gives reasonable results, we conducted replications of our simulation over a number of individuals ranging from 200 to 1000. Across these entrances, the 8AM shift has an average wait time of roughly 1.2 seconds, 12PM is roughly 3 seconds, and 4PM is roughly 27 seconds (see Appendix A). The 8AM and 12PM shifts' average wait time stays fairly consistent, independent of the number of people passing through the system during that shift. However due to 4PM being the highest foot traffic, it is feasible that the average wait time increases as the number of people increases. Each shift's average wait time fluctuates (small or large) as the number of individuals increases, eventually leveling out when the number of people entering the system surpasses 600.

VII. Extended Model

A. Motivation

We noticed a psychological phenomenon that an individual will wait behind scanner 1 with over a 68% probability, even if scanners 2 and 3 are available. We concluded that people may view the first scanner as the most convenient choice, leading to unnecessary pileups. From our data, we find that disruptions often occur on the first scanner, and due to the probability of waiting behind scanner 1, only a few individuals actually walk around this disruption. A potential reason for this can be due to inattention to surroundings, social etiquette, or being blocked by the disruptor physically. For instance, we noticed disruptions including bikes, scooters, strollers, and large items reduce the probability that an individual will walk around due to the vertical nature of the scanning setup. This results in pileups and increased wait times for those entering. Because of this, we explored ways to reduce wait time by redesigning the checkpoint.

B. Approach

Due to 74.65% of individuals using scanner 1 as an average of all shifts, we want to optimize the use of other scanners by opening new lanes (see Appendix B). To minimize waiting time, we will explore moving the pre-existing tables from Lane 1 and 2 to create 4 shorter lanes. Lane 1 is closest to Popovich Hall, Lane 2 and 3 are in the center, and Lane 4 is the lane adjacent to the car entrance. One scanner will be placed in Lane 1 and 4, and two scanners will be placed in Lane 2 and 3. This optimizes resources by maintaining the same number of tables, workers, and scanners. Additionally, we explore relocating the designated exit path to reduce the likelihood of wrong exiters. The optimal location for the exit path is on the opposite side of the vehicle entrance which neighbours the Price School of Public Policy. Utilizing this approach we re-optimized our enriched model to include 4 lanes each with their respective scanners. This will optimally encourage the use of convenient scanners, following our data, and allow for more individuals to scan in simultaneously (see Appendix D).

C. Analysis

By extending our model to include 2 more lanes and relocating the exit lane, we observe a relative reduction of 93.4% in average waiting time—averaged by all shifts. Details are explored further on the exact average waiting times across each shift (see Appendix A). Due to the reduction in waiting time we recommend implementing this new model with four lanes while utilizing pre-existing resources.

VIII. Extra Considerations

A. Robustness

To test the robustness of our enriched model, we introduced a one-second increase to each group's randomized service time. This adjustment was added to evaluate how sensitive our results were to small deviations in parameter choices. This specifically considers how human error-prone our data collection was. We then ran 100 simulations for each shift and calculated the 95% confidence intervals for the average wait times. The results increased slightly for each shift compared to our initial average wait times (see Appendix C). This suggests that if our model is to be used for potential considerations, minor deviations in data inaccuracy, particularly for the service time of each group, could make a difference to conclusions about average wait time. Data should be collected with as much accuracy as possible.

B. Limitations

One of the limitations in this analysis is the lack of access to partnership contracts between USC and the third-party company spearheading campus security. This prevents our team from exploring strategies to reduce cost or increase worker optimization. While we did notice that there tends to be a higher-than-necessary number of workers at the gates, this could be a stipulation within the contracts that a certain number of workers must be staffed at all times. Due to this ambiguity, we have chosen against thoroughly exploring such strategies such as cost optimization in our main analysis.

As mentioned above, our data is prone to human error and may not be perfectly reflective of holistic foot traffic trends. With only 5 days of data at specific time periods, we recognize that our dataset may impact the accuracy of our simulation.

C. Tradeoff

We made several tradeoffs to what our model could've been. We could've created our model to optimize for worst-case scenarios like tour groups entering, the LA Book Festival, welcome events, student convocation, student-parent weeks, or game days. Additionally, we also considered optimizing only clustered groups entering because groups are a major disruptor. We decided to minimize the average wait time of any person entering Pardee Way because this variable had the most influence on the optimality of the Pardee Way entrance queue and was the most representative of the types of groups seen day to day.

