Utilizing Autonomous Vehicles to Reduce Truck Turn Time in Ports with Application for Port of Montréal

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Abstract

Utilizing Autonomous Vehicles to Reduce Truck Turn Time in Ports with Application for Port of Montréal

This thesis develops a Discrete Event Simulation (DES) model to evaluate strategies for reducing truck turn time (TTT) and enhancing operational efficiency at the Port of Montreal's Viau Terminal. The model analyzes the complex landside operations, including gate processes, internal movements, staging, and yard handling, differentiating between Human-Driven Vehicles (HDVs) and Autonomous Vehicles (AVs) based on their distinct behavioral and efficiency attributes. The study aims to provide insights into the potential of AV integration and demand management strategies in mitigating port congestion. DES, with integrated agent-based logic, is employed to simulate four distinct scenarios: a baseline representing current operations, a scenario implementing a Truck Appointment System (TAS) only, a scenario with partial AV integration (35% AVs) under shared resources, and a final scenario with AVs benefiting from dedicated staging areas and partitioned yard cranes. The model's conceptualization is informed by real-world data from port cameras and official reports, and its credibility is established through rigorous verification and validation against observed TTT metrics. The simulation findings reveal that the baseline scenario exhibits an average TTT of 88.2 minutes, characterized by significant internal congestion. The introduction of a TAS reduces TTT to 78.37 minutes. Partial AV integration (Scenario 3) further decreases the overall TTT to 55.91 minutes, with AVs achieving a TTT of 45.33 minutes. The scenario with dedicated AV staging and cranes (Scenario 4) results in the lowest AV TTT of 32.86 minutes; however, the overall system TTT unexpectedly increases to 57.13 minutes, as HDV TTT rises to 70.20 minutes. The study concludes that a multi-faceted approach involving demand management, vehicle technology, and strategic investment in infrastructure has a key function in maximizing port efficiency. Quantitative evidence and actionable recommendations are offered in this research to port authorities, with an emphasis on the necessity of nuanced resource allocation plans in the evolution towards automated port logistics.

Keywords: Autonomous Vehicles, Discrete Event Simulation, Truck Turn Time, Port Congestion, Port of Montreal

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List of acronyms

TEU	Twenty-foot Equivalent Unit
DES	Discrete Event Simulation
AV	Autonomous Vehicles
HDV	Human Driven Vehicles
TTT	Truck Turn Time
AGV	Autonomous Guided Vehicles
ATT	Autonomous Terminal Trucks
TAS	Truck Appointment System

Chapter 1:

Introduction

1.1 The Growing Challenge of Port Congestion and Truck Turn Time

The efficiency of the world supply chain relies, to a large degree, on the efficiency of handling terminal ports. The efficiency of such ports, which are critically located interface points between sea and land transportation, determines the cost and speed of world trade. The deployment of larger container ships and increasing levels of global commerce have posed serious operating issues to port efficiency. These inefficiencies include extra traffic congestion and unnecessary delays in the handling and transportation of cargo (Lange et al., 2017). Excessive truck waiting times and the creation of bottlenecks in operations, which have been a long-running issue of truck congestion in terminal ports, are a major source of these inefficiencies (Lange et al., 2017; Alagesan, 2017). These longer truck turnaround times have several adverse impacts, including higher fuel use by idle trucks, increased emissions, higher trucking company operating expenses, and substantial supply chain disruption (Azab & Eltawil, 2016). Therefore, the ability to effectively manage and reduce truck turn time is vital for enhancing port efficiency and promoting sustainable logistics practices.

1.2 The Potential of Autonomous Vehicles in Transforming Port Logistics

Autonomous vehicles (AVs) are quickly transforming into a disruptive technology with the potential to transform logistics and supply chain management operations in all industries (Ibiyemi & Olutimehin, 2024). Particularly within the port environment, the adoption of AVs, such as autonomous trucks and AGVs, has a lucrative potential for increasing the productivity levels, contributing to safety features, and being eco-friendly (Ibiyemi & Olutimehin, 2024; Motunrayo

Oluremi Ibiyemi & David Olanrewaju Olutimehin, 2024). Autonomous trucks provide the ability to be driven on a non-stop 24/7 shift, potentially lower cases of human error in operations, improve routes of transport for efficiency, and ultimately reduce total operational costs. These qualities fully resolve the long-standing issues of truck turn time at port terminals, as noted by Natarajan in 2019. Additionally, AGVs and more sophisticated Autonomous Terminal Trucks (ATTs) are also being researched and applied to a large extent for horizontal cargo handling operations in port terminals to standardize cargo handling processes and remove current operational bottlenecks (Graf & Anner, 2021).

The capacity of AVs to operate without the limitations imposed by driver hours-of-service regulations presents a considerable advantage in the context of port logistics. This continuous operational capability has the potential to significantly increase cargo throughput within ports and mitigate the growing concerns surrounding driver shortages that are increasingly prevalent in the trucking industry(Ibiyemi & Olutimehin, 2024; Graf & Anner, 2021). Moreover, the seamless integration of AVs with advanced Artificial Intelligence (AI) and Internet of Things (IoT) technologies can facilitate more data-driven and highly optimized logistics operations within port environments. This synergy enables enhanced tracking and management of goods, as well as improved decision-making processes concerning truck movements and overall cargo handling(World Economic Forum, 2021).

Figure 1 Volvo electric, connected and autonomous Truck, Vera

1.3 Leveraging Discrete Event Simulation for Analysis and Optimization

Discrete Event Simulation (DES) stands out as a robust and versatile modeling tool for comprehensive analysis of complex system performance characteristics, including the sophisticated operation in port terminals (Bottani & and Casella, 2024a; Said et al., 2014). By developing a simulated replica of the port environment, DES has the capability to facilitate the simulation of dynamic truck flows, containers, and other critical resources (Srisurin et al., 2022). This feature can assist in intensive analysis of different operation strategies and the possible effect of new technology integration such as autonomous vehicles (Kotachi et al., 2013a). In developing this virtual simulation, DES is capable of give relevant insights into the impacts of the deployment of autonomous vehicles on truck turn time and port operational efficiency (Alagesan, 2017).

Additionally, DES offers a powerful tool for simulating rival congestion relief strategies as well as optimizing the AV implementation and application in the concerned port environment (Neagoe et al., 2021).

DES offers a cost-effective and risk-free methodology to experiment with the integration of autonomous vehicles into the highly dynamic and complex setting of a port. Virtual experimentation enables possible operational challenges to be realized, and optimization potential to be explored, prior to being committed to actual implementation, thus avoiding substantially related risks and expenses (Said et al., 2014). The stochastic nature of most port operations, including the random truck arrival time and fluctuating duration of service processes, makes DES an especially suitable tool for analysis (Neagoe et al., 2021) as it can accurately model and examine the effect of intervention such as AVs on system performance.

1.4 Focus on the Port of Montreal: A Critical Node in North American Trade

The Port of Montreal is one of the leading container ports in the Eastern side of Canada, serving as a critical node within the long supply chains that link Canada to the rest of the North American continent (Port Authority Report, 2024). The port processes considerable volumes of both non-containerized and containerized trade as an important gateway for one of Canada's and America's major consumer markets in geographical locations around Canada and the United States. As with all the world's large ports, the Port of Montreal experiences truck congestion and long truck turn times, especially at peak operating volumes (AbuAisha et al., 2020). In its pursuit of efficiency improvement and promotion of sustainability, the port has already embarked on a very diversified list of amazing initiatives, ranging from the Trucking PORTal mobile app for optimal truck flow to rail capacity optimization initiatives for increasing the movement of cargo by rail. In order to optimize the use of new solutions, it is evident and continuous in the Port of Montreal to transition to new technologies such as automation and possible incorporation of autonomous vehicles to further expand its performance abilities.

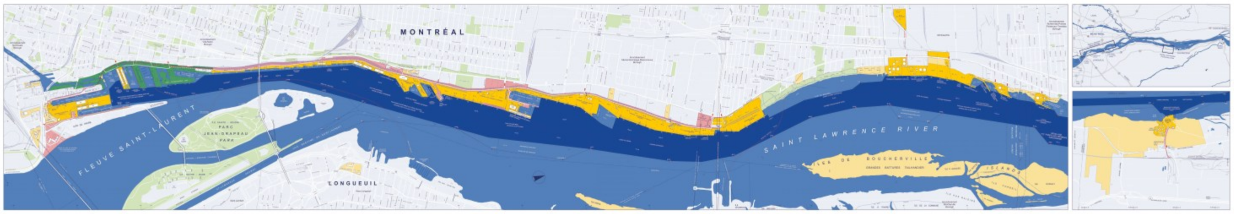

Figure 2 Map of Port of Montréal (Port Website, 2025)

Given its status as a major port facing tangible issues with truck congestion and its demonstrated commitment to embracing innovation, the Port of Montreal provides a highly relevant and valuable case study for in-depth investigation into the potential of exploring different initiatives to effectively reduce truck turn time(Alagesan, 2017). A thorough understanding of the specific operational context, the existing challenges, and the current infrastructure landscape at the Port of Montreal is paramount for developing realistic and ultimately effective solutions that involve the strategic deployment of autonomous vehicles and the application of DES modeling.

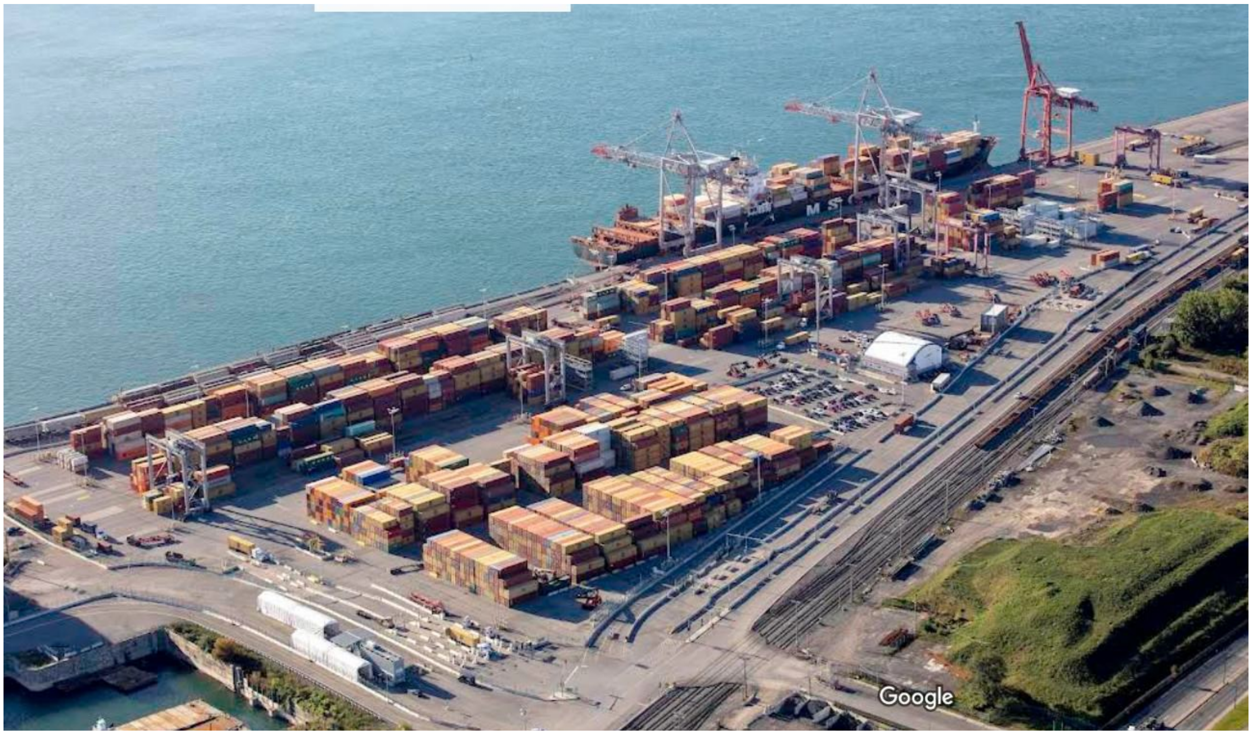

Figure 3 Port of Montreal, Viau Terminal (Google Maps,2025)

1.5 Research Objectives and Thesis Statement

The main research objective of this thesis is to examine the use of autonomous vehicles to minimize truck turn time within the terminal port setting, and in this specific case study for the Port of Montreal, through the means of DES. In trying to accomplish this aim, a set of precise sub-goals will be followed:

- To analyze the current state of truck traffic patterns and truck turn time at the Port of Montreal to establish a baseline scenario for evaluation.
- To develop a well-defined DES model that accurately represents the key operational processes affecting truck movements within the Port of Montreal.
- To incorporate autonomous vehicle technology into the developed simulation model considering multiple deployment scenarios and operation parameters

- To compare the effects of various autonomous truck deployment scenarios on key performance measures, with particular emphasis on reducing truck turn time.
- To evaluate the potential benefits, challenges, and practical issues with respect to autonomous truck deployment at the Port of Montreal.

According to these aims, this thesis investigates the potential of utilizing autonomous vehicles, analyzed through DES, to significantly reduce truck turn time and improve operational efficiency at the Port of Montreal, considering the associated challenges and implementation strategies."

This thesis is organized into six chapters. Chapter 2 reviews the literature on port congestion, truck turn time, simulation modeling, and autonomous vehicles, identifying key research gaps. Chapter 3 presents the methodology and case study of the Viau Terminal at the Port of Montreal, including input modeling, process mapping, simulation design, and output analysis. Chapter 4 reports the results of the baseline, truck appointment system, partial autonomous vehicle integration, and dedicated AV infrastructure scenarios, along with sensitivity analyses. Chapter 5 explain the process of simulation in AnyLogic and discuss the findings, comparing the effectiveness of different strategies in reducing congestion and truck turn time. Finally, Chapter 6 concludes with the main contributions, limitations, and recommendations for future research.

Chapter 2:

Literature Review

In this chapter, we present the literature review on the definition of congestion in context of container terminal ports, measures to reduce congestion inside port terminal, simulation methods used to address them, and finally the research gap which led to creation of this research project.

2.1 What Is Congestion

Congestion refers to the condition in transportation and logistics systems where demand for infrastructure or resources exceeds their capacity, leading to delays, inefficiencies, and increased operational costs (Button & Hensher 2005). In ports, congestion can be felt as bottlenecks in ship, truck, train, and freight flow, often in the form of excessive traffic, insufficient infrastructure, or operational inefficiency. Congestion threatens supply chain continuity as well as trade flows. Button and Hensher define congestion in Handbook of Transport Strategy, Policy, and Institutions as "the condition where traffic demand approaches or exceeds the available capacity of a transportation network, resulting in delays and inefficiencies" (p. 486).

2.1.1 Congestion in Ports

Port congestion refers to the state where the demand for port services, particularly for truck traffic, exceeds the available capacity, leading to significant delays and inefficiencies (Lange et al., 2017). This phenomenon is intensified by factors such as increasing global trade volumes, larger container ships, and non-uniform truck arrival patterns. In The Geography of Transport Systems, the authors mention "Port congestion occurs when port service demand exceeds infrastructure capacity, resulting in queuing, delay, and elevated cost along the supply chain" (Rodrigue, 2020). Notteboom & Rodrigue in Their paper, Containerization, box logistics and global supply chains: The integration of ports and hinterlands, published in Maritime Policy & Management, state that port congestion results from "imbalances between the operational capacity of port facilities and fluctuating demand patterns," which hinder supply chain efficiency (Notteboom & Rodrigue, 2013).

2.1.2 Causes of Congestion in Ports

Truck turn time (TTT) is a critical metric, defined as the total time a truck spends within the terminal, from entry to exit. Port congestion and extended truck turn times (TTT) are pervasive problems of global supply chains, the product of a multifaceted interrelation of internal business inefficiencies and outside world pressures (Lange et al., 2017; Lee & Lam, 2015). Internally, congestion is typically an immediate result of unbalanced or insufficient supply of resources, such as a lack of gate lanes, yard equipment (e.g., reach stackers, rubber-tyred gantry cranes, yard trucks), or manpower to deal with the fluctuating streams of truck and ship arrivals(Azab & Eltawil, 2016; Huynh et al.,2004). Poorly management of yard handling, with indiscriminate container piling and inefficient truck traffic movement inside the terminal, aggravates the issue by prolonging truck dwell times within the terminal in order to look for or drop off containers. In addition, the absence of coordination and communication among port stakeholders, including shipping lines, terminal operators, trucking companies, and customs, employing real-time information can lead to information asymmetry, making truck arrivals unpredictable and scheduling inefficient (Huang et al., 2025).

Externally, port congestion is more or less influenced by elements beyond the control of terminal operators. Growing sizes of mega-vessels, and hence peaks of concentrated cargo on arrival, stretch current landside facilities and capacities (Ozbas et al., 2014; Yasuda et al., 2024). In addition, port road network capacity constraints close to ports, city-road traffic, and limited intermodal links also contribute to creating bottlenecks, leading to trucks waiting in line on entry roads before even reaching terminal gates (Du et al., 2023; Javaudin, 2024; Thennakoon et al., 2024). Economic cycles, seasonal peaks in demand, unforeseen interruptions in supply chains (including labor disputes, natural disasters, and geopolitics), and shifts in trade trends also result in spikes or stoppages in cargo flows, overwhelming port facilities and causing severe congestion and long truck turn times(Gomes et al., 2025; Lange et al., 2017; Morais & Lord, 2006). Knowledge of these complex causes is necessary to formulate effective and efficient mitigation measures. The summary of various factors causing congestion is shown in the figure 4.

Truck turn time is both an indicator and a consequence of port congestion. If capacity is exceeded because there is fluctuating demand, there is inefficient infrastructure, and there is inefficient asset utilization, delay occurs in terminal gates, yards, and loading areas. Bottlenecks translate directly into increasing truck dwell times in the port system. Lee and Lam (2015) point out that long truck turn times are a central indicator of congestion, illustrating the extent of mismatch between serving capacity and truck arrival rates. Likewise, Huynh et al. (2004) argue that truck turnaround time offers an objective measure of congestion severity as it encompasses the collective delays incurred during gate processing, yard handling, and drop-off or pick-up of the containers. Thus, improvements to operations or technology initiatives aimed at congestion alleviation usually have quantifiable impacts on truck turn time on the average (Notteboom & Rodrigue, 2013; Azab & Eltawil, 2016).

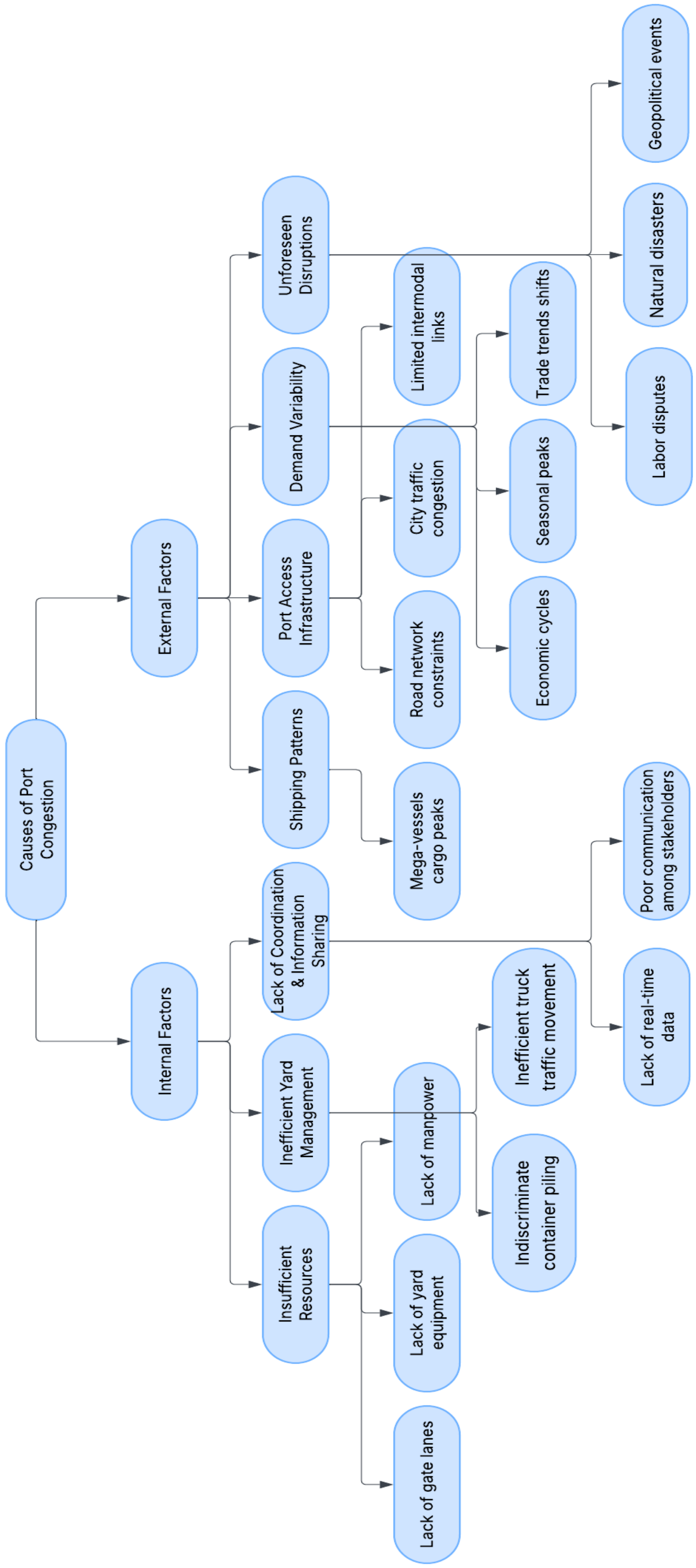

Figure 4 Cause of congestion in ports

2.2 Truck Turn Time and its Role in Congestion Management

Truck turn time (TTT) is a fundamental metric to calculate terminal port efficiency, defined as the time a truck spends within the walls of a terminal between the time it reaches the entry gate and eventually exits via the exit gate (Lange et al., 2017). This parameter is one of the most important performance indicators that play a significant role in the measurement of total efficiency in landside operations for a port and the level of services offered to trucking companies (Azab & Eltawil, 2016). TTT offers important information regarding smoothness in cargo flow, severity of congestion faced by the terminal, and operating process efficiency in the terminal (Shin et al., 2024). A shorter TTT reflects a more productive and efficient terminal, and this is a good thing for all the port stakeholders, from trucking companies, terminal businesses, to shippers (Huynh, 2005). Long TTT, on the other hand, produces a ripple effect of negative occurrences, affecting the economic viability and operational efficiency of the entire supply chain (Shin et al., 2024).

2.2.1 Factors Contributing to high Truck Turn Time

There are some interconnected reasons that can cause truck turn time delays in terminal port environments, commonly known as gate operational problems, yard operational problems, and external ones. Terminal gate delay commonly arises from the congestion that is related to too many trucks arriving at the same period, ineffectively processed protocol for paperwork and vehicle inspections, and lack of or ineffectively implemented truck appointment systems (Lange et al., 2017). Delays within the terminal yard occur because of congestion caused by inefficient yard operating practices, the limited amount of cargo equipment such as yard cranes, and slow or uncoordinated loading and unloading operations (Azab & Eltawil, 2016). External forces also significantly affect TTT. Heterogeneous truck arrivals with peak truck arrivals during specific hours tend to overburden the capacity of the terminal. Congestion on roads to the port also has the ability to cause delay on trucks even prior to approaching the gate, and unexpected congestion in transport systems can prolong delays too (Abdelmagid et al., 2022). The intricate interdependence among these gate operations, yard performance, and outside traffic conditions results in a dynamic system where bottlenecks in one location can ripple through and have a substantial impact on the total time it takes a truck to visit its terminal stop (Alagesan, 2017).

