Enhancing Logistics Performance through Agent-Based Modeling of Truck Yard Operations

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This capstone project investigates inefficiencies in truck yard operations at logistics hubs, focusing on a leading U.S. beverage manufacturer's facilities, where prolonged queueing times contribute to increased fuel consumption, elevated emissions, and higher operational costs. The study employs agent-based simulation, implemented through AnyLogic, to model and simulate truck flow within the yard, addressing challenges such as congestion, suboptimal layouts, and the complexity of diverse shipping methods, including less-than-truckload freight, parcel deliveries, and customer pick-ups. The primary objectives are to develop a baseline simulation model for a specific plant — replicating the layout of one of the sponsor company's most critical facilities — to test operational scenarios such as adding a secondary check-in gate, and to deliver a dashboard for what-if analysis to evaluate potential improvements. By integrating real-world data on truck arrival patterns, yard configurations, process times, and operational rules, the simulation captures the dynamic interactions of autonomous entities within the system, offering a granular analysis of spatial competition, temporal coordination, and behavioral adaptations. The project identifies high-quality yard configurations and strategies that minimize queueing times, enhance throughput, and improve overall efficiency under diverse circumstances, providing the sponsor with a data-driven tool to support decision-making for existing and new facilities. The project also offers actionable recommendations and scenarios, contributing to more sustainable and cost-effective logistics operations by reducing turnaround times and operational bottlenecks.

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1 Introduction

1.1 Background

Truck queueing at logistics hubs, such as ports and distribution centers, is a significant challenge that leads to increased idling times and potential financial repercussions. Idling means trucks burn fuel while stationary, which wastes resources and increases emissions and maintenance costs. For example, the U.S. Department of Energy reports that a typical long-haul truck idles for about 1,800 hours a year, consuming around 1,500 gallons of diesel fuel, costing roughly US$4,500 at US$3 per gallon (U.S. Department of Energy, 2015).

Methods like simulation and machine learning are often used to tackle this challenge. A study by Flores da Silva et al. (2023) found that integrating these technologies in truck appointment systems at a Brazilian port helped reduce waiting times by 90.4%, a significant improvement. Another example is Amazon, which used agent-based modeling, a simulation approach, to optimize truck yard operations, especially during busy periods like Prime Day, improving efficiency and reducing delays (Mohsin et al., 2023). These approaches seem promising, but modern supply chains are complex, suggesting more advanced tools are needed.

Beyond fuel costs, idling adds at least US$2,000 annually in maintenance and can reduce engine life by 20%, according to the American Trucking Association (Zima, 2022). In the United States, idling during rest periods consumes up to 1 billion gallons of fuel, costing around US$3 billion, highlighting the broader economic and environmental impact (U.S. Department of Energy, 2015).

Efficient management of logistics and transportation systems is critical for businesses operating in today's fast-paced global economy. As the demand for freight services continues to grow and supply chains become increasingly complex, organizations face numerous challenges in optimizing their logistics operations. These challenges are particularly evident in large distribution centers and warehouses, where the increasing adoption of e-commerce and omnichannel strategies has led to more frequent, smaller shipments and the need for more agile and responsive truck routing within facilities. For instance, the rise of same-day and next-day delivery options has intensified the pressure on internal logistics systems to efficiently manage truck flows, minimize congestion, and reduce turnaround times (Boysen et al., 2023).

Despite technological and methodological advancements, there remains a need for more integrated and comprehensive simulation tools that can handle the complexity of modern supply chains. Current methods often focus on macro-level environments, such as port terminals or supply chain networks. They may not fully account for the nuances at the micro-level, such as truck yard operations inside a facility.

This capstone project addresses these gaps by developing an advanced, customized truck flow simulation model that reduces queueing times. By leveraging state-of-the-art simulation techniques and tools, and integrating data from different systems, such as electronic data interchange (EDI) that contains transactional data about truck arrivals, service times, and operations around the warehouses, the project contributes to more efficient and sustainable logistics operations. The focus on reducing queueing times aligns with economic and environmental goals, potentially offering a model that can be adapted across different yard layouts.

1.2 Motivation

One of the key areas requiring attention is managing on-premises vehicle flow, which can significantly impact overall operational efficiency. Many companies struggle with congestion, suboptimal yard layouts, poor system coordination, and limited loading capacities. These problems often lead to operational delays, increased fuel

consumption, higher labor costs, and potential safety hazards, negatively affecting productivity and profitability (Cusihuaman-Torres et al., 2023). Our sponsor, a leading U.S. beverage manufacturer, sought insights to improve the layout of their upcoming plants for more efficient truck and product flow. Their operations are highly complex, and they use multiple shipping methods—less-than-truckload (LTL) freight, parcel, owned carriers, third-party logistics (3PL), customer pick-ups (CPU), and rush deliveries. Since real-life piloting for intralogistics optimization may be costly and time-consuming, the sponsor is interested in using simulation methods to test and validate multiple what-if scenarios before making significant investments.

The sponsor provided insights into their typical yard layouts, which share common characteristics across many facilities. These layouts generally feature multiple lanes that accommodate various types of truck flow, including inbound and outbound shipments, parcel deliveries, 3PL, customer pick-ups (CPU), and rush deliveries. The manufacturing facilities might encounter numerous loads daily, often in the range of several hundred. As production typically relies on a handful of primary raw materials, efficient management of inbound shipments is crucial for maintaining smooth operations.

Improving yard layouts and truck flow can yield significant benefits, such as reduced truck wait and dwell times, lower operational costs, and increased capacity to handle fluctuations in demand. However, making informed decisions about yard layout improvements or designing efficient layouts for new facilities requires model- and data-driven approaches.

This project proposes an agent-based simulation model to comprehensively understand truck flows within the sponsor's facilities and optimize their yard layouts. By developing a versatile approach capable of testing various scenarios, the company will gain valuable insights into its operations, enabling it to make data-driven decisions, identify efficiency opportunities, and create compelling business cases for implementing strategic improvements. This holistic perspective enhances the overall performance and productivity of their facilities.

1.3 Problem Statement

The sponsor currently operates with over 40 plants and faces challenges in improving its yard layouts and truck flow management. While the current layouts are functional, there is uncertainty about their efficiency, particularly in peak periods. The company lacks a standardized, data-driven method or a quantitative approach to evaluate and enhance yard operations across its facilities under dynamic circumstances. This situation presents several interdependent issues:

- *Uncertainty in layout suitability:* The sponsor cannot confidently assess whether its current yard configurations are adequate for handling diverse truck traffic patterns or arrival times, including inbound/outbound shipments, parcel deliveries, third-party logistics, customer pick-ups, and rush orders.
- *Limited ability to predict impacts:* The sponsor struggles to accurately forecast truck flow and efficiency effects when considering layout modifications or new plant constructions.
- *Difficulty justifying improvements:* Creating compelling business cases for yard layout improvements or changes becomes challenging without quantifiable data on potential benefits.

Truck flow management in yard operations faces significant challenges due to the complexity and variability of layouts and scenarios. Existing approaches struggle to fully capture the dynamics of different yard configurations and truck movement patterns, leaving gaps in understanding how these systems perform. There is also no precise, measurable data to evaluate current inefficiencies or predict how changes might impact operations. Additionally,

anticipating future needs and conditions remains difficult, as the tools available are not equipped to handle the evolving demands of the sponsor's operations.

The sponsor wanted to gain insight into the current performance of its facilities and address operational inefficiencies, particularly the issue of long queueing times caused by unoptimized processing. A tool capable of analyzing these dynamics and identifying potential improvements is essential to meet these goals effectively.

In that context, the research questions to be answered include:

- What layout (i.e., road infrastructure around the warehouse) would work better with the facility's constraints and characteristics?
- What are the critical factors affecting yard efficiency? And how can these be improved through simulation?
- How may these insights apply to existing or new facilities?

A systematic and quantitative approach is needed to evaluate and optimize yard operations under various real-world conditions to address these challenges. By developing a robust simulation model tailored to the sponsor's facility, this project provides actionable insights into possible bottlenecks and supports data-driven decision-making. The following section outlines the specific goals and deliverables of the project, detailing how the proposed methodology will enable scenario testing, inform layout improvements, and ultimately enhance truck flow management across the sponsor's network of facilities.

1.4 Scope: Project Goals and Expected Outcomes

The project generates a simulation model for the sponsor's specific warehouse to improve the processing time of the trucks outside the logistics facility. The simulation will be used for scenario testing and as a replicable model for other facilities. The sponsor can use this model to justify facility design decisions for new locations or potentially redevelop existing ones if the investment is justified.

The expected outcomes include a methodological approach containing the following characteristics and recommendations based on the obtained results:

- A baseline model that can simulate the original conditions from the sponsor's operations.
- A scenario that can simulate the bifurcation of the entrance to divert trucks to a secondary check-in gate.
- Several scenarios test what-if analysis for different parameters and represent various circumstances.
- A dashboard that enables the performance assessment across different scenarios.

In summary, this project delivers several key contributions to both our sponsor and the broader practice of logistics simulation:

- A validated, agent-based model of the sponsor's yard that replicates real-world truck flow dynamics and can be readily adapted to other facilities.
- A suite of sixteen data-driven scenarios, including bifurcation strategies, batch arrivals, and varied check-in times, that isolate critical operational levers.
- A decision-support "what-if" dashboard and ROI calculator translating technical metrics (queue lengths, service times) into business KPIs (carrier hours saved, penalty cost reductions).
- A dynamic gate-activation policy that balances utilization and cost by deploying the secondary gate only when arrival rates exceed 30 trucks/hour or check-in times exceed 4 minutes.

- A dynamic gate-activation policy that balances utilization and cost by deploying the secondary gate only when arrival rates exceed 30 trucks/hour or check-in times exceed 4 minutes.
- A methodological advance in combining DES and ABS within AnyLogic to capture both process flows and emergent driver behaviors in micro-level yard environments.

Our main takeaways include:

- Under a stress scenario of 30 trucks/hour and a 5-minute average check-in, bifurcation cuts penalty costs by 15.1%, equivalent to saving 196.6 minutes of carrier time per operating hour (i.e., 3.28 carrier-hours saved).
- Check-in delays over 8 minutes trigger a 702% increase in average queue time, underscoring the criticality of process efficiency at the gate.
- Batch arrivals (3 trucks per arrival) can be stabilized through gate bifurcation, although not entirely, reducing average facility time by 8.6%.

The remainder of this document proceeds as follows. Section 2 reviews the state of practice in yard simulation and hybrid ABS/DES methods. Section 3 describes our data-gathering approach, model construction, and experimental design. Section 4 presents the scenario definitions, detailed results, and business-focused analyses. Finally, Section 5 offers recommendations, discusses limitations, and outlines avenues for future work.

2 State of the Practice

Poor truck yard designs in container terminals can create bottlenecks in supply chains by restricting the flow of goods into and out of a facility. This issue creates inefficiencies as the additional production risks mean increased gate operation costs and longer truck turnaround times (Bett et al., 2024). Congestion can also lead to higher transport costs, particularly during morning and evening peak hours. To address these issues, many container terminals are adopting truck appointment systems (TAS) to manage truck arrivals more efficiently throughout the day (Xu et al., 2021). However, implementing such systems requires careful consideration of various factors, including the balance between productivity and service time, while accounting for yard area congestion (Bett et al., 2024).

Strategic decisions about yard operations often require high precision to overcome these challenges. Rarely is this high precision not feasible with conventional mathematical models, historical benchmarking, or personal judgment within a short time. Unique approaches are needed, and simulation is one of the most used tools for risk management in the supply chain industry (Farhan et al., 2023).

As the central problem of this capstone is centered on utilizing simulation to improve the processing time of trucks inside our sponsor's facilities, focusing on queueing times, we reviewed the literature in several areas. First, we explored recent simulation studies on truck yards. Second, we reviewed general simulation methods and their applications. Lastly, we investigated several simulation approaches as powerful methods for modeling complex systems like truck yards, as well as some implementation tools like AnyLogic.

2.1 Truck Yard Simulation

Truck yard simulation has emerged as a robust method for analyzing and optimizing the complex dynamics of truck movements within logistics facilities. A truck yard typically consists of interconnected components, including inbound gates for registration and assignment, docking areas for loading and unloading operations, parking zones for trailer storage, and outbound gates for exit processing. The efficacy of these yard operations significantly impacts

overall supply chain performance, with inefficiencies potentially causing substantial delays and increased operational costs.

Modern computational yard simulation approaches predominantly employ discrete event simulation (DES) and agent-based simulation (ABS) or agent-based modeling (ABM), which are sometimes integrated into hybrid models. Mohsin et al. (2024) developed a comprehensive data-driven agent-based model for transportation yards at Amazon, which captures detailed features and processes of yard operations. Their simulation model helps identify potential bottlenecks, inefficiencies, and risks in the system by analyzing performance indicators such as yard utilization, parking slip usage, dock door availability, entry and exit gate queues, and late departure counts. They note that analytical models are inadequate for simulating the random behavior inherent in yard operations, as simulation can better represent the complex, stochastic, and dynamic nature of these environments.

Integrating discrete-event and agent-based approaches has proven particularly effective for complex yard modeling. According to a case study of Amazon warehouse operations, engineers developed a hybrid simulation model using AnyLogic software that combines these methodologies to optimize yard workflows (Farhan et al., 2023). The discrete-event components model sequential processes like truck arrivals and departures, while agent-based elements simulate the autonomous behaviors of trucks, drivers, and yard staff. This approach captures the process-oriented nature of yard operations and the decision-making dynamics of individual actors, providing a more realistic representation of the system.

Digital twin technology is increasingly revolutionizing truck yard simulation by creating virtual replicas of physical yard environments that update in real-time. Digital twins represent a significant advancement beyond traditional simulation models. As described in a comprehensive report by DHL, these virtual models continuously update the entire yard operations lifecycle, allowing for direct representation of operational data (DHL, 2022). The integration of Internet of Things (IoT) devices, sensors, and real-time data collection systems enables these digital twins to reflect the current state of the yard accurately. Terminal operators can then visualize current operations, predict future states, and test operational changes virtually before implementing them physically.

The efficacy of agent-based modeling for simulating decision-making processes in yard operations has been demonstrated by Huynh and Vidal (2010) in their research on yard cranes at seaport container terminals. They modeled cranes as utility-maximizing agents with specific decision functions that capture the essential process of choosing which truck to service next. Their implementation in NetLogo, a multi-agent programmable modeling environment, demonstrated that distance-based service strategies produced the best results for minimizing any truck's average and maximum waiting times. Such findings directly affect truck yard management, where similar service prioritization decisions must be made.

Recent advancements have also seen the integration of machine learning with simulation models to enhance predictive capabilities and optimization potential. These integrated approaches use historical data to train machine learning algorithms that can improve the accuracy of simulation models or optimize decision rules within the simulation. The Amazon team responsible for transportation yard simulation acknowledged the potential of this integration, noting that future work involves incorporating machine learning techniques to mine rules from historical data instead of relying solely on predefined standards (Mohsin et al., 2023). This approach promises to improve both the accuracy of the model and its prediction performance.

The deployment of these simulation technologies in cloud environments represents another significant advancement in the field. Cloud-based deployment enables handling large-scale simulations and real-time data processing, which are crucial for optimizing yard operations in dynamic environments. The scalability offered by

cloud platforms allows for multiple simulation runs with different parameters, facilitating comprehensive scenario analysis without requiring extensive local computing resources (Farhan et al., 2023).

These simulation approaches provide numerous benefits for truck yard optimization. They enable risk-free testing of operational changes, identifying bottlenecks, validating proposed solutions, and quantifying potential improvements before physical implementation. Yard managers can use simulation results to make evidence-based decisions regarding resource allocation, scheduling policies, and physical layout modifications. However, the effectiveness of these models depends heavily on the quality of input data and the accuracy with which they represent real-world operations and will likely be shaped by several emerging trends in logistics and technology, such as blockchain integration for enhanced supply chain visibility by enhancing transparency, traceability, and efficiency (Snigdha and Oyshi, 2025).