D. Future Extensions

There were various strategies we thought to incorporate into the simulation but which we decided to forgo because of time constraints and technical feasibility. One of these possible extensions that would enhance the current model is the idea of pileups.

With more resources, we would create a conditional distribution for when pile-ups occur. Currently, we model our distribution for anyone entering and/or needing assistance. However, the amount of wait time it takes for an average person entering is not the same for pile-ups—groups of people who are waiting for an available scanner. We would try to minimize pile-up wait time because that is when wait times are the most severe.

IX. Conclusion

The USC experience starts from the moment people walk through its gates. Therefore, addressing some of these operational deficiencies in a queuing system simulation is important for USC's perception as a leading academic institution. Being able to streamline these entry systems further shows the commitment to the USC reputation.

In our simulation of the Pardee Way checkpoint, we aimed to capture how factors such as physical layout constraints, varied human behaviour, and scanner distribution affect its efficiency. We hope that by uncovering the complexities these factors pose, we can create a formal blueprint to improve checkpoints such as Pardee Way. We introduced gradual enrichments from observed data to the initial base model to formulate an extended model that incorporated the impact of wrong exiters, scanner prioritization, and different disruptor service times. Further extending the model, we used our understanding of key efficiency bottlenecks to create a strategy that would reduce wait times. Ultimately, adjustments in the flow of traffic and reconfiguration of existing infrastructure led to an impressive 93.4% reduction in relative wait time.

While there were limitations in regards to the comprehensiveness and quality of data, these results provide a strong foundation for introducing low-cost strategies to better optimize USC's campus entry systems.

Appendix A: Extended Model

To calculate λ and μ, we observed our data and the frequency of disruption occurrences.

Average wait time comparison between the pre-existing 2-lane model and the optimized 4-lane model. As the number of people increases, the average wait time reaches a steady state for our extended system, often within one second.

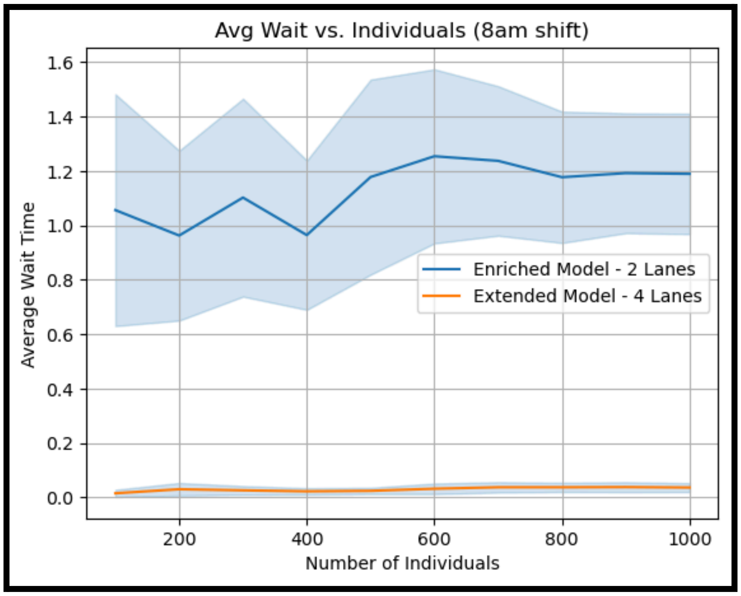

Figure A1: Average Wait Time of Individuals in the Morning (7:40 - 8:10 AM)

We replicated the simulations 100 times to reduce variability and included the 95% confidence interval to show how fluctuation may change the average wait time.

The 8am shift noticed an absolute waiting time reduction of 0.71 seconds, and a relative reduction of 94.3%. We take the relative reduction to understand the normalized improvement across wait times, for equal comparison.