2.2.2 Consequences of Long Truck Turn Times

Extended truck turn times in port terminals have far-reaching and detrimental consequences across various dimensions, including operational efficiency, environmental impact, and economic stability (Lange et al., 2017). One of the most immediate consequences is increased congestion, both within the terminal itself and in the surrounding road networks. Trucks waiting in long queues to enter or exit the terminal, or moving slowly within the yard, contribute significantly to traffic buildup and further exacerbate delays for all port users(Alagesan, 2017) (Neagoe et al., 2021). This idling of trucks for prolonged periods also has a substantial environmental impact, leading to increased fuel consumption and the emission of harmful air pollutants and greenhouse gases, contributing to air pollution and climate change(Azab & Eltawil, 2016).

Economically, longer TTT relates to increased trucking firm operating costs in the form of greater fuel usage and driver idle time, ultimately to be transferred to the consumer. Even cargo handling delays could result in possible demurrage fees, paid upon longer-than-free-time cargo at the port. Secondly, chronically congested ports and longer turn times for trucks can deter shipping firms and businesses from utilizing their terminals, hence being less competitive generally in the global economy (Azab & Eltawil, 2016; Abdelmagid et al., 2022). These adverse effects highlight the dire necessity of seeking and avoiding effective mechanisms for reducing truck turn time for port terminals.

2.2.3 Strategies for Reducing Truck Turn Time

To mitigate the negative effects of long truck turn times, several strategies and technologies have been tried and researched at terminals globally. Truck appointment systems (TAS) are among the most prominent techniques that have been utilized to help control truck arrivals at terminal gates. Through pre-book windows of desired arrival times, TAS contribute to lessening truck arrivals to smooth out, reducing gate congestion and improving terminal operation foreseeability (Abdelmagid et al., 2022; Neagoe et al., 2021). Automation technologies also contribute to minimizing TTT. Automation gate systems can enable rapid entry and departure using optical character recognition (OCR) and other technology to rapidly identify trucks and containers and thereby reduce manual checks. Automated yard equipment, including automated stacking cranes and possibly autonomous vehicles in the form of AGVs and ATTs, can optimize container movement around the yard, minimizing truck waiting times (Zou et al., 2022).

Beyond technological solutions, various operational improvements can contribute to reduced TTT. Optimized yard management practices, including efficient container stacking and retrieval strategies, can minimize truck movements and waiting times within the terminal. Streamlining the processes for loading and unloading containers from trucks, ensuring adequate staffing and equipment availability, and potentially extending gate operating hours to distribute truck traffic over a longer period can also lead to significant reductions in TTT (Huynh, 2009; Lange et al., 2017). A combination of these strategic approaches, encompassing better scheduling through appointment systems, leveraging automation technologies, and implementing operational best practices, is often necessary to achieve substantial and sustainable reductions in truck turn time(Mpacd, 2021; Chen, 2025).

2.2.4 Benchmarking Truck Turn Time in Ports

Benchmarking truck turn time and other related performance metrics against efficient ports is essential for terminal operators to assess their current performance, identify areas for potential improvement, and set realistic targets for operational efficiency(Notteboom et al., 2022). Various metrics are commonly used to measure TTT and overall port efficiency, including the average truck turn time, the percentage of trucks experiencing excessive delays, gate processing times, and the utilization rates of yard equipment (Huynh, 2005; Mbanefo, 2020). Analyzing the operational strategies and technologies employed by high-performing ports can provide valuable insights into the factors that contribute to efficient truck processing. These factors might include the effective implementation of truck appointment systems, the level of automation in gate and yard operations, optimized traffic management within the terminal, and seamless integration of intermodal transportation modes(Mbanefo, 2020). By understanding the benchmarks achieved by efficient ports such as the ones mentioned in Table 1 and the practices that underpin their success, terminal operators can gain a clearer understanding of achievable TTT levels and develop targeted strategies to enhance their own operational performance(Spoel et al., 2016).

Table 1 Comparison of Truck Turn Time Metrics in Efficient Ports

Port Name	Average TTT (Minutes)	Key Factors Contributing to Efficiency	Source
Port of Oakland	Approximately 84	Truck wait-time outside gates, truck turn-time within terminal	(Truck Drivers USA, 2024)

Tanjung Priok Port	Reduced from 99.28 to 48.72	Truck losing system, scheduling truck arrivals using TTT method	(Nurcahyo et al., 2020)
Port of Rotterdam	Approximately 60	Integration of multi-source data, advanced machine learning techniques	(Chen, 2025)

2.3 Congestion modeling in ports

Congestion modeling in ports typically involves formulating models for the complex interactions among various entities (e.g., cranes, ships, trucks) and activities (e.g., intermodal transfers, gate operations, handling of cargo). The goal is to see the way these interactions create delays and bottlenecks, and how well various strategies are working to streamline flow and decrease turn times (Kotachi et al., 2013). The models may include stochastic factors, e.g., random service time and arrival rates, to achieve a simulation of the dynamic and relatively unpredictable character of port operations (Azab & Eltawil, 2016).

Simulation modeling has emerged as a versatile and powerful tool for analyzing and optimizing complex systems, and its application in the context of terminal port operations is extensive. Three primary simulation methodologies are commonly employed in this field: discrete-event simulation, agent-based simulation, and system dynamics.

2.3.1 Discrete-Event Simulation (DES)

DES is a modeling approach that focuses on the system's state changing at specific points in time, triggered by the occurrence of discrete events (Kiani et al., 2010). In the context of terminal ports, events such as truck arrivals, gate processing completions, crane loading/unloading operations, and truck departures are modeled. DES is particularly well-suited for analyzing systems where the flow of entities (e.g., trucks, containers) through a series of processes is central to the system's behavior(Palmer, 1996). The ability of DES to incorporate stochastic elements, such as variability in truck arrival times and service durations, makes it a valuable tool for capturing the inherent uncertainties of real-world port operations (Azab & Eltawil, 2016). Studies have extensively utilized DES to analyze various aspects of truck turn time reduction. For instance, Kiani (Kiani et al., 2010) employed DES to model queuing at terminal gates and weighbridges, proposing and evaluating solutions such as modifying weighbridge operations and adding infrastructure. Alagesan (Alagesan, 2017) developed a DES model for the Port of Montreal to investigate the effectiveness of different congestion mitigation scenarios, including technology upgrades and changes in truck arrival patterns. Azab and Eltawil (Azab & Eltawil, 2016) utilized DES to study the impact of various truck arrival patterns on truck turn time, demonstrating the methodology's capability to analyze the influence of stochastic arrival behaviors. Similarly, studies such as those by Huynh and Walton (N. Huynh & Walton, 2008) and Alagesan (2017) have employed DES to simulate and evaluate the impact of different truck appointment rules and congestion mitigation strategies on truck turn time. These examples illustrate the broad applicability of DES in modeling specific operational processes within the terminal, such as truck arrivals and service times at gates, the movement of trucks within the yard and their interaction with yard cranes, and the impact of different management policies like truck appointment systems(Brunetti et al., 2020). The granular level of detail that can be achieved with DES allows for the identification of specific bottlenecks and the quantification of the impact of targeted interventions on truck turn time.

2.3.2 Agent-Based Simulation (ABS)

Agent-based simulation provides an alternative modeling paradigm in which the system is represented as a set of autonomous agents interacting with one another and their environment. For port terminals, agents can represent entities such as trucks, yard cranes, containers, and even trucking companies, each with their own set of behaviors and decision-making rules(Riaventin et al., 2024). ABS is particularly advantageous for capturing the complex interactions and decentralized decision-making processes that characterize port operations(Fleming et al., 2013). For example, an agent-based model can simulate how individual truck drivers choose their arrival times based on terminal congestion information, or how yard crane operators prioritize service requests from different trucks based on predefined strategies. Several studies have successfully applied ABS to model truck scheduling and yard crane operations with the aim of reducing truck turn time. The study by Riaventin et al. (2024) proposed an agent-based simulation to analyze the synchronization of truck arrival and yard crane scheduling, comparing different yard crane scheduling strategies (e.g., First-Come-First-Served, Nearest-Truck-First-Served) and truck appointment system approaches (centralized vs. decentralized). Their findings indicated that certain scheduling strategies, like Nearest-Truck-First-Served, can lead to lower average truck turn times. Similarly, research by Ramadhan et al. (2020) developed an agent-based model of a truck appointment system incorporating a decentralized negotiation mechanism, demonstrating that allowing trucking companies to adjust their arrival times based on terminal information can result in shorter average truck turnaround times(Ramadhan & Wasesa, 2020). These applications highlight the strength of ABS in modeling scenarios involving autonomous entities, decentralized control strategies, and the emergent behavior resulting from the interactions of individual agents within the port environment.

2.3.3 System Dynamics (SD)

System dynamics provides a high-level perspective on the modeling of complex systems, focusing on the feedback loops, accumulations, and delays that influence the system's behavior over time(Yu et al., 2014). Unlike DES and ABS, which often focus on operational details and the flow of discrete entities, SD aims to capture the broader systemic factors and their long-term impacts. In the context of terminal ports, SD can be used to model the interrelationships between various subsystems, such as the flow of cargo, the utilization of resources, and the impact of policy decisions on overall port performance, including truck turn time. For example, researchers have applied SD to analyze the land transportation system in a port city, considering the interplay between the economy, the transport network, and transportation investments. Other studies have utilized SD to simulate the factors affecting inventory optimization at seaports, where cargo dwell time, a related concept to truck turn time, is a key variable (Mohammadhashem et al., 2024). While direct applications of SD specifically focused on reducing truck turn time might be less prevalent compared to DES and ABS, the methodology offers valuable insights into the broader dynamics of port logistics and how strategic decisions and external factors can indirectly influence truck turn time (Oztanriseven et al., 2014). For instance, an SD model could be used to assess the long-term impact of investing in inland port facilities or implementing new regulations on the overall efficiency of the port system and its effect on truck-related operations. The strength of SD lies in its ability to capture the interconnectedness of different elements within the port and its external environment over extended periods, making it suitable for policy analysis and long-term strategic planning.

2.3.4 Hybrid Simulation Approaches

In order to gain a more comprehensive understanding of the complex dynamics within port logistics dynamics, researchers have utilized more integrated hybrid simulation techniques that integrate DES with other models (Ebrahim et al., 2022). These hybrid approaches are bound to leverage the strengths of DES in detail capture and stochasticity, complemented with other approaches like agent-based simulation (ABS) to model the behavior of individual decision makers like truckers or dispatchers, traffic flow modeling to model the movement of vehicles around the port and its environs, and optimization techniques to locate the optimal solution for resource allocation or scheduling problems (Du et al., 2023; Kotachi et al., 2016). The advantages of integrating various model approaches are that they can potentially be able to capture several aspects of the functioning of a port that could be challenging to communicate effectively through one approach. For instance, the integration of DES and ABS can allow for an insight into the impact of the decision and action of certain agents on the performance of the system at the port level (Augustine, 2021). Similarly, the integration of DES with traffic flow models will aid in providing a more realistic traffic congestion simulation as well as its impact on terminal performance (Li et al., 2016). Hybrid techniques of this kind can facilitate a better port logistics understanding as well as enable better analysis of intricate issues and more effective strategic and operational decision-making (Oudani et al., 2018).

This study adopts a hybrid simulation approach, combining DES to model the structured flow of trucks through the port terminal and agent-based modeling (ABM) to represent individual truck attributes and behaviors. While DES captures the operational process and resource constraints, ABM allows for dynamic decision-making and differentiation between autonomous and human-driven trucks based on individual characteristics such as acceleration, speed, and reaction time. Table 2 shows the comparison between these approaches.

Table 2 Alternative approaches to simulation modeling

Simulation Approach	**Description**	**Advantages**	**Disadvantages**	**Application**
Discrete-Event Simulation (DES)	Models system as a sequence of discrete events occurring in time (e.g., truck arrivals, crane operations).	- High level of operational detail - Well-suited to process flows and resource constraints - Can incorporate stochasticity in arrivals and service times	- Less effective in modeling autonomous decision-making - Scalability can be challenging with very large systems	Operational Modeling, evaluating infrastructure or policy changes
Agent-Based Simulation (ABS)	Models system as autonomous agents with individual behaviors and interactions (e.g., trucks, cranes, dispatchers).	-Captures decentralized decision-making and emergent behavior -Flexible representation of dynamic interactions	-Higher computational complexity - Requires detailed behavior rules for each agent	Simulation individual decision-making processes

System Dynamics (SD)	Models feedback loops and accumulations in a continuous, high-level system over time.	-Captures long-term systemic effects -Suitable for policy and strategic analysis-Simpler to calibrate at aggregate level	- Lacks fine-grained operational detail - Not suited for modeling discrete events or agent behaviors	Evaluating strategic policy impacts, infrastructure investment scenarios, and long-term dynamics influencing congestion.
Hybrid Simulation Approaches	Combines DES, ABS, and sometimes traffic flow or optimization models to leverage strengths of each.	- Integrates operational detail and agent behaviors - Allows holistic analysis of complex systems - Ability to simulate both micro and macro effects	- Higher modeling and computational complexity -Requires multidisciplinary expertise -Longer development time	Integrating detailed operations with agent decision-making and traffic impacts for comprehensive analysis.

2.4 Why Discrete Event Simulation?

DES is a powerful modeling tool that replicates the behavior of an evolving system over a period of time based on a sequence of discrete events. In contrast to continuous simulation, where the system state is continuously altered over time, DES simulates systems whose changes are discrete at specific time points and triggered by an event occurring, for example, a truck arriving at a gate or a container being loaded onto a truck (Said et al., 2014). DES is great at modeling complicated logistics systems, especially those with stochastic factors like dynamic arrival rates, service time, and available capacity. Its capability of simulating dynamic interactions of different system components and the impact of randomness enables it to be a suitable tool for logistics activity understanding and optimization (Azab & Eltawil, 2016). The application of DES has wide-ranging uses in numerous logistics and supply chain management fields, including manufacturing, warehousing, transportation, and port operations (Srisurin et al., 2022).

2.4.1 Discrete Event Simulation in Logistics

Within the context of port terminal operations, DES has proven to be highly effective for modeling a variety of complex processes, including the flow of trucks through gates, the management of containers within the yard, and the activities of quay cranes in loading and unloading vessels(Said et al., 2014). DES allows for the creation of detailed virtual representations of these processes, capturing the sequence of activities, the resources involved, and the potential for queuing and delays at different stages(Bottani & and Casella, 2024). Furthermore, DES is extensively used for simulating vehicle traffic flow within and around port terminals. This includes modeling the movement of trucks along internal roadways, the formation of queues at gates and yard blocks, and the impact of traffic congestion on overall terminal performance(Li et al., 2016). Various simulation software tools, such as Arena, AnyLogic, and Simphony.NET, provide specialized features and libraries that facilitate the development and analysis of DES models for port operations, offering functionalities for modeling traffic, resources, and events in a maritime logistics context(Neagoe et al., 2021).

By precise simulation of the interactions between various resources and entities within a port setting, DES models have the capability to derive good insight in identifying the operation bottlenecks and estimating the effect of different operation modifications or introduction of new technologies on important performance metrics like truck turn time (Kotachi et al., 2013). These models allow terminal operators to model various situations in a virtual environment, enabling them to make decisions based on facts about resource usage, process optimization, and technological adoption without affecting actual business.

2.4.2 DES Applications in Maritime Transportation and Port Logistics Optimization

The usage of DES has been supported in numerous case studies of port logistics optimization and shipping transportation as a powerful and versatile instrument for addressing various operation problems (Rusgiyarto et al., 2017). DES has been employed to replicate and optimize operations in various forms of ports, i.e., container ports, bulk cargo ports, and inland container depots (Lakhmas & Sedqui, 2018). Some of these include the application of DES in berth allocation problems where one tries to schedule optimally vessels into available berths to optimize waiting time and maximize throughput (Said et al., 2014). Resource scheduling, such as in the scenario of determining the right amount of quay cranes or yard equipment needed to manage cargo efficiently, is another where DES has been used. Apart from that, DES has been used mainly to handle port congestion, where various methods have been tried to eliminate bottlenecks and enhance ship and landside traffic movement (Bottani & and Casella, 2024). Several studies have also concentrated on applying DES to examine the effects of disruptions and uncertainties, like weather delays or equipment breakdown, on port operations, and gaining insights into system resilience and mitigation strategies (Alagesan, 2017; dos Santos Silva et al., 2011; Neagoe et al., 2021). The wide variety of successful uses of DES in marine transportation and port operations demonstrates its value as an effective method for breaking down complicated operational issues and analyzing the promise of myriad solutions (Srisurin et al., 2022).

2.4.3 Impact of Different Operational Strategies on Port Efficiency

Numerous simulation studies have been conducted to evaluate the impact of various operational strategies on port efficiency and truck turn time using DES. Strategies such as the implementation of truck appointment systems, the extension of gate operating hours, and modifications to yard layout and management have been analyzed using DES models to quantify their effects on congestion and terminal productivity (AbuAisha et al., 2020; Alagesan, 2017; Neagoe et al., 2021). These studies often involve creating a baseline simulation model of the existing port operations and then running various scenarios that incorporate the proposed operational changes. By comparing the performance metrics, such as truck turn time, queue lengths, and resource utilization, across these different scenarios, researchers and terminal operators can gain a better understanding of the potential benefits and drawbacks of each strategy (Alagesan, 2017; Gracia et al., 2025). Simulation modeling also plays a crucial role in optimizing the allocation of resources within a port terminal, such as the number of yard cranes or gate personnel required to handle a given level of traffic efficiently (Bett et al., 2024). Furthermore, DES is a valuable tool for capacity planning, allowing port authorities to evaluate the impact of increased cargo volumes or changes in vessel size on the existing infrastructure and operations, and to identify potential bottlenecks before they occur (Bottani & and Casella, 2024). The empirical evidence generated from these simulation studies provides a strong foundation for informed decision-making by terminal operators seeking to improve their efficiency and reduce truck turn times.

2.5 Using simulation to model truck turn time reduction strategies

Simulation studies in the domain of terminal ports have focused on modeling a wide array of operational processes and conditions that directly or indirectly impact truck turn time. These factors can be broadly categorized into gate operations, yard management, quay crane operations, and traffic flow and external influences.

2.5.1 Gate Operations

A significant portion of research has focused on simulating gate operations to identify and mitigate bottlenecks affecting truck turn time. One key aspect modeled is the pattern of truck arrivals at the terminal gate(Shin et al., 2024). Studies have shown that the distribution of truck arrivals, whether uniform, clustered, or following a specific statistical distribution, can have a substantial impact on gate congestion and waiting times. For example, simulation models have been used to compare the effects of different arrival patterns on average truck turn time(Bett et al., 2024). Another extensively modeled factor is the implementation and optimization of truck appointment systems (TAS). TAS aim to regulate the flow of trucks into the terminal by assigning specific time slots for arrivals, thereby smoothing traffic and reducing congestion. Simulation has been instrumental in evaluating the effectiveness of various TAS designs, determining optimal appointment quotas, and assessing their impact on truck turn time and other performance metrics(Zehendner & Feillet, 2014). Furthermore, the impact of automation and technology upgrades at the gate has been explored through simulation(Alagesan, 2017). For instance, the potential benefits of implementing automated gate systems, which can expedite truck processing, or technologies that allow for in-motion weighing and identification, have been analyzed using simulation models to quantify their effect on reducing truck turn time(Kiani et al., 2010).

2.5.2 Yard Management

Efficient yard management practices are crucial for minimizing the time trucks spend within the terminal yard. Simulation has been widely used to analyze and optimize yard crane scheduling strategies and their impact on truck waiting times (Obasi et al., 2024). Different scheduling algorithms, such as First-Come-First-Served, Nearest-Truck-First-Served, and hybrid approaches, have been modeled and compared using simulation to determine which strategies result in the lowest truck waiting times and the highest yard crane utilization (Riaventin et al., 2024). Additionally, simulation has been employed to evaluate the influence of container storage strategies on the efficiency of truck servicing. The way containers are organized and stored in the yard directly affects the time it takes for yard cranes to locate and load or unload containers from trucks(Cheng et al., 2025). Simulation models can be used to test different stacking rules and storage allocation policies to minimize the number of moves and the travel distances of yard equipment, thereby reducing truck service times(Bett et al., 2024). Internal traffic flow and congestion within the yard are also important factors that have been modeled using simulation. Congestion on internal roadways can cause delays for trucks moving between different operational areas within the terminal. Simulation studies have analyzed traffic patterns, identified bottlenecks in the internal transportation network, and evaluated the effectiveness of different traffic management strategies in improving truck movement and reducing overall turn time(Carboni et al., 2024).

2.5.3 Quay Crane Operations

The efficiency of quay crane operations and their coordination with landside transportation, particularly trucks, play a significant role in the overall terminal performance and can impact truck turn time. Simulation has been utilized to study the coordination between quay cranes and trucks, especially in terms of the timing of container discharge and loading(Said et al., 2014). Models can simulate the process of transferring containers from vessels to trucks and vice versa, allowing for the analysis of potential delays and inefficiencies at this interface(Zeng & Yang, 2009). Furthermore, the impact of quay crane efficiency and scheduling on overall terminal throughput and, consequently, on truck turn time has been evaluated through simulation(S. Qi & Haoyuan, n.d.). Bottlenecks in quay crane operations can lead to delays in the availability of containers for trucks, affecting the entire landside operation. Simulation models can help assess the impact of factors such as the number of quay cranes deployed, their operational speed, and their scheduling on the flow of containers and truck servicing times(Yang, 2012).

2.5.4 Traffic Flow and External Factors

Beyond the internal operations of the terminal, simulation has also been used to model the influence of external factors on truck turn time. The impact of external road traffic on truck arrivals and departures has been analyzed in several studies(Shin et al., 2024). Congestion on roadways leading to the port can cause delays for trucks before they even enter the terminal gates, thus increasing their overall turn time. Simulation models can incorporate data on external traffic patterns and analyze their effect on truck arrival times and the efficiency of gate operations(Bottani & and Casella, 2024a). Additionally, the role of intermodal connections and their influence on truck turn time has been explored through simulation(Toukan & Chan, 2018). The efficiency of the interface between different modes of transport, such as ships, trucks, and trains, can impact the overall flow of cargo through the port(Wang et al., 2023). Delays in vessel arrivals or departures, or inefficiencies in rail operations, can affect the timing and volume of truck traffic at the terminal. Simulation models can be used to analyze these intermodal connections and their potential impact on truck turn time(Stergiopoulos et al., 2018).

2.5.5 Effectiveness of Simulation in addressing Congestion

A significant advantage of utilizing simulation in the context of terminal port operations is its effectiveness in identifying critical bottlenecks that contribute to increased truck turn times (Kiani et al., 2010). By creating a virtual representation of the port's processes and tracking the movement of trucks and containers, simulation models can pinpoint areas where congestion occurs, waiting times are excessive, or resources are underutilized (Y. Qi et al., 2021). For instance, by analyzing queue lengths and waiting times at different stages of the truck's journey within the terminal, such as the gate, the yard, or specific loading/unloading zones, simulation can reveal specific bottlenecks that hinder the smooth flow of traffic (Arango-Pastrana, 2019). The visual and quantitative outputs generated by simulation models, such as utilization rates of equipment and average waiting times at different locations, provide valuable insights for terminal operators to understand the root causes of delays and identify areas requiring intervention(Riches, 2023).

Furthermore, simulation plays a crucial role in optimizing the allocation of resources within the terminal to minimize truck waiting times and enhance overall efficiency(Kotachi et al., 2013). Terminal operators can use simulation models to test the impact of different resource deployment strategies in a controlled environment(Ilati et al., 2014). For example, simulation can be used to determine the optimal number of gate lanes to operate during peak hours to avoid excessive queuing(Kiani et al., 2010). Similarly, the effect of deploying additional yard cranes or adjusting the number of personnel assigned to specific tasks can be evaluated using simulation to identify the resource configuration that minimizes truck waiting times and maximizes the utilization of available assets(Liu et al., 2021). This capability allows terminal operators to make data-driven decisions regarding resource allocation, leading to improved service levels for trucking companies and enhanced operational efficiency for the port(Riaventin et al., 2024).