The gradual introduction of autonomous vehicles presents opportunities and challenges for yard management, requiring new simulation approaches to model mixed traffic environments during transition periods. Similarly, the growing adoption of Internet of Things (IoT) technologies in logistics facilities will generate massive data streams for model calibration and validation, potentially improving simulation accuracy and applicability.

2.2 Simulation Types and Process

A well-defined approach ensures simulation models accurately represent the real system, produce reliable results, and lead to meaningful insights. Without a proper methodology, simulations may yield misleading outcomes or fail to capture critical aspects of the system under study. By adhering to established simulation methods and types, researchers and practitioners can create virtual representations of yard operations that allow them to explore various scenarios and strategies without disrupting real-world processes.

Banks (2016) defines simulation as the imitation of the operation of a real-world process or system over time. Banks further explains that it is used to ask what-if questions about the real system and aid in designing real systems. Despite simulation being a powerful tool, poorly planned simulation runs can result in a significant loss of information or, even worse, provide misleading results (Kelton & Barton, 2004). That is why a methodology should be followed to design a simulation of the experiment correctly. The following steps from Banks provide a general approach for simulation:

1. Problem formulation
2. Setting objectives and the overall project plan
3. Model conceptualization
4. Data collection
5. Model translation
6. Verification of the model
7. Validation of the model
8. Experimental design
9. Production runs and analysis
10. Documentation and reporting

11. Implementation

Simulation models such as Discrete Event Simulation (DES), Multi-Agent Simulation (MAS), and System Dynamics (SD) are used to analyze specific test cases in logistics and supply chain management. These modeling approaches differ in their fundamental structures and applications:

DES models systems as a series of discrete events occurring over time, focusing on individual entities and their interactions. It is beneficial for analyzing queues, resource utilization, and process flows (Veloquie et al., 2014). In contrast, MAS/ABM/ABS models systems as collections of autonomous agents that can make decisions and interact with their environment. This approach is well-suited for simulating complex systems with multiple decision-makers and adaptive behaviors (Torbali & Alpan, 2023). System Dynamics (SD), on the other hand, uses stocks, flows, and feedback loops to model the behavior of complex systems over time, focusing on aggregate behaviors and system-level patterns. SD is especially useful for understanding long-term system behavior and the effects of supply chain and logistics feedback.

Veloqui et al. (2014) used DES and queueing theory to determine the sources of congestion at the Port of Naples. Their goal was to analyze the landslide congestion problem in the container terminal. The study developed five simulation models to evaluate different solutions. Their main results showed that all processes inside the terminal were strongly dependent, and the solution to congestion should consider simultaneously decreasing the service time at both the access gate and the yard.

Torbali and Alpan (2023) employed a hybrid model combining MAS and DES to analyze the performance of a cross-dock warehouse operation with a single inbound and outbound door. The goal was to develop a real-time multi-agent truck scheduling model for fast synchronization of inflows and outflows. The study's main results demonstrated that the stock policy (SP) outperformed other strategies by maintaining low stock and high on-time deliveries across all traffic levels. They also found that time-related strategies were adequate for cases where outbound traffic was more elevated than inbound traffic.

As the problem to be solved in this project is based on the interactions of trucks with each other and their tasks, a DES & MAS approach could be used as DES can provide insight into process-related performance. At the same time, MAS can simulate the interactions of agents within a physical space.

2.3 Agent-Based Simulation

The selection of agent-based simulation (ABS) arises from its unique capacity to model complex interactions between autonomous decision-makers within constrained physical environments – a fundamental characteristic of truck yard operations. Unlike discrete-event simulation (DES), which focuses on process flows and resource utilization through predefined sequences, ABS enables dynamic representation of heterogeneous entities (trucks, dock operators, gate systems) that adapt their behaviors based on local interactions (Zankoul et al., 2015). This distinction becomes critical when analyzing queue formation mechanisms, as congestion in truck yards often emerges from the interplay between individual vehicle routing decisions, parking space allocation conflicts, and real-time responses to bottleneck conditions (Ying and Kittipittayakorn, 2018).

Through their cross-dock warehouse study, Torbali and Alpan (2023) demonstrate that ABS outperforms pure DES approaches in scenarios requiring simultaneous optimization of multiple adaptive systems. Their hybrid model revealed that agent-based components could capture truck drivers' real-time decisions when encountering congestion. Similarly, Farhan et al. (2023) established that ABS provides superior modeling fidelity for yard operations through the following key capabilities: granular representation of individual truck characteristics (load type, priority status, fuel

constraints) and dynamic interaction modeling between trucks and infrastructure elements (traffic signals, docking bays).

The project's focus on queue time reduction requires a simulation approach that can capture three interdependent phenomena:

- Spatial competition for truck maneuvering in confined yard areas.
- Temporal coordination challenges during peak arrival periods.
- Behavioral adaptation patterns as drivers respond to congestion signals.

The ability of ABS to simulate emergent behaviors is significant in our context. In truck yards, the collective actions of individual trucks and drivers can lead to unexpected patterns or bottlenecks that are not immediately apparent from studying the system's components in isolation. One example of unexpected patterns could be adding other agents, such as cars, to add a layer of complexity to traffic jams. ABS can capture these emergent phenomena, providing insights into complex system dynamics that other simulation approaches might miss. ABS addresses this gap by enabling each truck agent to autonomously select parking locations based on current occupancy, adjust speeds according to nearby vehicle density, and modify docking sequences in response to operational delays.

This behavioral granularity proves essential for identifying more sophisticated relationships between yard layout configurations and queue formation patterns. Murarev's intermodal terminal study confirmed that ABS could reveal congestion hotspots emerging from otherwise efficient individual routing decisions. This capability becomes critical for our sponsor's facility when evaluating how localized improvements (e.g., expanded parking zones) might inadvertently create downstream bottlenecks at dock access points.

The methodology aligns with Bett et al.'s (2024) framework for congestion analysis in container terminals, emphasizing the need to model physical infrastructure constraints and operational decision-making processes. By implementing ABS, the project can simultaneously assess:

- Macro-level yard throughput metrics.
- Micro-level truck interaction patterns.
- Emergent congestion states arise from their interplay.

This multi-scale analysis capability positions ABS as the optimal approach for developing robust queue reduction strategies under varying traffic conditions and operational constraints.

At the stakeholders' request, AnyLogic will be the tool used to simulate the truck yard. AnyLogic is commonly used to solve DES & ABS problems. Compared to code-oriented solutions, like SimPy, AnyLogic provides a friendly user interface that lets our sponsor distribute the simulation model to a broader audience. This selection process is discussed further in Section 3.1.1.

One example of using AnyLogic is from Farhan et al. (2023), where they developed a cloud-based hybrid simulation model for optimizing warehouse yard operations using this software. Their approach combined agent-based and discrete-event techniques. The agent-based component modeled elements like trucks, parking spots, and hostlers with individual characteristics and behaviors. The discrete-event component translated real-world processes into model blocks using AnyLogic's process and transporter libraries. These processes included outbound flows, live loads, empty trailer moves, hostler operations, and inbound/outbound box truck handling. The model incorporated

inputs such as truck arrival schedules, trailer processing times, and truck types (53-foot or box trucks), which align with the characteristics of this study.

2.4 Gaps and Summary of the Section

Despite advances in truck yard management, current industry practices and research often overlook the dynamic, agent-driven interactions that cause persistent bottlenecks and inefficiencies, especially during peak periods. Most existing studies rely on traditional mathematical models, historical benchmarking, or discrete event simulation (DES), which excel at process flow analysis or macro-level studies but fall short in capturing the autonomous decision-making and spatial competition among trucks that drive real-world congestion.

Few works have leveraged agent-based simulation (ABS) to its full potential, and even fewer have applied hybrid approaches to model sequential processes and emergent driver behaviors. While recent studies (e.g., Mohsin et al., 2024; Farhan et al., 2023) have begun to explore these methods, there remains a gap in applying such advanced simulations to real-world, like micro-level interactions inside facilities and evaluating operational value in different yard configurations.

This capstone addresses these gaps by:

- Developing an agent-based simulation tailored to a critical U.S. beverage manufacturer's yard, capturing spatial and behavioral dynamics.
- Integrating real operational data to test scenarios, including secondary gate activation and batch arrivals, that have not been thoroughly analyzed in prior literature.
- Providing actionable, data-driven insights for facility design and operational decision-making beyond what existing DES or TAS approaches can offer.

Focusing on the interplay between check-in processes and queue formation, this project delivers a more realistic and strategic evaluation of yard operations solutions where conventional models fall short.

3 Methodology

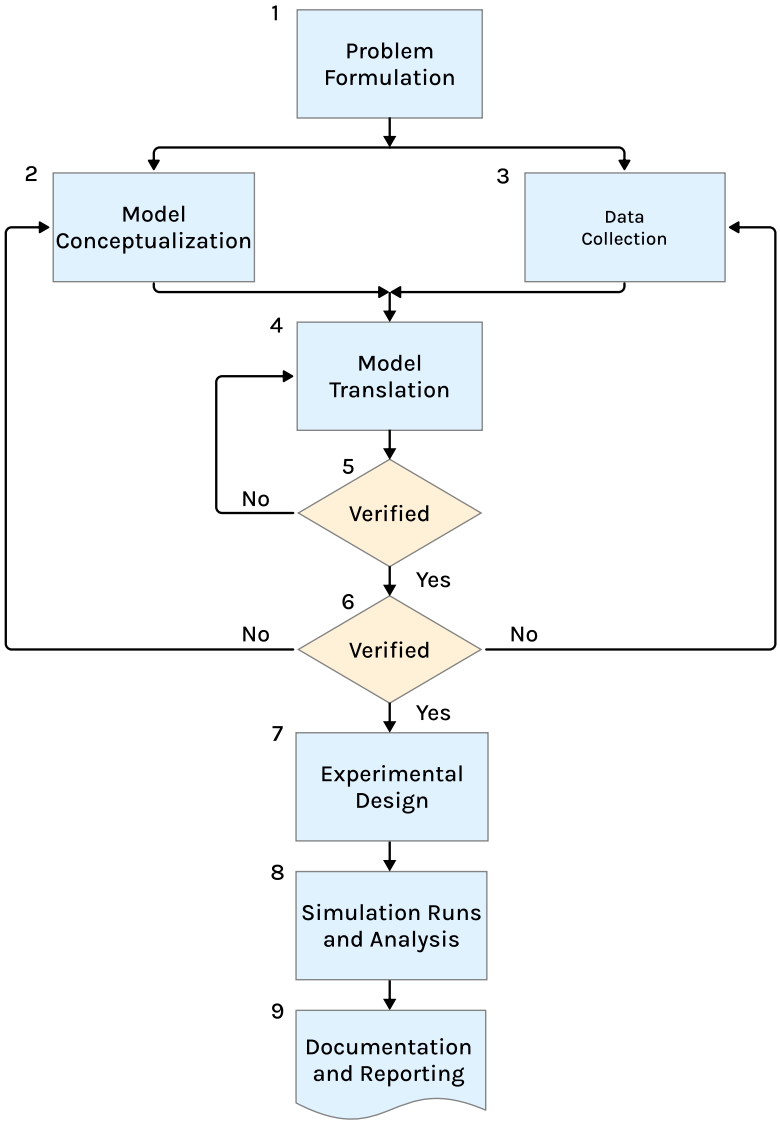
This section presents the methodology adopted for simulating the truck yard operations, focusing on addressing the sponsor's specific requirements. Section 3.1 outlines the overall simulation framework, drawing on established best practices and the literature review to justify using agent-based simulation (ABS) as the foundation for this study. Data gathering procedures are summarized in Section 3.2.1, detailing the inputs required for accurate model construction. The subsequent sections address the treatment and analysis of critical variables: Section 3.2.1.1 examines the distribution of truck interarrival periods, Section 3.2.1.2 focuses on gate check-in times, and Section 3.2.1.3 covers overall yard time. The systematic application of the methodology is detailed in Section 3.2. Section 3.1.1 introduces AnyLogic, the selected simulation platform, explaining its capabilities and relevance to the project. Section 3.1.2 discusses key limitations inherent to the modeling approach, particularly those related to the chosen software and the level of process detail. Metrics for evaluating model performance and interpreting simulation outcomes are presented in Section 3.2.4, which leads to Section 3.2.2, which provides a comprehensive assessment of the yard's operational process. Finally, the step-by-step construction of the simulation model and process flows is described in Section 3.2.3.

3.1 Methodology Selection

Based on our literature review, our methodology follows a structured and iterative approach that combines established best practices in simulation with specific considerations for logistics and transportation systems. This section outlines the steps involved in conducting a simulation study, which served as the foundation for this project.

Our approach is based on a consolidation of methodologies found in the reviewed literature, adapted to the unique challenges of truck yard optimization (see Figure 1). While initially adopting a generic simulation approach, we will later focus on agent-based simulation (ABS).

Figure 1. Simulation Methodology Flow Chart (adapted from Banks, 2016)



The general simulation methodology consists of eight key steps:

1. **Problem Formulation:** In this stage, we identify the individual agents that play crucial roles in the yard operations. These agents could include vehicles (e.g., trucks, trains), drivers, and warehouse operators. We also define the scope of the problem and state the objectives of the simulation, and the level of granularity required for each agent type and their interactions. Interviews were conducted with the director of the facility and the director of Supply Chain Solutions to understand the problem and map each process a truck follows from arriving to leaving the facility.

2. **Conceptual Model Development:** In this phase, a detailed conceptual representation of the logistics system was created, including all relevant entities, processes, interactions, and decision-making processes for each

agent type. For vehicles, this includes vehicle spawning and route selection depending on which type of vehicle it is, such as parking or connecting to a dock. Also, rules were established for agent interactions, such as how vehicles communicate with different sources, like the check-in or check-out gates.

3. **Data Collection:** Comprehensive data on system parameters, process times, resource utilization, and other relevant metrics were gathered to inform the model. This involved collecting historical data on vehicle movements, loading/unloading, and processing times. The sponsor had to work with the business analytics internal team and their third-party logistics to ensure the data was as complete and clean as possible.

4. **Model Translation:** This phase implemented the conceptual model using ABS-specific software (i.e., AnyLogic) suitable for transportation and logistics simulations. If necessary, the agent's behavior was translated, and decision-making rules were incorporated into the code, ensuring they accurately reflect the conceptual model. Visualizations were created to support the results of the simulation.

5. **Verification and Validation:** After the model was implemented, thorough verification was conducted to ensure that the implemented model accurately represents the conceptual model. This involved debugging code and checking logical consistency in agent behaviors while the sponsor validated internally that the outputs were close to reality. Conversely, the validation was performed by comparing simulation outputs with real-world data from our sponsor and including subject-matter experts, like the Director of the Facility and the Director of Supply Chain Solutions, to provide feedback.

6. **Experimental Design:** A series of experiments were designed to test different agent configurations and yard layout modifications or to alter logistics policies. These experiments involved varying the parameters of main drivers, such as inter-arrival times, check-in times, and the ratio of inbounds against outbounds, to determine how the queue and the system behaved when these parameters changed. "What-if" scenarios were planned with the sponsor, such as the impact of changing the route of the trucks to a bifurcation at the facility's entrance.

