Ouput Analysis

In this project, we delve into an intricate airport simulation, meticulously tracking the journey of passengers from entrance to boarding while managing the flow of planes on the runway. Our simulation is a comprehensive depiction of airport operations, encompassing various stages such as check-ins, security procedures, and boarding protocols.

1. **Passengers Flow:** We meticulously monitor the influx of passengers into the airport, their progression through check-in counters, security checkpoints, and ultimately, their boarding onto aircraft.

2. **Runway Operations:** Alongside passenger activities, we closely observe the dynamic movements of aircraft on the runway, ensuring efficient scheduling and safe take-offs and landings.

3. **Queue Length Analysis:** Our analysis includes graphing the average queue length over time, providing insights into the fluctuations and patterns within different areas of the airport.

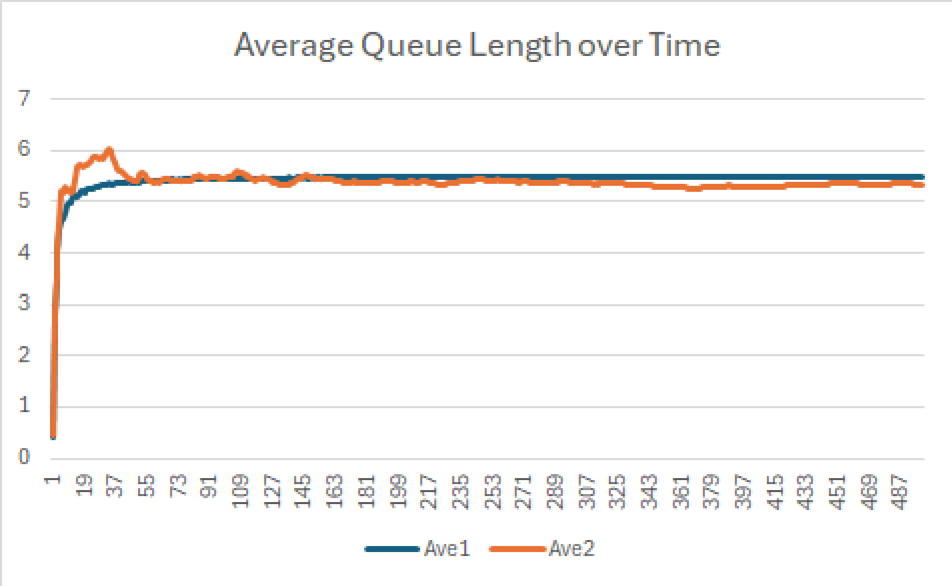
4. **Gate Queue Analysis:** Furthermore, we conduct a detailed examination of queue lengths at various gates, pinpointing potential bottlenecks and areas for optimization.

5. **Moving Average Evaluation:** Extending our analysis, we compute the moving average of airport simulation data over 50-minute intervals, offering a broader perspective on system performance trends.

6. **Capacity Adjustments:** By adjusting international capacity to 40 minutes and Plane A capacity to 20 units, we explore their effects on system behavior, including changes in cumulative distribution functions (CDFs).

8. **Integrated Analysis**: Finally, we synthesize the data from all simulations, enabling a holistic evaluation of airport operations and identifying overarching patterns and insights.Through this comprehensive data output analysis, we aim to unravel the intricacies of airport dynamics, facilitating informed decision-making and optimization strategies for enhanced efficiency and passenger satisfaction.

Original simulation (without any changes)



Ave1 = Average Queue length of Gate 1 queue length to board aeroplane A

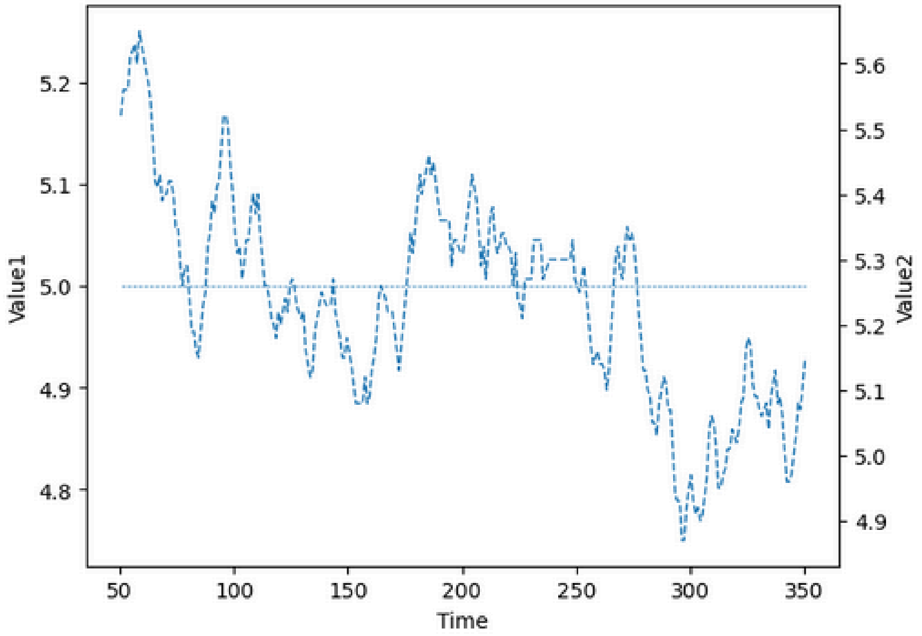
Ave2 = Average Queue length of Gate 2 queue length to board aeroplane B