In addition to highlighting bottlenecks and optimizing resource utilization, simulation is also an good vehicle for testing and validating different operational strategies before their actual implementation (Alagesan, 2017; Im et al., 2021). Simulation models can be employed by terminal operators in order to assess the possible effects of planned changes in operating practices, the adoption of new technology, or policy change, e.g., the introduction of a truck appointment system (Alagesan, 2017). By modeling multiple scenarios and measuring their impact on truck turn time and other applicable KPIs, terminal operators can better see the potential benefits and limitations of any new strategy (Toukan & Chan, 2018; Neagoe et al., 2021). This risk-free environment allows for experimentation and refinement of strategies before committing resources to real-world implementation, reducing the likelihood of costly failures or disruptions.

Table 3 summarizes the key operational strategies in simulation studies and their relative effectiveness in reducing truck turn time. The effectiveness assessment is based on evidence reported in the reviewed literature.

Table 3 key operational strategies modeled in simulation studies

Operational Element	**Description**	**Effectiveness in Reducing Truck Turn Time**
Gate Automation and Technology Upgrades	Automated gates, in-motion weighing, OCR, and other tech improving truck processing speed.	**High:** Reduces processing times and human error.
Yard Crane Scheduling Optimization	Algorithms prioritizing truck service order (FCFS, Nearest Truck, hybrid strategies).	**Moderate–High:** Improves yard throughput and reduces waiting time.

Container Storage Strategies	Improved stacking and storage allocation to minimize crane moves and travel distance.	**Moderate:** Can reduce handling time significantly when well implemented.
Internal Traffic Flow Management	Measures to reduce congestion inside the terminal (dedicated lanes, optimized routing).	**Moderate:** Reduces delays in transit between yard and gates.
Quay Crane Scheduling and Efficiency	Coordination of quay crane operations with truck loading/unloading processes.	**Variable:** Effectiveness depends on vessel schedules and landside synchronization.
External Road Traffic Management	Considering congestion and delays outside terminal gates.	**Variable:** Can be highly impactful but often beyond terminal control.
Intermodal Coordination	Aligning truck operations with rail and vessel schedules.	**Moderate–Variable:** Helps balance flows but often dependent on external actors.

2.6 Autonomous Vehicles

Autonomous Vehicles (AVs) represent a paradigm shift in transportation, relying on a set of advanced technologies to perceive their environment and navigate without direct human intervention (Garikapati & Shetiya, 2024; Graf & Anner, 2021). AV technologies usually involve a sophisticated set of sensors like LiDAR (Light Detection and Ranging), radar, and cameras offering nanosecond details about the surroundings of the vehicle. GPS technology provides accurate location tracking, whereas AI and machine learning algorithms interpret the sensor data and make real-time choices in navigation, avoidance of obstacles, and route management (Willems, 2021). The Society of Automotive Engineers (SAE) has also created a widely adopted classification system with six distinct levels of driving automation, from Level 0 (no automation) up to Level 5 (full automation) (Bergvall & Gustavsson, 2017). These levels offer a common foundation for translating the capability of various AV technologies, with Level 3 being conditional automation, Level 4 being high automation where the vehicle is able to drive all driving scenarios under some conditions, and Level 5 covering full autonomy under all conditions (Othman, 2022).

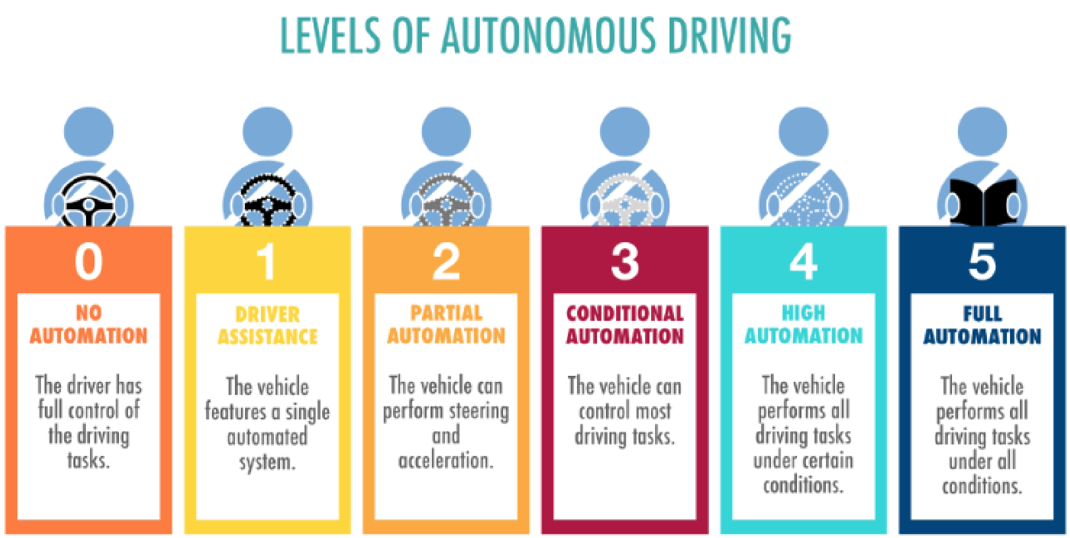

Figure 5 Levels of Driving Automation, SAE International Standard (2021)

The journey of AV research and development spans several decades, and it started as experiments during the 1980s when universities started performing various approaches to automating vehicles (U.S. department of Transportation, 2018). Research in those days was majorly focused on technologies that needed roadway infrastructure or were independent. U.S. Defense Advanced Research Projects Agency (DARPA) Grand Challenges of the 2000s significantly boosted the pace of development of AVs and capability testing (Othman, 2022; Sadaf et al., 2023). Eventually, advancements in sensor technology, computing power, and artificial intelligence drove the industry to the establishment of firms such as Google (Waymo), Tesla, and Volvo as top companies in the development and potential commercialization of autonomous driving technology (Faisal et al., 2019).

The varying autonomy levels should be given consideration when recommending AV solutions for adoption in port settings. Different operational tasks within a port, e.g., long-haul trucking to and from the port versus container movement within the terminal yard, may require different autonomy levels and hence vary as far as infrastructural support and technology leverage are concerned. As an example, autonomous vehicles (Level 4 or 5) may be appropriate for some repetitive tasks in a designated port environment, while partially automated systems (Level 2 or 3) can be used for tasks with some degree of human observation or control (Bergvall & Gustavsson, 2017; Kristoffersson & Pernestål Brenden, 2018).

2.6.1 Autonomous Vehicles and Congestion

Autonomous vehicles (AVs) have emerged as a promising technological solution to alleviate congestion challenges in port environments. Truck congestion within and around container terminals is often driven by unpredictable arrival patterns, inefficient staging processes, human errors in maneuvering, and inconsistent adherence to schedules. AVs' application on the ports can solve these inefficiencies by automation, accurate routing, and round-the-clock functionality without driver fatigue.

Some studies have highlighted the potential of AVs to minimize truck congestion and minimize queuing times at bottlenecks. For instance, Shahedi et al. (2023) showed that autonomous fleets of trucks under optimized scheduling algorithms can smooth arrival patterns at entry gates, minimizing peak congestion by up to 25%. Likewise, Meldert and Boeck (2016) examined Autonomous Terminal Truck (ATT) application in staging and yard regions and found a quantifiable decrease in mean truck turn time through systematic and coordinated vehicle movement.

AVs' effect on congestion is also tied to their integration with real-time data systems, like terminal operating systems and appointment scheduling systems. Dynamic re-assignment of vehicles to shorter-queue-length gates and loading points is made possible by high-level coordination, thus preventing localized congestion and ensuring balanced resource utilization (Willems, 2021). This feature can be particularly beneficial for terminals with extremely volatile truck arrival rates and constrained staging space. Aside from optimizing operations, AVs can help decongest traffic by allowing tighter spacing in queues and smoother maneuvering in confined areas. Autonomous driving technology can execute accurate movements while parking, berthing, and maneuvering yards, minimizing delays due to variability and human error (Sadaf et al., 2023). Whereas autonomous vehicle adoption has potential to alleviate congestion significantly, there must be prudence in appreciating that success overall will be contingent on factors like infrastructure preparedness, regulation, and seamless interoperability of AVs with existing infrastructure (Graf & Anner, 2021). The totality of the evidence suggests, though, that integration of AVs is a feasible means of alleviating congestion and improving throughput for contemporary port terminals.

2.6.2 Applications of Autonomous Vehicles in Supply Chain and Port Operations

The applications of autonomous vehicles are increasingly expanding to other aspects of logistics, like freight transport over long distances, last-mile delivery services, and automation of warehouse infrastructures (Engesser et al., 2023). For freight transport, autonomous trucks have massive potential for increased efficiency and cost savings. These trucks are currently being built with the ability to carry long distances with less human interaction, with the possibility of maximum fuel efficiency and shorter transit times (Engesser et al., 2023). Autonomous trucks would especially be beneficial on long-distance transportation, where constant speeds and reduced requirement of stops can ensure quicker and lower-cost transfer of products (Neuweiler & Riedel, 2017).

In the case of container terminals in general, Automated Guided Vehicles (AGVs) have increasingly been used to transport containers horizontally. AGVs are driverless vehicles which are pre-programmed to transport containers from quayside where ships discharge to storage yards within the terminal (Zou et al., 2022). AGVs usually operate on pre-defined paths via an assortment of different guidance systems, like magnetic tapes or laser, and are often combined with automated stacking cranes to develop highly effective container handling schemes (Thylén et al., 2025). Autonomous Terminal Trucks (ATTs) recently became a more general alternative to the conventional AGVs in port terminals. Based on Autonomous Mobile Robot (AMR) studies implemented in intralogistics, ATTs are more flexible in navigation and can handle variable terminal configurations and operating conditions without the need for fixed infrastructure. This shift to ATT suggests growing demand for autonomous technology that is operational in more dynamic and less organized harbor settings (Meldert & Boeck, 2016).

2.6.3 Benefits of Autonomous Vehicles in Ports: Efficiency, Safety, and Sustainability

The integration of autonomous vehicles into port operations brings with it a range of potential advantages, primarily on the efficiency, safety, and environmental fronts. From the efficiency aspect, AVs, such as autonomous trucks and AGVs/ATTs, have the ability to assist in unintermittent operation without interruption, leading to higher throughput and decreased turnaround time for trucks and ships (Ibiyemi & Olutimehin, 2024). Efficient routing protocols utilized by AVs can also optimize efficiency by reducing travel distance as well as decreasing congestion in the terminal of the port. Security is another applicable advantage because AVs are equipped with state-of-the-art sensor hardware and AI-based decision-making capabilities that minimize human mistakes, which are the leading cause of accidents in extremely risky port environments (Graf & Anner, 2021). By isolating human labor from heavy machinery and automating risky tasks, AVs have potential to build a safer workplace for the port (Zou et al., 2022).

From a sustainability perspective, the adoption of AVs in ports can contribute to a reduction in environmental impact. Optimized driving patterns and the potential for transitioning to electric propulsion systems in AVs can lead to lower emissions of greenhouse gases and other pollutants (Engesser et al., 2023). Furthermore, the improved traffic flow and reduced idling times facilitated by AVs can also contribute to a more sustainable port operation by minimizing fuel consumption and emissions within the port area (Gehlken et al., 2019). The potential for autonomous electric vehicles to operate within ports aligns with global efforts towards environmental sustainability in the logistics sector (Ibiyemi & Olutimehin, 2024).

2.6.4 Challenges and Barriers to the Adoption of Autonomous Vehicles in Port Terminals

Despite the numerous potential benefits, wide-scale implementation of AVs in port terminals is confronted with a number of substantial challenges and hurdles. Among the major technological challenges are maintaining the optimal functioning of AV sensors like LiDAR, radar, and cameras in the typically complicated and dynamic port environment, which could be subject to poor weather conditions like fog, rain, or snow (Shahedi et al., 2023). Regulatory and legal frameworks governing the use of AVs in terms of logistics and ports are still evolving, and uncertainty may hamper large-scale deployment. Cybersecurity and data privacy are also possible issues, as connected and autonomous vehicles are open to cyber attacks that may slow their movement or intrusion of personal data (Durlik et al., 2024; Motunrayo Oluremi Ibiyemi & David Olanrewaju Olutimehin, 2024).

The social and economic impacts of AV adoption, with reference to the likely displacement of the workforce and loss of employment among truck drivers and port workers, is another major hurdle. These issues need to be addressed through retraining programs and through the generation of new occupations related to AV use and servicing if the transition is to proceed successfully (Engesser et al., 2023). Moreover, winning the support of the public and acceptance of AV technology should be achieved to effectively deploy it. This entails a reaction to the public's concern about safety, security, and ethical implications of AI-driven decision-making in autonomous vehicles by being transparent in testing procedures, having high levels of safety demonstration, and focusing on passenger and worker protection in AV design (WEF, 2021).

2.6.5 Adoption Rates and Future Trends of Autonomous Vehicles in Ports

Implementation of full autonomy in ports is, nevertheless, still to take off since very few ports worldwide have adopted autonomous systems. That said, there is an increasing awareness of the benefits AVs can bring to ports, and investments are increasingly being directed to research, development, and pilot schemes worldwide (Zou et al., 2022). Regions like Asia Pacific, and specifically China, are set to drive port autonomous driving technologies adoption as a result of aggressive port infrastructure investment and development towards automation. North America and Europe are also set to experience a substantial rise in the market as a result of upgrading existing port facilities and the mounting demand for operating efficiency and ecological sustainability (Sharma, 2023). As illustrated in figure 6, testing and deployment of autonomous vehicles are concentrated in several hubs across North America, Europe, and Asia

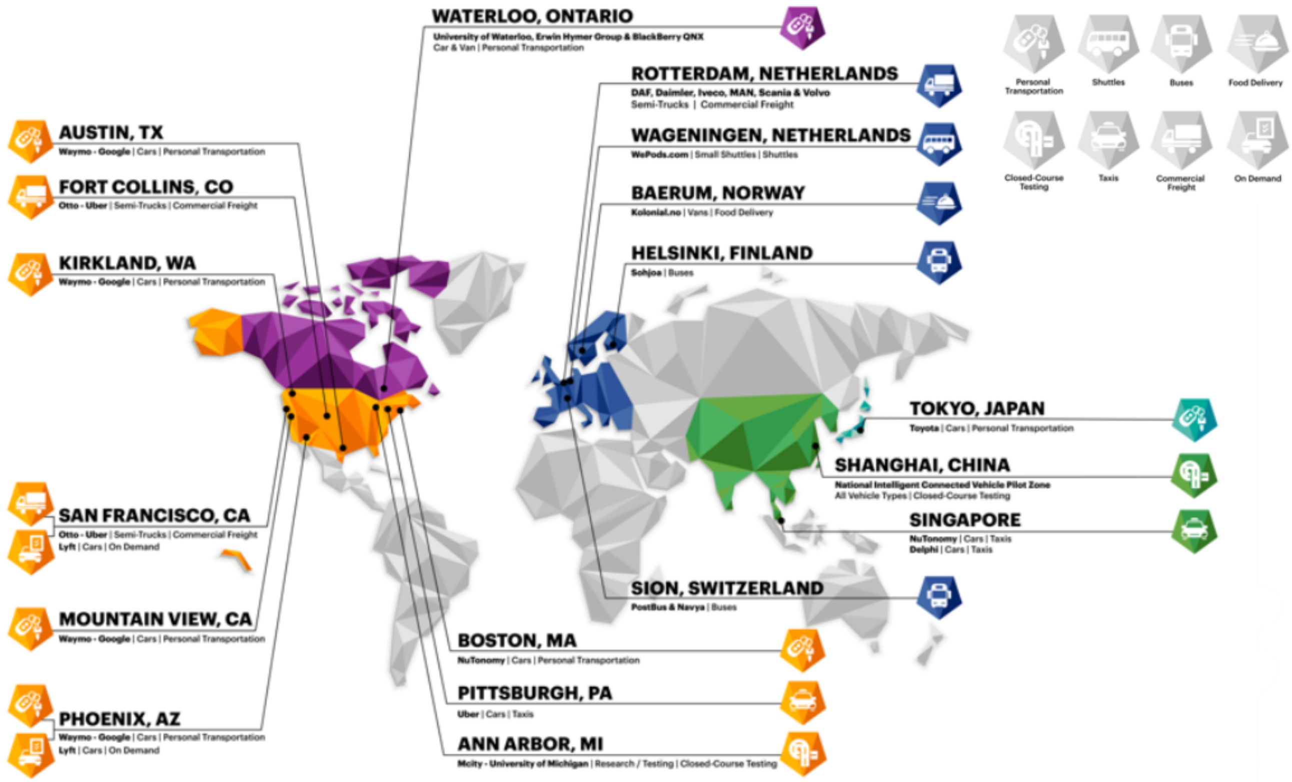

Figure 6 Locations of autonomous vehicle testing and deployment worldwide, Accenture

The projected growth of the autonomous port equipment market is substantial, with forecasts indicating a significant compound annual growth rate in the coming years. Future trends in AV technology for port logistics are likely to focus on advancements in sensor fusion, AI-powered decision-making, and seamless integration with existing port management systems (Riviera News, 2023). Factors such as increasing global cargo volumes, the ongoing shortage of truck drivers, and the imperative to achieve greater operational efficiency are key drivers behind the accelerating adoption of AVs in ports(Hasiri & Kermanshah, 2024). While challenges remain, the trajectory suggests a future where autonomous vehicles play an increasingly integral role in the operation of port terminals worldwide(Graf & Anner, 2021; Zou et al., 2022).

Globally, countries are taking different approaches toward the implementation of autonomous vehicles in freight transportation. The United States has led early experimentation, with companies such as Waymo, Aurora, and TuSimple conducting long-haul AV truck pilots across major interstate corridors. In China, the government has heavily invested in smart port infrastructure and AV logistics, with cities like Shanghai and Shenzhen deploying autonomous trucks in commercial settings. In Europe, countries such as Germany and Sweden have focused on AV integration through strong regulatory frameworks and public-private partnerships, including autonomous freight corridors and platooning trials. Meanwhile, Singapore has invested in developing autonomous truck platoons at the Tuas Port and is exploring full-scale AV integration in port and urban freight. As shown in figure7, Canada, while still in earlier stages of deployment, has initiated AV freight pilots and invested in digital infrastructure, particularly in Ontario and British Columbia, indicating growing interest in using AVs to address congestion and labor shortages in freight logistics.

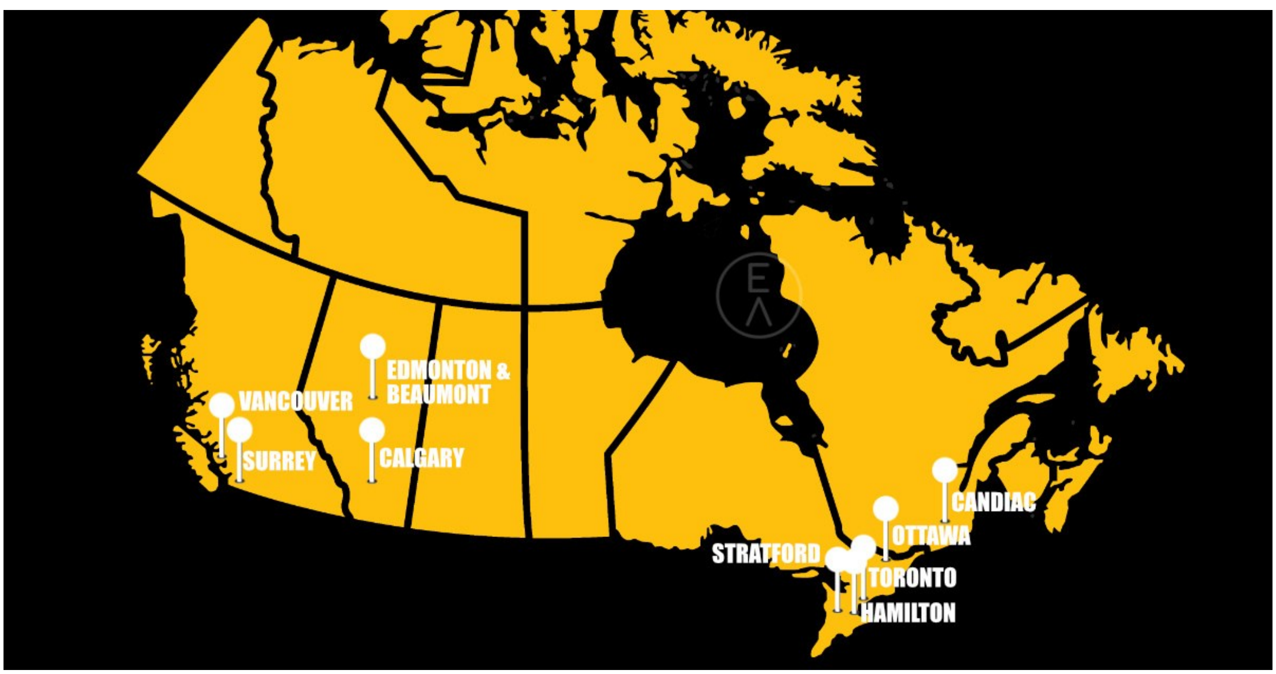

Figure 7 Overview of autonomous vehicle pilot projects across Canada, Electric Autonomy Canada

2.7 The Port of Montreal: Operational Context and Challenges

Strategically located in Eastern Canada, the Port of Montreal serves as a critical gateway to international trade, playing a central position in the regional and national supply chains of North America and Canada. The port receives significant volumes of diversified cargo consisting of containerized products, liquid bulk commodities like petroleum products, and dry bulk cargo like minerals and grains. Its in-built value as an operation is supplemented by the vast consumers' population that it caters to within Canada and the United States and thus constitutes a vital artery for the flow of a diverse range of goods (Port Authority Report, 2025). One of the distinguishing characteristics of the infrastructure of Port of Montreal is that it is situated on an extensive intermodal network, especially on-dock rail directly linking to port terminals and enjoying excellent connectivity with the big rail networks of Canadian National (CN) and Canadian Pacific (CP), offering easy movement of cargo to and from inland markets (Transport Canada, 2021). With its primary role of facilitating trade and economic activity across a wide geographic space, smooth operation at the Port of Montreal is a critical indicator of aggregate supply chain performance and economic competitiveness at the national and regional levels (Port Annual report, 2022). The geographical location of the port can be seen from the figure 8.

Figure 8 Port of Montreal Location

2.7.1 Truck Congestion and Turn Time at the Port of Montreal

The Port of Montreal, like the majority of other prominent international ports, tends to have some truck congestion and associated truck turn times issues, especially when there is a heightened state of operational activity (AbuAisha et al., 2020). The port has a very high truck volume per day, and terminals receive around 2500 trucks in the peak season, thus resulting in serious bottlenecks and delays at entry and exit gates and terminal yards (Alagesan, 2017). Smooth commodity transportation is also affected by the intricacy of intermodal transport within the port, causing congestion not just within the terminal but even in the vicinity as trucks change modes of transportation (AbuAisha et al., 2020). Moreover, some operational or facility conditions at the Port of Montreal, such as terminal design, distance between berth and intermodal transfer point, and effectiveness of handling processes, can cause delays in truck turn times (Spoel et al., 2016). These problems highlight the need for continuous improvement and the creation of new solutions to improve truck operation efficiency at the port. Figure 9 shows the one instance of congestion in Viau terminal on April 3rd, 2025.