7. **Simulation Runs and Analysis:** The planned experiments outlined in the previous step were conducted by running multiple replications of each scenario, ensuring the results accounted for the inherent stochasticity of agent-based models. The analysis focused on both agent-level behaviors and system-level outcomes, particularly on performance criteria. These metrics included the average time spent in the entrance queue and the facility (from entry to exit), the average and maximum number of trucks in the queue, and the associated penalty costs incurred due to excessive dwell times (demurrage). This is detailed in Section 3.2.4. Statistical techniques were applied to these metrics across simulation replications, enabling robust conclusions and actionable managerial insights regarding operational efficiency, bottleneck identification, and the financial impacts of various yard configurations and policies. The tested operational scenarios involved various combinations of truck arrival rates, check-in time, and truck arrival batches. These scenarios were tested against the baseline model and the bifurcated model.

8. **Documentation and Reporting:** Finally, results from the entire simulation process were produced, including the conceptual model, interactions, and the overall result of the simulation runs. The model was labeled with instructions to enable the sponsor to use the simulation model for future efforts.

3.1.1 Simulation Software: AnyLogic Overview

A consideration was whether a Discrete Event Simulation (DES) approach, which focuses on event-driven processes and resource utilization, or an Agent-Based Simulation (ABS) approach, which emphasizes individual agent behaviors and emergent phenomena, was more appropriate for capturing the intricacies of this specific problem.

AnyLogic has more flexibility to adjust and implement either DES or ABS, ensuring that the approach can be adapted to best represent and analyze the sponsor's complex systems.

The team and the sponsor representatives compared commercial software to run the simulation model. We compare diverse alternatives based on the best ABM/ABS and DES combinations. We found that AnyLogic, as the simulation platform, is in a favorable alignment with the problem's methodological requirements. AnyLogic provides a user-friendly interface while supporting DES and ABS methodologies, supporting the integrated methodology identified as optimal for the sponsor's challenge. As Farhan et al. (2023) demonstrated, AnyLogic effectively supports the modeling of truck yard operations through its process and transporter libraries, representing both structured operational procedures and autonomous agent behaviors.

Furthermore, AnyLogic's built-in statistical distributions and data import capabilities will facilitate the integration of the sponsor-provided data to determine accurate probability distributions for key model parameters. This data-driven approach enhances model validity by ensuring simulated behaviors reflect real-world operational patterns. The platform also supports dynamic visualization of simulation results, enabling stakeholders to observe and understand queueing behaviors and bottleneck formation in an intuitive manner, which proves particularly valuable for communicating findings to non-technical decision-makers.

The model was built to test the performance of the check-in setup, with AnyLogic, as it is directly related to the queuing process. The primary packages used to replicate a functioning yard were:

- Process Modelling—This library simulates processes, including arrival rates, processing rates, and operational flowcharts.
- Road Traffic – This package simulates a road network environment, considering vehicle routing, physics, and basic driver behaviors.

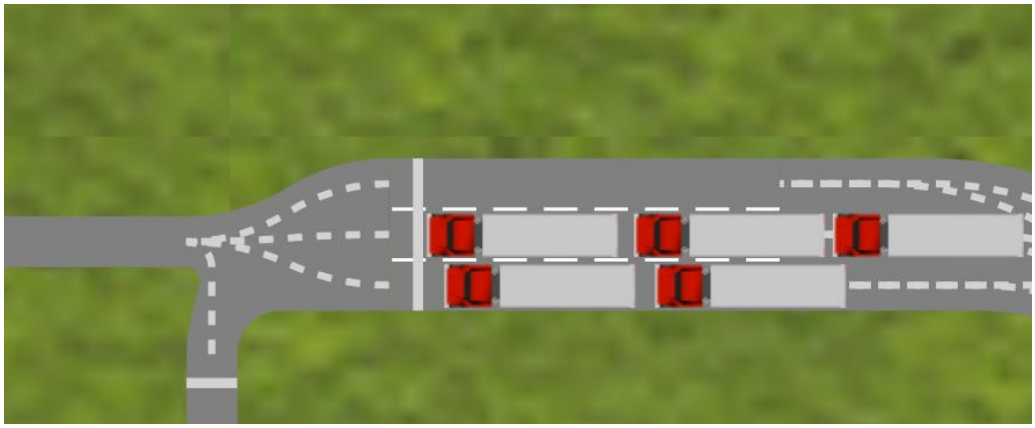
Each package contains agents, blocks, and space markups that can be used in the simulation to perform actions and build logic. Agents, such as cars or people, represent actors within the simulations.

Blocks can be used in the flowchart to tell agents to perform actions or execute logic. The blocks of key relevance to this simulation are:

- The *Delay block* holds the agent in the simulation for a given time.
- The *CarMoveTo block* gives vehicles routing instructions and executes the route in the physical simulation.
- The *Service block* processes agents one at a time, with the service time acting as a delay between each; this ensures that agents are spaced out. This is helpful when making batch arrivals.

The third type of tool is the *space markups*, which are objects that can be placed in the physical model to set up the physical space of the simulation. The key markups used for this report are roads, stop lines, and parking lots. Roads are used to build the road network upon which the simulation was run. Stop lines enable routing and location-based processes by designating a physical location on the layout for the truck's physics to interact with. They can force specific routing or halt a vehicle to complete a process. For example, the following figure shows how the trucks stop at a stop line that triggers a *Delay block* that mimics the time distribution of the Check-In gate of the facility.

Figure 2. Check-In Gate Stop Line in AnyLogic's Simulation



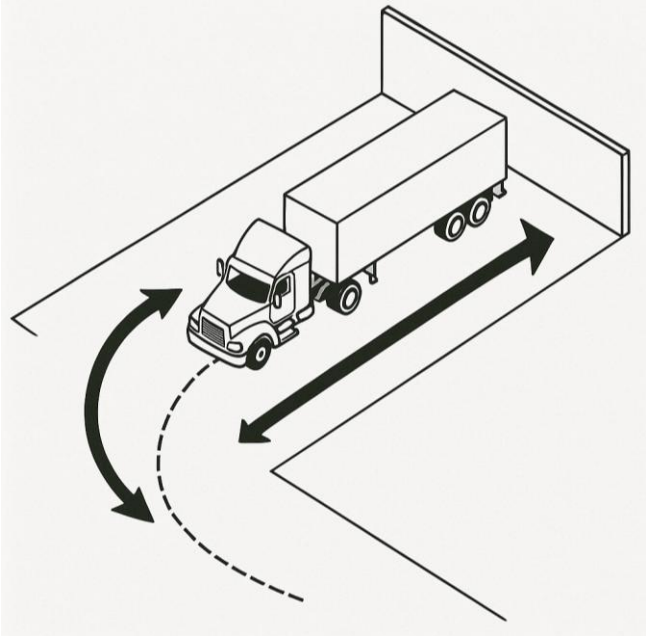
Parking lots provide physical space for vehicles to be staged in the simulation and can be used as a target for vehicle routing. When the parking lot is targeted in the vehicle routing, and a truck arrives at the parking lot, the AnyLogic physics simulation for the truck performs a simple parking maneuver to simulate a truck being parked. There are limitations to this physics model, which are discussed in section 3.1.2. Parking lots are a target for routing and can act as a spawn location for generated vehicles.

3.1.2 AnyLogic Limitations

One limitation of using AnyLogic for yard simulation is that the road package is intended for macroscopic road network simulations, whereas the capstone problem involves microscopic road simulation. Macroscopic simulations examine congestion across a road network by simulating basic car physics, behavior models, and complex traffic management.

The vehicle behavior model of AnyLogic means that complex trucking maneuvers typically performed in a yard have not been programmed into the base library. No packages are available to implement complex behaviors, either. This means that AnyLogic cannot simulate yard operations without heavy use of custom scripting for yard-like driver behavior.

Figure 3. An example of a truck maneuver not supported in the base library



As the focus of this study is to test the truck queue from the entrance of the facility to the check-in gate, it was decided in consultation with the sponsor to treat the internal yard as a black-box process where the yard activities are not simulated in Anylogic and the processing and yard motion time is taken from the data provided by the sponsor.

This decision implies that any queue delays caused by inefficient yard layouts or protocols cannot be tested as the root cause of trucking delays within the model. This decision was made in consultation with the sponsor and the academic staff. The sponsor has an external team that looks at continuous yard operations improvement and is confident that any delays caused by internal yard processes will be identified outside this project's scope.

3.2 Application of the Methodology

This section outlines the systematic approach to developing and analyzing the truck flow simulation for the sponsor's facility. It includes details of the data collection and analysis process. Subsequent subsections detail the model construction and simulation process, including truck spawning, check-in, and yard operations, along with the metrics captured to evaluate performance and conclude with an interpretation of the results.

3.2.1 Data Collection & Analysis

As part of the data collection plan, the following inputs were requested from the sponsor and used with the simulation model to provide improved layouts and solutions to the problem:

- Truck arrival patterns
  - Inter-arrival times from historical data (modeled with probability distributions).
  - Truck types include inbound, outbound, 3PL, CPU, and rush deliveries.
- Yard layout
  - Number and configuration of lanes.
  - Loading/unloading dock locations and capacities.
  - Traffic flow patterns and constraints.
- Process times

- Check-in to check-out durations.
- Loading/unloading times.

The sponsor provided two datasets that contained the following structure:

- Truck Flow Data
  - Size: 13 columns by 67,057 rows
  - Granularity: One row per shipment
  - Examples of columns: Warehouse name, shipment ID, Order ID, Timestamps (Check-In, Start, Load, Close Trailer, Check-Out, Pick-Up Appointment, and Delivery Appointment), Carrier, and Load Type.
- Truck Arrivals Data
  - Size: 12 columns by 39,558 rows
  - Granularity: One row per shipment
  - Examples of columns: Peak/Non-Peak Flag, Period/Date, Warehouse, Shipment Category, Shipment Sub-Category, Arrival Timestamp, Check-In Timestamp, and Shipment Timestamp.

The subsections below describe in more detail how the data obtained were used to determine the right distributions to use for the simulation model.

3.2.1.1 Truck Interarrival Period

The initial process analyzed was the interarrival period of trucks arriving at the facility. A critical determination of this distribution is whether the interarrival time follows an exponential distribution. The resultant distribution will be exponential if truck arrivals constitute a Poisson point process. A Poisson point process is a discrete event process where each event is memoryless and independent. The exponential distribution relies on a consistent rate parameter to fit a distribution. The randomness of truck arrivals at the facility is not entirely memoryless, as the 3PL spaces out dispatches throughout the day. Additionally, the facility receives trucks at varying rates depending on the time of day, the day of the week, and the production schedule.

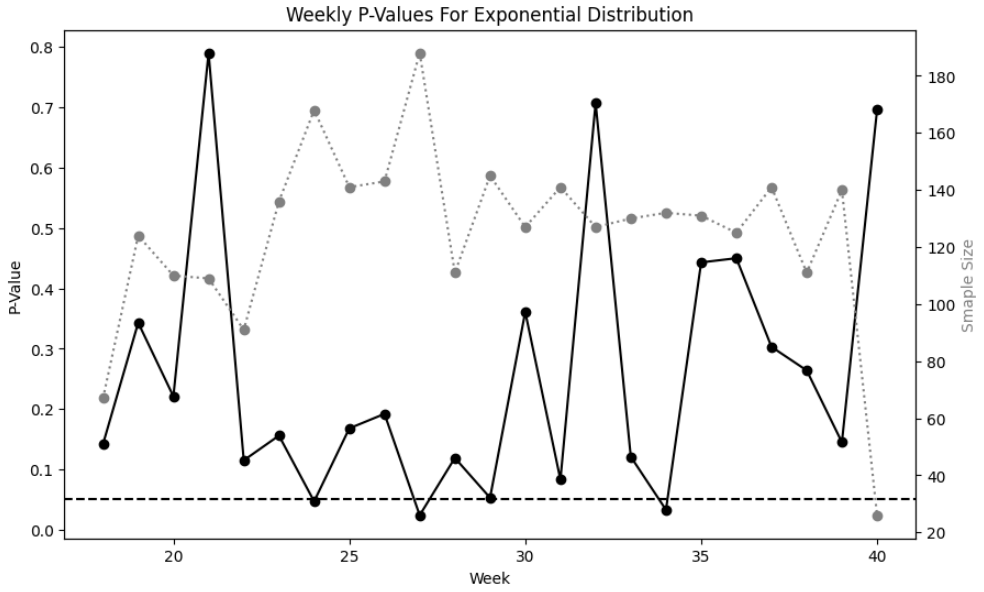
The data provided by the sponsor was inconsistent and originated from a service provider. Some timestamps were rounded to the nearest hour, and some truck arrivals had missing data. The assumption was made that the distribution of trucks arriving at the facility followed an exponential distribution at an underlying rate based in queueing theory, as the most common used distributions include the Poisson distribution for arrival processes (counting events in a fixed interval) and the exponential distribution for interarrival times (time between events).

To verify the suitability of this approach, the available data were used to demonstrate that the exponential distribution could not be rejected based on the extractable data. Inconsistent and missing entries were removed, impacting the fitted parameters, but the sample still fit an exponential distribution based on the additive property of exponential distributions.

A sample of trucks from each week was taken during peak periods (8:00 AM to 4:00 PM, Monday to Friday). These samples were chosen because the facility's production is stable throughout each week but may vary week by week. An exponential distribution was fitted to each week of data, and the p-values were examined. Week 40 was excluded because it was the end of the dataset, so it was incomplete. From 22 weeks of sample data taken from the peak season, for 18 weeks, there was insufficient evidence to suggest that an exponential distribution did not fit the data at a p-value of 0.05. As sample sizes were typically between 80 and 160 trucks per week, the p-value of 0.05 is a reasonable threshold for testing.

Given that this was the only available data, this fit was deemed acceptable for simulating yard operations.

Figure 4. Weekly p-Values of Exponential Distribution for Truck Interarrival Period



In summary, despite data gaps and rounding issues, weekly goodness-of-fit tests indicate that an exponential interarrival process provides a statistically sound and analytically convenient representation of truck arrivals during peak hours. With the arrival pattern reliably characterized, attention now turns to the service side of the queue and the gate check-in time, described in Section 3.2.1.2.

3.2.1.2 Gate Check-In Time

The gate check-in time is the duration required to process a truck at the facility entrance. This metric is critical to queue performance as it is the key driver of queue length. A clean data sample of this time could not be provided as it has not been captured systematically. A triangular distribution based on anecdotal evidence from interviews with the sponsor was used to simulate this process. Subject matter experts suggested that most trucks could be processed between 90 seconds and 5 minutes, commonly taking 3 minutes. They also had internal meetings with the managers from the facility to determine a minimum of 1 minute and a maximum of 5 minutes to be used in the baseline triangular distribution. Additionally, further research was performed with DC experts from retail companies to understand their average processing times and create additional scenarios for sensitivity analysis. An average of 5, 8, 10, and 12 minutes was obtained.

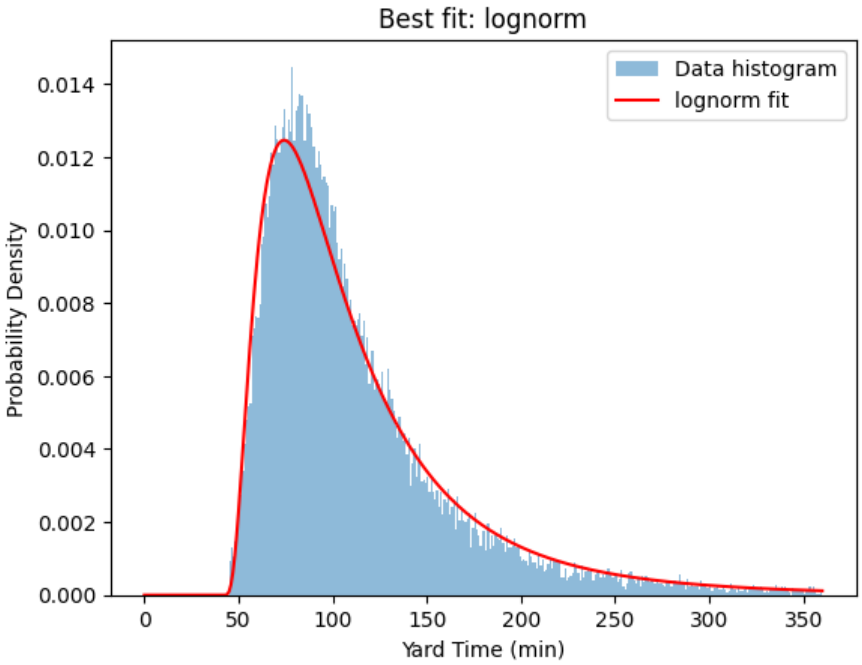
3.2.1.3 Yard Time

The facility yard time is the duration measured between a truck clearing the check-in gate and its exit from the facility. This time encompasses various processes, including docking, loading, unloading, parking, and trailer storage. As this study focused on gate performance rather than the performance of individual yard processes, these subprocesses were aggregated into a single variable.