Observations:

Ave1 Peaks and Stability: At approximately t = 50 hours, the average number of passengers (Ave1) peaks around 6, indicating a temporary surge in activity. Subsequently, it stabilizes around 5.4 passengers by t = 55 hours, suggesting a consistent level of throughput.

Ave2 CDF Behavior: The cumulative distribution function (CDF) of Ave2 demonstrates a smooth exponential distribution, as programmed in Jaamsim. Similar to Ave1, it stabilizes around 5.4 passengers, indicating a steady state of the system.

By closely analyzing these observations, we aim to discern any correlations between the number of trucks on the road network and the resultant production rate at the warehouse. This analysis will contribute valuable insights into the dynamics of the system and inform strategies for optimizing production efficiency.



Value 1 = Discrete values of Gate 1 waiting queue length at time t, thinner blue line represents this
Value 2 = Discrete values of Gate 2 waiting for queue length at time t, thicker blue line represents this

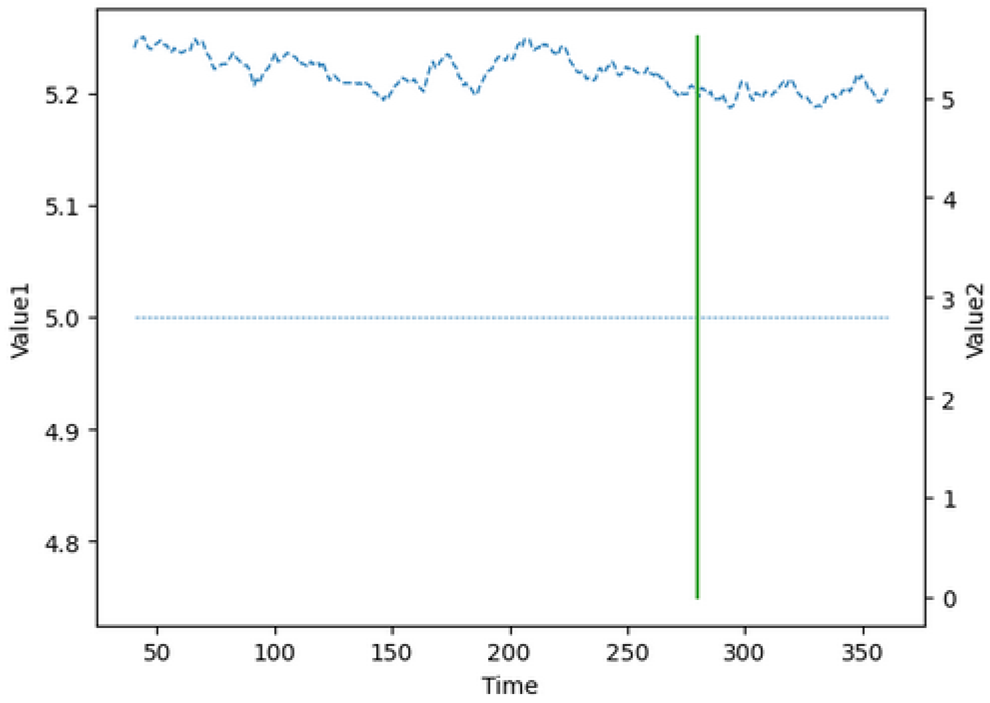
Computation of the moving average over the last t periods to be able to observe general trends.

Observation:

Gate 1 Queue Length: The queue length at Gate 1 remains relatively constant throughout the observation period, hovering around 5 passengers. This consistent queue length suggests a steady flow of passengers at Gate 1 without significant fluctuations.

Gate 2 Queue Length: Conversely, the queue length at Gate 2 exhibits more dynamic behavior. Initially, from time 0 to 150 hours, there is a gradual decline in queue length, indicating a decreasing number of passengers waiting at Gate 2 over this period. Subsequently, from approximately 150 to 250 hours, the queue length at Gate 2 rises and stabilizes. This plateau suggests a period of sustained passenger activity, leading to a stable queue length during this interval.