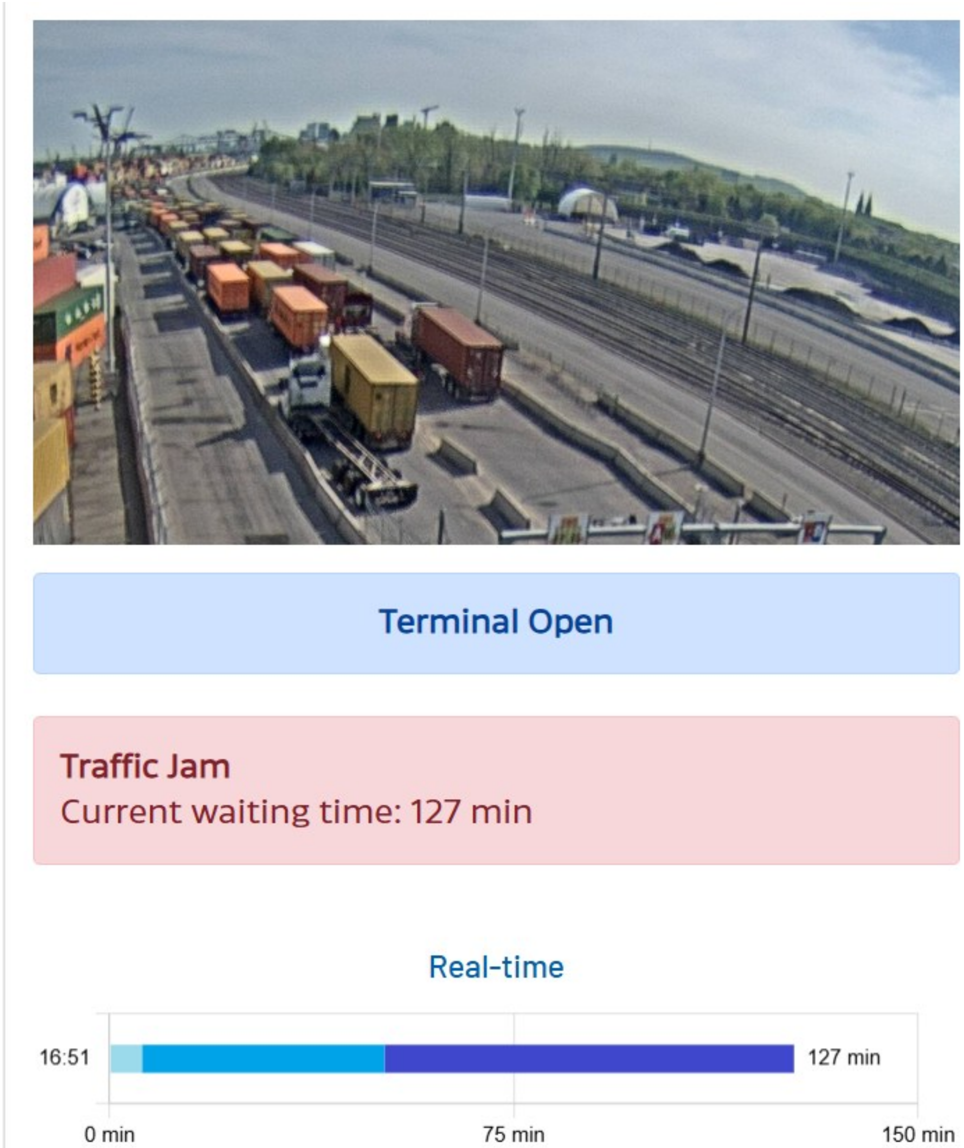

Figure 9 Congestion in Viau Terminal on April 3rd, 2025

2.7.2 Existing Initiatives and Technologies at Port of Montreal

The Port of Montreal has taken proactive measures to introduce many initiatives and technologies to improve its operational efficiency and reduce issues like truck congestion. These initiatives are described as followed:

- **Trucking PORTal and Real-Time Traffic Information:** One of the best examples is the Trucking PORTal application (Figure 10); an internet and cell-based application that gives real-time and predictive insights into truck traffic and waiting times for the port's container terminals. This system enables truckers and dispatchers to more effectively schedule their arrival times and routes through the port, thereby dispersing traffic and reducing congestion.

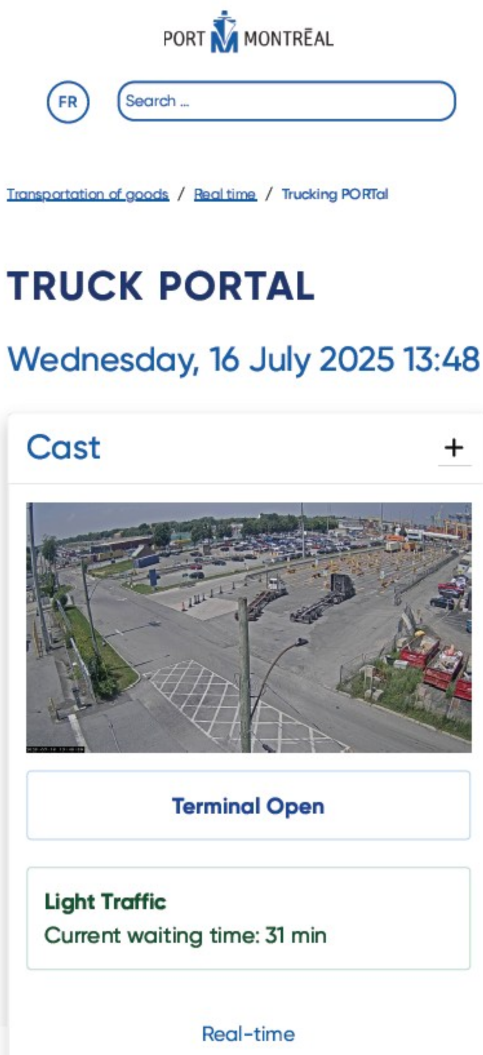

Figure 10 Trucking PORTal of port of Montreal

- **Rail Capacity Enhancement and Intermodal Investments:** The port has also invested heavily in rail capacity enhancement, including building additional tracks as well as upgrading the current rail infrastructure, to enhance the movement of goods transported by rail, which in turn would reduce some of the pressure on truck traffic.

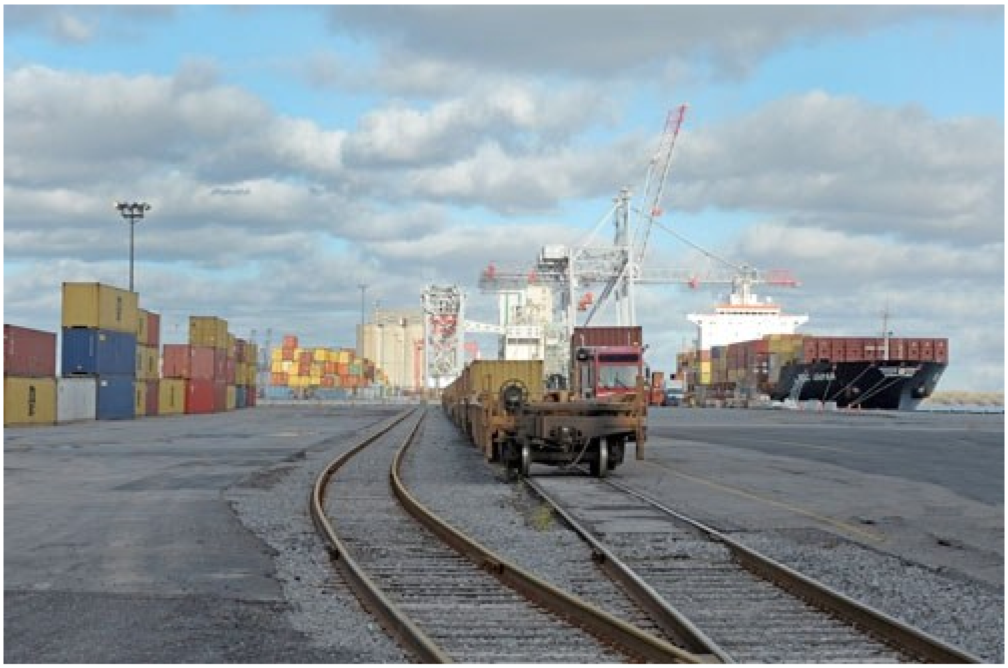

Figure 11 Rail expansion in Viau Terminal, port of Montreal

- **Environmental Responsibility and Sustainability Initiatives:** Beyond operational improvements, the port has advanced several environmental initiatives. Besides individual projects, the Port of Montreal is concentrating its environmental responsibility and sustainability through several efforts that minimize its impact on the environment, including encouraging shore power for ships and advocating cleaner-burning fuel, which can make the port a more efficient and environmentally friendly operation.

Figure 12 Shore power at the Port of Montreal

- **Automation, AI, and Emerging Technologies:** The Port of Montreal is actively exploring and implementing various automation initiatives as part of its strategy to enhance efficiency and competitiveness. These initiatives encompass a range of technologies, including the development of an Intelligent Document Processing (IDP) tool using AI for improved data transparency, the use of augmented reality for infrastructure planning, and the implementation of AI-powered systems for tasks such as detecting defective containers and planning freight trains. The port has also been involved in projects focused on measuring vessel carbon footprint and streamlining the supply chain for critical goods using AI (PortofMontreal, 2020).

Figure 13 Future of port terminals

These latest initiatives indicate the port's dedication to utilizing technology and infrastructural investment to make it a more efficient whole. Various study reports and research studies have been centered on analyzing the operations and problems of the Port of Montreal, e.g., those pertaining to truck congestion and operational efficiency (AbuAisha et al., 2020). The studies used more than one method, e.g., simulation modeling, to examine more than one dimension of port operations. For example, studies have been carried out in using DES in evaluating truck turn time to potentially relieve congestion at the Port of Montreal (Alagesan, 2017). There has also been other academic work on solving the problem of layout optimization at container terminals of the Port of Montreal for maximizing intermodal transportation efficiency and port operations as a whole as a function of variables such as transport cost and emissions (AbuAisha et al., 2020).

In addition, academic research has also considered the broader context of Canadian port efficiency, and the Port of Montreal is a common focus case study (Lei & Bachmann, 2020). Identification and critique of these existing academic works are required in order to grasp the state of the scholarship in the Port of Montreal as well as situate new scholarly activity within this already established context. Table 4 summarize the initiatives and technologies in port of Montreal and their effectiveness in reducing TTT and ultimately congestion.

Table 4 existing initiatives and technologies in port of Montreal

Initiative	**Objective**	**Impact on Truck Turn Time**	**Effectiveness Assessment**
Trucking PORTal & Real-Time Traffic Info	Provide live and predictive data on terminal congestion	Direct impact – Enables drivers to avoid peak congestion periods	High effectiveness – Immediate operational benefits
Rail Capacity Enhancement & Intermodal Investments	Shift cargo volumes from truck to rail to reduce road congestion	Indirect impact – Frees capacity but depends on shipper behavior	Moderate effectiveness – Valuable but slower to realize
Environmental Responsibility & Sustainability	Reduce emissions and improve environmental performance	Minimal direct impact on truck turn time	Low effectiveness – Focused primarily on environmental goals
Automation, AI, and Emerging Technologies	Improve operational efficiency, scheduling, and data transparency	Potentially high impact – Supports faster processing and resource optimization	High effectiveness (long term) – Dependent on implementation and adoption

Notably, there have been specific projects aimed at automating container data capture and tracking at some of the port's major terminals. While the integration of fully autonomous vehicles, particularly autonomous trucks for on-road operations to and from the port, might still be in the early stages of consideration, the port's existing on-dock rail network and its commitment to intermodal efficiency could provide a foundation for exploring the use of autonomous vehicles within the more controlled environment of the terminal itself (Buzinkay, 2023). It is important to consider also, like many major ports, the Port of Montreal has experienced some labor concerns and resistance related to automation initiatives, which will need to be carefully taken into consideration in any plans for autonomous vehicle integration. Understanding the port's current automation trajectory and its openness to technological innovation will be crucial for evaluating the feasibility and potential impact of integrating autonomous vehicles for the specific purpose of truck turn time reduction.

2.8 Research Gaps

The studies that were examined point to the increasing issue of port congestion and the pivotal role that reduction of truck turn time plays in overall port efficiency and supply chain productivity. Self-driving vehicles have been noted as a promising technological development which has the potential to transform logistics operations, providing efficiencies through efficiency, safety, and environmental sustainability in port environments. DES has proven to be an important tool in the case of modeling complex port systems, examining the effect of substitute operational plans, and resource allocation optimization. The Port of Montreal, being a prime contributor to North American trade, also faces particular issues with truck congestion and has already undertaken several initiatives towards optimizing efficiency as well as adopting technological innovation, e.g., automation. Based on the review of literature, following research gaps were identified:

- Despite the vast body of research on autonomous vehicles in logistics, truck turn time in ports, and the application of DES in maritime transportation, there appears to be a gap in the specific investigation of utilizing autonomous vehicles to directly reduce truck turn time at the Port of Montreal.

- While previous research has explored the general feasibility of AVs in port environments and applied DES to simulate truck flows and terminal operations in the Port of Montreal, no study has integrated these two aspects to address this port's unique operational challenges.
- Majority of the papers concentrate mainly on the modeling of yard process, berthing area and not on the movement of trucks in DES.

This thesis is intended to contribute to the existing literature by bridging the above gap and conducting a specific examination of the potential advantages and disadvantages of applying autonomous vehicles to improve truck turn time at the Port of Montreal using DES modeling.

Chapter 3:

Methodology

The chapter begins by presenting the overall research design, followed by a detailed description of the case study context. The conceptual framework underlying the simulation model is then introduced, along with the tools and software used for implementation. The structure of the simulation model and the assumptions made in the modeling process are also explained. Finally, the chapter describes the methods used for model validation and verification.

3.1 Research Design

This study employs a simulation-based research methodology to assess the potential impact of Autonomous Vehicles (AVs) on reducing truck congestion at the Viau Terminal of the Port of Montreal. Given the conceptual nature of AV implementation in port settings, DES is chosen as the primary tool for modeling dynamic system behavior under different scenarios. DES enables the modeling of process flows, resource constraints, and time-based interactions between entities, making it suitable for port terminal operations where queueing, waiting, and service times are critical.

As seen in the flowchart below, there are several steps to have a successful simulation study. It starts with having a clear, precise problem formulation which lead to have a well-defined objective. The increasing truck congestion at the Viau Terminal of the Port of Montreal poses significant operational challenges, including extended truck turnaround times and reduced terminal efficiency. The primary objective of this research is to explore the possibility of various scenarios including integration of autonomous vehicles, in mitigating these challenges through discrete event simulation method.

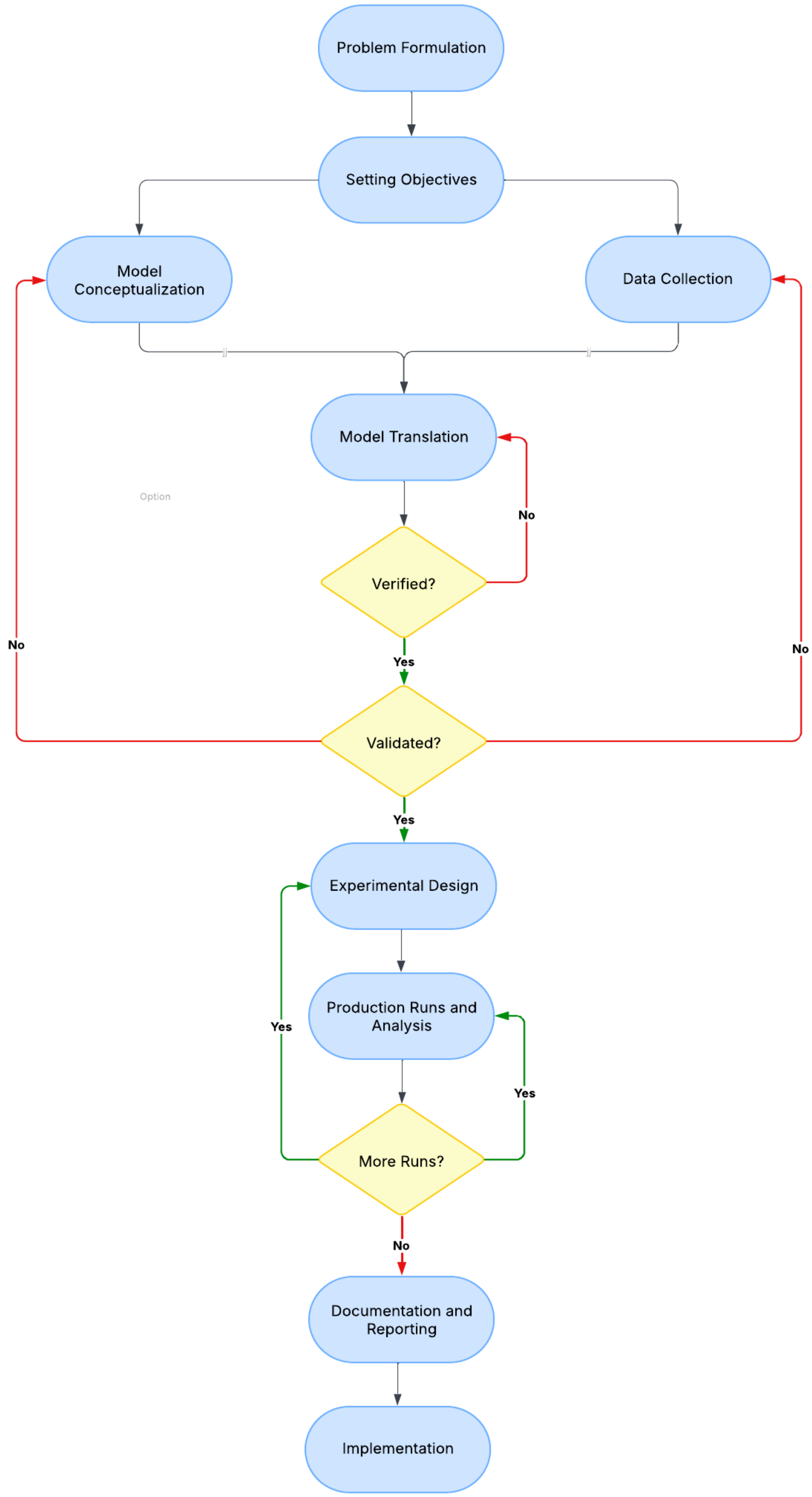

Figure 14 Steps in simulation study, Banks et al., 2010

3.2 Problem Formulation

The major research interest in this study is chronic truck congestion and long truck turn time (TTT) at Montreal's container terminals. Truck congestion causes increased wait times, reduced operating effectiveness, raised transportation cost, and adverse environmental effects through fuel consumption from idling and emission. While past studies have thought about different kinds of congestion-reducing interventions—everything from truck appointment systems and infrastructure improvement to process refinement—little has been done to consider autonomous vehicles (AVs) as a focused intervention to enhance truck turn time in particular at this port.

This is a research problem that results from interaction among terminal assets (e.g., gates, cranes, yard equipment), stochastic truck arrival processes, and heterogeneity of fleets. All these three requirements converge to cause serious operation difficulties in functioning traffic flow maintenance and efficient cargo handling. In an effort to mitigate this problem, there must be a need for one to develop a simulation-based framework to allow one to model and assess the potential benefits and trade-offs associated with integrating autonomous trucks into the port's operations.

3.3 Research Objectives

The following are the objectives of this study that are set to present a systematic solution to the problem that was identified earlier. The primary and secondary objectives are outlined below:

- Primary Objective:

  To investigate the capacity of autonomous vehicles in minimizing truck turn time at the Port of Montreal by creating a DES model with both autonomous and human-operated trucks.

- Secondary Objectives:
  - To conceptualize and model the operational processes involved in truck entry, container handling, and departure within the port terminal.
  - To design simulation scenarios comparing baseline (normal) operation with alternative operations that incorporate different percentages of autonomous vehicles.
  - To explore the impact of autonomous vehicle integration on such critical performance measures as average truck turn time, resource use, and queue lengths.
  - To carry out sensitivity analyses to analyze the impact of variation in penetration rates of AVs, truck arrival rates, and resource deployment on system performance.
  - To give advice to port operators on the feasibility and potential worth of using autonomous vehicles as an anti-congestion policy.

3.4 Input Modelling and Data Collection

Although the simulation model developed in this study is primarily conceptual, real-world data was used to inform model parameters and support validation. Multiple data sources were consulted to better reflect actual operating conditions at the Viau Terminal of the Port of Montreal.

First, truck turn time data was gathered through live access to publicly available port cameras, which provided a visual understanding of truck traffic flow patterns throughout the day. This enabled the identification of peak congestion windows, typically occurring during afternoon (around 13:00–19:00 p.m.) as shown in figure 15 and 16. Port cameras show TTT live consisting of three different parts: port entry waiting time, terminal staging time, and terminal turn time. Terminal turn time can be a little misleading since it is indeed the time trucks spend in the yard area to load and unload containers. It can be justified as the academic terminology is different than the industrial terminology as this time is referred to as "yarding time" or "yard crane operations" in academia.

Figure 15 TTT in Viau terminal, PORTal, 2025

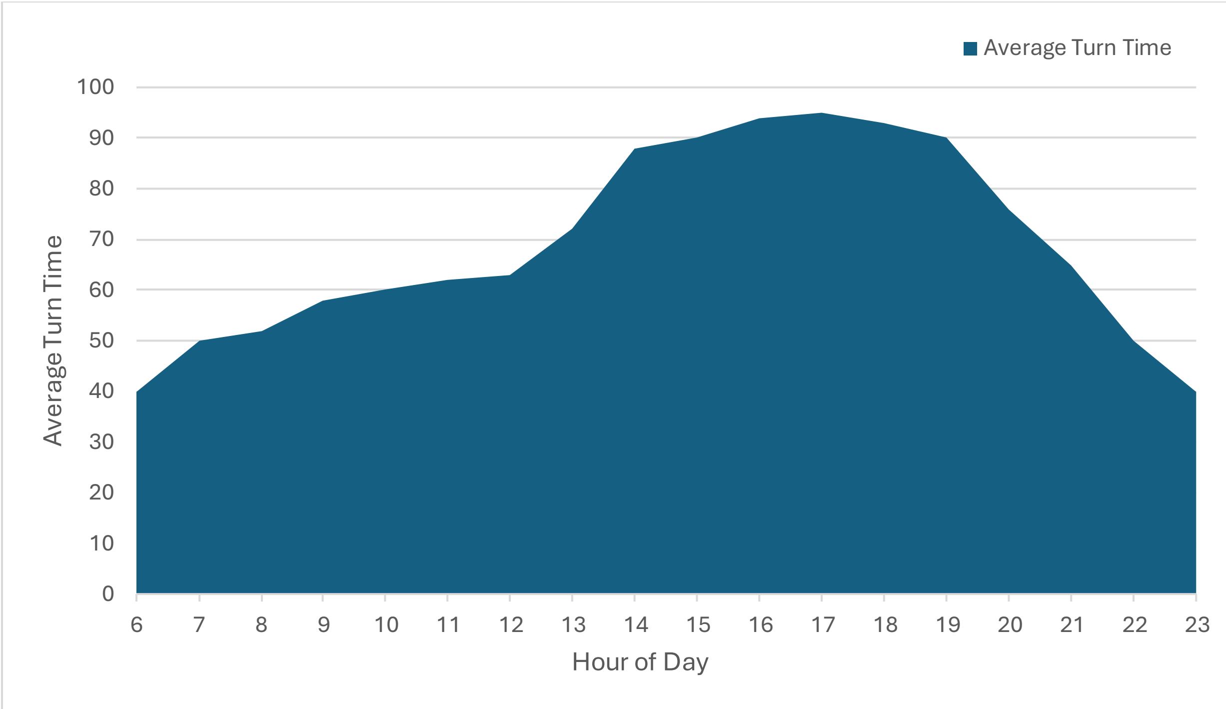

Figure 16 Average TTT during operation hours in Viau terminal

Additionally, operational statistics and documents published on the Port of Montreal's official website were used to estimate average truck turn time (the total time from gate entry to gate exit), along with daily truck volumes and gate processing characteristics including:

- T0, T1, T2, T3 Gate service delay.
- T2 gate paperwork service delay.
- Yard service time.