The data provided by the sponsor was thorough, as their internal systems capture this process well. However, the data was recorded based on trailers, not truck movements. The data were filtered based on live-load trailers. The truck for these consignments remains connected to the same trailer throughout the process. This filtering removed pre-loaded trailers from the dataset, as these trailers can remain in the yard for days and do not reflect the truck's portion of the process.

Various semi-definite distributions were tested for goodness of fit, and a shifted lognormal distribution was chosen. The logarithm of the variable being normally distributed characterizes the lognormal distribution.

Figure 5. Goodness of Fit Test for Yard Time

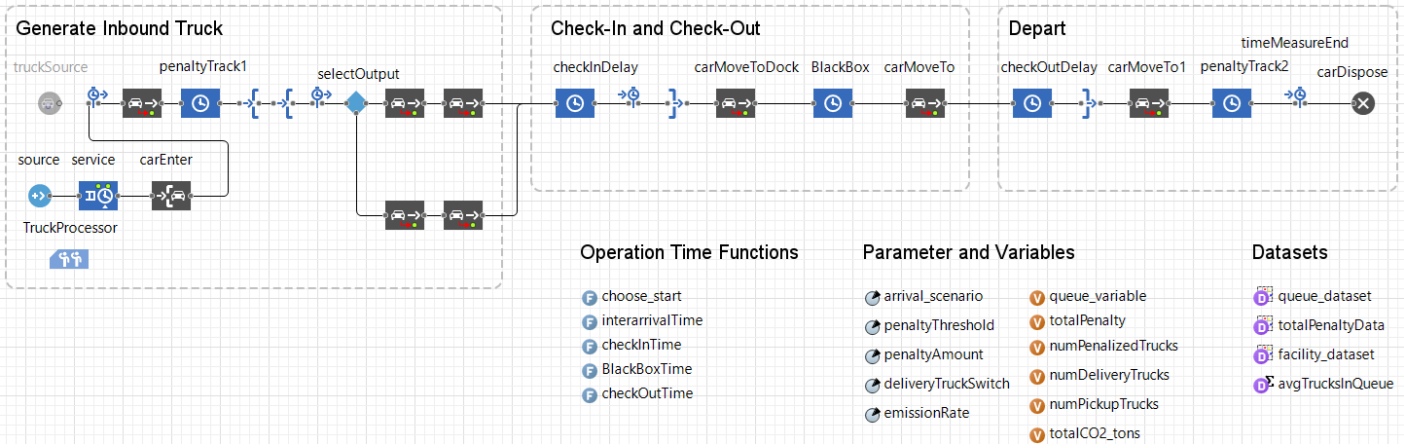


As the yard process was not examined as part of this simulation, it was important for the yard layout in the simulation not to be constrained by the yard process. This is because this paper aims to examine the check-in process. Any significant queuing in the yard could flow back to the gate process. To account for this, more trailer slots were placed in the physical simulation for the yard process than in the actual facility. Adding yard time to the simulation meant mimicking the conditions that may cause yard demurrage costs. As the gate is only a part of the demurrage cost, the whole facility time was needed to calculate the gate's impact on the total demurrage.

3.2.2 Process

The process flow in AnyLogic is designed to replicate the activities of a yard truck at the facility. The main packages used to simulate each vehicle's procedure are the process modeling and road libraries, as discussed in section 3.1.1, and the whole process flow can be seen in the following figure:

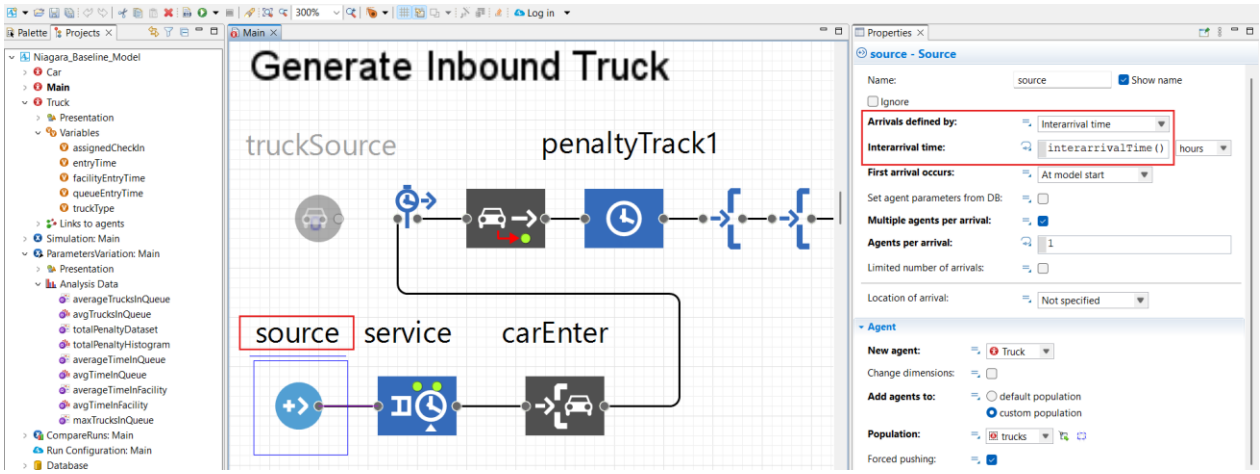
Figure 6. Yard Process Flow



3.2.2.1 Truck Spawning Approach

First, a *car source block* generates vehicles in the simulation. The trucks are generated randomly using an exponential distribution consistent with the observed data, as discussed in Section 3.2.1. As there is no known bias in the direction from which trucks enter the expressway, the trucks are randomly spawned outside the facility at the border of the road network. Trucks are then instructed to pass through the stop line when approaching the facility. The purpose of this intermediate step is so that the model can capture how many trucks are currently "queued" at the facility's entrance by using the area restriction block to count the number of trucks currently at the gate. This method was used to physically queue the trucks within the physical space of the model instead of using the queue block. The queue block exists in the flow chart space, so using it would result in inconsistencies between the physical and the flow chart space. For example, if a truck is stuck in the physical queue but is the next released from the flow chart block, then the process would get stuck in the conflict.

Figure 7. Source Block used for Spawning Trucks

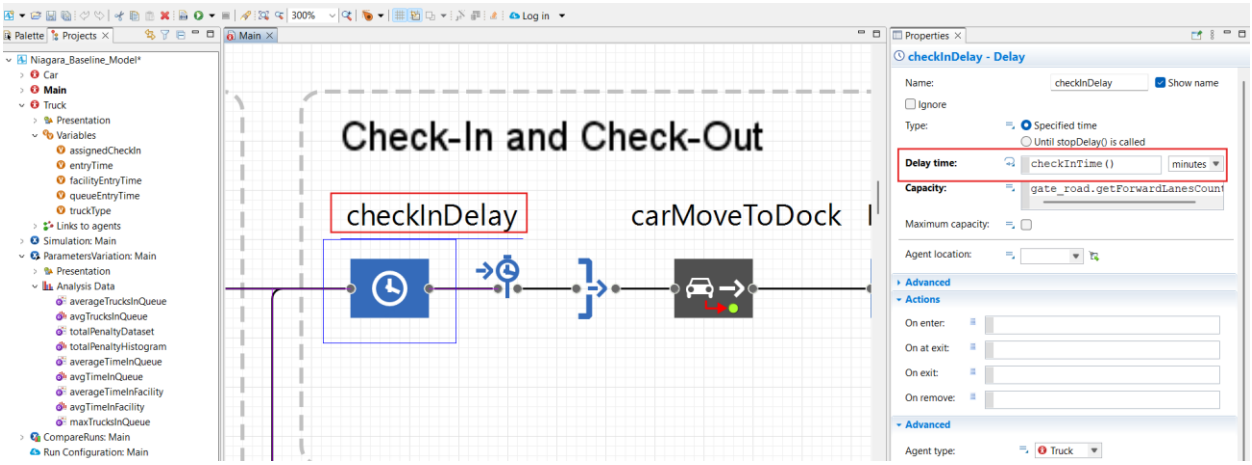


Trucks are initially directed to a single check-in gate at the facility, where they may need to wait in a queue if the gate is already in use. A key hypothesis was tested by integrating an alternate check-in gate into the process to explore whether adding a second gate could enhance operational efficiency. This adjustment allows trucks to be routed to the original or the alternate gate, potentially reducing delays and improving throughput. Once processed through either gate, trucks continue through the same subsequent steps without further variation.

3.2.2.2 Check-Ins

When a truck reaches the check-in gate, it enters a delay block, which holds the truck for a given time. This simulates the check-in process for trucks. The time held is determined randomly from a distribution of real data the sponsor provided (as discussed in Section 3.2.1.2). This delay will be the primary cause of queues forming as the remaining processes are in a "black box" and assumed to be unconstrained. As this delay is the key source of queues, it was essential to test the sensitivity of the average check-in delay time in the simulation to test how queues form due to this factor.

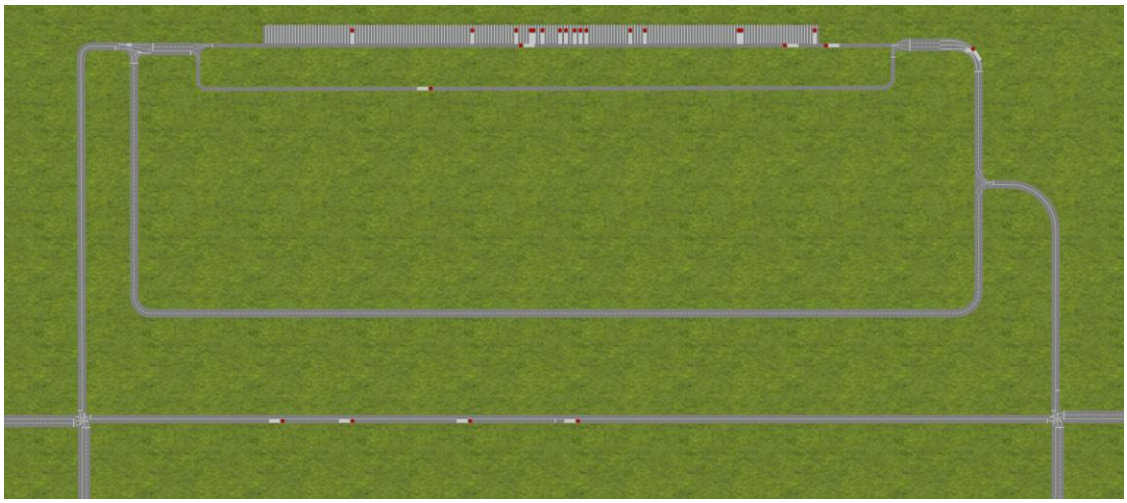
Figure 8. Delay Block used for the Check-In Service Time



3.2.2.3 Yard Processes

The simulation is run to show the flow of trucks for the rest of the yard process (see Figure *9* to see the yard layout during a simulation). After the check-in, the truck enters the yard by being routed to the yard parking lot. The slot reserved for the truck is random. The truck then approaches its assigned slot and parks. A delay block holds the truck in the slot. This delay is determined from data provided by the sponsor for live-loaded trucks. This delay simulates the loading or unloading of trucks. Finally, the truck is routed to the check-out gate, where it is again held for a short time before being routed out of the simulation by assigning the truck to a random point on the border of the road network and routing the truck to it. The whole process is supposed to be unconstrained, so factors for the number of available docks and the gate check-out times were chosen to prevent constraining the simulation, not based on the actual docks and check-out times of the plant.

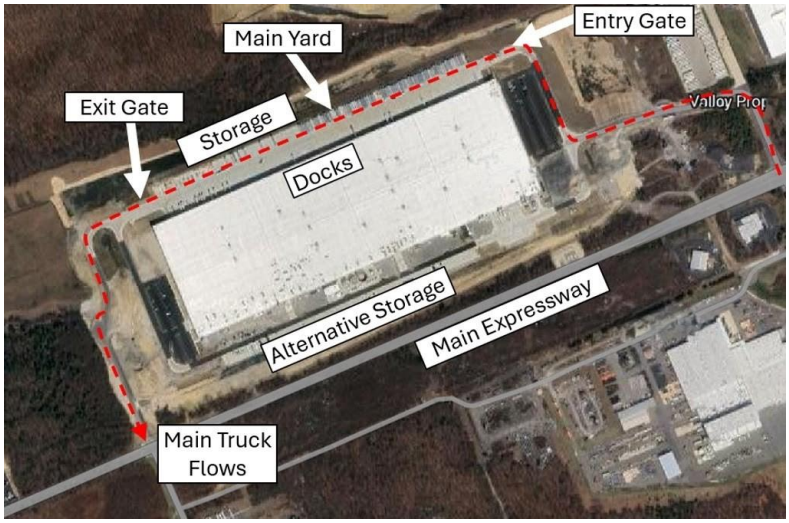
Figure 9. Yard Layout during a Simulation Run



3.2.3 Model Translation

The physical model used for this report is based on the layout of one of their plants (see Figure *10*), which was specifically chosen by the sponsor company. The facility has an entrance road and an exit road off the expressway. The main yard area with loading docks and the primary trailer storage is to the north, with a ring road around the entire facility. There are three entry gates located on the north-east corner of the facility and two exit gates to the north-west.

Figure 10. Sponsor's Plant Layout (obtained from Google Maps)



This physical layout was replicated in AnyLogic. Roads were placed in the same layout and length scale as the sponsor's facility. The road system was limited to 250 meters beyond the facility intersections to the expressway. Stop lines represent the entry and exit gates. As discussed in Section 3.1.1, stop lines give the simulation a marker for vehicle routing and a location to halt the trucks to perform the gate check-in procedure. Using a *delay block* in the software, a parking lane is placed on the main yard road to simulate docking trucks. While truck docking and loading are considered an unconstrained "black box" for analysis, docking is still a key component of the overall yard simulation.

Delay blocks are central to the model's realism, as they inject stochastic variability into three key processes:

1. Truck interarrival timing
2. Gate check-in service
3. Aggregated yard "black box") processing

Each delay block is parameterized with the probability distributions detailed in Sections 3.2.1.1–3.2.1.3, ensuring that every simulation run samples from the empirically fitted interarrival, check-in, and yard service time distributions.

As this report examines the check-in gates' performance, alternative storage and delivery docks on the south side of the plant have been ignored.

3.2.4 Performance Metrics

Performance metrics were systematically captured to evaluate the performance of the simulation model. Key metrics include the average time spent in the queue, the average number of trucks in the queue, the maximum number of trucks in the queue, the average total time spent in the facility, and the incurred penalty costs. The penalty cost is a fee charged by third-party logistics (3PL) providers when a truck's time in the facility exceeds an agreed threshold. For the sponsor, this penalty is US$1 per truck per minute after two hours spent onsite. In the simulation model, the timer for each truck starts at the facility entrance and stops at the exit.