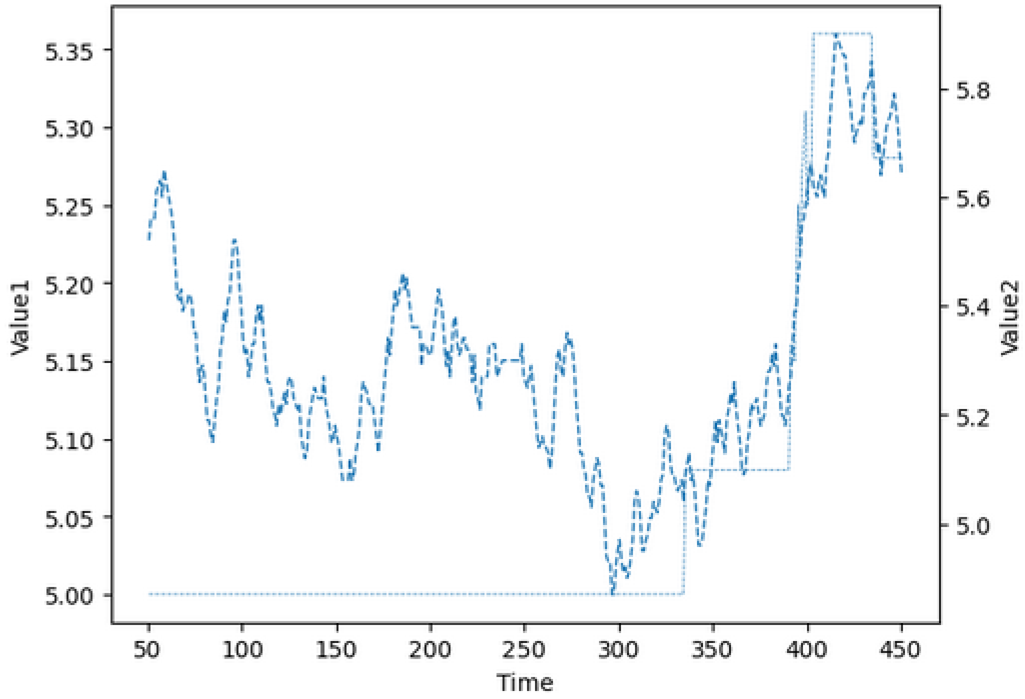
Beyond 250 hours, there is a notable shift in the trend, with the queue length at Gate 2 experiencing a sharp decline to below 4.9 passengers. This sudden decrease indicates a significant reduction in passenger waiting times or a decrease in passenger arrivals at Gate 2 during this phase.



Additionally, the burn-in period, represented by the green line, serves as an indicator of system stabilization. It marks the point at which the average queue lengths stabilize, providing a baseline for subsequent analysis.

By computing the moving average over the last t time periods, we gain insights into the general trends of queue length dynamics at both Gate 1 and Gate 2. This analysis enables a deeper understanding of passenger flow patterns and helps inform decision-making regarding resource allocation and queue management strategies.

Airplane distribution with 50 mins instead of 5 mins

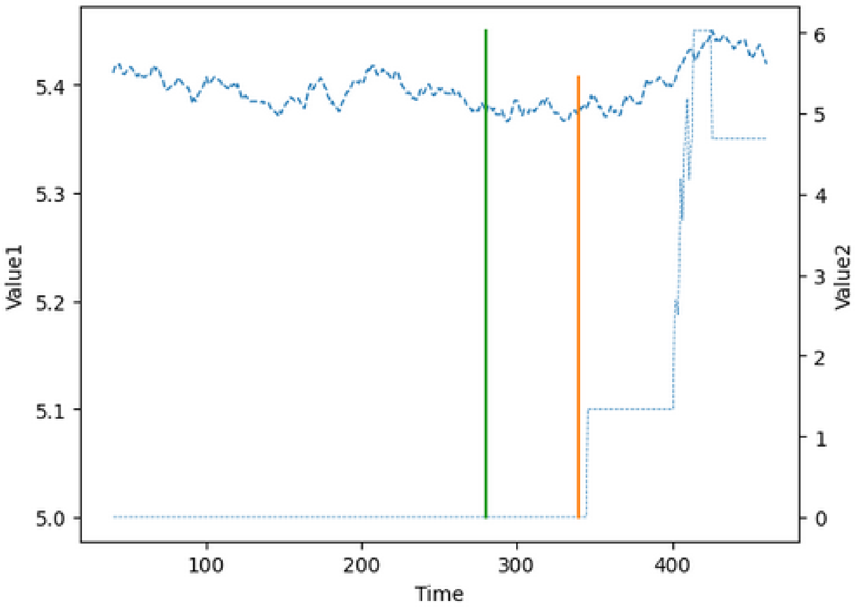


Moving averages observation:

Upon implementing a significant change in the aeroplane exponential distribution from 5 minutes to 50 minutes, a comparative analysis of moving averages reveals intriguing insights into the behavior of Gate 1 and Gate 2 queue lengths:

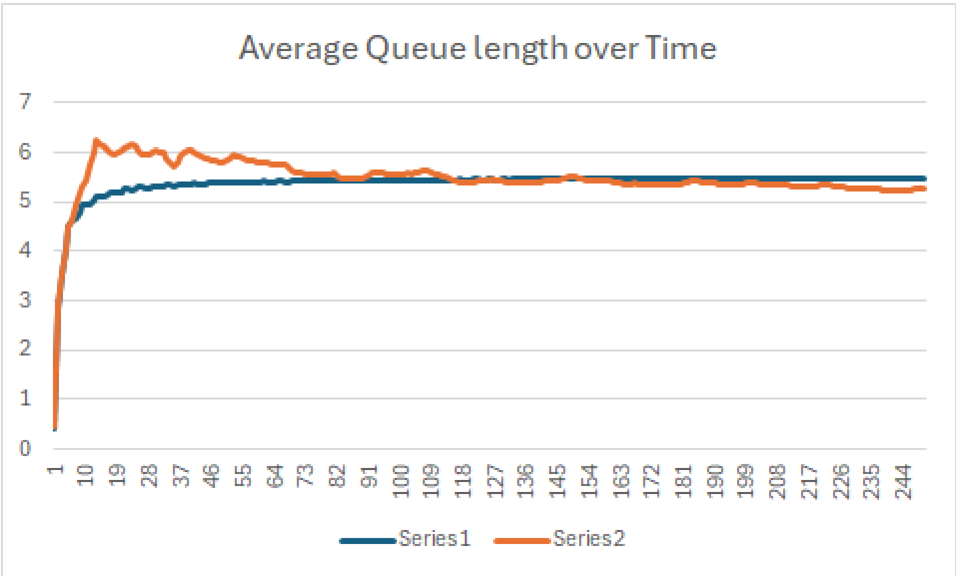
Gate 1 Queue Length: Following the adjustment in the airplane exponential distribution, the moving average of Gate 1 queue length exhibits a notable deviation from the original trendline. At approximately t = 340 hours, there is a sharp increase in the queue length at Gate 1, indicating a sudden surge in passenger volume. This elevated queue length persists until approximately t = 400 hours, remaining relatively constant during this period. Subsequently, there is a spike in Gate 1 queue length, reaching 5.3 passengers. This spike suggests a temporary influx of passengers or a bottleneck situation at Gate 1, leading to increased waiting times and queue lengths.

Gate 2 Queue Length:In contrast, the moving average trendline for Gate 2 queue length exhibits a similar trajectory to the original simulation, despite the significant alteration in the airplane exponential distribution. The queue length at Gate 2 follows a pattern characterized by fluctuations within a certain range, maintaining consistency with the original trendline.



As shown, Burn in period by inspection for Gate 1 is around 340 hours. Moving average stabilises from 0 to 340 h from Gate1 before having a similar trendline to a step-wise function.

International capacity to 40 units



Ave1 = Average Queue length of Gate 1 queue length to board aeroplane A

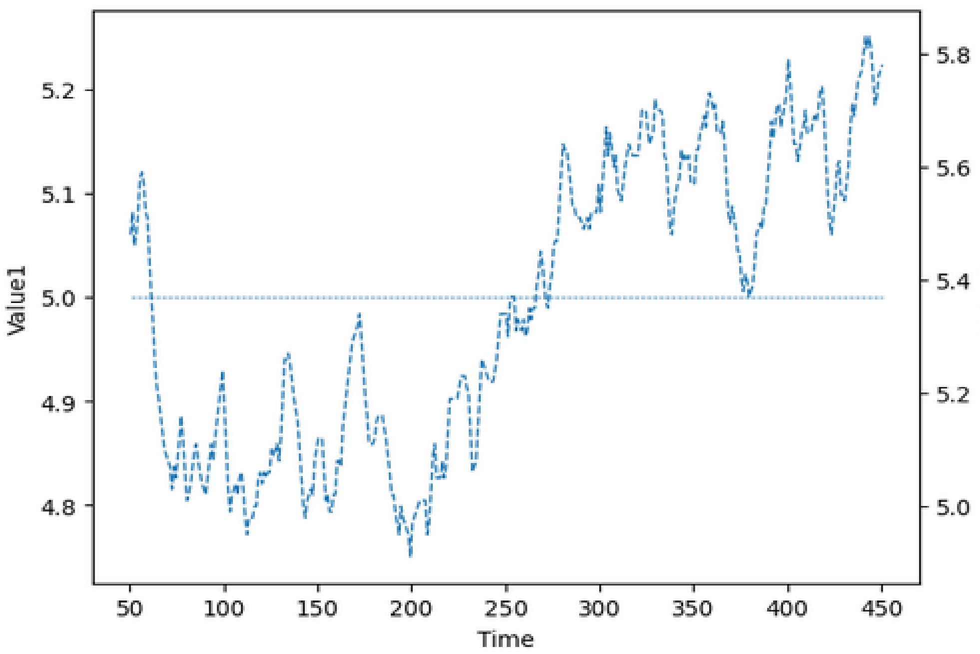
Ave2 = Average Queue length of Gate 2 queue length to board aeroplane B

Observation:

Ave1 Behavior: Ave1, representing the average queue length at Gate 1 to board airplane A, exhibits a distinct pattern over the observation period. At approximately t = 20 hours, Ave1 reaches its peak around 6 passengers, indicating a temporary surge in passenger activity or increased demand for boarding airplane A at Gate 1. Following the peak, Ave1 gradually stabilizes around 5.5 passengers, suggesting a consistent level of passenger queue length at Gate 1. This stabilization occurs at approximately t = 118 hours, indicating a period of sustained equilibrium in passenger flow for boarding airplane A.