These values were instrumental in calibrating the simulation inputs and evaluating the realism of the baseline scenario. Where direct figures were not available, estimates were triangulated from prior studies, port authority reports, and related academic sources, ensuring that all key assumptions remained plausible. This data also contributed to the validation of the simulation model, allowing for a qualitative comparison between simulated truck turnaround times and observed real-world behavior. The goal was not to replicate exact figures but to ensure that the system's outputs were within a reasonable operational range, and subsequently lending credibility to the model's conclusions. Table 5 represent the inputs to the model and their distribution:

Table 5 Summary of Input Modelling Parameters

Input Parameter	Description	Distribution / Type
Truck Arrival Process	Arrival pattern of trucks at terminal gate	Poisson Process
Truck Service Time	Time to process a human-driven truck in a gate	Triangular Distribution
Truck Paperwork Time	Time to process an autonomous truck fin a gate	Triangular Distribution
Crane Capacity	Number of container moves handled per hour per crane	Fixed Parameter
Proportion of Autonomous Vehicles	Share of AVs in truck fleet	Fixed Parameter
Yard Service Time	Average time for a truck to move between gate, yard, and quay cranes	Triangular Distribution

3.5 Model Conceptualization

The conceptual model is the real-world depiction of a system or simulation model in the form of a process chart, flowchart, or activity diagram, that aids in understanding workflow and operations. The process flow that aids in the construction of the DES model is defined in this step. The simulation model in this thesis is based on a conceptual port truck flow model adapted from a 2017 study on port operations, with updates to reflect known changes, such as the automation of the truck gate system at the Port of Montreal. The model represents the inbound and outbound truck flow, including entry gates, marshalling yards, and staging areas. Two categories of trucks are modeled: **Human-Driven Vehicles (HDVs)** and **Autonomous Vehicles (AVs)**, which differ in behavior and efficiency attributes. A custom flowchart was developed to visualize the truck handling process from arrival to departure, outlining interaction points and delays. This flowchart served as a foundation for translating the process into DES model in AnyLogic.

How a truck enters the port area and navigates the terminals is described in the process map in figure 17. The trucks first arrive at the port with a T0 gate delay, then there is a T1 delay, staging before their respective terminals, and a T2 gate delay. After that, they enter the yard process, pass through the T3 gate, and finally find their way out.

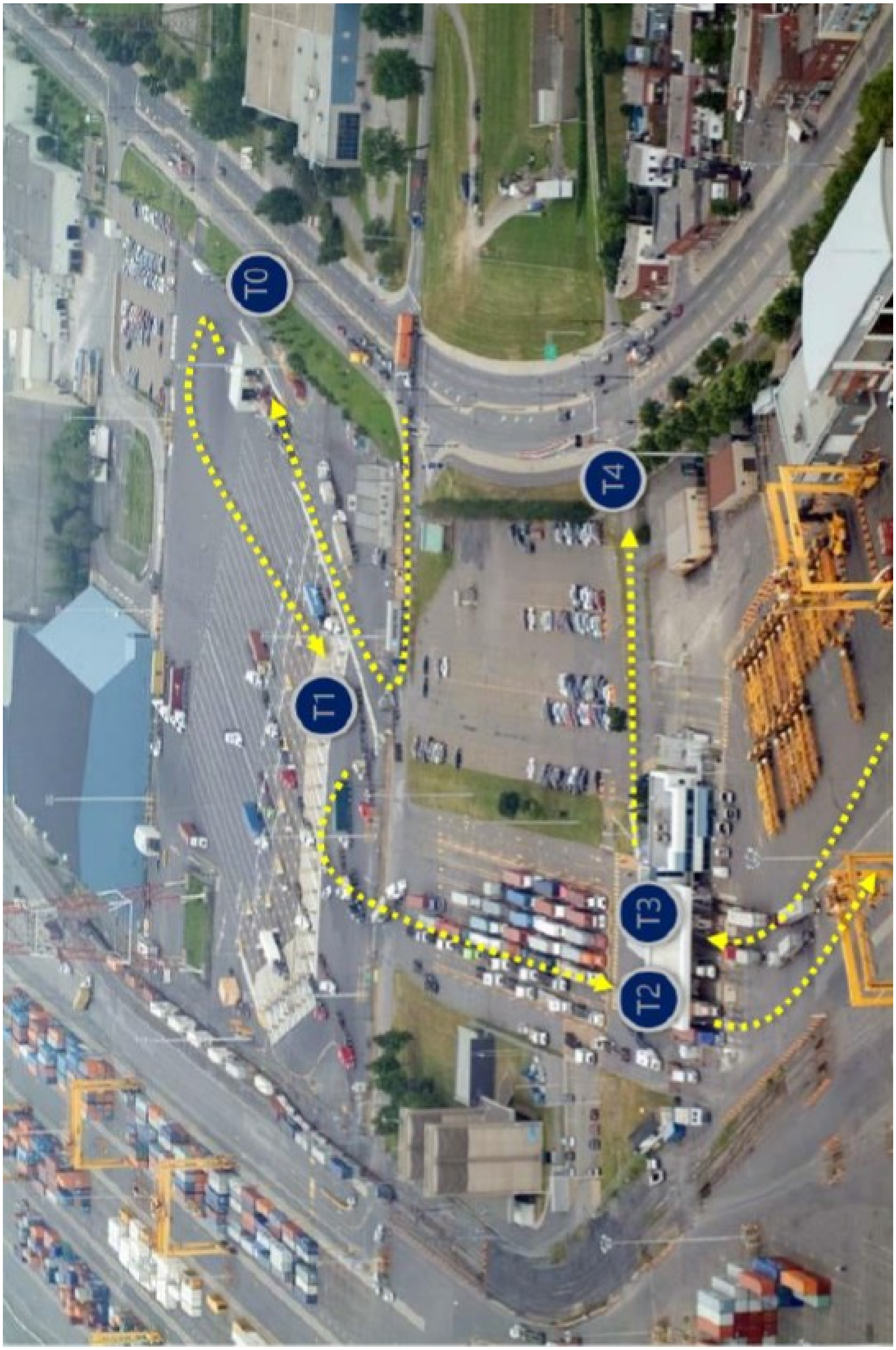

Figure 17 Typical Truck Transaction in port of Montreal, Alagesan, 2017

3.6 Model Structure and translation

Figure 18 displays the full high-level process map for the movements in Figure 17. The process map does not specify the number of lanes at each terminal staging and queuing area. However, it includes the capacity of each processing gates. Table 6 shows the gates names and capacities.

Table 6 Simulation model structure and gate parameters

Process	Resource / Module Name	Resource Capacity
Entry to port through first gate; start of truck turn time recording	T0_Gate	30 resources
Queueing before terminal entry	T1_Queue	30 resources
Entry through terminal gate	T1_Gate	4 resources
Selection of staging area queue before yard processing	T2_Queue	18 resources
Entry through yard processing gate	T2_Gate	2 resources
Yard operations (loading/unloading containers)	Yard Processing	Delay process (duration modeled)
Exit through yard exit gate	T3_Gate	2 resources
Final exit from the port	T4_Gate	N/A

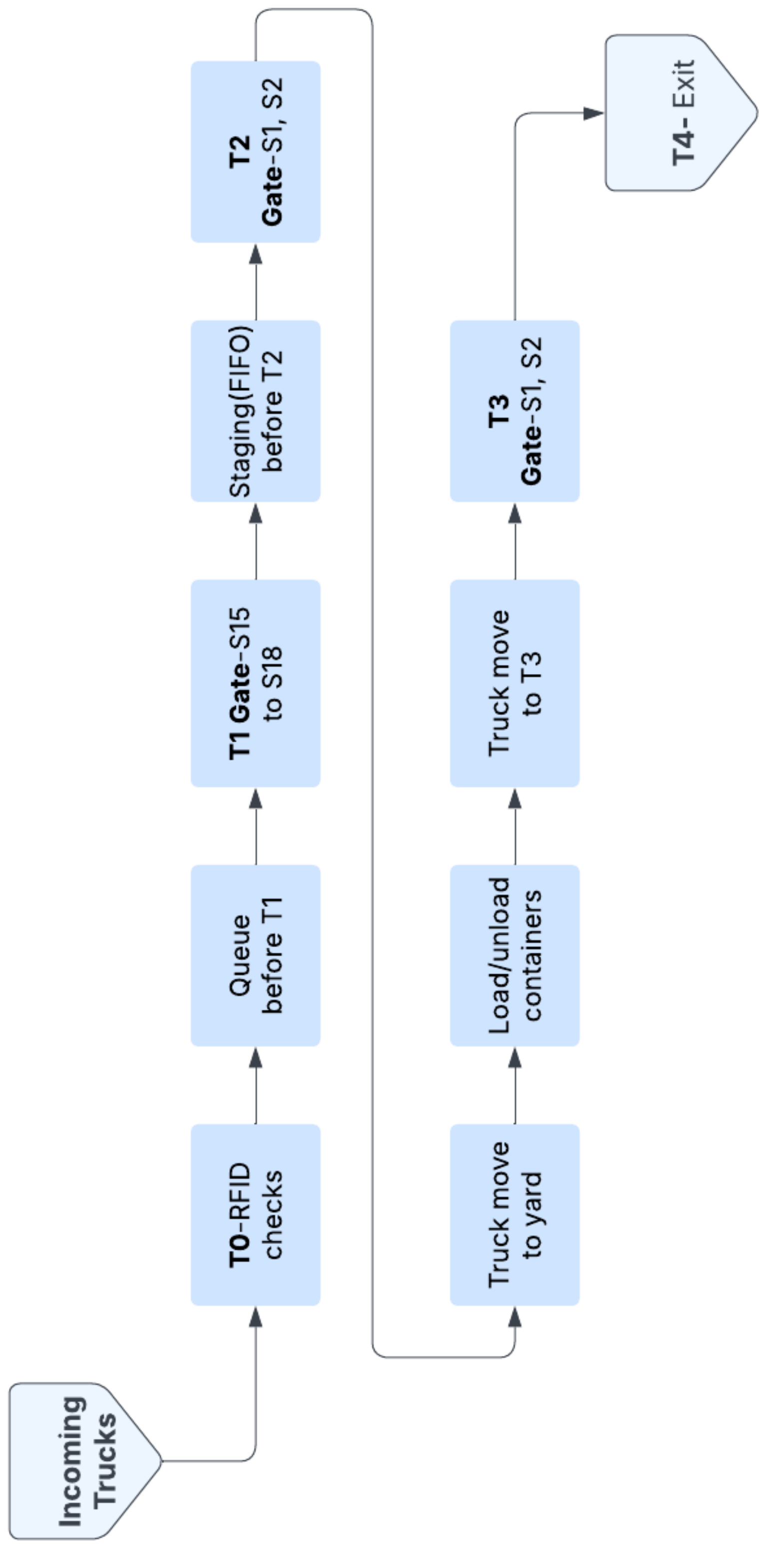

Figure 18 Process Map

The system's process map serves as the foundation for DES modelling. In our model, it specifies how entities move and make decisions. The following is an explanation of this flow:

1. The truck entities are generated all together at once.
2. Then the truck entities are assigned their type, attributes, and their arrival rate.
3. Then the truck entities enter the first gate, T0_Gate. They merge into T0 to enter the port. Truck turn time starts being recorded after this gate.
4. These truck entities then move to the second gate queue. It has 30 resources. It is called T1_Queue.
5. Then the entities enter the T1 Gate for terminal entry. The number of resources for T1 gate in Viau terminal is 4.
6. Then the entity selects the staging area before entering the yard. The entities select the T2_Queue resources which is empty, and the capacity is 18.
7. Once the entities are served at T2_Gate with the capacity of 2, they move into the yard processing where they are delayed for the yard operations (load or unload containers).
8. After the completion of the yard operations, the entities go towards the fourth gating operation T3_Gate to exit the yard with capacity of 2.
9. Before exiting the port, entities move through the time measure module where the entity statistics are recorded such as truck turn time and count.
10. Finally trucks entities go to the dispose module to exit the port which is called T4_Gate.

3.9 Model Verification

To establish that the simulation model behaves as predicted and fits the conceptual model, an actual process of model verification was conducted. The goal was to confirm the internal consistency of agent routing, attribute handling, and system logic under a range of controlled conditions.

First, agent-level flow tracing was used to verify that trucks followed their intended paths. AVs were observed to correctly route through the staging area and seize cranes from the dedicated AV resource pool, while HDVs bypassed staging and used a separate queue and crane pool. Console outputs and internal counters were added to validate that 35% of all trucks were correctly flagged as AVs and handled accordingly throughout the simulation.

Next, extreme condition testing was performed to validate logical responses to atypical inputs. Under 0% and 100% AV arrival scenarios, all trucks correctly followed their respective routes without exceptions. When crane capacities were reduced to 1 or increased to 30, the model displayed expected congestion and flow improvements, respectively. Arrival rates ranging from 0 to 100 trucks per hour triggered expected variations in queue sizes and system saturation without breaking flow continuity.

Statistical outputs such as average turn times and queue lengths aligned with logical expectations across all scenarios. AVs consistently exhibited shorter yard delays and overall turn times than HDVs. No deadlocks, routing errors, or agent starvation were observed, and all agents exited the system properly. As shown in Table 7, the model was also visually inspected using path animations to confirm proper synchronization of gate, queue, and crane resources.

Table 7 Verification results

Component Tested	**Expected Results**	**Model Results**	**Verified**
AVs follow AV staging path	All AVs enter staging area and wait before crane processing	All AVs correctly routed to AV_Staging before Seize	✅
HDVs bypass staging and queue at T2	HDVs skip AV staging and queue directly at T2_Queue	All HDVs routed correctly to T2_Queue	✅

Component Tested	Expected Results	Model Results	Verified
AVs seize only AV cranes	AVs can only seize from AV_Yard_Cranes	Confirmed via console output and logic test	✅
HDVs seize only HDV cranes	HDVs can only seize from HDV_Yard_Cranes	Confirmed via block tracking and utilization monitoring	✅
Turn time increases with higher arrivals	Turn time increases when arrival rate is increased to 70/hr	Avg. turn time rose from 48.4 to 53.2 mins in Scenario 4D	✅
System handles 0% AVs (all HDVs)	All trucks follow HDV path and seize HDV cranes	Confirmed in custom test scenario	✅
Trucks do not get stuck in system	All agents eventually exit within 300 min	No agent trapped or delayed infinitely	✅
Crane utilization at peak	Higher during 70/hr arrivals, lower at 50/hr	Observed crane utilization range: 70%–98%	✅

3.10 Model Validation

Although this thesis relies on a conceptual simulation model rather than real-time operational data, validation was performed to ensure that key model behaviors and assumptions align with known characteristics of the Viau Terminal at the Port of Montréal.

To validate the conceptual simulation model developed for the Viau Terminal at the Port of Montréal, I used real-world observational data collected through terminal camera recordings and public reports on truck turnaround times. While the model was not calibrated using granular, sensor-level datasets, the validation focused on ensuring that key performance outputs, particularly average truck turn time, aligned with known operational metrics at the terminal. The primary data used for validation consisted of observed truck turn times recorded by terminal camera systems at Viau Terminal. These observational logs provided an estimated average truck turnaround time during peak hours of approximately 85–90 minutes under standard conditions, prior to the implementation of a Truck Appointment System (TAS). This range is also consistent with findings from the 2017 MASc thesis by Alagesan, which reported similar performance levels in pre-TAS conditions at the same terminal.

In addition, terminal operating reports and secondary literature were reviewed to confirm typical truck arrival rates and congestion timeframes. Based on these sources, the peak congestion period was identified as 2:00 PM to 7:00 PM, aligning with:

- Afternoon delivery windows for drayage operators
- Import/export processing cycles at nearby distribution centers
- Observed queue growth and dwell time spikes from video review

This 300-minute window (2 PM–7 PM) was therefore used as the standard simulation duration across all scenarios to model the system during its most operationally stressed conditions.

The autonomous vehicle (AV) logic was designed conceptually, with parameters such as lower reaction times, more consistent yard delays, and staging advantages derived from literature on AV performance in structured terminal environments. While the Port of Montréal does not currently deploy AVs, the modeling of their behavior is aligned with practices documented in studies of AV container terminals such as Rotterdam, Singapore, and Tianjin. Table 8 shows the results of the validation of the model.

Table 8 Model validation results

Parameter / Output	Source or reference (Real)	Model Value (Sim)	Alignment
Avg. Turn Time (Baseline)	~85–90 minutes (camera logs, 2017 thesis)	88.2 mins	✅ Close
AV delay reduction	Literature on AV yard operations	-20% delay	✅ Plausible
Avg. Arrival Rate (estimated)	Port activity reports (peak hours)	60/hr	✅ Realistic
Crane pool sizing	Terminal crane capacity info	15 cranes	✅ Reasonable

3.11 Output Analysis

The outputs of the simulation model are presented in table 9. They demonstrate the baseline performance of the Viau Terminal truck operations over the simulation period of 5 hours. A comparison was made between the simulation results and available reference values from historical operational reports and previous studies (e.g., Alagesan, 2017) to validate the plausibility of model behavior.

Table 9 Output results of the simulation modeled

Output Metric	Description	Results
Average Truck Turn Time (minutes)	Total time from port entry to final exit for each truck	88.2

Truck Throughput	Total number of trucks processed by the terminal during the simulation period	144
Queue Size at Terminal Entry Gate (T1_Queue)	Average number of trucks waiting before the terminal entry	3.01
Queue Size at Yard Entry Gate (T2_Queue)	Average number of trucks waiting before the yard entry	12.01
Yard Delay Time (minutes)	Average delay experienced during yard processing (load/unload operations)	64.81
Resource Utilization	Utilization rates of yard cranes	96%

An important modeling simplification affecting turn time is that the model assumes all trucks have identical operational characteristics (size, speed, and acceleration). In practice, the fleet consists of both standard and specialized vehicles with variable maneuvering and processing times, which can cause additional variability in the real system. In the model, this variability was not explicitly modeled, and all trucks were assumed to have homogeneous performance to reduce complexity. Moreover, truck arrival rates were generated based on the average arrival pattern over the modeled period rather than replicating daily fluctuations. This may lead to differences in queue formation and congestion compared to real-world operations, especially during peak arrival intervals. By analyzing the output, it was concluded that there are several factors that affect output:

- **Assumption of Uniform Truck Characteristics:**

  The simulation assumes all trucks are identical in size and operational performance. This simplification reduces model complexity but can underestimate the variability of turn times observed in practice due to mixed vehicle configurations.

- **Fixed Arrival Pattern:**

The arrival rates were modeled as an averaged distribution over the entire period rather than explicitly replicating observed peaks and troughs, which could lead to differences in congestion patterns compared to the actual system.

- **Simplified Resource Availability:**

  Dynamic adjustments in gate and staging capacities that occur in real operations, such as temporarily adding processing lanes or reprioritizing truck flows, were not incorporated into the baseline model.

These modeling decisions were necessary to maintain tractability but should be taken into account when interpreting results. The scenario analysis in Chapter 4 provides comparative outputs under alternative configurations, including the introduction of autonomous vehicles and different yard processing capacities, to evaluate their potential impact on average truck turn times and system throughput.

Chapter 4:

Case Study for Port of Montreal

In this chapter, we discuss the application of the proposed DES model through a case study for Port of Montreal's Viau Terminal. This chapter presents the comprehensive results derived from the DES, evaluating the performance of the Viau Terminal at the Port of Montreal under various operational scenarios. The analysis focuses on key performance indicators (KPIs) such as Average Truck Turn Time (TTT), queue lengths, throughput, and resource utilization. These results provide empirical evidence to assess the effectiveness of a Truck Appointment System (TAS) and the integration of Autonomous Vehicles (AVs) in mitigating port congestion. The findings from each scenario are systematically presented and compared to the established baseline, followed by a detailed discussion of the model's limitations and the broader implications of the results.

4.1 Why Viau Terminal?

The case study selected for this research is the Viau Terminal at the Port of Montreal, one of Canada's busiest and most strategically important ports. This port serves as a critical gateway for international trade, handling more than 35 million metric tons of cargo annually. Its operations are diverse, involving containerized, bulk, and breakbulk cargo, and it plays a key role in supporting the logistics and supply chain systems of Quebec and central Canada.

Figure 19 Viau Terminal, PORTofMontreal, 2025

The Viau Terminal specifically was chosen for this study due to its specialization in container handling and its relevance to truck-based freight flows. It is operated by Termont Montréal since 2016 and has seen increased investment in recent years, including gate automation and expanded yard space. Located in the Mercier–Hochelaga–Maisonneuve borough, it handles approximately 600,000 TEUs and serves as a key gateway for global container flows, primarily via Mediterranean Shipping Company (MSC).

Despite these improvements, truck congestion remains a significant operational challenge, particularly during peak hours when long queues at the gates and staging areas cause delays, reduce efficiency, and contribute to environmental impacts. The truck turn time in Viau terminal is accessible through PORTal of port of Montréal live during operation hours, and as shown in figure

20, there is a high level of congestion in different stages of port operations during different hours of day.

Figure 20 TTT in Viau terminal, PORTal, 2025

As depicted in figure 20, although the port forecasting systems expects truck turn time in Viau terminal to be 50 minutes, but due to different factors in different stages of port operations, it has been increased to 112 minutes. Therefore, this terminal is well-suited for a simulation-based study for several reasons:

- **Operational Complexity**: Viau Terminal features multiple interaction points, including entry gates, inspection areas, staging zones, and yard cranes, making it a suitable environment for modeling DES.
- **Truck Traffic Volume**: As a container terminal, it receives a high volume of truck arrivals and departures daily, especially during operational windows from 6:00 a.m. to 11:00 p.m., making congestion management crucial.
- **Potential for Innovation**: The terminal has already adopted technologies like optical recognition systems and automated gate processes, suggesting openness to further technological innovations.
- **Lack of Real-Time AV Implementation**: While AVs are not yet deployed in this terminal, studying their potential impact through simulation provides actionable insights for future planning and investment.

The selection of Viau Terminal also aligns with the broader goals of this thesis: to assess the feasibility and impact of introducing AVs into existing port infrastructures. By simulating different scenarios—including the current state, a truck appointment system, partial AV adoption, and the use of dedicated AV staging zones—this case study allows for an in-depth exploration of how such technologies could improve throughput and reduce truck wait times at the Port of Montreal.

4.2 Model Parameters and Data Inputs

This section meticulously details all numerical parameters and data inputs used to populate the simulation model, ensuring transparency and reproducibility.

4.2.1 Truck Arrival Patterns and Volumes

The simulation will simulate operations in peak hours, i.e., between 2:00 PM to 7:00 PM, a 300-minute window. This has been selected based on real-world observational data from terminal camera and public reports and corresponding afternoon delivery windows, import/export processing cycles, and queue formation observed at the Port of Montreal. Truck arrivals at a constant rate of 60 trucks per hour is assumed in the baseline scenario. This rate is considered realistic based on port activity reports for peak hours. The model assumes arrival patterns follow a time-dependent schedule, informed by previous studies. While the average rate is fixed, the actual arrival times are modeled using a statistical distribution (poison distribution for inter-arrival times) to reflect the inherent randomness of real-world truck arrivals. This stochasticity is fundamental, as port operations are characterized by random truck arrival times and fluctuating service durations, making DES particularly suitable for analysis. The use of distributions, rather than fixed averages, is critical for accurately capturing the variability that causes queues and delays in real operations. These parameters are shown in Table 10.

Table 10 Simulation parameters and values for truck arrivals

Parameter Name	**Value/ Distribution**	**Unit**	**Source/Justification**
Simulation Time Horizon	300 (2 PM - 7 PM)	Minutes	Peak congestion period/ Port cameras
Average Arrival Rate (Baseline)	60	Trucks/hour	Port activity reports (peak hours)
Arrival Pattern (TAS)	Time-dependent schedule	-	Previous studies
Arrival Distribution	Exponential	-	Reflects stochasticity

4.2.2 Gate Processing Times and Delays

Parameters for gate processing times and associated delays (T0, T1, T2, T3) are derived from operational statistics and documents published on the Port of Montreal's official website. These values were instrumental in calibrating the simulation inputs and evaluating the realism of the baseline scenario. Delays simulated explicitly include T1 Gate Service Delay (arrival at the terminal), T2 Gate Paperwork Service Delay (special paperwork processing), and T3 Gate Service Delay (departure from yard). In order to simulate real-world variability, these service times are most modeled with statistical distributions (e.g., triangular, normal, or exponential distributions) as opposed to determinate values, replicating the stochastic nature of terminal operations. These parameters are shown in Table 11.