To ensure the robustness of the results, 300 simulation iterations were conducted using different random seeds, with the median and standard deviation calculated for each metric. We settled on 300 replications using AnyLogic's built-in Parameter Variation Experiment and then monitoring the convergence of the key metrics. In practice, we ran a series of test-batches at 50, 100, 200, 300, and 1000 iterations and plotted the running mean and standard error of, for example, average queue time and penalty cost. By 300 replications, additional runs produced negligible shifts (<0.5 %) in median and standard deviation, so 300 represents a good trade-off between statistical precision and computation time.

As detailed in Section 3.3.4.1, an intermediate stop line was implemented within the model to record the number of trucks physically present in the queue. This approach allowed for accurate tracking of queue length, a critical indicator of facility performance, since consistently long queues may suggest inefficiencies or design issues.

More pertinent to direct financial results is the truck's total time at the facility. In alignment with typical third-party logistics (3PL) contracts, extended dwell times can incur demurrage penalties modeled directly within the simulation. Specifically, the time measure block (the clock icons in Figure 6*)* records the facility time for each truck, enabling the calculation of penalty costs. For the sponsor's case, a penalty of one dollar per minute is applied to each truck exceeding a two-hour stay; for example, a truck remaining for 130 minutes would result in a ten-dollar penalty.

Additionally, the model can potentially estimate aggregate CO_2 emissions from idling trucks. However, more precise calculations, such as those accounting for load-specific emissions, would require further modeling of individual truck characteristics, which may be explored in future model iterations.

3.2.5 Interpretation of Results

Due to the limitations of the commercial software (discussed in section 3.3.1.1), only five hours of yard time can be simulated. For some scenarios, this may not be enough time to reach the yard's steady state for a given truck's interarrival rate. This means the queue may still form in the simulation after five hours. The average queue lengths and times are limited in their usefulness individually if the parameters being tested result in gate utilization being close to or greater than 1, as the final state of the yard is likely to still be in a transient state.

Where utilization is less than 1, average metrics can be used because the steady state is likely to include a high probability of time where the total number of trucks in the process equals 0. Therefore, the simulation should already be approximately in its steady state.

To overcome this, multiple simulation iterations were run for each tested scenario. A histogram of results was produced to assess the relative likelihood of the queue state for each scenario. Statistical metrics could then be produced to produce the stochastic average of the key performance drivers for the yard. The distribution and statistics were used to assess the performance change and the spread of the results from the simulation.

4 Results and Discussions

This section presents the findings from the agent-based simulation model of truck flow in yard operations, developed using AnyLogic for the sponsor's facility. The simulation investigated inefficiencies such as prolonged queueing times contributing to increased operational costs, fuel consumption, and emissions. By leveraging real-world data on the truck arrival patterns to the facility, yard layout, and operational processes, this study replicates the dynamics of queue generation at the facility entrance. It evaluates the potential benefits of a second check-in gate during peak seasons.

The simulation results reveal significant patterns in queue formation and resource utilization across different scenarios, highlighting the relationship between arrival patterns, processing capabilities, and overall system efficiency. By capturing the dynamic interactions between autonomous truck entities within the system, critical bottlenecks were identified along with potential optimization opportunities that address the core inefficiencies outlined in the problem statement. The analysis indicates that strategic modifications to gate operations could yield substantial benefits in reduced waiting times and lower operational costs during high-volume scenarios.

The following subsections provide an overview of the tested scenarios, establishing the baseline conditions and experimental variations implemented in the model. Then, the following subsection offers a detailed comparative analysis of the baseline configuration versus the bifurcation model incorporating a secondary check-in gate. This analysis examines the significance of check-in gate processing times and their impact on overall system performance. Finally, a penalty cost analysis is presented to quantify the economic implications of various operational decisions.

Section 4.1 provides an overview of the key findings obtained from simulations. Section 4.2 summarizes the sixteen “what-if” scenarios we designed to isolate these effects; Section 4.3 presents the detailed comparative and cost analyses that validate our conclusions. Finally, in Section 4.4, we provide managerial insights and recommendations for our sponsor company.

4.1 Key Findings Overview

This subsection presents an executive summary of the most critical insights from our simulation, expressed in business-relevant terms. All dollars saved from the penalty cost translate directly into "minutes saved" (at $1 / min penalty) or "hours saved" to the carriers. Refer to Section 4.2 for detailed information on each scenario.

- Carrier hours saved under high-volume scenarios (Scenario 14 vs. Scenario 6)
    - Baseline (30 trucks/hr, 5 min check-in): penalty cost $260/hr
    - With bifurcation (100% deliveries diverted): $220/hr
    - Savings = $40/hr ⇒ Given that every US dollar is equivalent to 1 minute, we can say that 40 minutes/hr were saved ⇒ 0.66 hours saved to carriers for each operating hour
    - Extrapolation to 1 year (8 hr shift × 120 peak days per year) ⇒ 634 carrier-hours saved

- Queue time and length reductions (Scenario 14 vs. Scenario 6)
    - Average time in queue falls from 42.8 min to 22 min (–48.5%)
    - Average number of trucks in queue drops from 18.9 to 9.8 (–48.5%)
- Facility-throughput improvements (Scenario 14 vs. Scenario 6)
    - Average total time in facility decreases from 132.4 to 122.4 min (–7.5%)
    - This compounds the carrier-hour savings and further reduces downstream demurrage
- Check-In Time Threshold Effect
    - At 3 minutes average check-in, the yard handles up to 30 trucks/hr with stable queues (average queue ≤ 6 min, < 4 trucks)
    - When the average check-in is ≥ 8 minutes, the queue becomes unstable:
        - Average queue time jumps from 5.0 min to 40.2 min (+702%)
        - Average trucks in queue rises from 1.7 to 13.1 (+683%)
        - Penalty cost +56% ⇒ each hour of operation wastes an extra 63 minutes in carrier time
- Light-load vs. heavy-load bifurcation benefits
    - Under normal peak (20 trucks/hr, 3 min), the secondary gate is under-utilized (< 3% penalty-cost reduction)
    - Under stress (30 trucks/hr, 5 min), bifurcation delivers a 15.1% penalty-cost reduction (39 min/hr saved), and the level of utilization of the queue is reduced by 48.5% on both average trucks and average time.
- Resilience to batch arrivals (multiple trucks per arrival)
    - 3-truck batches (effective 60 trucks/hr):
        - Average facility time decreased by 8.6% (–11.9 min)
        - Average queue time dropped by 22.6% (–10.5 min)
        - Even at extreme surges, bifurcation improves the performance of the queue but does not stabilize it
- Recommended dynamic gate policy
    - Activate the second gate when either:
        - Arrival rate is ≥ 30 trucks/hr
        - The average check-in time is > 5 min
    - This "on-demand" strategy maximizes carrier-hour savings while avoiding gate under-utilization.

4.2 Scenarios Overview

Sixteen scenarios were designed to isolate the effects of five key factors on gate queue performance and to test the potential of a secondary check-in gate under varying conditions. Table 1 summarizes the scenarios analyzed, highlighting their defining characteristics and manipulated variables. A detailed version with full input parameters and statistical distributions is available in Table A.1 from the Appendix for reproducibility and extended analysis.

Table 1. Scenarios Overview and main features

#	Model	Scenario	Arrival Rate	Check-In Gate Time (Min)	% Diverted Delivery Trucks	Trucks per Arrival
1	Baseline	Baseline	20 Trucks/Hour	Min: 1, Mean: 3, Max: 5	0%	1
2	Baseline	5 min Check-In	20 Trucks/Hour	Min: 2, Mean: 5, Max: 10	0%	1
3	Baseline	8 min Check-In	20 Trucks/Hour	Min: 3, Mean: 8, Max: 15	0%	1
4	Baseline	10 min Check-In	20 Trucks/Hour	Min: 5, Mean: 10, Max: 20	0%	1
5	Baseline	30 Trucks/Hour	30 Trucks/Hour	Min: 1, Mean: 3, Max: 5	0%	1
6	Baseline	30 Trucks/Hour + 5 min Check In	30 Trucks/Hour	Min: 2, Mean: 5, Max: 10	0%	1
7	Baseline	2 Trucks per Arrival	20 Trucks/Hour	Min: 1, Mean: 3, Max: 5	0%	2
8	Baseline	3 Trucks per Arrival	20 Trucks/Hour	Min: 1, Mean: 3, Max: 5	0%	3
9	Bifurcation	30% Deliveries	20 Trucks/Hour	Min: 1, Mean: 3, Max: 5	30%	1
10	Bifurcation	100% Deliveries	20 Trucks/Hour	Min: 1, Mean: 3, Max: 5	100%	1
11	Bifurcation	10 min Check-In + 30% Deliveries	20 Trucks/Hour	Min: 5, Mean: 10, Max: 20	30%	1
12	Bifurcation	10 min Check-In + 100% Deliveries	20 Trucks/Hour	Min: 5, Mean: 10, Max: 20	100%	1
13	Bifurcation	30 Trucks/Hour + 5 min Check In + 30% Deliveries	30 Trucks/Hour	Min: 2, Mean: 5, Max: 10	30%	1
14	Bifurcation	30 Trucks/Hour + 5 min Check In + 100% Deliveries	30 Trucks/Hour	Min: 2, Mean: 5, Max: 10	100%	1
15	Bifurcation	2 Trucks per Arrival + 100% Deliveries	20 Trucks/Hour	Min: 1, Mean: 3, Max: 5	100%	2
16	Bifurcation	3 Trucks per Arrival + 100% Deliveries	20 Trucks/Hour	Min: 1, Mean: 3, Max: 5	100%	3

Table 1 summarizes all scenarios, while Appendix A.2 contains detailed input parameters and full simulation results for reference.

Baseline (Scenario 1)

- Single check-in gate
- Average check-in time ≈ 3 min
- Arrival rate ≈ 20 trucks/hour
- One truck per arrival

Check-in Time Variations (Scenarios 2–4)

- Service times increased to 5, 8, and 10 minutes
- All other inputs are held at baseline values
- Assess how long gate processing alone destabilizes queues

Higher Arrival Rate (Scenarios 5–6)

- Arrival rate increased to 30 trucks/hour (peak-demand stress test)
- Scenario 6 combines this with a 5-minute check-in
- Measure the joint impact of volume surge and slower service

Batch Arrivals (Scenarios 7–8)

- Bundles of 2 or 3 trucks per arrival event
- Simulate sudden volume spikes
- Evaluate system resilience to clustered arrivals

Bifurcation under Normal Load (Scenarios 9–10)

- Introduction of a second check-in gate
- Scenario 9 diverts 30% of inbound deliveries to the new gate

- Scenario 10 diverts 100% of deliveries
- Test the benefit of bifurcation when queues are modest

Bifurcation under Stress (Scenarios 11–16)

- Apply 30 % or 100 % diversion to each of the unstable scenarios (2–8)
- Examine whether a secondary gate restores queue stability under heavy-load, slow-service, or batch-arrival conditions

By systematically varying one or two parameters at a time—service time, arrival intensity, batch size, and diversion rate—we can pinpoint which levers most effectively reduce queue lengths, waiting times, and penalty costs, and under what circumstances adding a second gate becomes worthwhile. Further details about the scenarios are provided below.

4.3 Operational Performance Analysis

This section offers an in-depth analysis of the results in three critical areas: the effect of the bifurcation on the baseline, the impact of the yard processing performance, and a penalty cost analysis.

4.3.1 Impact of Bifurcation Strategy on Queue Efficiency

This section compares the performance of the baseline single-gate configuration with bifurcation scenarios where a secondary check-in gate is introduced. The analysis focuses on the proposed key operational metrics—queue length, time, penalty costs, and overall facility throughput—across regular and high-volume conditions.

To assess the effectiveness of the bifurcation strategy, representative scenarios from both baseline and high-volume periods were considered. A summary of the results is provided in Figure *11*, with the median of each metric and the percentage delta from the bifurcation scenarios to the baseline scenario. Extended results for all scenario pairs are available in Appendix Table A.2

Figure 11. Comparative Result Matrices: Baseline vs. Bifurcation

Peak-Season Demand (Scenario 1 vs. Scenarios 9 and 10)

Metric Name	Avg Time in Facility		Avg Time in Queue		Avg Trucks in Queue		Max Trucks in Queue		Penalty Cost	
Model	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %
Baseline										
1: Baseline	110.04	0.0%	5.01	0.0%	1.67	0.0%	6.00	0.0%	565.23	0.0%
Bifurcation										
9: 30% Deliveries	110.10	0.1%	4.87	-2.7%	1.61	-3.6%	6.00	0.0%	561.75	-0.6%
10: 100% Deliveries	109.87	-0.1%	4.97	-0.7%	1.63	-2.6%	6.00	0.0%	559.52	-1.0%

Operational Delays in Check-In Gate (Scenario 4 vs. Scenarios 11 and 12)

Metric Name	Avg Time in Facility		Avg Time in Queue		Avg Trucks in Queue		Max Trucks in Queue		Penalty Cost	
Model	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %
Baseline										
4: 10 min Check-In	148.51	0.0%	65.47	0.0%	20.91	0.0%	37.00	0.0%	1,044.76	0.0%
Bifurcation										
11: 10 min Check-In + 30% Deliveries	145.38	-2.1%	60.89	-7.0%	19.87	-5.0%	36.00	-2.7%	1,011.08	-3.2%
12: 10 min Check-In + 100% Deliveries	142.00	-4.4%	51.23	-21.7%	17.77	-15.0%	33.00	-10.8%	1,010.57	-3.3%

High-Volume Demand and Moderate Check-In Delay (Scenario 6 vs. Scenarios 13 and 14)

Metric Name	Avg Time in Facility		Avg Time in Queue		Avg Trucks in Queue		Max Trucks in Queue		Penalty Cost	
Model	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %
Baseline										
6: 30 Trucks/Hour + 5 min Check In	132.39	0.0%	42.79	0.0%	18.93	0.0%	35.00	0.0%	1,298.71	0.0%
Bifurcation										
13: 30 Trucks/Hour + 5 min Check In + 30% Deliveries	128.84	-2.7%	37.34	-12.7%	16.46	-13.1%	31.50	-10.0%	1,258.97	-3.1%
14: 30 Trucks/Hour + 5 min Check In + 100%	122.44	-7.5%	22.02	-48.5%	9.75	-48.5%	20.00	-42.9%	1,102.14	-15.1%

Key Findings

Peak-Season Demand (Scenario 1 vs. Scenarios 9 and 10)

Introducing a secondary check-in gate yields minimal operational benefit under baseline arrival rates of 20 trucks per hour. Suppose 30% of the deliveries are diverted to the bifurcation gate. In that case, the average time in queue decreases by only 2.7%, the average number of trucks decreases by 3.6%, and penalty cost reductions are marginal. If 100% of the deliveries are diverted to the bifurcation, queuing time, length, and penalty improvements are not meaningful. This indicates that under peak season demand and normal demand conditions, where the arrival rates are lower than 20 trucks per hour, the secondary gate remains idle for extended periods, without a corresponding improvement in throughput or penalty costs.

Operational Delays in Check-In Gate (Scenario 4 vs. Scenarios 11 and 12)

Considering a baseline arrival rate, increasing the service time at the main check-in gate considerably impacts the queue stability and the penalty cost, as seen in Figure *12*. Going from a service time of 3 minutes on average to 10 minutes increases the average time in the queue by 1207%, the average trucks in the queue by 1150%, and the penalty cost by 85%. Considering that 30 trucks in the queue is already an unstable scenario, 8 minutes of service time is already a problem, and 10 minutes is already a bottleneck factor.