Ave2 Behavior: In contrast, Ave2, representing the average queue length at Gate 2 to board airplane B, demonstrates a different behavior characterized by a smooth cumulative distribution function (CDF) resembling an exponential distribution.Similar to Ave1, Ave2 also stabilizes around 5.5 passengers, indicating a consistent queue length at Gate 2 for boarding airplane B. This stabilization reflects a steady state of passenger flow for boarding airplane B at Gate 2 throughout the observation period.

By analyzing the trends in Ave1 and Ave2, we gain valuable insights into the dynamics of passenger boarding processes for airplanes A and B respectively. These observations provide a basis for optimizing boarding procedures, resource allocation, and queue management strategies at Gate 1 and Gate 2, ultimately enhancing the efficiency and passenger experience within the airport environment.



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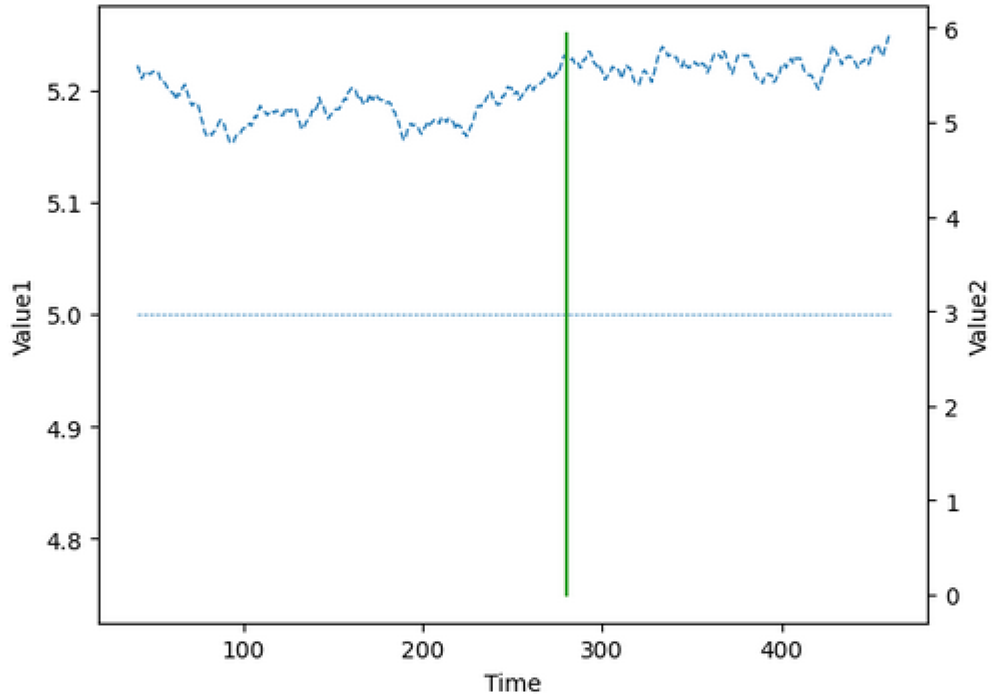
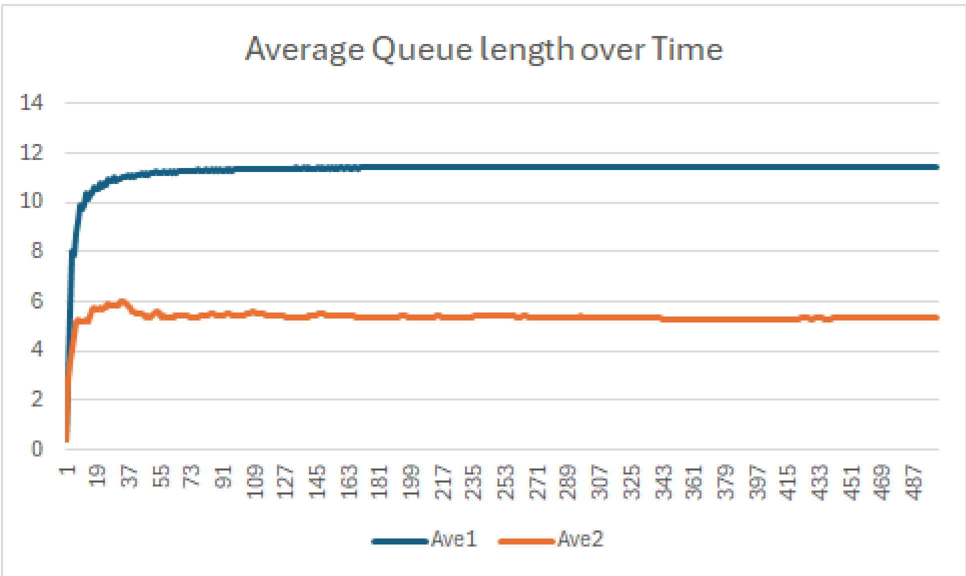


As shown, the burn-in period by inspection for Gate 1 stabilizes at 5 passengers since the start. The moving average stabilizes from 280h for Gate2 before having a steady incline.