Relative Reduction = Enriched Wait Time Mean - Extended Wait Time Mean / Enriched Wait Time Mean

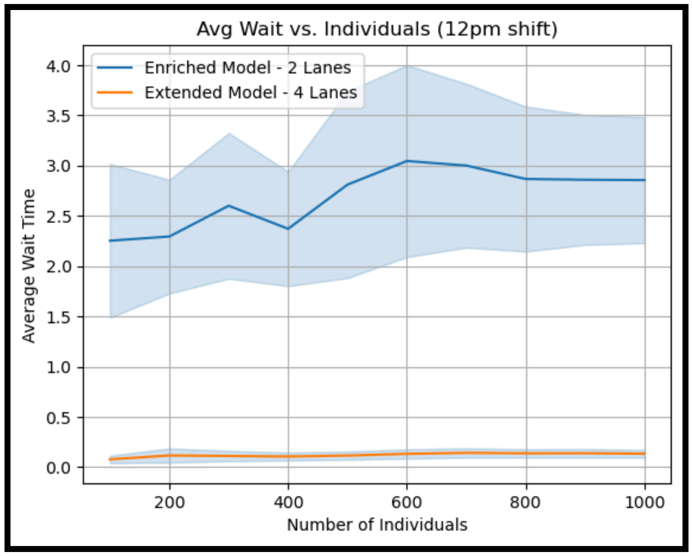

Figure A2: Average Wait Time of Individuals in the Afternoon (11:40 - 12:10 PM)

The 12pm shift noticed an absolute waiting time reduction of 1.67 seconds, and a relative reduction of 91.1%.

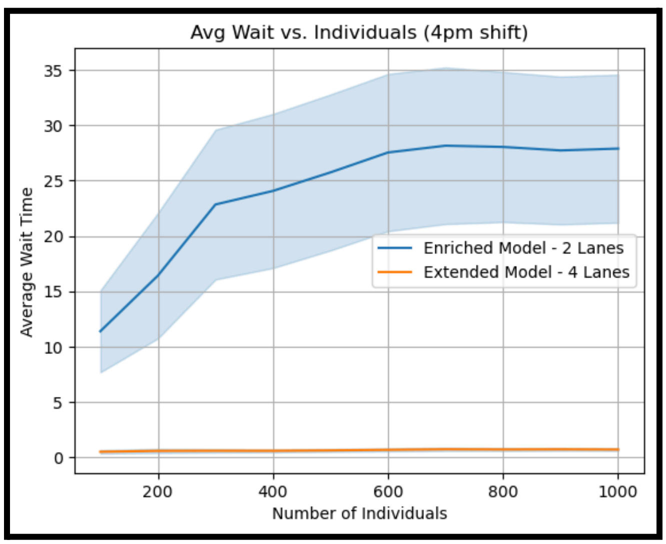

Figure A3: Average Wait Time of Individuals in the Late Afternoon (3:40 - 4:10 PM)

The 4 pm shift noticed an absolute waiting time reduction of 12.22 seconds, and a relative reduction of 94.8%.

Appendix B: Scanner Frequency

Frequency Table For Shift 8:00:

Scanner used	Frequency	Probability
1.0	156	0.631579
2.0	67	0.271255
3.0	24	0.097166

Frequency Table For Shift 12:00:

Scanner used	Frequency	Probability
1.0	253	0.863481
2.0	26	0.088737
3.0	14	0.047782

Frequency Table For Shift 4:00:

Scanner used	Frequency	Probability
1.0	70	0.744681
2.0	10	0.106383
3.0	14	0.148936

Figure B: Frequency of Scanner Utilization

Across all shifts, scanner 1 is the most predominantly used scanner with a 74.65% chance, taking the average of all frequencies

Appendix C: Average Wait Time Computations

```
--- Shift: 8am ---

Average wait time by lane:
     lane 1: 0.89 sec
     lane 2: 0.40 sec

Overall average wait time: 0.71 sec

--- Shift: 12pm ---

Average wait time by lane:
     lane 1: 1.91 sec
     lane 2: 0.11 sec

Overall average wait time: 1.26 sec

--- Shift: 4pm ---

Average wait time by lane:
     lane 1: 0.85 sec
     lane 2: 19.78 sec

Overall average wait time: 15.58 sec
```

Figure C1: Average Wait Time

Given an error of service time of 1 second, we calculated the average waiting time and 95% confidence intervals across all shifts.

```
--- Shift: 8am (Service time +1s) ---

Mean wait time: 0.91 sec
95% Confidence Interval: [0.88, 0.95]

--- Shift: 12pm (Service time +1s) ---
Mean wait time: 2.19 sec
95% Confidence Interval: [2.11, 2.26]

--- Shift: 4pm (Service time +1s) ---
Mean wait time: 20.11 sec
95% Confidence Interval: [19.17, 21.06]
```

Figure C2: 95% Confidence Intervals

Appendix D: Extended Design

Below consists of the original layout of the Pardee Way Security Checkpoint and our suggested reconfiguration to minimize wait time.