Figure 12. Comparison of Scenarios with Check-in Time Changes

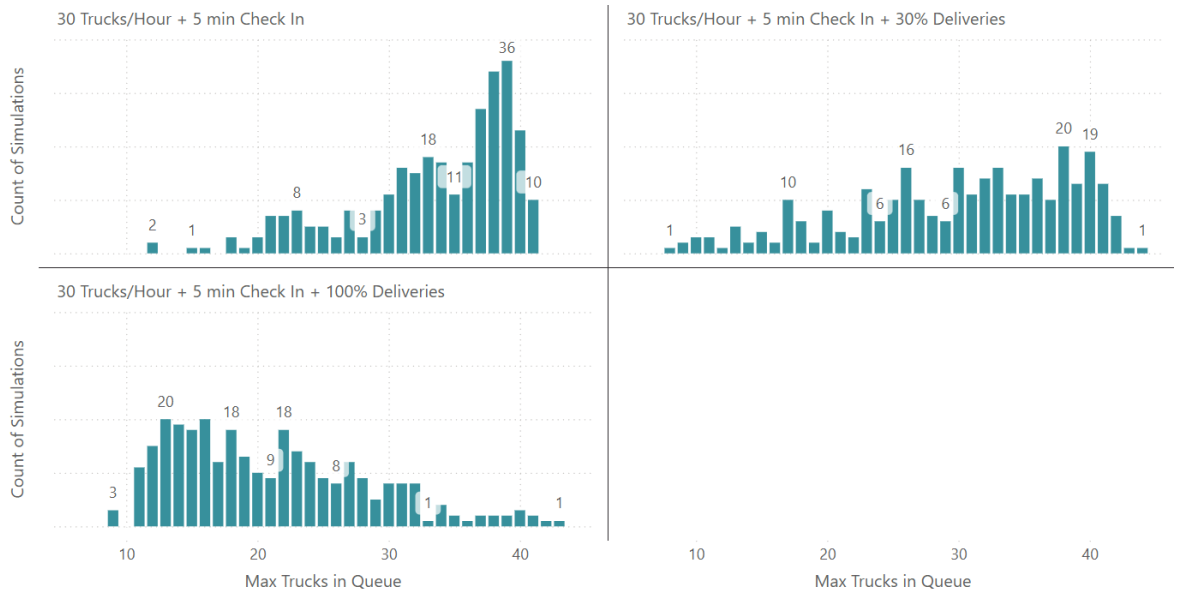
Metric Name	Avg Time in Facility		Avg Time in Queue		Avg Trucks in Queue		Max Trucks in Queue		Penalty Cost	
Model	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %
Baseline										
1: Baseline	110.04	0.0%	5.01	0.0%	1.67	0.0%	6.00	0.0%	565.23	0.0%
2: 5 min Check-In	117.05	6.4%	12.65	152.6%	4.10	145.2%	11.00	83.3%	665.91	17.8%
3: 8 min Check-In	133.80	21.6%	40.15	701.7%	13.11	683.5%	26.00	333.3%	881.64	56.0%
4: 10 min Check-In	148.51	35.0%	65.47	1207.2%	20.91	1149.4%	37.00	516.7%	1,044.76	84.8%

Once the bifurcation is applied to the 10 minutes service time, it can be seen from Figure *11* that sending all the delivery trucks to the secondary check-in gate can reduce queuing time by 21.7% on average and reduce the number of trucks in the queue by 15% on average, still with marginal improvements in the penalty cost. Considering these results, it is critical to avoid any downtime or delays at the check-in gate during peak seasons; increasing the average service time at the check-in gate from 3 to 10 minutes can increase the penalty cost by 85% from the baseline with $209 per hour (instead of $113 per hour).

High-Volume Demand and Moderate Check-In Delay (Scenario 6 vs. Scenarios 13 and 14)

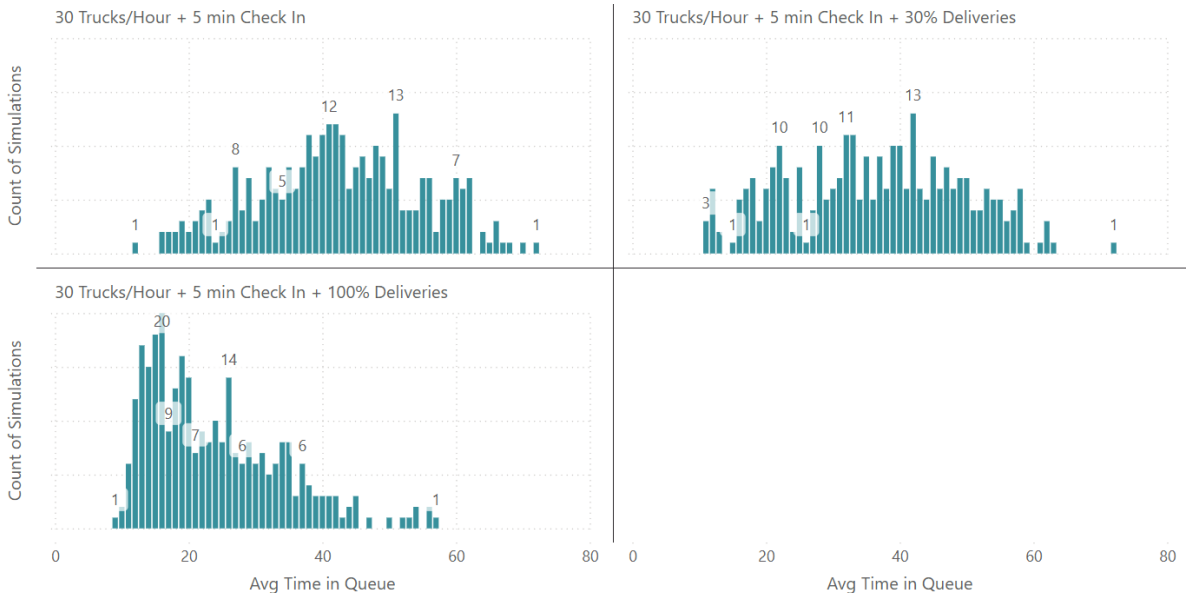
In contrast, during high-volume scenarios with a 50% higher arrival rate and a moderate delay in the check-in gate of 5 minutes of average service time, the bifurcation strategy demonstrates clear advantages when diverting all the deliveries. Both average queueing time and average trucks in the queue drop by 49%, and the penalty cost drops by 15%. These improvements are especially pronounced during sustained demand surges, where the baseline system becomes unstable. Figure *13* and Figure *14* show frequency charts, or histograms, displaying the maximum number of trucks and average time in the queue by each iteration of the simulation, displaying the dispersion of the data. *Figure 11* shows that the maximum number of trucks in scenario 6 (top left quadrant) is skewed to the right with high amplitude (i.e., high variability). The introduction of bifurcation and the sending of critical deliveries reduced the amplitude. They spread wider, whereas the fully utilized secondary check-in gate skews the graph to the left, reducing the number of iterations where the queue becomes unstable.

Figure 13. Comparison of Scenarios 6, 13, and 14: Maximum Trucks in Queue



A similar behavior can be seen in Figure *14* as diverting all the delivery trucks to the secondary check-in gate skews the iteration results to the left, improving the queue's overall efficiency.

Figure 14. Comparison of Scenarios 6, 13, and 14: Average Time in Queue



Batch Arrival Stress Test (Scenarios 7 and 8 vs. Scenarios 15 and 16)

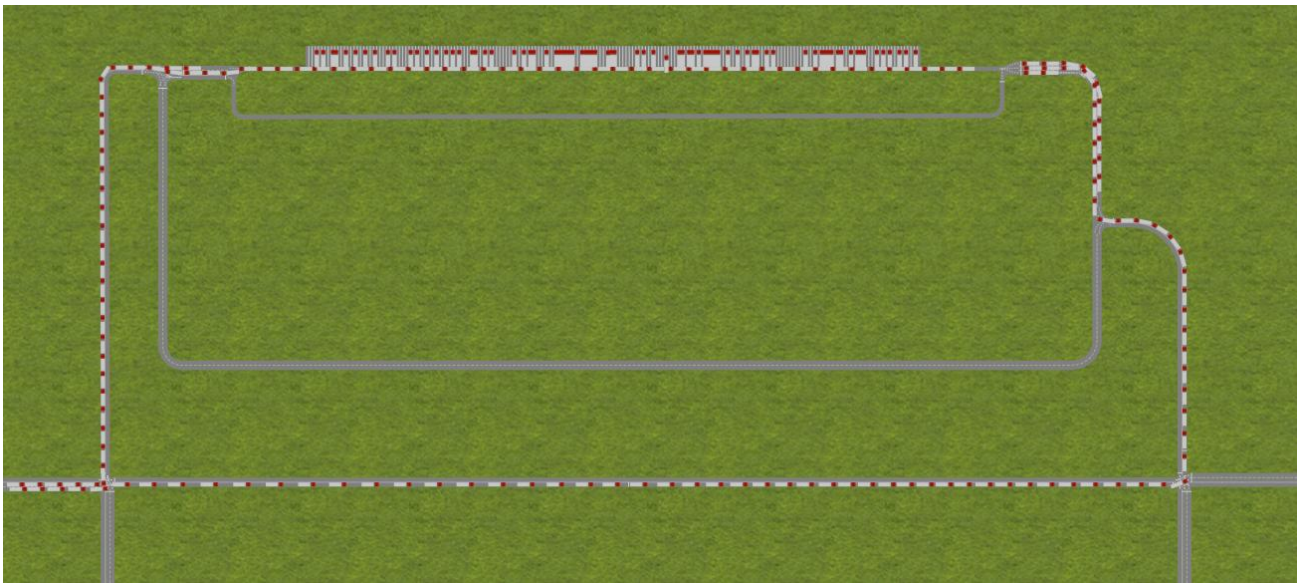
When simulating batch arrivals of two or three trucks at a time, the bifurcated system significantly improves queue performance by reducing the average time spent in the queue and the number of trucks in the queue, as shown in Figure *15*. The workload is distributed more evenly across both gates, alleviating congestion and resulting in an 8.6% reduction in average facility time in the three-truck batch scenario. This three-truck batch configuration is included to stress-test the model under concurrent arrival surges, replicating real-world dispatch clustering and assessing the robustness and capacity of the bifurcated gate strategy under extreme inflow conditions.

Figure 15. Metric Comparison Between Batch Arrival Scenarios

Metric Name	Avg Time in Facility		Avg Time in Queue		Avg Trucks in Queue		Max Trucks in Queue		Penalty Cost	
Model	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %
Baseline										
7: 2 Trucks per Arrival	116.90	0.0%	14.01	0.0%	8.43	0.0%	21.00	0.0%	1,334.32	0.0%
Bifurcation										
15: 2 Trucks per Arrival + 100% Deliveries	114.30	-2.2%	7.93	-43.4%	5.41	-35.8%	15.00	-28.6%	1,328.47	-0.4%
Baseline										
8: 3 Trucks per Arrival	137.61	0.0%	46.31	0.0%	28.52	0.0%	39.00	0.0%	2,593.16	0.0%
Bifurcation										
16: 3 Trucks per Arrival + 100% Deliveries	125.75	-8.6%	35.85	-22.6%	24.22	-15.1%	44.00	12.8%	2,495.75	-3.8%

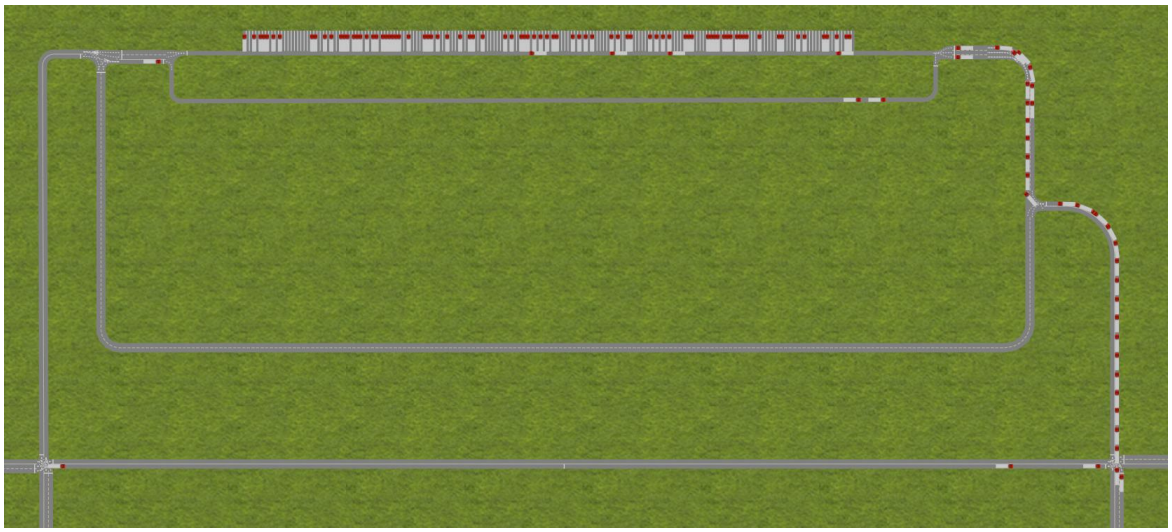
Penalty cost reductions were modest, with a maximum decrease of only 3.84% when 100% of the deliveries are diverted to the bifurcation. This limited impact is due to the extreme volume in batch scenarios. Specifically, the three-truck batch scenario effectively triples the arrival rate to 60 trucks per hour. Since penalty costs are influenced by the total time spent in the facility, not just queue time, further reductions would require improvements in internal facility processes ("black box" time). Notably, the maximum number of trucks in the queue did not improve for the three-truck scenario. This is because, under such high volume, the baseline system becomes unstable (see Figure *16*), making it impossible to accommodate additional trucks in the queue and the system.

Figure 16. Visualization of realization for simulation of Scenario 8, 3-truck batches per Arrival



It can be seen in Figure *17* how leveraging the bifurcation relieves the system and allows a better flow of the trucks into the facility. Routing all the delivery trucks through the secondary lane reduces the load on the primary gate, and the exponential queue buildup seen in the previous figure is averted. Parallel processing across two service points prevents queue spillback onto the road and maintains consistent throughput during demand surges. Although the queue is still considerably long enough to consider it a problem, this stress-test scenario might not be frequent in real-life practices.

Figure 17. Visualization of realization for simulation of Scenario 16, 3-Truck batch per Arrival, and 100% Delivery Trucks Diverted



This comparative analysis reveals that bifurcation is justifiable only under high-volume or stress-test conditions. For normal operations, the incremental benefits do not outweigh the additional operational costs. However, activating a secondary gate can stabilize queues, shorten waiting times, and yield penalty cost savings during peak periods (15.1% improvement) or in scenarios with batch arrivals (3.8% improvement).

Based on our results, a dynamic approach—where the second gate is activated only when demand exceeds a defined threshold—may offer the best balance between efficiency and cost-effectiveness. This strategy aligns with the sponsor's objectives of minimizing turnaround times, particularly during seasonal peaks.

4.3.2 Yard Processing Times: Check-In and Blackbox

As discussed previously, the check-in gate service time significantly impacts queue dynamics and overall facility throughput. Even minor delays or fluctuations can trigger cascading effects, resulting in unstable queues under high-volume conditions. Figure 18 illustrates how increased check-in times affect key performance metrics compared to the baseline scenario.