Plane A capacity to 20 units



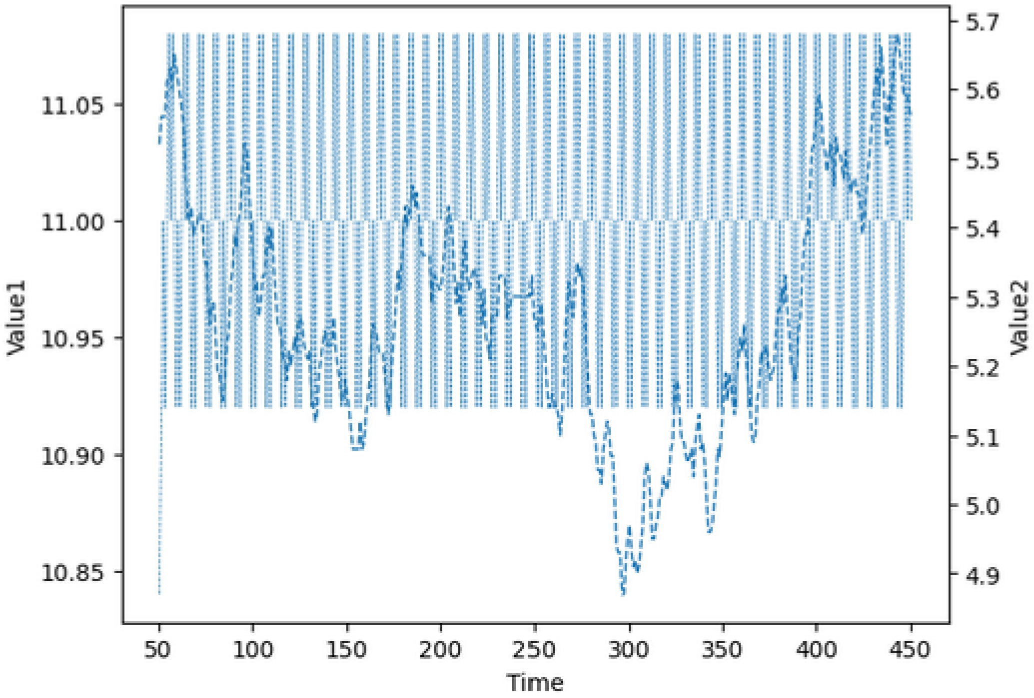
Ave1 = Average Queue length of Gate 1 queue length to board airplane A

Ave2 = Average Queue length of Gate 2 queue length to board airplane B

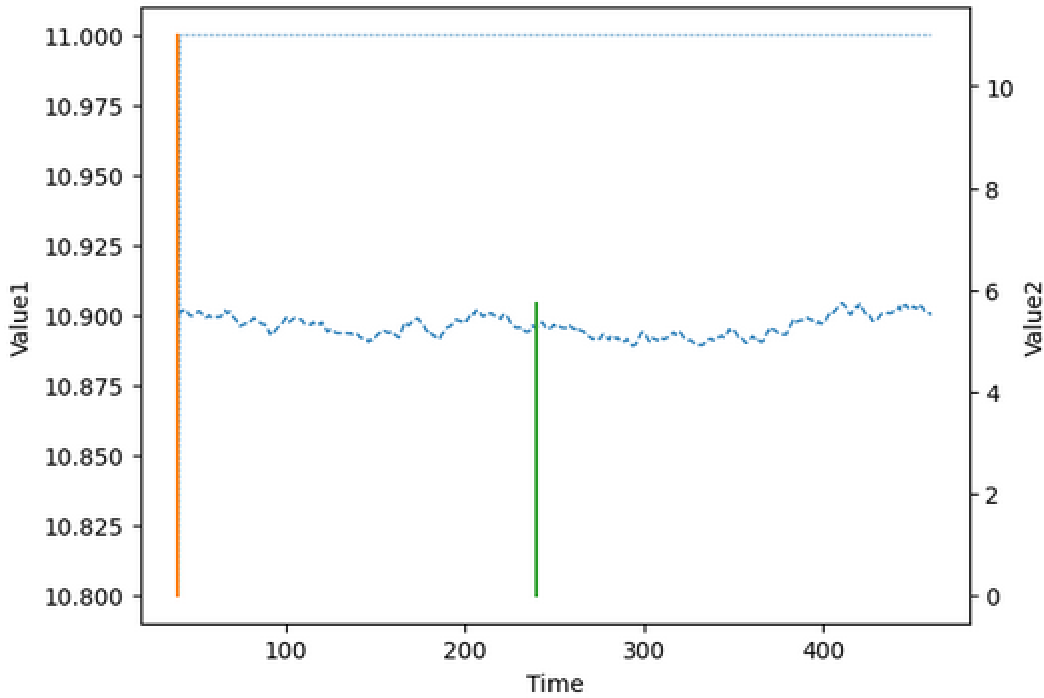
Observation:

Ave1 peaks around 11 passengers at t = 20 hours and stabilises around 12 passengers at t = 200 hours. Indicating a smooth CDF exponential distribution .