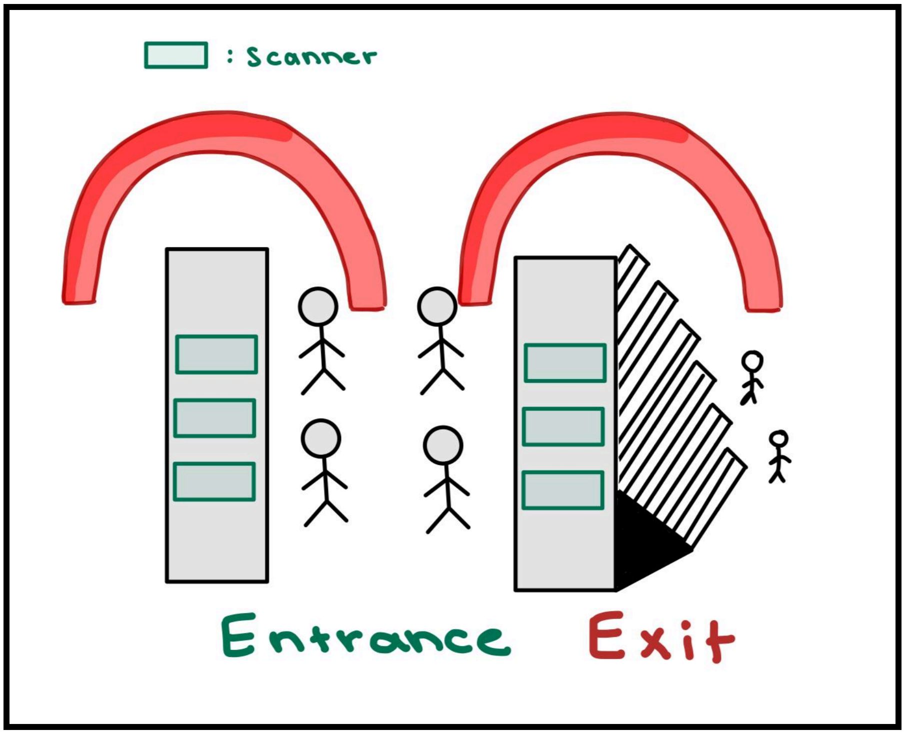

Figure D1: Current Layout of Pardee Way Security Checkpoint

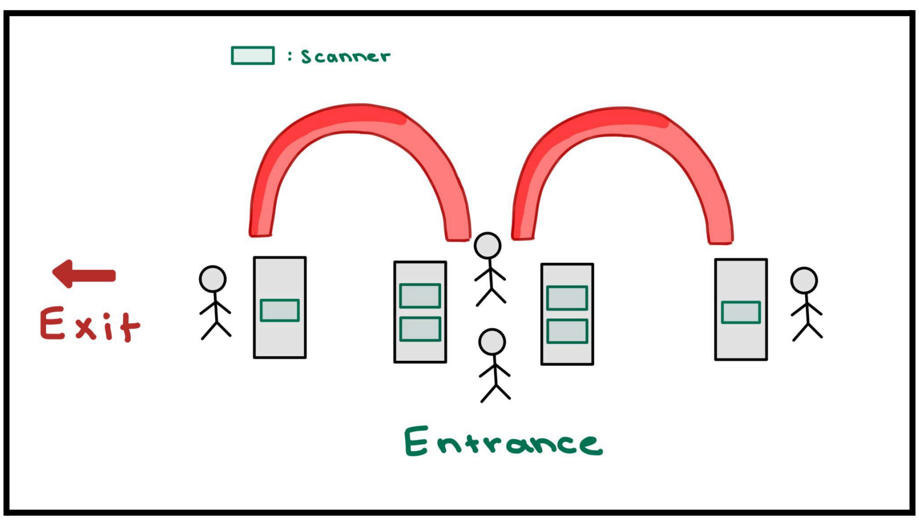

Figure D2: Optimized Pardee Way Security Checkpoint