Table 11 Simulation parameters and values for gate operations

Parameter Name	Value/ Distribution	Unit	Source/Justification
T1 Gate Service Delay	1	Minutes	Port operational statistics
T2 Gate Service Delay	1	Minutes	Port operational statistics
T3 Gate Service Delay	1	Minutes	Port operational statistics
T2 Gate Paperwork Delay	1.25	Minutes	Port operational statistics
T1 Gate Resources	4	Lanes	Viau Terminal capacity
T2 Gate Resources	2	Lanes	Viau Terminal capacity

T3 Gate Resources	2	Lanes	Viau Terminal capacity

4.2.3 Yard Operations and Service Times

The Yard Service Time parameter represents the duration trucks spend within the yard for loading or unloading containers. This is often referred to as "yarding time" or "yard crane operations" in academic literature. Similar to gate delays, yard service times are calibrated using operational statistics from the Port of Montreal's website and triangulated with prior studies. The efficiency of yard management practices, including container stacking and retrieval strategies, directly influences this service time. These parameters are shown in Table 12.

Table 12 Simulation parameters and values for yard operations

Parameter Name	Value/ Distribution	Unit	Source/Justification
Yard Service Time	triangular (17.5, 27, 40.5)	Minutes	Port operational statistics
Total Yard Cranes	15	Cranes	Terminal crane capacity info
T2 Staging Area Capacity	18	Trucks	Viau Terminal capacity

4.2.4 Autonomous Vehicle (AV) Specific Parameters

In Scenario 3 and 4, Autonomous Vehicles constitute 35% of the total truck arrivals. The model is also designed to allow for sensitivity analysis on this parameter, exploring proportions such as 25%, 50%, and 75% AVs. AVs are assigned inherently lower reaction times compared to HDVs, reflecting their automated decision-making and lack of human physiological limitations, which allows for quicker responses to dynamic conditions within the terminal. AVs are modeled with more consistent (and generally shorter) yard delay durations. This is based on the premise that automated systems can optimize container movement and minimize human error-induced delays, leading to more predictable and efficient operations. The validation section indicates a plausible -20% delay reduction for AVs in yard operations, derived from relevant literature. In Scenario 4, AVs benefit from dedicated staging areas, implying they can be held and released more precisely based on crane availability, further reducing overall wait times. A crucial parameter in Scenario 4 is the dedicated crane allocation: at least 4 out of the total 15 cranes are exclusively reserved for AV processing. This parameter quantifies the infrastructural investment assumed for optimal AV integration. These parameters are shown in Table 13.

Table 13 Simulation parameters and values for AVs

Parameter Name	Value/ Distribution	Unit	Source/Justification
AV Proportion (Scenarios 3 & 4)	35%	% of total trucks	Scenario definition
AV Yard Delay Reduction	-20% (relative to HDV)	%	Literature on AV yard operations

4.2.5 Simulation Time Horizon and Run Length

Each simulation run is set for a 300-minute window (5 hours), specifically from 2:00 PM to 7:00 PM. This duration is chosen to capture the most operationally stressed conditions during peak congestion periods at the Viau Terminal. To account for stochastic variability and ensure statistical significance of results, multiple independent replications will be performed for each scenario. The precise number of replications will be determined during the experimentation phase to achieve desired confidence intervals for the output metrics.

The meticulous detail in parameter calibration, drawing from sources like publicly available port cameras, the Port of Montreal's official website, and prior studies, is crucial. This demonstrates that while the model is conceptual, its design is informed by and reflective of actual operational challenges and characteristics, lending significant credibility to its findings. The conceptual nature applies more to the future scenarios involving AVs, which are not yet deployed, rather than the baseline, which is firmly grounded in real-world observations. This careful grounding makes the subsequent hypothetical AV scenarios more believable and relevant for future planning.

4.3 Performance Metrics for Evaluation

This section clearly defines the key performance indicators (KPIs) that will be measured and analyzed from the simulation outputs. The indicators are closely associated with the research aims of examining the effect of AVs on port efficiency. The utilization of several KPIs represents a sophisticated performance measurement approach. It recognizes that decreasing TTT is not the sole purpose if it is to occur at the cost of other measures, i.e., severely underutilizing resources or introducing new bottlenecks elsewhere. This systems perspective gives a more complete picture of system performance.

4.3.1 Primary Performance Metric: Average Truck Turn Time (TTT)

Truck Turn Time (TTT) is defined as the total time a truck spends within the terminal, from its entry gate (T1) to its eventual exit (T4 dispose module). This is the fundamental metric for assessing terminal port efficiency. The simulation model includes a dedicated "time measure module" where TTT is recorded for each truck entity before its disposal. The average TTT across all processed trucks will be a primary output for each scenario. A reduction in average TTT is the central objective of this thesis, directly addressing the "Growing Challenge of Port Congestion and Truck Turn Time".

4.3.2 Congestion Indicators

The average queue lengths at various critical bottlenecks within the terminal will be measured. This includes queues at the T1 Gate (T1_Queue), T2 Gate (T2_Queue), and the yard processing area. Additionally, average waiting times experienced by trucks at each of these queueing points will be recorded. This provides granular understanding into where delays are most significant. High queue lengths and waiting times are direct manifestations of congestion and contribute significantly to extended TTT. Identifying and quantifying these allows for pinpointing bottlenecks within the system.

4.3.3 Throughput

Throughput is defined as the total number of trucks processed and exiting the terminal within the simulation time horizon (300 minutes) for each scenario. While TTT focuses on individual truck efficiency, throughput measures the overall productivity and capacity of the terminal. Improvements in TTT should ideally correspond with increased throughput, indicating enhanced operational efficiency.

4.3.4 Resource Utilization

The percentage of time that key resources i.e. yard cranes, are busy or occupied will be tracked. Heavy utilization of resources may reflect effective utilization of assets, but very high utilization (e.g., consistently over 90%) can also reflect a bottleneck and impending congestion. Low utilization may, on the other hand, reflect over-resourcing or inefficient flow management. It aids the resource planning optimization.

4.3.5 Yarding Time

Yarding time is the specific duration trucks spend within the yard area for loading and unloading containers. This is a component of the overall TTT. This specific delay is captured within the yard processing block of the simulation. As AVs are specifically modeled with reduced yard delay durations, this metric will directly show the impact of AVs on this critical internal process, distinguishing it from gate delays or external waiting.

The combination of TTT reduction and resource utilization metrics provides critical data for informing investment decisions. For example, if Scenario 4 (special AV cranes) is indicating a very high TTT reduction and very low use of special AV cranes, then it can be an indicator that investment in 4 special cranes for a 25% AV fleet is too expensive. This enables more nuanced discussion of peak resource consumption and infrastructure design in the discussion and results chapters, from easy "does it work?" to "is it cost-effective and efficient?" that is at the heart of valuable practical recommendations for port authorities.

4.4 Scenario Outputs

To assess the impact of truck appointment systems (TAS), autonomous vehicles (AVs), and AV-focused infrastructure strategies on port congestion, four simulation scenarios were developed. Each scenario builds upon the previous one to incrementally introduce congestion mitigation strategies. The scenarios were chosen to reflect both current operational realities and proposed near-future interventions that are relevant to the Port of Montréal's Viau Terminal.

4.4.1 Output of baseline scenario

The baseline scenario (Scenario 1) describes the existing operational situation of the Viau Terminal with no integrated advanced Truck Appointment System (TAS) or Autonomous Vehicle (AV) implementation. The baseline scenario is used as the control group to determine the effect of follow-up interventions. The simulated outcome for the baseline scenario, at 300-minute peak operational time and 60 trucks per hour average rate of arrival, showed severe congestion.

Table 14 Scenario 1 Results

Scenario	**Average TTT (minutes)**	**T1 Queue Size**	**T2 Queue (Staging) Size**	**Yarding Time (minutes)**	**Throughput (Trucks)**	**Yard Resource Utilization**
Scenario Baseline	88.2	3.01	12.01	64.81	144	96%

As shown in Table 14, the average Truck Turn Time (TTT) of baseline Scenario was 88.2 minutes. This aligns closely with real-world observational data from terminal camera systems and prior studies, which reported average TTTs of approximately 85-90 minutes under similar conditions. This validation confirms the model's ability to accurately represent the existing operational challenges.

Analysis of congestion indicators showed substantial queue lengths and waiting times, particularly at the T2-Queue (staging area before yard operations), with an average size of 12.01 trucks, and within the yard processing area, indicated by a high Yarding Time of 64.81 minutes. These two points emerged as the primary bottlenecks, consistent with observations from port camera data. T1-Queue, with an average size of 3.01, is another congestion indicator which happens in the entry to the terminal. The unmanaged, continuous arrival of trucks led to unpredictable surges in demand, overwhelming the fixed capacities of these critical resources.

The throughput for the baseline scenario was 144 trucks, observed to be lower than optimal, directly constrained by the extended TTT and the inability of the system to efficiently process trucks during peak demand. Yard Resource Utilization was 96%, which, while seemingly high, was often indicative of congestion rather than efficient flow, as cranes were frequently occupied, but trucks were still experiencing long wait times due to upstream bottlenecks. The high TTT and significant queuing underscore the urgent need for intervention to improve efficiency and reduce operational costs at the Port of Montreal.

4.4.2 Output of scenario-2 (TAS systems)

Scenario 2 introduced a simplified Truck Appointment System (TAS) as the sole intervention, aiming to regulate truck arrivals and smooth out demand peaks. This scenario maintained all other parameters from the baseline, including the absence of AVs and shared yard crane resources.

Table 15 Scenario 2 Results

Scenario	Average TTT	T1 Queue Size	T2 Queue (Staging) Size	Yarding Time	Throughput (Trucks)	Yard Resource Utilization
Scenario 2-TAS	78.37	0.38	11.83	52.44	171	96%

As shown in Table 15, TAS implementation reduced Average Truck Turn Time (TTT) sharply to 78.37 minutes. This is improved compared to the baseline of 88.2 minutes, which shows that the appointment scheduling was sufficient to manage demand. The TAS was able to handle the uneven arrival patterns, and therefore there was more even truck flow into the terminal.

Congestion metrics such as T1 Queue Size were significantly enhanced to 0.38 trucks from 3.01 in the base line. This shows that TAS was good at controlling truck arrival at the first gate. T2 Queue (Staging) Size remained high at 11.83 trucks, showing that although TAS enhanced entry flow, the internal staging area prior to yard operation still had significant queuing. Noticeably, the Yarding-Time was reduced to 52.44 minutes, reflecting more effective utilization of yard resources as a result of smoother arrivals.

Scenario 2 throughput was 171 trucks, showing that by regulating arrivals, the terminal would be able to handle more trucks over the same 300 minutes. Yard Resource Utilization was still 96%, but the system itself was more efficient since even arrival patterns left it with some space to schedule loading/unloading operations, minimizing idle time caused by random truck queues. This scenario confirms that even a basic TAS can yield substantial operational benefits by improving flow predictability and reducing congestion at critical junctures.

4.4.3 Output of scenario-3 (AV integration)

Scenario 3 built upon Scenario 2 by integrating Autonomous Vehicles (AVs) into the truck fleet, comprising 35% of total truck arrivals, while maintaining the TAS and existing shared yard crane resources. This scenario aimed to quantify the benefits of AVs when operating within the same infrastructure as Human-Driven Vehicles (HDVs).

Table 16 Scenario 3 Results

Scenario	**Average TTT**			**T1 Queue Size**	**T2 Queue (Staging) Size**	**Yarding Time**		**Throughput (Trucks)**	**Yard Resource Utilization**
	Total	**AV**	**HDV**			**HDV**	**AV**		

Scenario 3-AV Integration	55.91	45.33	61.62	0.35	4.81	39.64	29.54	223	97%

As shown in Table 16, the average Truck Turn Time experienced a further significant reduction, dropping to 55.91 minutes. This improvement over Scenario 2 (78.37 minutes) highlights the inherent efficiencies brought by AVs. Specifically, the AV turn time was 45.33 minutes, significantly lower than the HDV turn time of 61.62 minutes. This clear differentiation in performance underscores the advantages of AVs, attributed to their reduced reaction times, more consistent yard delay durations (modeled with a 20% reduction), and faster acceleration and speed. The T1 Queue Size remained low at 0.35 trucks, consistent with the continued effectiveness of the TAS. The most notable improvement in this scenario is T2-Queue size. It was reduced to 4.81 trucks on average indicating that AVs with their inherent efficiencies, can decongest bottlenecks in terminals. Although there was a 59% improvement in staging area bottleneck, this suggests that while AVs are faster once they seize a resource, their queuing behavior in a shared environment can still be a bottleneck. The Yarding Time HDV was 39.64 minutes, while the Yarding Time for AVs was 29.54. These results were expected as AVs are faster in transiting in yard area, faster once they seize and release a resource, and have a lower error rate in comparison to HDVs.

Throughput continued to increase to 223 trucks, reflecting the combined positive impact of TAS and the introduction of more efficient AVs. Yard Resource Utilization increased slightly to 97%, indicating a higher demand on the shared crane pool. This scenario demonstrates that even without dedicated infrastructure, the integration of AVs can significantly enhance terminal efficiency, particularly for the autonomous fleet itself, though shared resource contention can still lead to unexpected queuing for AVs.

4.4.4 Output of scenario-4 (Separate staging area for AVs)

Scenario 4 represents the most advanced intervention, combining the Truck Appointment System (TAS) with a 35% AV integration and significant infrastructure modifications: dedicated staging areas for AVs and a partitioned yard crane allocation (4 cranes for AVs, 11 for HDVs). This scenario was designed to explore the maximum potential for TTT reduction through optimized AV handling.

Table 17 Scenario 4 Results

Scenario	Average TTT			T1 Queue Size	T2 Queue (Staging) Size		Yarding Time		Throughput (Trucks)	Yard Resource Utilization
	Total	**AV**	**HDV**		**HDV**	**AV**	**HDV**	**AV**		
Scenario 4-AV + Staging Area	57.13	32.86	70.20	0.48	3.01	2.88	54.68	19.88	224	95%

The simulation results for Scenario 4, as detailed in Table 17, demonstrated a complex impact on terminal efficiency. The Average Truck Turn Time (TTT) for the entire system was 57.13 minutes. While this is an improvement over the baseline (88.2 minutes) and Scenario 2 (78.37 minutes), it is unexpectedly higher than Scenario 3 (55.91 minutes). This counter-intuitive result warrants further discussion in Section 5.6.

A closer examination reveals that the impact on AVs was particularly pronounced and positive: AV TTT dropped significantly to 32.86 minutes, representing the lowest AV TTT across all scenarios. This is a substantial improvement from Scenario 3's AV TTT of 45.33 minutes. This benefit is directly attributable to the dedicated staging area for AVs and the reserved crane allocation. The T2-Queue (Staging) size for AVs was drastically reduced to 2.88 trucks, an approximately 50%

improvement, and Yarding Time AV was 19.88 minutes, both indicating highly efficient and virtually unobstructed flow for autonomous vehicles within the terminal.

In this scenario, 35% of trucks were designated as autonomous vehicles (AVs) and assigned to a separate staging area and a dedicated subset of cranes (4 out of the total 15 cranes). The remaining 11 cranes and staging area were reserved exclusively for human-driven vehicles (HDVs). This configuration was designed to evaluate whether physical and operational segregation of AVs would enhance their performance and reduce overall congestion. The HDV turnaround time increased to 70.20 minutes in Scenario 4, which is remarkably higher than the HDV turnaround time of 61.62 minutes in Scenario 3. This suggests that while dedicating resources to AVs greatly benefits the autonomous fleet, it may come at the expense of HDV efficiency if the remaining shared resources (11 cranes for HDVs) become more constrained. The T2-Queue (Staging) size for HDVs was 3.01 trucks, and Yarding Time HDV was 54.68 minutes. This outcome is consistent with principles observed in queueing systems and resource allocation studies. By dedicating cranes and staging infrastructure to Avs The effective processing capacity available to HDVs was reduced (from 15 cranes shared to only 11 cranes), even though the total truck arrival rate remained constant. Also, the variability inherent in human-driven truck arrivals and processing times was no longer smoothed by the more predictable AV flows sharing the same resources and thus, HDVs had to wait for longer queues and spend more waiting and yarding times. Throughput was still high at 224 trucks, a modest rise from Scenario 3, which showed the ability of the terminal to handle large numbers of trucks. In general, the system throughput was enhanced, but non-uniformly, and at the cost of AV operation at the expense of HDV performance. This finding suggests that, in practice, dedicated infrastructure for AVs can produce operational gains for the AV fleet but at the cost of degrading service for human-driven vehicles unless compensatory capacity adjustments are implemented.

This scenario clearly illustrates that a synergistic approach, combining demand management (TAS), advanced vehicle technology (AVs), and targeted infrastructure investment, yields the most significant improvements in port operational efficiency and truck turn time for the AV fleet, but careful consideration of resource partitioning is needed to avoid negative impacts on the HDV fleet.

4.5 Sensitivity Analysis

To present a comprehensive analysis of simulation model robustness and determination of most significant operational parameters influencing truck turn time (TTT), sensitivity analysis was done. The analysis took the one-at-a-time (OAT) procedure where each significant input parameter was altered alone while keeping all other parameters constant at base-case values. The message-case scenario, as per Scenario 3, has a hypothetical level of 35% adoption of Autonomous Vehicle (AV), 15 yard cranes, and a truck arrival rate of 60 trucks per hour. The systematic structure provides for comfortable understanding of the standalone impact of every variable on the performance measures of the system, most importantly the system's overall TTT, AV TTT, and Human-Driven Vehicle (HDV) TTT.

4.5.1 Sensitivity to Autonomous Vehicle (AV) Proportion

The share of Autonomous Vehicles (AVs) of the total truck fleet was also recognized as one of the significant parameters affecting terminal efficiency. To estimate its effect, the share of AVs was experimented with at 25%, 35% (base-case), 50%, and 75% of overall truck arrivals as presented in Table 18 and graphically in Figure 21.

Table 18 Sensitivity of Truck Turnaround Time to % of Autonomous Vehicles

% of AVs	Mean TTT (minutes)	AV TTT (minutes)	HDV TTT (minutes)	Observations
25%	66.83	58.04	69.76	Lower AV share increases congestion.
35%	55.91	45.33	61.62	Reference scenario.
50%	41.51	33.66	49.37	Moderate improvements in flow.
75%	23.48	20.22	33.27	Substantial reduction in turn time.

As observed in table 10, increasing the share of AVs consistently led to a reduction in Mean TTT. At 25% AV adoption, the Mean TTT was 66.83 minutes, significantly higher than the base-case 35% AV adoption (55.91 minutes). The trend continued, with a steep decline to 23.48 minutes when AV penetration increased to 75%. This improvement in performance is due to the inherent efficiency of AVs, such as their reduced reaction time, more stable yard delay times, and greater acceleration and velocity, leading to greater predictability and improved resource utilization in the terminal. The remarkable discovery is the non-linear character of these gains with more steep rises as the ratio of AV grew over 50%. In addition, the analysis revealed a positive spillover effect: as the AV ratio grew, not only did AV TTT diminish (from 58.04 minutes for an AV ratio of 25% to 20.22 minutes for an AV ratio of 75%), but HDV TTT decreased significantly as well (from 69.76 minutes for an AV ratio of 25% to 33.27 minutes for an AV ratio of 75%). This can be due to decreased overall system congestion. As more of the efficient AVs are available, the common facilities experience less contention, and hence, faster queues and steadier flow for HDVs as well. This outcome points out that the benefits of AV integration do not only happen at the autonomous fleet level but also accrue to the overall terminal ecosystem as well.

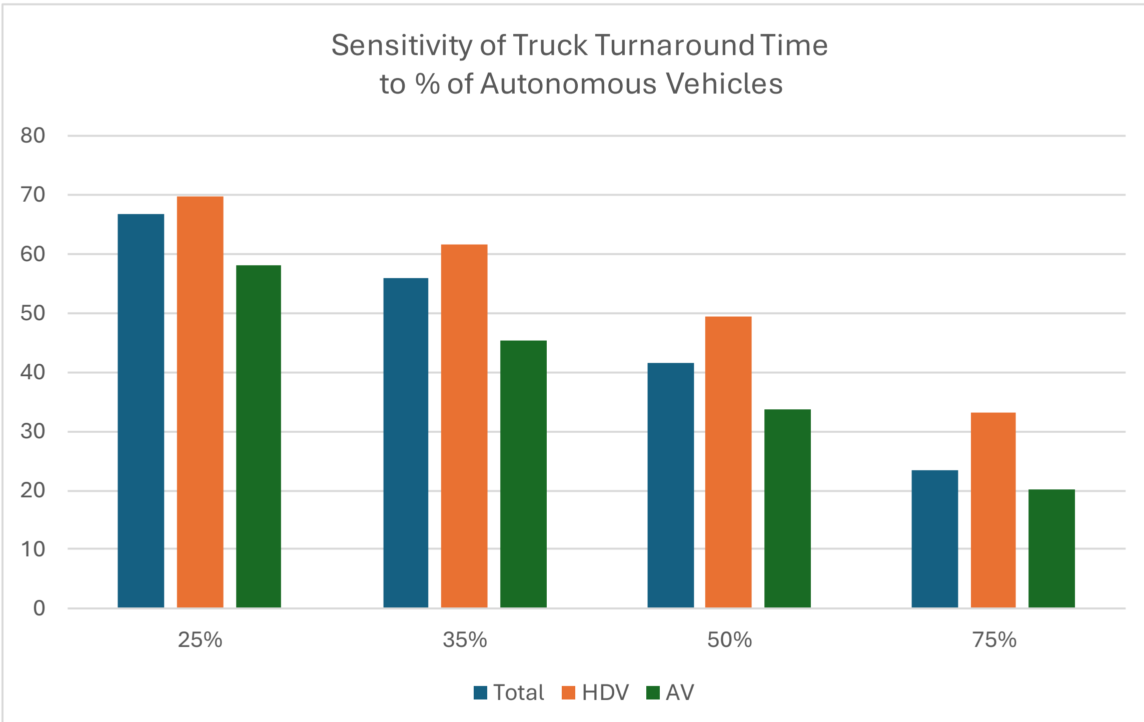

Figure 21 Sensitivity of Truck Turnaround Time to % of Autonomous Vehicles

4.5.2 Sensitivity to Crane Capacity

The availability of yard cranes, a critical resource for container loading and unloading, was investigated for its impact on TTT. The total number of cranes was varied from 12 to 21, with the base-case set at 15 cranes (Table 19, Figure 22).

Table 19 Sensitivity of Turnaround Time to Crane Capacity

Number of Cranes	Mean TTT (minutes)	AV TTT (minutes)	HDV TTT (minutes)	Observations

12	76.76	69.71	80.56	Lower capacity significantly worsens congestion.
15	55.91	45.33	61.62	Reference scenario.
18	35.77	25.23	41.46	Additional cranes reduce queues.
21	29.18	17.88	35.27	High capacity alleviates bottlenecks.

The outcomes easily prove that crane capacity plays a big role in system performance. Reducing crane capacity from the base level of 15 to 12 cranes caused Mean TTT ballooning significantly to 76.76 minutes, which proves that reduced capacity badly aggravates AV and HDV congestion. In contrast, increasing the number of cranes to 18 and 21 gave considerable reductions in Mean TTT to 35.77 minutes and 29.18 minutes, respectively. This underscores that more cranes substantially eliminate queues and congestion at the processing yard phase. The proportionate elimination of both AV TTT and HDV TTT with added crane capacity further underscores the value of this resource for overall terminal fluidity. This finding underscores that even with advanced technologies like AVs, sufficient infrastructure investment in critical resources like cranes remains paramount for optimizing port operations.