Ave 2 shows a somewhat steady CDF of an exponential distribution as coded in Jaamsim. Similarly, it also stabilises around 6 passengers. Current plane capacity has to be more than 8 for simulation to run as any number lesser would prove to be a choke point.

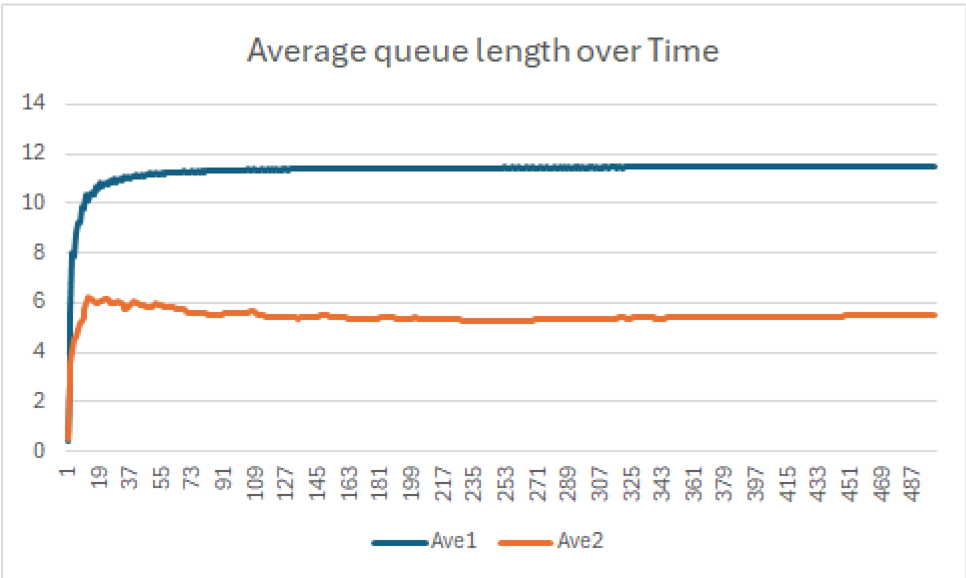


After changing the Plane A queue capacity from 10 to 20 units, Gate2 queue length show steady decline from t = 50h to 300h to around 10.8 passengers before steady increase from 300h to 450h to 11 passengers. On the other hand, Gate1 showed an erratic behaviour, jumping from 10.9 to 11.1 passengers throughout.



Further inspection of the burn in period shows Gate1 averaging and staying constant at 11 passengers at 40 h. Gate2 burn in time at 240h averaging around 10.9 passengers.

All 3 conditions above combined run



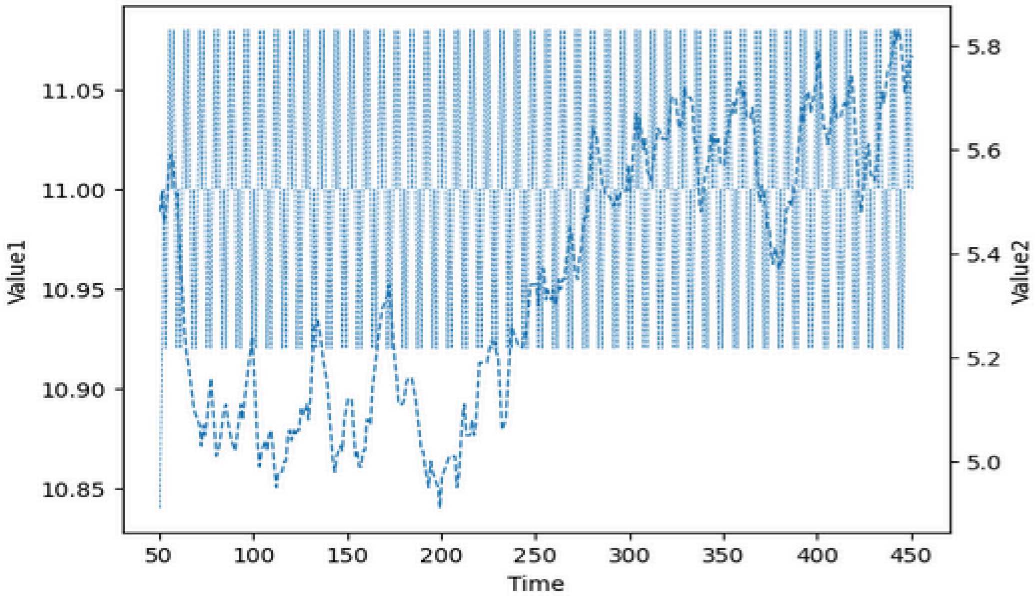
Ave1 = Average Queue length of Gate 1 queue length to board airplane A