Figure 18. Metric Comparison for Check-In Time Delays

Metric Name	Avg Time in Facility		Avg Time in Queue		Avg Trucks in Queue		Max Trucks in Queue		Penalty Cost	
Model	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %
Baseline										
1: Baseline	110.04	0.0%	5.01	0.0%	1.67	0.0%	6.00	0.0%	565.23	0.0%
2: 5 min Check-In	117.05	6.4%	12.65	152.6%	4.10	145.2%	11.00	83.3%	665.91	17.8%
3: 8 min Check-In	133.80	21.6%	40.15	701.7%	13.11	683.5%	26.00	333.3%	881.64	56.0%
4: 10 min Check-In	148.51	35.0%	65.47	1207.2%	20.91	1149.4%	37.00	516.7%	1,044.76	84.8%
5: 30 Trucks/Hour	111.31	1.2%	6.25	24.8%	3.09	84.3%	9.00	50.0%	880.86	55.8%
6: 30 Trucks/Hour + 5 min Check In	132.39	20.3%	42.79	754.5%	18.93	1031.3%	35.00	483.3%	1,298.71	129.8%
Bifurcation										
11: 10 min Check-In + 30% Deliveries	145.38	32.1%	60.89	1115.9%	19.87	1087.2%	36.00	500.0%	1,011.08	78.9%
12: 10 min Check-In + 100% Deliveries	142.00	29.0%	51.23	922.9%	17.77	961.6%	33.00	450.0%	1,010.57	78.8%
13: 30 Trucks/Hour + 5 min Check In + 30% Deliveries	128.84	17.1%	37.34	645.7%	16.46	883.4%	31.50	425.0%	1,258.97	122.7%
14: 30 Trucks/Hour + 5 min Check In + 100% Deliveries	122.44	11.3%	22.02	339.7%	9.75	482.7%	20.00	233.3%	1,102.14	95.0%

Figure 18 presents the median values for five key performance metrics—average time in facility, average time in queue, average trucks in queue, maximum trucks in queue, and penalty cost—across a range of what-if scenarios. Three factors emerge as the primary levers for improving yard utilization:

1. Check-in processing time
    - Comparing Scenario 1 (3 min average check-in) with Scenario 4 (10 min check-in) shows average queue time exploding from 5.01 min to 65.47 min (+1,207 %) and penalty cost jumping from $565.23 to $1,044.76 (+84.8 %). This underscores that keeping gate service times below 8 minutes is essential to prevent runaway queues.
2. Truck interarrival rate
    - Raising the arrival rate from 20 to 30 trucks/hour (Scenario 1 vs. 5) increases average queue time by 24.8 % (from 5.01 to 6.25 min) and penalty cost by 55.8 % (from $565 to $881). Even with stable check-in times, higher throughput drives significant cost.
3. Combined high volume and slower check-in
    - Under Scenario 6 (30 trucks/hr with 5 min check-in), average queue time rises to 42.79 min (+754.5 %) and penalty cost to $1,299 (+129.8 %). Introducing a secondary gate in Scenario 14 cuts queue time by 48.5 % and penalty cost by 15.1 %, demonstrating that bifurcation is most impactful when both demand and service delays are elevated.

By walking through these rows of Figure 18, it becomes clear that the most effective interventions for the sponsor are: (1) tightly controlling check-in times, (2) smoothing or capping peak arrival rates, and (3) deploying a secondary gate dynamically when both factors threaten to destabilize the system.

4.3.3 Penalty Cost Analysis

Since penalty costs depend on the total time spent in the facility, both check-in and internal "black box" processing times are critical. If the "black box" time is fixed, minimizing delays at the check-in gate becomes especially important. As shown in Figure 18, increasing the average check-in time from 3 to 10 minutes raises penalty costs by 85%. Even when bifurcation is implemented in the 10-minute scenario, reducing average queue time by 21.7% (Figure 19*)*, the overall penalty cost drops by only 3.2% with 30% and 100% of the deliveries diverted, as the total facility time improves by just 4.4% in the scenario with 100% deliveries diverted.

Figure 19. Penalty cost comparison between scenarios 4, 11, and 12

Scenario 4 vs 11 and 12

Metric Name	Avg Time in Facility		Avg Time in Queue		Avg Trucks in Queue		Max Trucks in Queue		Penalty Cost	
Model	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %
Baseline										
4: 10 min Check-In	148.51	0.0%	65.47	0.0%	20.91	0.0%	37.00	0.0%	1,044.76	0.0%
Bifurcation										
11: 10 min Check-In + 30% Deliveries	145.38	-2.1%	60.89	-7.0%	19.87	-5.0%	36.00	-2.7%	1,011.08	-3.2%
12: 10 min Check-In + 100% Deliveries	142.00	-4.4%	51.23	-21.7%	17.77	-15.0%	33.00	-10.8%	1,010.57	-3.3%

A noteworthy finding from Figure 18 is observed in Scenario 6, which simulates a higher truck volume (30 trucks per hour) and a moderate check-in delay (5 minutes per truck). Here, penalty costs rise by 130% compared to the baseline, reflecting the increased system load. However, when all deliveries are diverted to a secondary gate (Scenario

14), penalty costs improve by 15%, driven by a 7.5% reduction in average facility time and a 48.5% decrease in average queue time (see Figure *20* for a detailed comparison between these scenarios).

This analysis highlights that while bifurcation can mitigate penalty costs under moderate delays and high volumes, its effectiveness diminishes as check-in service times increase. Thus, optimizing check-in efficiency remains critical, as simply adding a second gate may not yield significant benefits if gate processing times are excessively long.

Figure 20. Comparison between scenarios 6, 13, and 14

Scenario 6 vs 13 and 14

Metric Name	Avg Time in Facility		Avg Time in Queue		Avg Trucks in Queue		Max Trucks in Queue		Penalty Cost	
Model	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %	Median	Delta %
Baseline										
6: 30 Trucks/Hour + 5 min Check In	132.39	0.0%	42.79	0.0%	18.93	0.0%	35.00	0.0%	1,298.71	0.0%
Bifurcation										
13: 30 Trucks/Hour + 5 min Check In + 30% Deliveries	128.84	-2.7%	37.34	-12.7%	16.46	-13.1%	31.50	-10.0%	1,258.97	-3.1%
14: 30 Trucks/Hour + 5 min Check In + 100%	122.44	-7.5%	22.02	-48.5%	9.75	-48.5%	20.00	-42.9%	1,102.14	-15.1%

In the following subsection, the most relevant takeaways are discussed and highlighted.

4.4 Managerial insights and recommendations

Under typical peak-season loads (20 trucks/hour, Scenarios 1–4), adding a secondary gate delivers only marginal improvements, average queue lengths shrink by 2–4 percent, and penalty costs by less than 1 percent (Scenarios 9–10). In these conditions, the sponsor's existing three-gate configuration remains adequate; rather than investing in new infrastructure, efforts should concentrate on sustaining check-in performance at or below five minutes.

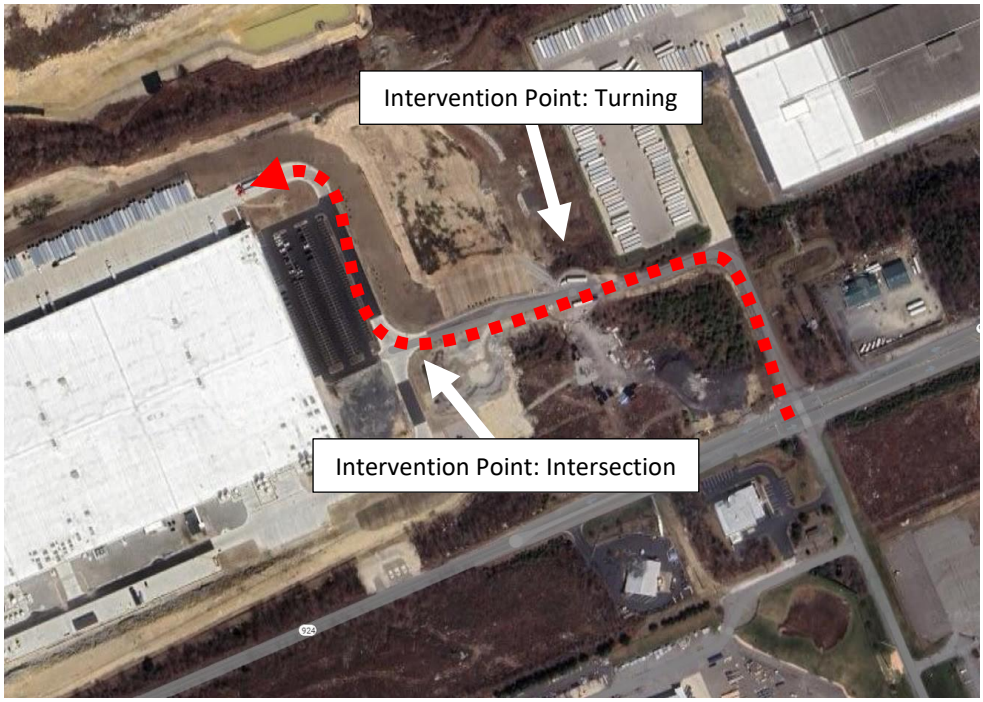
When arrival rates surge to 30 trucks/hour (Scenarios 5–6), the single-gate system destabilizes (queue time +755 percent, penalty costs +130 percent). However, diverting 100 percent of deliveries to a secondary lane (Scenario 14) cuts the average queue time by 49 percent and penalty costs by 15 percent. These results support a threshold-based staffing policy: maintain the secondary gate in reserve, then activate it automatically when the rolling arrival rate exceeds 30 trucks/hour or average check-in times climb above four minutes. Such an on-demand approach balances gate utilization with service levels while avoiding unnecessary fixed costs.

Scenarios with extreme check-in delays (8–10 minutes, Scenarios 3–4) reveal a clear tipping point: beyond eight minutes, queue times explode (+1,200%), and penalty costs skyrocket (+85%), and no amount of added capacity can fully offset gridlock. Before expanding gate infrastructure, managers should prioritize refining 3PL appointment windows to ensure service times remain under eight minutes. Negotiating more evenly distributed dispatch schedules with carriers and 3PL providers will smooth arrival patterns and substantially enhance the effectiveness of any future lane expansions.

This study has shown the importance of implementing the correct number of gates for the planned throughput of a facility. The original three gates can handle the average number of intended trucks over 24 hours. However, the actual pattern of truck arrivals means that the utilization of gates nears 100% during regular work hours in peak season. This simulation shows that when the total truck arrivals reach 30 trucks per hour, the three existing gates are insufficient and may cause a queue of trucks to build up. This queue can cause significant supply chain costs. While most trucks stay under the 2-hour demurrage cutoff, there is still a cost to the trucking provider that would factor into contract negotiations. Trucks idling in the queue would also cause CO_2 emissions.

Adding a bifurcated lane for peak periods reduced the risk of a substantial queue forming. It also reduced the risk of critical deliveries being stuck in the queue. Our study revealed that the policy setting to divert trucks to the new gate also has a significant bearing on the effectiveness of the new gate and the bifurcation strategy. The exact policy determining which trucks use the gate can impact the critical delivery risk and the overall queue time. For example, using the gate for only critical deliveries will underutilize the new gate and not materially reduce the congestion at the main gate. Sending all deliveries to the new gate will cause the new gate to form its own queue, which can take longer to get through than the original gate. The challenge is setting an adaptable policy based on available communication with the truck drivers and 3PLs before arriving at the facility. Figure *21* shows the entrance road to the facility. Once a truck is in the queue (along the black dotted line), there are only a few intervention points where a truck can be extracted from the queue and sent to the alternate gate. Ideally, a truck would be allocated to a gate immediately before arriving at the facility, but this level of intervention may not be possible. Further analysis is required to determine the optimal policy for truck gate routing based on available communication with drivers, truck arrival rates, criticality of inbounds, and the existing queue length.

Figure 21. Sponsor's Facility Close-Up Entrance View



5 Final Remarks

5.1 Conclusions

Truck operations are a critical part of consumer freight, as bottlenecks caused by inefficiencies can impact the throughput of factories and warehouses. The freight industry can approach the analysis of truck movements in several ways depending on the level of abstraction. Using an agent-based simulation in AnyLogic, this project could evaluate the impact of different yard layouts at a micro-traffic level, accounting for truck physics and driver behavior within the system. The simulation was set up to replicate the processes at the yard and operational data was used to calibrate the simulation to real-world performance. The simulation was used to randomly simulate yard performance

and produce a set of stochastic tests for the yard to evaluate the likelihood of queue lengths, queue times, and penalty costs.

The findings directly address our three research questions. First, by mapping simulated flows onto the sponsor's actual plant layout, we show that an entrance bifurcation—diverting high-priority deliveries onto a secondary check-in lane—best leverages the available road infrastructure to maintain stable throughput under up to 30 trucks/hour. Second, our sensitivity analyses identify average check-in time and arrival intensity as the primary levers driving queue buildup and demurrage costs; for example, reducing mean gate service from 5 to 3 minutes or dynamically activating the second gate cuts average queue time by nearly 50% and penalty costs by 15%. Third, by stress-testing these optimized layouts and policies on the existing facility and hypothetical new yard configurations like bifurcation, we demonstrate the model's applicability as a decision-support tool for any of the sponsor's plants.

5.2 Limitations

This study was subject to several limitations, as outlined in Section 3.1.2. Most notably, the Personal Learning Edition (PLE) of AnyLogic restricts simulation runs to a maximum of five hours. This constraint is significant because, even if some scenarios appear to have stable queues within this window, the system may not have reached a steady state. Queue formation could still be ongoing, and the statistical results are tied to that window. Access to a full AnyLogic license would enable more extended simulation periods—such as 8-hour shifts, full days, or weeks—providing a more comprehensive understanding of queue dynamics over time.

Another key limitation is the absence of remarkable truck maneuvering capabilities in the simulation's road package. Currently, trucks move seamlessly within the Blackbox without interacting with other vehicles. Maneuvers such as parking or docking after check-in can temporarily block other trucks, potentially creating additional bottlenecks. Therefore, the model's inability to capture these interactions may underestimate real-world congestion and queueing effects.

In addition to software and modeling constraints, the accuracy of our simulation was limited by gaps in the underlying data. Truck interarrival times were sourced from multiple third-party logistics providers, each using different timestamp conventions and data-sharing protocols, making it challenging to obtain consistently and integrate with the sponsor's internal records. The resulting dataset suffered from inconsistent timestamp formats and numerous missing entries, restricting the ability to accurately characterize arrival patterns, especially during peak congestion periods. As a result, the interarrival process was modeled as an exponential distribution based on the best available weekly samples. Still, this simplification may not fully capture underlying variations caused by dispatch coordination or production scheduling. Likewise, no systematic timestamp captured the gate check-in process, so processing durations had to be represented by a triangular distribution based solely on expert judgment. These data limitations, in both arrival patterns and service times, introduce uncertainty into queue dynamics and penalize cost estimates, reducing our ability to precisely quantify the benefits of layout or policy changes.

Finally, another limitation of the model lies in how penalty costs are calculated. Currently, the timer for each truck starts only when it enters the facility. In reality, if the queue extends onto the freeway, drivers begin accruing waiting time—and thus penalty costs—even while waiting outside the facility. As a result, the model underestimates total penalty costs in scenarios where the queue extends beyond the facility entrance.

5.3 Future Work

The scope of this study entailed reviewing the gate process and queuing at the entrance to the facility. Many other processes and potential causes of bottlenecks were excluded from the analysis. While the outcome of this

study shows the benefit of an alternate gate, introducing trucks into the yard from a different direction may cause unintended congestion within the yard as a cross-flow of traffic is introduced. The analysis is required to confirm that introducing the new gate does not cause any unintended consequences to aspects of the operation outside the scope of this study.

The following list outlines several promising directions for building on this work:

- Disaggregate truck queues by type and product family: Model separate arrival-and-service processes for inbound vs. outbound, 3PL vs. CPU vs. rush deliveries to uncover bottlenecks specific to each flow and tailor policies accordingly.
- "Open" the yard Blackbox to simulate dock management and scheduling: Replace the aggregated yard-time distribution with a detailed representation of docking, loading/unloading, and hostler movements, enabling analysis of yard layout and resource allocation.
- Experiment with in-facility layouts and scheduling rules: Test alternative dock configurations, slot assignment algorithms, and work-shift patterns to evaluate their impact on check-in and processing times under varying demand.
- Incorporate complementary simulation paradigms: Leverage System Dynamics or hybrid DES-SD approaches to capture high-level feedback (e.g., appointment systems, driver behavior) and qualitative factors (e.g., labor learning curves, equipment reliability) that lie beyond the scope of agent-based models.