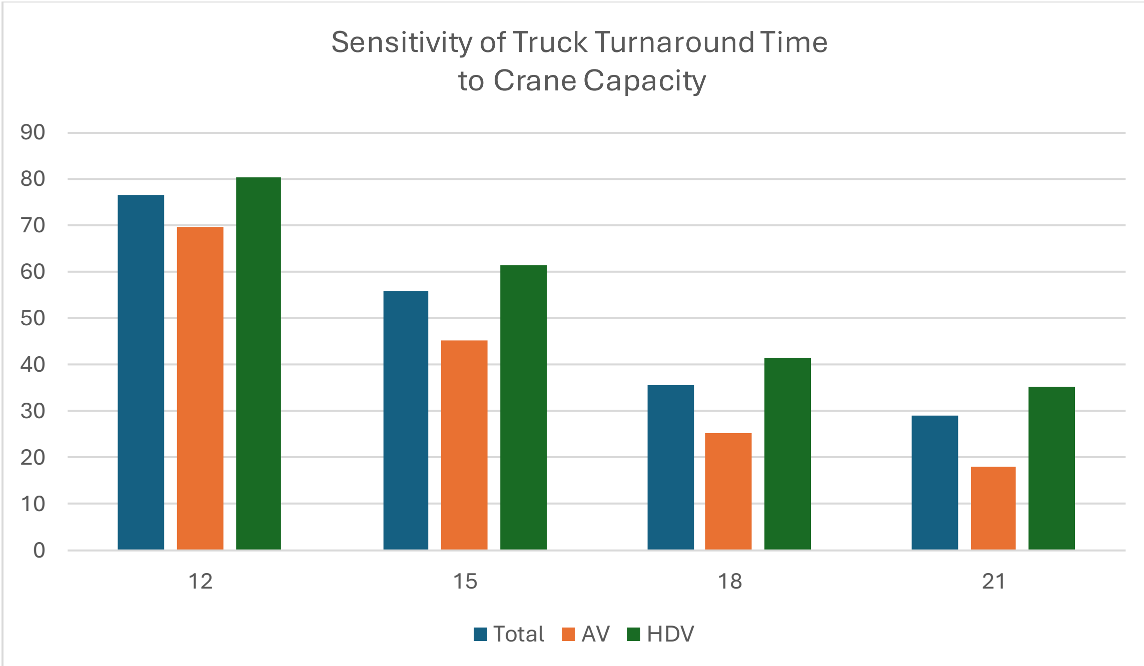

Figure 22 Sensitivity of Turnaround Time to Crane Capacity

As shown in figure 22, crane availability strongly impacts system performance. Increasing crane capacity reduces turnaround times substantially, while reducing crane numbers leads to sharp increases in delays.

4.5.3 Sensitivity to Truck Arrival Rate

The impact of fluctuating truck arrival rates on TTT was analyzed by varying the hourly arrival rate from 50 trucks to 80 trucks per hour, while the base-case is 60 trucks per hour (Table 20, Figure 23).

Table 20 Sensitivity of Turnaround Time to Truck Arrival Rate

Arrival Rate (trucks/hour)	Mean TTT (minutes)	AV TTT (minutes)	HDV TTT (minutes)	Observations

50	31.12	20.70	36.74	Lower arrival rate improves flow.
60	55.91	45.33	61.62	Reference scenario.
70	74.13	64.45	79.35	Higher congestion.
80	87.44	77.88	92.59	Severe delays due to overloading.

The simulation results clearly show truck turnaround times growing exponentially with rates of arrival over the processing capacity of the system. At a lower rate of 50 trucks per hour, Mean TTT was much less at 31.12 minutes, which clearly proves that lower demand clearly enhances flow. Yet, under higher arrival rates of 70 and 80 trucks per hour, the Mean TTT ballooned to a high 74.13 minutes and 87.44 minutes, respectively. This sharp increase in TTT for HDVs and AVs under high arrival rates emphasizes the pressing need for effective demand management measures, like the Truck Appointment System (TAS). In the absence of proper control on incoming truck flows, even the efficiencies brought about by AVs and dedicated infrastructure may be consumed and be highly negatively impacted by system overloading caused delays.

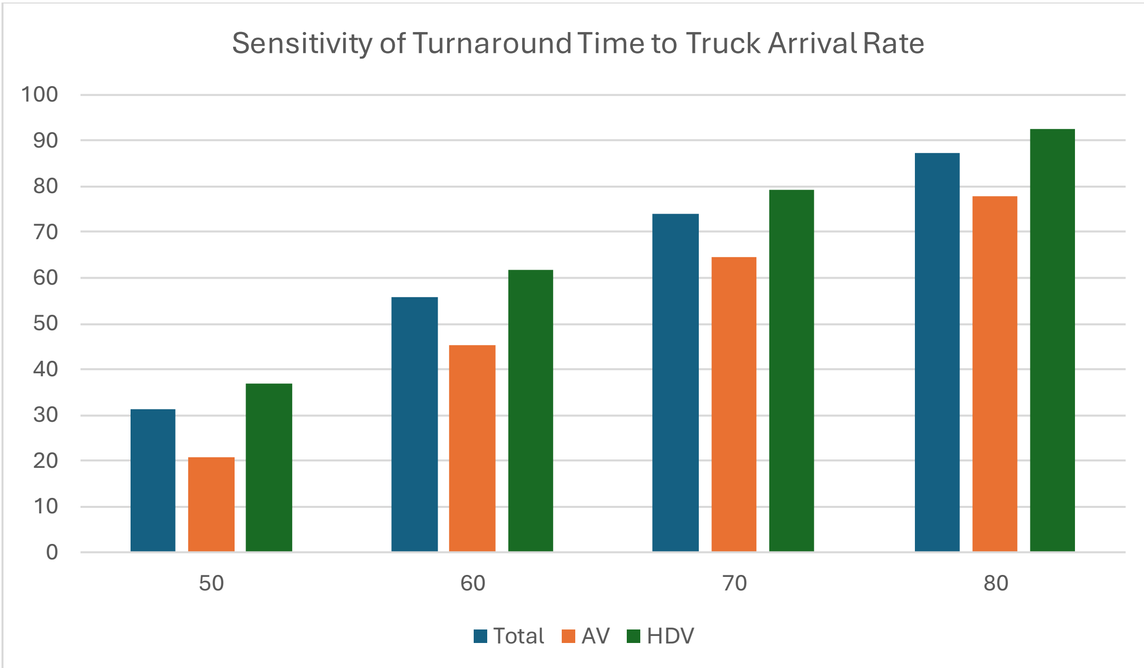

Figure 23 Sensitivity of Turnaround Time to Truck Arrival Rate

As shown in figure 23, turnaround times increase steeply as arrival rates exceed the system's processing capacity, highlighting the importance of demand management.

These findings underscore the importance of infrastructure investments (crane capacity), operational strategies (scheduling), and the gradual adoption of autonomous vehicles in reducing congestion and improving overall terminal performance. Collectively, these sensitivity analysis findings demonstrate the interdependency of the dimensions of truck turn time reduction in port terminals. They highlight the fact that even though autonomous vehicle uptake has tremendous potential for securing efficiency savings, they are optimized when complemented by well-planned infrastructure investment (e.g., sufficient crane capacity) and robust operating mechanisms (e.g., sound demand management by scheduling systems). The analysis gives an in-depth picture of how each of these key parameters relates to overall terminal performance and provides useful insight to guide planning and implementation strategies going forward for the Port of Montreal.

4.6 Model Limitations

This part explicitly lays down all the assumptions made while developing and executing the simulation model. All these assumptions are crucial for defining the model's scope and understanding the context within which the results are valid.

The physical layout of the Viau Terminal is simplified to its key operational steps, such as gate arrival, pre-yard handling, yard crane operation, and departure. This is an abstraction to the logical progression rather than to exact geographical space. Gate capacities (e.g., number of T1, T2, T3 gate lanes) remain constant during the simulation throughout all scenarios. Equivalently, crane operating times (e.g., loading/unloading time) are assumed to be deterministic for a particular truck type, but variability is introduced through distributions. Trucks are otherwise assumed to have a First-In-First-Out (FIFO) service discipline in each queue unless otherwise modified by a scenario (e.g., the TAS in Scenario 2, which effectively puts priority on scheduled arrivals).

The model does not include unnecessary variables influencing port operations like weather (fog, rain, or snow), equipment failure (e.g., crane failure), or random traffic congestion outside the immediate port boundary. Rail interference or system failure is also ruled out. These omissions are conscious decisions to balance model realism with computational tractability and the specific focus of the research. By simplifying the terminal layout and excluding external disruptions, the model isolates the impact of AVs and TAS on TTT within the controlled port environment, allowing for cause and effect to be more easily attributed. If every real-world variable were included, the model would become too complex to analyze, and the specific impact of AVs might be obscured by other confounding factors. This is in accordance with the scientific principle of controlling variables within an experiment.

On Autonomous Vehicle (AV) traits, AVs are not thought to experience rest periods or driver-dependent delays, which are their ability to run around the clock. AVs are thought to run more consistently and frequently, resulting in reduced reaction times and more predictable yard delays compared to HDVs. Uniform truck sizes are assumed, simplifying the handling process and removing variability related to different vehicle dimensions. While time-dependent, the overall arrival patterns are assumed to follow a schedule based on previous studies, implying a predictable demand profile for the simulation period. Lastly, while real-world data informs parameters, the model maintains that the available data (port cameras, official website, prior studies) are representative and credible in order to utilize them for conceptual model calibration. These assumptions, especially those disregarding external influences and equipment failure, indicate that the outputs of the model are most immediately valid for the simplified terminal conditions. This is something that should be taken into consideration for application to the real world, since the model is less applicable because of such simplifications. But these deliberate exclusions are also pointing us directly to where future work should be conducted, such as incorporating stochastic breakdowns, external traffic, or multi-terminal interactions, which would further expand the model's scope.

4.7 Results Discussion

The simulation results provide credible proof that a multi-faceted approach can reduce truck turn time (TTT) at Viau Terminal of Port of Montreal. Consecutive improvements between the four scenarios present proof of synergy in the positive effects of using strategies of demand management with the integration of autonomous vehicle technology and targeted infrastructure upgrades.

Table 21 Summary of results

Scenarios	Mean Turn Time (min)	HDV Turn Time (min)	AV Turn Time (min)	Improvement compared to Baseline
1. Baseline (No TAS, No AVs)	88.2	-	-	-
2. TAS Only	78.37	-	-	11%
3. TAS + 35% AV (Shared Cranes)	55.91	61.61	45.33	37%
4. TAS + 35% AV + AV Staging + Dedicated Cranes	57.13	70.20	32.86	35%

As shown in table 21, the baseline scenario had evidently established the significantly congested issues that the Viau Terminal was experiencing, where the mean TTT was 88.2 minutes. This aligned with the problem statement and established a key benchmark to consider planned interventions. The first intervention, a Truck Appointment System (TAS) in Scenario 2, had achieved a noticeable decline in TTT to 78.37 minutes approximately an 11% improvement. This highlights the inherent value of regulation of truck arrivals to smooth demand peaks and enhance predictability even without the use of automation. TAS is an inexpensive software-based solution that can yield a quick and quantifiable return through optimization of available assets.

Introduction of Autonomous Vehicles (AVs) under Scenario 3, on the same shared resource paradigm, reduced the overall mean TTT to 55.91 minutes, approximately a 37% reduction compared to baseline scenario. This captures the inherent benefits of AVs, including their ability to process quicker and with fewer human-induced delays. The dramatic performance difference between AVs (45.33 minutes) and HDVs (61.62 minutes) here provides strong incentive for trucking firms and port authorities to invest in automated fleets. Even without special infrastructure, the operating consistency and velocity of AVs benefit terminal throughput.

The result of Scenario 4, with the inclusion of dedicated staging area and cranes for AVs, is less pronounced. Though the TTT od Avs declined most precipitously to 32.86 minutes, demonstrating the feasibility of autonomous operation facilitated by dedicated infrastructure, the overall average TTT of 57.13 minutes was unexpectedly higher than for Scenario 3 (55.91 minutes). This unexpected result is largely a function of the large jump in HDV TTT to 70.20 minutes under Scenario 4 compared to 61.62 minutes under Scenario 3. It suggests that having 4 of 15 cranes dedicated to AVs significantly improves autonomous fleet performance but perhaps hurts congestion and turn times for the big HDV fleet if the other 11 cranes become an even worse bottleneck or if the system dynamics for HDVs worsen overall under partitioning of resources. This would imply a core trade-off: maximizing the efficiency of AVs through specialized resources could come at the expense of system performance overall if the non-AV fleet remains large and its resource usage significantly constrained. Results demonstrate a classic resource allocation trade-off, allocating capacity to the more efficient, schedulable AV fleet maximizes their performance at the cost of decreased shared flexibility and capacity for HDVs, leading to increased HDV turnaround times.

Sensitivity analysis also made interdependence among factors more solid. It made it extremely clear that a larger proportion of AVs does reduce overall TTT on average, but gains are non-linear and susceptible to other influences. Similarly, truck arrival rates and crane capacity were the strongly significant parameters, indicating even with advanced technologies like AVs, proper demand management and sufficient investment in infrastructure are crucial to an efficient port operation. The unexpected findings in Scenario 4 highlight that the optimal resource allocation strategy under a mixed fleet environment is complex and relies on tuning to avoid unintended negative effects for the non-autonomous portion.

4.7.1 Recommendations for Port Authorities

Based on these findings, the Port of Montreal authorities should consider a phased implementation strategy for congestion reduction, with a critical eye on resource allocation:

1. **Prioritize and Optimize Truck Appointment Systems (TAS):** A robust TAS should be the immediate focus. It offers significant TTT reduction with relatively lower capital investment, providing a foundational layer for future automation. Continuous refinement of slot capacities and dynamic adjustment mechanisms based on real-time terminal conditions will maximize its effectiveness.

2. **Encourage Gradual AV Adoption with Strategic Integration:** Port authorities should work with trucking companies to encourage the adoption of autonomous vehicles. The benefits of AVs are evident even in shared infrastructure (Scenario 3), providing a strong business case for early adopters. However, simply introducing AVs without considering their flow paths can lead to new bottlenecks (as seen with the high AV queue in Scenario 3).

3. **Cautious and Optimized Planning for Dedicated AV Infrastructure:** While dedicated infrastructure for AVs (Scenario 4) can drastically improve AV-specific TTT, the simulation indicates it would have detrimental effects on HDV TTT and hence overall TTT unless conservatively balanced. Future planning for dedicated staging areas and reserved cranes should involve detailed analysis of the optimal proportion of dedicated resources relative

to the AV adoption rate and the impact on the remaining HDV operations. A more dynamic or flexible resource allocation model, rather than strict partitioning, might be beneficial.

4. **Holistic System View and Continuous Monitoring:** The simulation results, particularly from Scenario 4, highlight the complex interdependencies within the terminal. Optimization in one segment (AV efficiency) can have cascade effects in others (HDV TTT). The port authorities have to take a systematic view, continually monitoring and optimizing the all-important resources and processes so that interventions yield system-wide benefits and not local gains at the cost of other segments.

4.7.2 Benefits of Investing in AVs

Despite the difficulties, investment in autonomous vehicles offers diversified benefits over simple TTT reduction:

- **Enhanced Operational Efficiency:** Continuous 24/7 operation without human driver limitations, leading to enhanced throughput and faster cargo movement.
- **Improved Safety:** Reduced human error in a high-risk working environment, reducing accidents and associated costs.
- **Environmental Sustainability:** Optimized driving patterns, reduced idling, and the potential of electric AVs contribute to lower emissions and a greener port.
- **Predictability and Reliability:** AVs provide more consistent performance, resulting in more predictable logistics operations and increased supply chain reliability.
- **Addressing Labor Shortages:** Reducing the increasing danger of truck driver shortages and strikes.

4.7.3 Role of TAS or Infrastructure Upgrades

Both terminal investments and Truck Appointment Systems have complementary and essential roles to play. TAS is a "soft" intervention that maximizes utilized capacity by improved scheduling and demand management. It is an investment in maximizing the pay-off of AVs through ensuring a planned arrival to the terminal. Infrastructure improvements, i.e., dedicated resources such as cranes and staging space, are "hard" ones that actually enhance the capacity and performance of the terminal for specific traffic. The simulation expressly demonstrates that having both, Scenario 4, will most profoundly affect the AV fleet, but that overall system gain is heavily based on the particular implementation of resource partitioning. A TAS guarantees that the trucks will arrive when the terminal is prepared, and custom infrastructure guarantees that when the AVs arrive, they can be processed with unparalleled efficiency if the operations of the HDVs are not disproportionately burdened.

Chapter 5:

Model Development in AnyLogic

In this chapter, we will discuss the application of the proposed DES model using AnyLogic. There are various scenarios tested in the Port of Montreal through our simulation model using AnyLogic PLE. The scenarios tested are the proposed solutions that can potentially address the high truck turn time (TTT) in the port terminal. The goal is to precisely define the model's architecture, specify all input parameters, and articulate the various scenarios designed to investigate the potential of autonomous vehicles (AVs) in reducing TTT.

5.1 Designing the Terminal in AnyLogic

The simulation was developed using AnyLogic, a Java-based simulation platform. This choice is justified by AnyLogic's robust support for DES and its capability to integrate Agent-Based Modeling (ABM) logic. The adoption of a hybrid DES-ABM approach is a foundational design decision for this study, allowing for the detailed modeling of process flows and resource constraints (DES) while simultaneously representing individual truck attributes and dynamic behaviors (ABM), such as varying acceleration, speed, and reaction times. This hybrid capability is particularly important for differentiating the behavior and efficiency between Human-Driven Vehicles (HDVs) and AVs. A pure DES model, while effective for general flow, might struggle to capture the nuanced behavioral differences, such as reduced human error or continuous operational capability, that define the advantages of AVs. ABM provides the granular distinction necessary to investigate these AV-specific performance improvements.

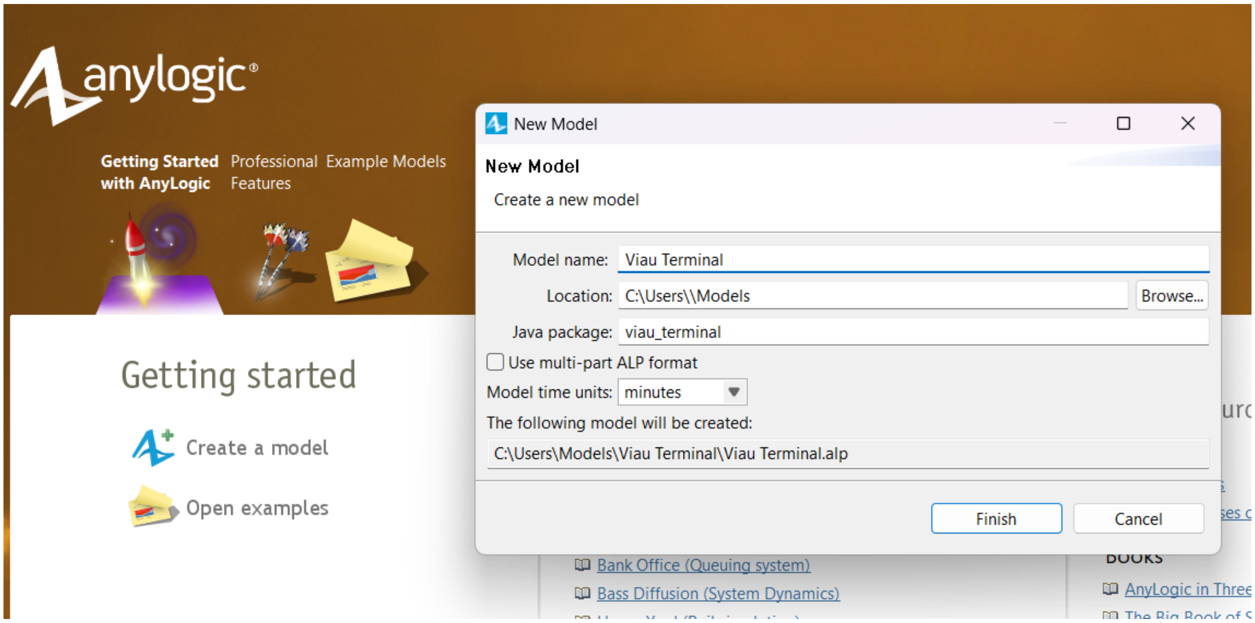

Figure 24 AnyLogic workspace

The model development directly addresses the core research objectives established in the first chapter and specifically, it aims "To develop a well-defined DES model that accurately represents the key operational processes affecting truck movements within the Port of Montreal" and "To incorporate autonomous vehicle technology into the developed simulation model considering multiple deployment scenarios and operation parameters". By detailing the model's construction, this chapter serves as the crucial link between the theoretical concepts of DES, autonomous vehicles, and port congestion from the literature review and their practical application to the Port of Montreal case study. This operationalization of abstract concepts into a functional tool provides the means for generating actionable understandings, thereby fulfilling a key aspect of Quality Systems Engineering. The subsequent analysis of these scenarios in Chapter 5 will then fulfill the objective of comparing the effects of various AV deployment scenarios on TTT.

5.1.1 System Boundaries and Scope

The simulation model specifically focuses on the landside operations of the Viau Terminal at the Port of Montreal. This encompasses the entire truck transaction process from the initial port entry to final exit, including gate operations, internal terminal movements, staging, and yard handling. The scope is intentionally confined to the internal terminal environment to mitigate the impact of the proposed interventions on truck turn time. Figure 25 shows the whole process, variables and function of this scope.

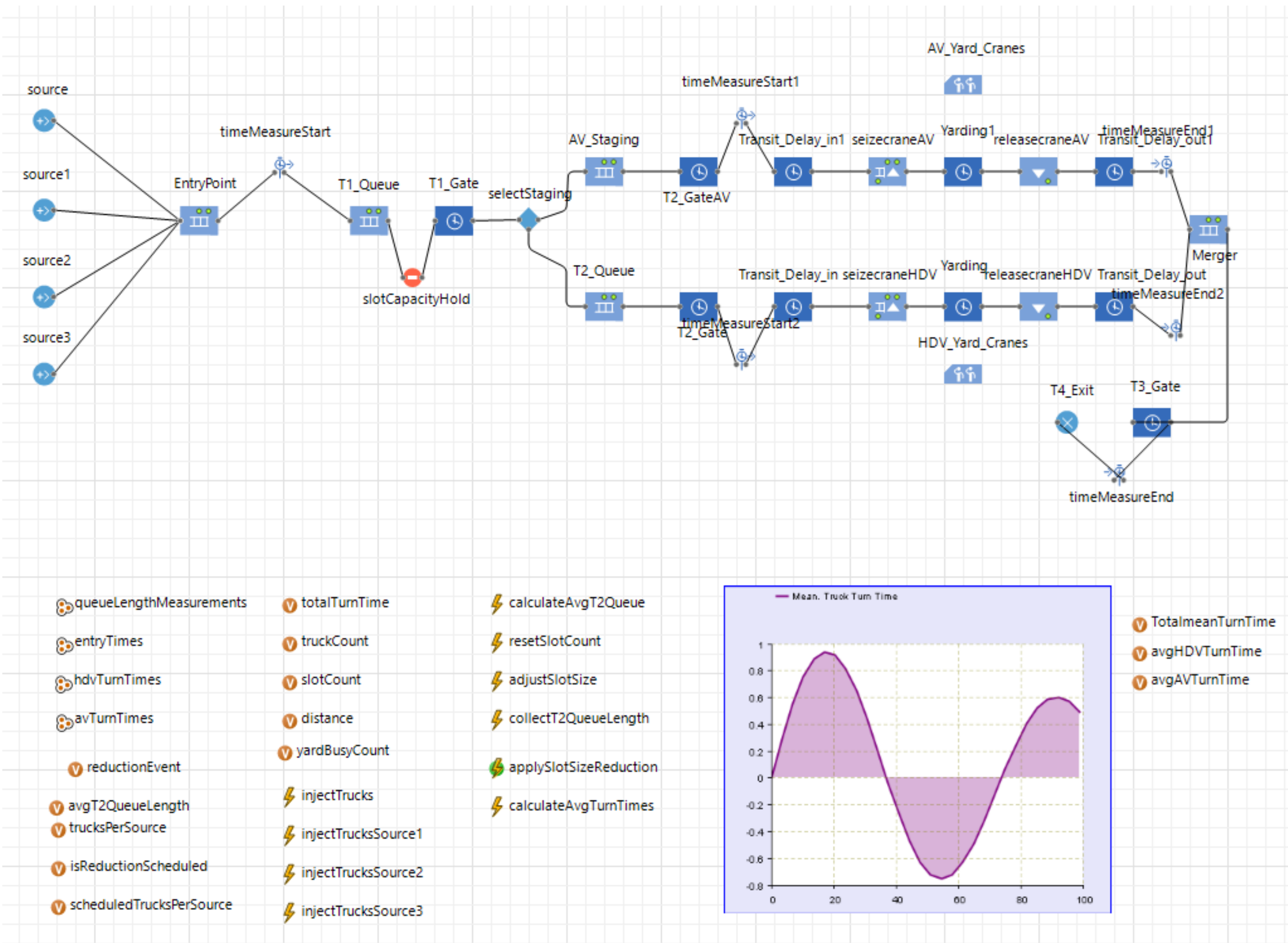

Figure 25 Simulation model overview of landside truck operations at the Viau Terminal.