Ave2 = Average Queue length of Gate 2 queue length to board airplane B

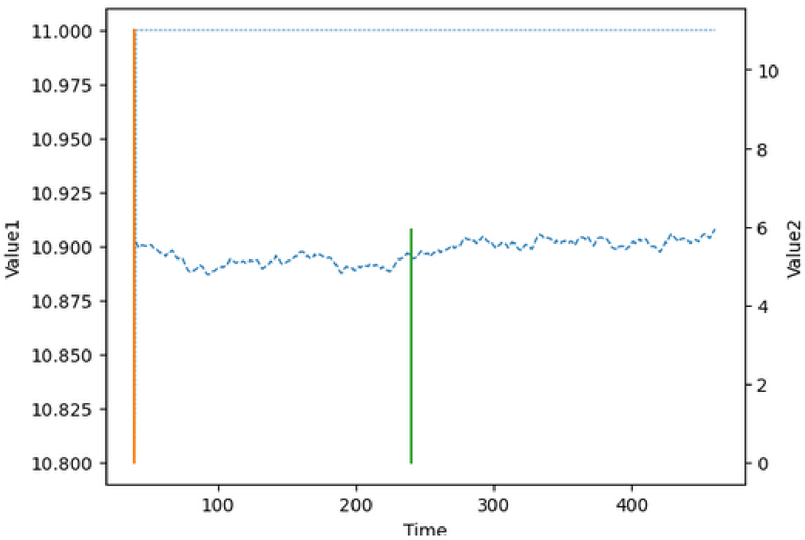
Observation:

Ave1 peaks around 12 passengers at t = 20 hours and stabilises around 12 passengers at t = 200 hours. Indicating a smooth CDF exponential distribution .

Ave 2 shows a somewhat steady CDF of an exponential distribution as coded in Jaamsim. Similarly, it also stabilises around 5 passengers. Changing all 3 independent variables does not seem like it has been effective in showing any jarring results.



Gate2 queue length show steady decline from t = 50h to 250h to around 10.8 passengers before steady increase from 300h to 450h to 11 passengers. On the other hand, Gate1 showed an erratic behaviour, jumping from 10.9 to 11.1 passengers throughout. Similar to when Plane A capacity was changed to 20 units instead of 10.



Further inspection of the burn in period shows Gate1 averaging and staying constant at 11 passengers at 40 h. Gate2 burn in time at 240h averaging around 10.9 passengers. before stabilizes.

Lessons Learned

Sensitivity of Queuing Length to Plane A Capacity: Our analysis revealed that the average queuing length, particularly at Gate 1, exhibits sensitivity to the capacity of Plane A. Specifically, we found that increasing Plane A capacity to more than 10, and particularly to 20 units, resulted in significant impacts on queuing length. This suggests that queuing length is only affected by a high enough volume of traffic of cars beyond this threshold. This finding underscores the importance of adequately sizing resources, such as aircraft capacities, to effectively manage queuing lengths and optimize passenger flow within airport environments.

Impact of Airplane Distribution Time on Gate 1 Average: We observed that Gate 1 average was sensitive to increasing airplane distribution time from 5 minutes to 50 minutes. This change led to notable deviations in the moving average of Gate 1 queue length, indicating a pronounced effect on passenger boarding processes and queue management strategies. This highlights the need for careful consideration and adjustment of airplane distribution times to maintain optimal queue lengths and passenger flow at boarding gates.

Sensitivity of Gate 2 Moving Average to Internal Queue Capacity: Our analysis demonstrated that the moving average of Gate 2 queue length was sensitive to increasing internal queue capacity to 40 minutes. This adjustment resulted in observable changes in queue length dynamics at Gate 2, emphasizing the significance of internal queue capacity in influencing system performance and passenger boarding efficiency. This finding underscores the importance of fine-tuning queue capacities to effectively manage passenger flow and minimize queuing delays at airport gates.

Conclusion

In conclusion, our extensive analysis of the airport simulation has provided valuable insights into the intricate dynamics of passenger flow, runway operations, and queue management. Despite implementing significant changes to key parameters such as airplane exponential distribution, international and plane queue capacities, and burn-in periods, the overall impact on system performance remained relatively limited, with observed fluctuations in queue lengths at Gate 1 and Gate 2 not significantly altering the system's behavior. Ave1 and Ave2, representing average queue lengths at the gates, exhibited stable trends throughout the observation period, indicating the resilience and consistency of the simulation model. While our study has identified potential areas for optimization, further research and experimentation may be required to uncover more substantial improvements in efficiency and performance. Nevertheless, our findings serve as a foundation for future endeavors aimed at enhancing airport operations, optimizing resource allocation, and ultimately improving passenger satisfaction within airport environments.