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Appendices

Appendix A

This Appendix provides tables with detailed characteristics and results from each scenario.

Table A1. Scenario Description and Parameters.

#	Model	Description	Arrival Rate	Distribution Interraival Rate	Check-In Gate Time (Min)	Distribution Check In Gate	Distribution Black Box	% of Diverted Delivery Trucks	Trucks per Arrival
1	Baseline	Baseline	20 Trucks/Hour	exponential(1/3,0)	Min: 1, Mean: 3, Max: 5	triangular(1, 3, 5)	lognormal(56.64, 0.75, 41.85)	0%	1
2	Baseline	5 min Check-In	20 Trucks/Hour	exponential(1/3,0)	Min: 2, Mean: 5, Max: 10	triangular(2, 5, 10)	lognormal(56.64, 0.75, 41.85)	0%	1
3	Baseline	8 min Check-In	20 Trucks/Hour	exponential(1/3,0)	Min: 3, Mean: 8, Max: 15	triangular(3, 8, 15)	lognormal(56.64, 0.75, 41.85)	0%	1
4	Baseline	10 min Check-In	20 Trucks/Hour	exponential(1/3,0)	Min: 5, Mean: 10, Max: 20	triangular(5, 10, 20)	lognormal(56.64, 0.75, 41.85)	0%	1
5	Baseline	30 Trucks/Hour	30 Trucks/Hour	exponential(1/2,0)	Min: 1, Mean: 3, Max: 5	triangular(1, 3, 5)	lognormal(56.64, 0.75, 41.85)	0%	1
6	Baseline	30 Trucks/Hour + 5 min Check In	30 Trucks/Hour	exponential(1/2,0)	Min: 2, Mean: 5, Max: 10	triangular(2, 5, 10)	lognormal(56.64, 0.75, 41.85)	0%	1
7	Baseline	2 Trucks per Arrival	20 Trucks/Hour	exponential(1/3,0)	Min: 1, Mean: 3, Max: 5	triangular(1, 3, 5)	lognormal(56.64, 0.75, 41.85)	0%	2
8	Baseline	3 Trucks per Arrival	20 Trucks/Hour	exponential(1/3,0)	Min: 1, Mean: 3, Max: 5	triangular(1, 3, 5)	lognormal(56.64, 0.75, 41.85)	0%	3
9	Bifurcation	30% Deliveries	20 Trucks/Hour	exponential(1/3,0)	Min: 1, Mean: 3, Max: 5	triangular(1, 3, 5)	lognormal(56.64, 0.75, 41.85)	30%	1
10	Bifurcation	100% Deliveries	20 Trucks/Hour	exponential(1/3,0)	Min: 1, Mean: 3, Max: 5	triangular(1, 3, 5)	lognormal(56.64, 0.75, 41.85)	100%	1
11	Bifurcation	10 min Check-In + 30% Deliveries	20 Trucks/Hour	exponential(1/3,0)	Min: 5, Mean: 10, Max: 20	triangular(5, 10, 20)	lognormal(56.64, 0.75, 41.85)	30%	1
12	Bifurcation	10 min Check-In + 100% Deliveries	20 Trucks/Hour	exponential(1/3,0)	Min: 5, Mean: 10, Max: 20	triangular(5, 10, 20)	lognormal(56.64, 0.75, 41.85)	100%	1
13	Bifurcation	30 Trucks/Hour + 5 min Check In + 30% Deliveries	30 Trucks/Hour	exponential(1/2,0)	Min: 2, Mean: 5, Max: 10	triangular(2, 5, 10)	lognormal(56.64, 0.75, 41.85)	30%	1
14	Bifurcation	30 Trucks/Hour + 5 min Check In + 100% Deliveries	30 Trucks/Hour	exponential(1/2,0)	Min: 2, Mean: 5, Max: 10	triangular(2, 5, 10)	lognormal(56.64, 0.75, 41.85)	100%	1
15	Bifurcation	2 Trucks per Arrival + 100% Deliveries	20 Trucks/Hour	exponential(1/3,0)	Min: 1, Mean: 3, Max: 5	triangular(1, 3, 5)	lognormal(56.64, 0.75, 41.85)	100%	2
16	Bifurcation	3 Trucks per Arrival + 100% Deliveries	20 Trucks/Hour	exponential(1/3,0)	Min: 1, Mean: 3, Max: 5	triangular(1, 3, 5)	lognormal(56.64, 0.75, 41.85)	100%	3

Table A2. Scenario Results for each Metric with Median and Standard Deviation.

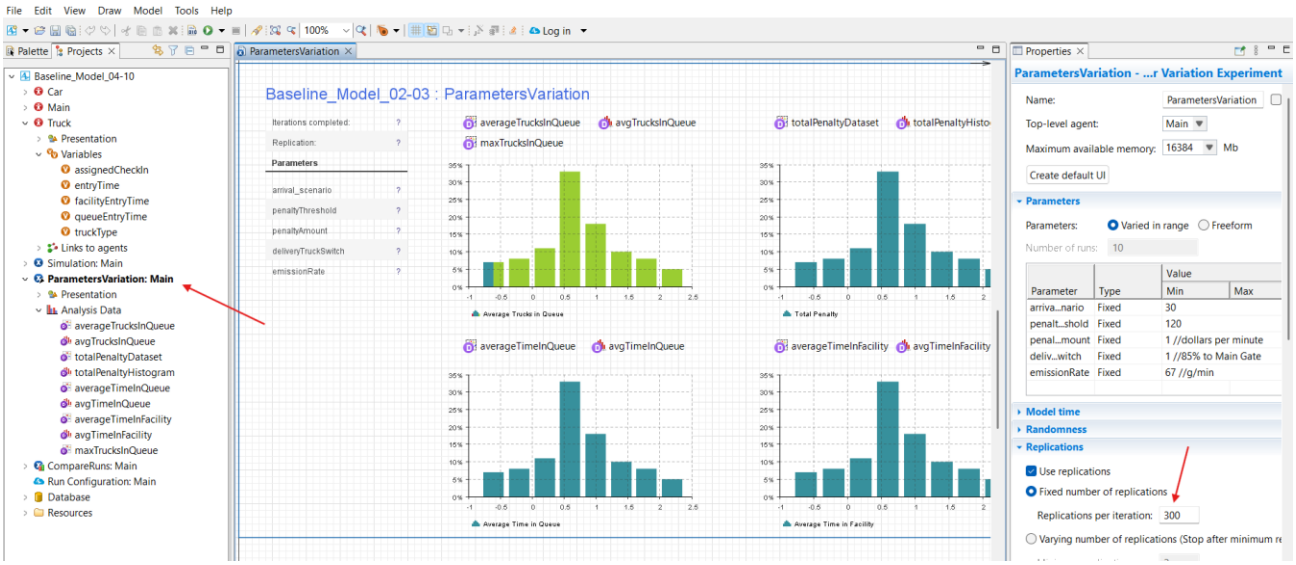
	Metric Name	Avg Time in Facility		Avg Time in Queue		Avg Trucks in Queue		Max Trucks in Queue		Penatly Cost	
Model	Scenario	Median	Std Dev	Median	Std Dev	Median	Std Dev	Median	Std Dev	Median	Std Dev
Baseline	Baseline	110.04	4.85	5.01	0.43	1.67	0.27	6.00	1.26	565.23	190.11
	5 min Check-In	117.05	6.04	12.65	4.61	4.10	1.88	11.00	3.78	665.91	233.28
	8 min Check-In	133.80	11.08	40.15	14.47	13.11	5.27	26.00	8.17	881.64	323.22
	10 min Check-In	148.51	11.45	65.47	14.90	20.91	4.07	37.00	4.12	1,044.76	342.25
	30 Trucks/Hour	111.31	4.32	6.25	1.58	3.09	0.80	9.00	2.73	880.86	252.44
	30 Trucks/Hour + 5 min Check In	132.39	10.15	42.79	12.13	18.93	5.09	35.00	6.21	1,298.71	426.33
	2 Trucks per Arrival	116.90	6.38	14.01	10.61	8.43	5.40	21.00	8.42	1,334.32	443.66
	3 Trucks per Arrival	137.61	8.59	46.31	4.31	28.52	3.11	39.00	1.03	2,593.16	507.62
Bifurcation	30% Deliveries	110.10	5.05	4.87	0.34	1.61	0.21	6.00	1.16	561.75	190.32
	100% Deliveries	109.87	4.85	4.97	0.28	1.63	0.24	6.00	1.08	559.52	198.58
	10 min Check-In + 30% Deliveries	145.38	10.03	60.89	13.14	19.87	4.20	36.00	5.15	1,011.08	289.87
	10 min Check-In + 100% Deliveries	142.00	10.65	51.23	11.37	17.77	4.65	33.00	7.41	1,010.57	346.08
	30 Trucks/Hour + 5 min Check In + 30% Deliveries	128.84	9.20	37.34	12.82	16.46	5.62	31.50	8.49	1,258.97	376.27
	30 Trucks/Hour + 5 min Check In + 100% Deliveries	122.44	6.93	22.02	10.10	9.75	4.66	20.00	7.45	1,102.14	361.66
	2 Trucks per Arrival + 100% Deliveries	114.30	3.97	7.93	2.62	5.41	1.96	15.00	4.51	1,328.47	312.02
	3 Trucks per Arrival + 100% Deliveries	125.75	8.02	35.85	10.66	24.22	7.34	44.00	8.55	2,495.75	652.03

Appendix B

This Appendix provides a series of steps for running the simulation model with N replications and exporting the data to the Power BI file for analysis.

To run the simulation with a fixed number of replications, open the Parameters Variation Experiment highlighted with the left arrow in Figure *22* and select the number of replications in the properties pane highlighted with the right arrow.

Figure 22. AnyLogic Screenshot on how to run a Parameters Variation Experiment



After running the Parameters Variation Experiment, the dataset objects can be opened with a click, as seen in Figure *23*, which is pointed out with the arrows. The data can be copied and then appended to the raw data sheets from the Excel file in Figure *24*.

Figure 23. Parameters Variation Experiment Results Screen

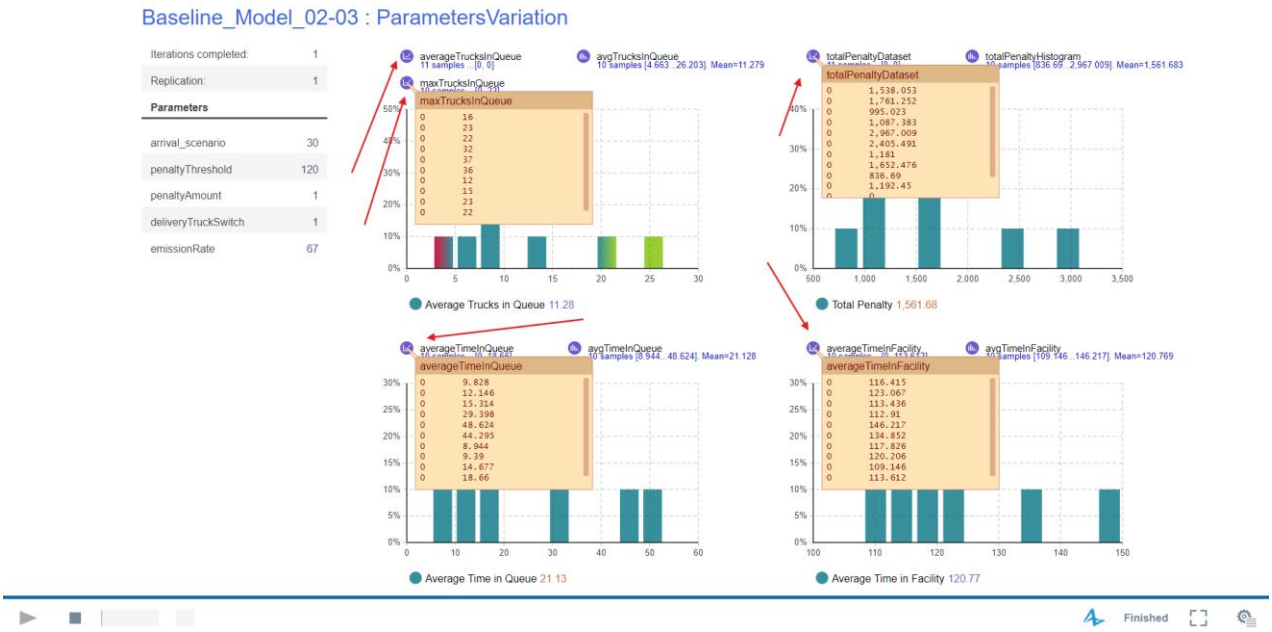
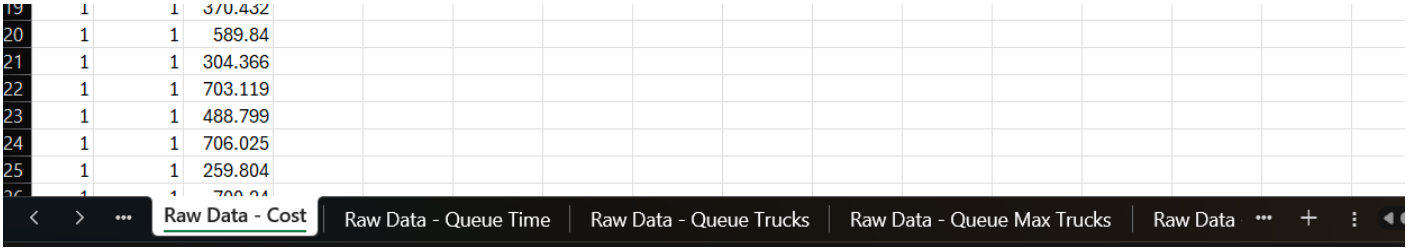


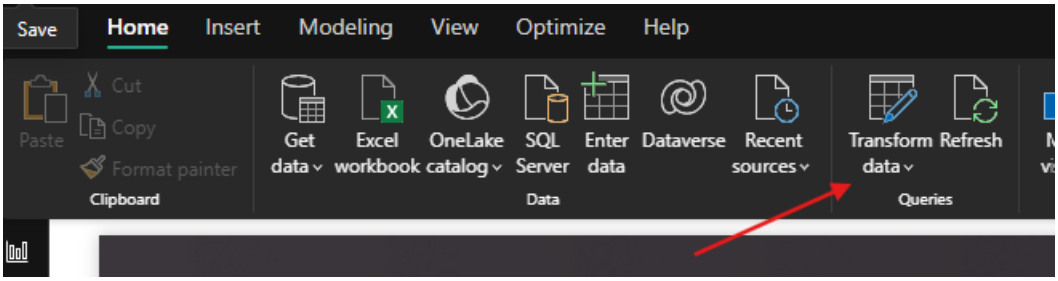
Figure 24. Excel File Screenshot Showing Raw Data Sheets for the Data Appends



Once the raw data is added to each sheet and the Scenarios are updated in the Summary page, the file is ready to be ingested in Power BI. Note that the appended data in each raw data sheet must have the scenario column updated and match the scenario number from the Summary page.

To update the Power BI data for the first time, you must access the Power Query indicated by the arrow in the image below.

Figure 25. Power Query button



Once in Power Query, click through each query from the red box on the left pane and go to the Advanced Editor to change the new path of the Excel file, following the arrows in the following figure. Once the path is updated for all the necessary queries, the option "Close & Apply" can be selected to update the data.

Figure 26. Power Query View to Update Excel File Path