Consistent with the methodology, the model specifically ignores external interference in the form of weather interference, equipment failure, and traffic jam outside the port perimeter. It likewise does not account for interference factors from the trains interference or system failures. Terminal design is simplified to its major operating stages instead of replicating actual geographical dimensions. These are deliberate boundary conditions for model tractability and focusing the analysis on the truck turn time problem within the controlled environment of the terminal. This allows for clearer cause-and-effect attribution, preventing the effect of autonomous vehicles and truck appointment systems from being masked by other confounding variables.

5.1.2 Entity Definition and Flow

The fundamental entity simulated in the model is the "Truck" agent. Each truck agent is dynamically generated at the beginning of its journey into the port system and assigned specific attributes upon creation.

The most critical attribute for each truck agent is its vehicle_Type, which categorizes it as a Human-Driven Vehicle (HDV) or an Autonomous Vehicle (AV). This is at the very core of the thesis, since HDVs and AVs possess different behavioral and efficiency characteristics. For instance, AVs are modeled with reduced reaction times and potentially shorter yard delay durations due to their automated processing capabilities. This allows for a direct comparison of their performance under various scenarios, enabling the study to quantify the specific advantages that autonomous technology brings to port logistics. Upon generation, truck entities are assigned their type (HDV or AV), other relevant attributes (such as an arrival rate that influences individual truck generation), and processing delays. Truck agents are produces by four “Sources”. Each source has an arrival rate and number of agents per arrival. Due to limitations of Personal Learning Edition

(PLE) version of AnyLogic, truck agents were created in resources and by calling a "initializeTruck" function they were assigned their attributes.

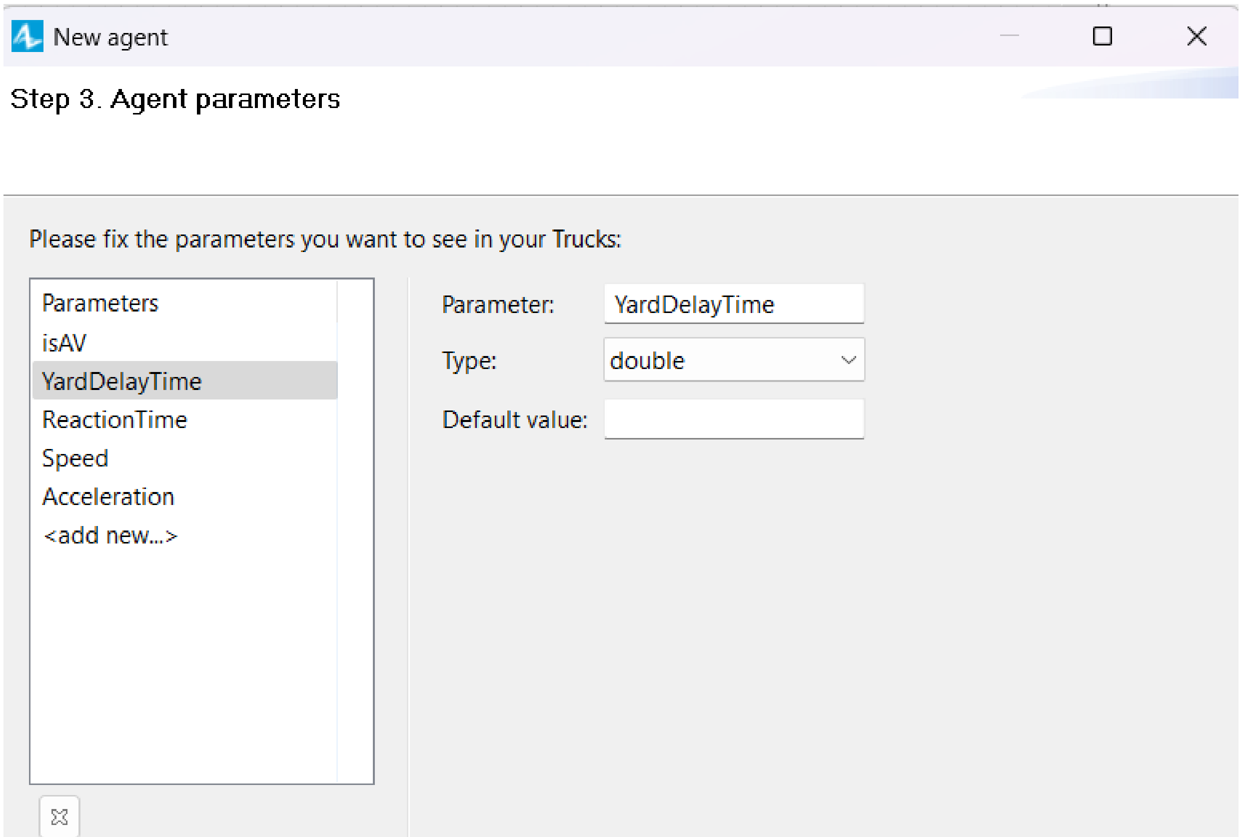

Figure 26 Assigning truck attributes in AnyLogic

5.1.3 Process Flow and Operational Logic

The simulation model replicates the typical truck transaction process within the Port of Montreal, as depicted in Figure 17 and further detailed in the process map (Figure 18). The flow captures the order of activities a truck undertakes from the moment it arrives at the port to when it finally departs. Except where stated otherwise in particular cases (e.g., the Truck Appointment System), trucks operate under a First-In-First-Out (FIFO) rule at all queuing locations. The specific designation of gate capacities (T1: 4, T2: 2, T3: 2) and yard crane quantities (15 in total, followed by a 4/11 split) makes one able to observe potential bottlenecks which are not just pattern-of-arrivals-related but also fixed infrastructure-related. This architectural limitation implies that even with optimal arrival handling, internal processing capacity can still dictate overall throughput. To use an example, if the T1 gate handles more than the T2 gate, then T2 can become the bottleneck, irrespective of optimization upstream. This highlights that truck turn time optimization demands an overall picture of the whole operation chain, not piecemeal improvements, which is the benefit of simulation in pinpointing bottlenecks. Figure 27 show the creation of a gate in AnyLogic.

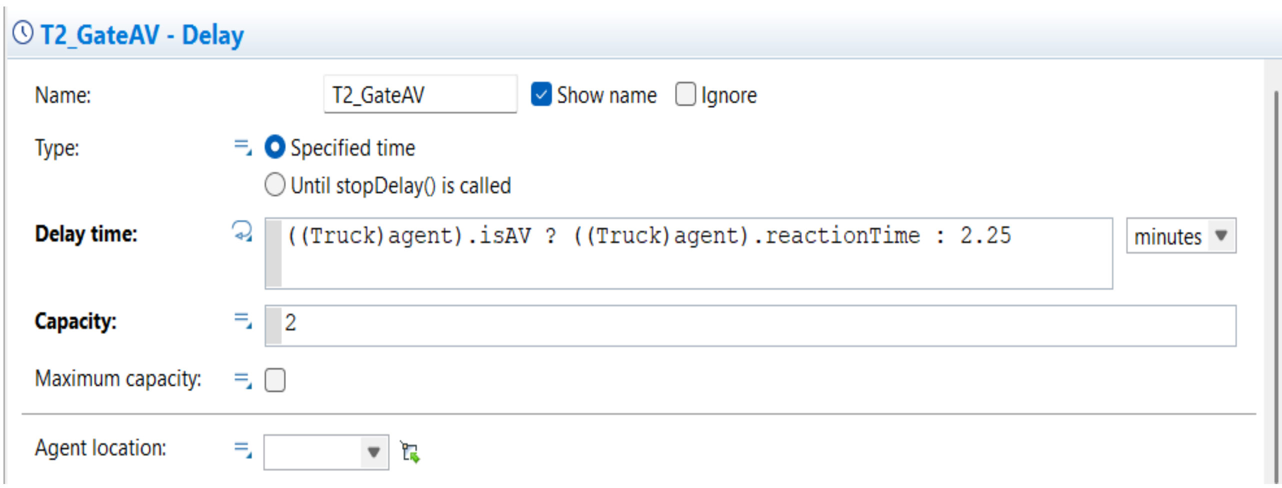

Figure 27 Creating gate blocks in AnyLogic

5.1.4 Resource Allocation and Management

The model explicitly defines the capacities of the various gates. For instance, the T1 Gate has 4 resources, the T2 Gate has 2 resources, and the T3 Gate has 2 resources. These represent the number of operational lanes or service points available. The total pool of yard cranes is set at 15 according to Port data. In the baseline and initial AV integration scenarios, these cranes are shared among all vehicles. However, Scenario 4 introduces a key structural change: dedicated crane allocation, where at least 4 cranes are reserved for AVs and 11 for HDVs. Figure 28 depicts the designing of yard operations in AnyLogic.

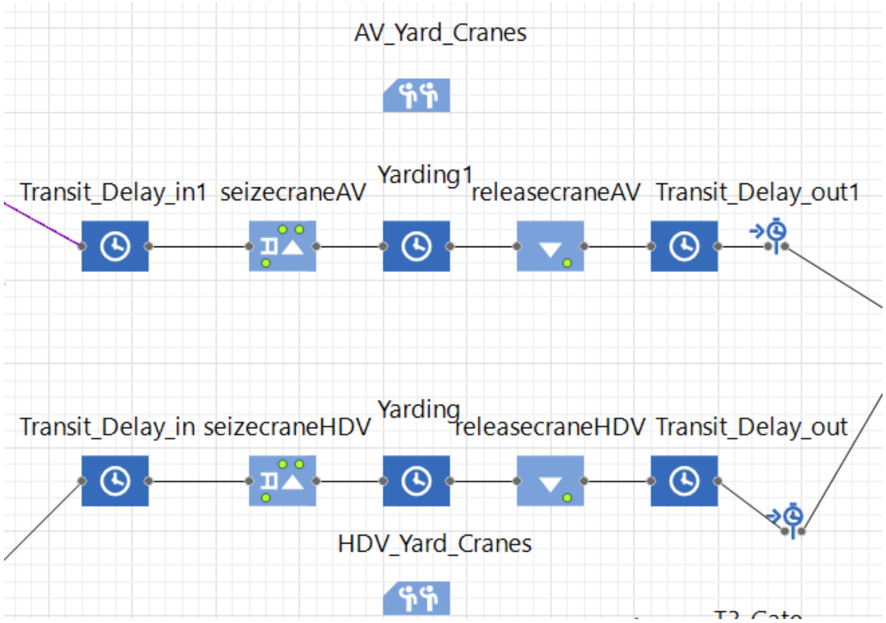

Figure 28 Designing yard operations and crane pools in AnyLogic

The model tracks the utilization rates of these resources (gates, cranes) to identify bottlenecks and assess efficiency, which are key performance metrics. The summary of how resources are allocated throughout the simulation process is shown in table 22.

Table 22 Resource allocation across scenarios

Scenario	**Gates**	**Cranes**	**Staging Areas**
Scenario 1 and 2 (Baseline and TAS)	Shared	All cranes used by HDVs	Shared queue for all trucks
Scenario 3	Shared	All 15 cranes shared between AVs and HDVs	Shared
Scenario 4	Separated T2_gate (Yard entry)	At least 4 cranes assigned to AVs, 11 to HDVs	Separated

5.2 Simulation Assumptions

This section outlines the key modeling assumptions, parameter values, and simulation setup used to evaluate congestion management strategies at the Viau Terminal of the Port of Montréal. The model is implemented using AnyLogic PLE and simulates discrete-event operations of a container truck terminal during peak hours. Several assumptions were taken during the modeling of this thesis, including:

- AVs do not require rest periods or driver-based delays.
- The terminal layout is simplified to key operational steps: gate entry, pre-yard processing, yard crane handling, and departure.
- Gate capacity and crane operation times remain constant across scenarios (Gate and yard capacities remain constant)
- Trucks follow a First-In-First-Out (FIFO) discipline unless otherwise stated.
- No weather disruptions, equipment failures, or traffic outside the port boundary are considered (No random breakdowns or weather disruptions included)
- Arrival patterns are assumed to follow a time-dependent schedule based on previous studies.
- Uniform truck sizes
- Excludes factors like train interference or system failures

5.3 Scenarios Modeled

This section provides a detailed exposition of the four distinct simulation scenarios developed with DES to assess the impact of various interventions on port congestion and truck turn time. Each scenario represents a progressive step in addressing the challenges at the Viau Terminal. The incremental design of these scenarios is a deliberate research strategy, allowing for the isolation and quantification of the impact of each intervention. For example, comparing Scenarios 1 and 2 will quantify the value of a Truck Appointment System (TAS) alone. Comparing Scenarios 2 and 3 will then quantify the value of AVs without dedicated infrastructure. Finally, comparing Scenarios 3 and 4 will quantify the value of dedicated AV infrastructure. This systematic decomposition provides more robust and nuanced understandings of the contribution of each factor.

5.3.1 Scenario 1 – Baseline (No TAS, No AVs)

Truck arrivals in the simulation were modeled as a Poisson process, implemented within AnyLogic's Source block at 15 trucks/hour rate. This is equivalent to having an average interarrival time of 4 minutes, with real interarrival spacings being distributed Exponentially. This choice reflects real-world variability in truck arrival patterns, so truck arrivals do not occur at fixed intervals but are randomly distributed around a mean rate. The assumption is widely used in port and logistics simulations because of its ability to capture stochastic arrival behavior under uncertain conditions.

This scenario as shown in figure 29 is the control group, which is what the current operating conditions at the Viau Terminal would be without any advanced truck appointment system (TAS) and autonomous vehicle (AV) integration. The goal is to establish a realistic baseline for comparison against proposed interventions.

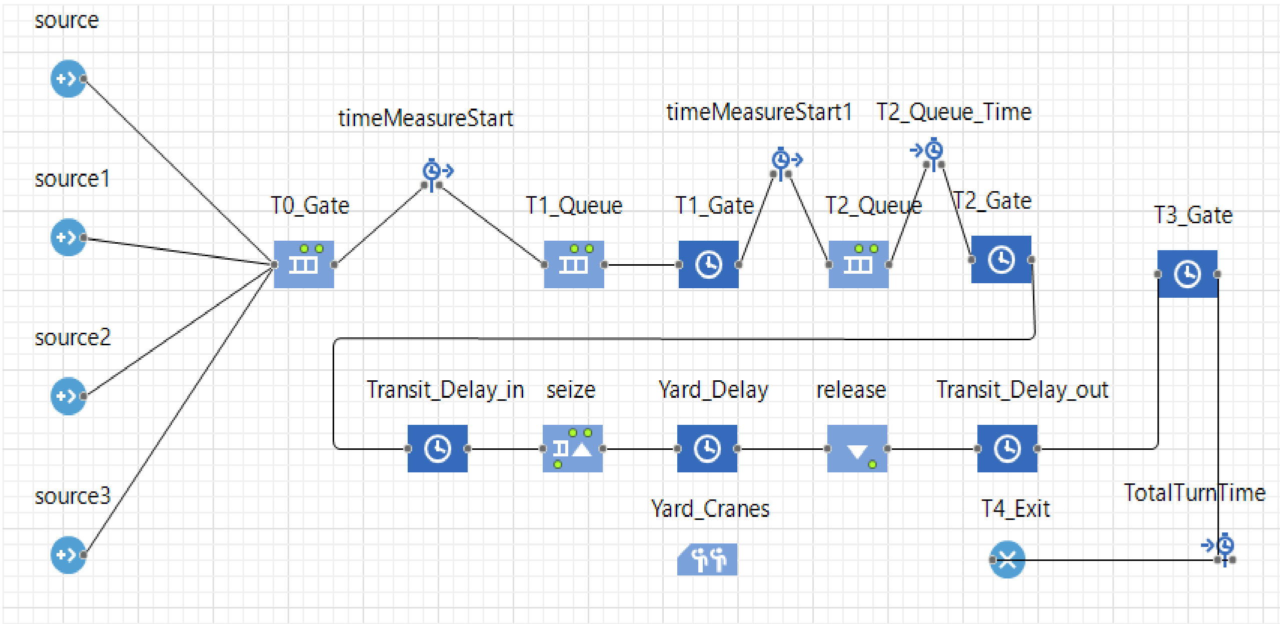

Figure 29 Baseline scenario model

Operationally, trucks arrive continuously at an average rate of 60 trucks per hour. The arrival pattern is assumed to follow a time-dependent schedule, reflecting observed peak periods. All trucks follow a First-In-First-Out (FIFO) strategy at all service points. There is no mechanism to control queue growth or manage truck flow based on real-time capacity. Furthermore, all 15 yard cranes are fully shared among all Human-Driven Vehicles (HDVs), with no distinction made for truck types or cargo priority. Consistent with real-world observations and previous studies, this scenario is expected to yield high truck turn times (TTT) due to unmanaged congestion, unoptimized peak flows, and potential bottlenecks at various operational stages. The validation process confirms a baseline average TTT of approximately 88.2 minutes, aligning with observed data. According to the baseline scenario and data from port cameras, there are two main congestion points in the port operations inside Viau terminal: Staging area before T2-gate and yard operations.

There is also some congestion observed in the queue before T1-gate at terminal entry, but it is usually not as prominent as two main one mentioned before.

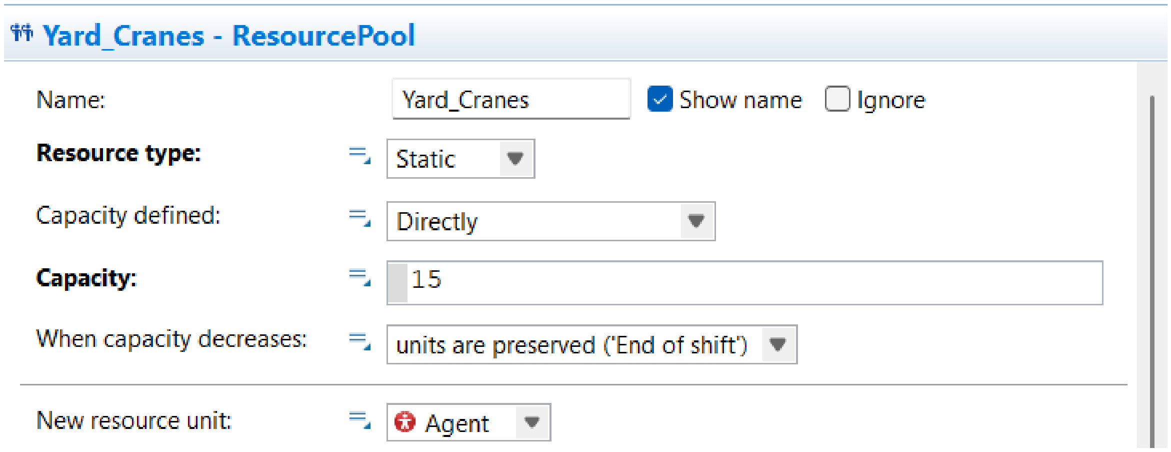

Figure 30 Yard crane specifications in AnyLogic

The yarding area was defined with a resource pool with capacity of 15 cranes as shown in figure 10. Each crane is occupied by one agent (truck) through seize module after it passes the T2_gate. After the agent spends the yard delay time for the loading/unloading operations in the yard, then the crane will be available for the next agent by a release module. There are also two transit delays within the yard operation as shown in figure 29, which make the model more accurate to the real-world operation efforts taking place in port logistics. These transit delays are calculated according to distance, speed and acceleration of the trucks. These variables are important players in the scenarios 3 and 4 with AV integration since they differ between HDVs and Avs.

Transit Time = Speed / Distance + Acceleration / Speed

As shown in figure 31, the yard delay was modeled with maximum, minimum and mean values to be more accurate as a baseline of this simulation. Hence a triangular distribution was selected which best represents the available.

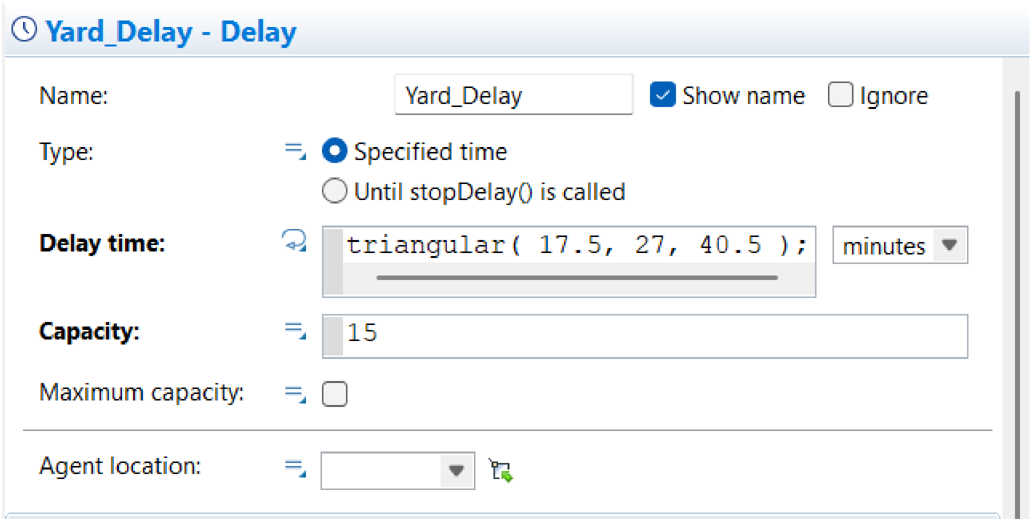

Figure 31 Yard specifications in AnyLogic

At the time of modeling the baseline scenario, the Viau terminal at the Port of Montréal had not yet implemented a truck appointment system (TAS). While the RDV Termont Montreal system became mandatory as of March 4, 2025, this implementation was relatively recent and followed years of traditional gate-based truck handling. The baseline scenario is therefore intended to reflect the terminal's operating conditions prior to TAS rollout, as described in earlier industry reports and port documentation. This allows for a clear, stepwise evaluation of how emerging solutions — including TAS, autonomous vehicles, and dedicated infrastructure — can incrementally reduce congestion and improve truck turn time.

The list of variables used in baseline scenario to calculate truck turn time and set parameters of truck agents are shown in table 23.

Table 23 Baseline scenario variables

Variable	Type
TotalTurnTime	Double

TruckCount	Double
EntryTimes	LinkedList
MeanTurnTime	Double
Distance	Double
Speed	Double

5.3.2 Scenario 2 – TAS Only (Slot-Based Arrival Control)

This scenario introduces a simplified Truck Appointment System (TAS) to mitigate congestion by regulating truck arrivals. It isolates the impact of a TAS, without the added complexity of AVs, allowing for a clear assessment of its effectiveness.

In this scenario, truck arrivals are no longer continuous and unmanaged. Instead, they are grouped into 20-minute time slots, with each slot having a fixed maximum capacity, simulating the pre-booking mechanism of a TAS. As depicted in figure 32, a "Hold" block within the simulation model is utilized to simulate appointment-based admission to the pre-yard processing stage. This hold block enforces a slot capacity (e.g., 20 trucks per 20-minute window) and if exceeded, delay trucks to the next slot, simulating overbooking penalties. Trucks arriving outside their designated slot or when their slot capacity is full would be held or redirected, although the model simplifies this to a controlled release into the system. Similar to the baseline, all 15 yard cranes remain fully shared across all trucks (HDVs), as no AVs are present in this scenario. The implementation of TAS is anticipated to smooth out truck arrivals, reducing gate congestion and improving the predictability of terminal operations. This should lead to a measurable reduction in average TTT and shorter queue lengths compared to the baseline, as demonstrated in literature on TAS effectiveness.

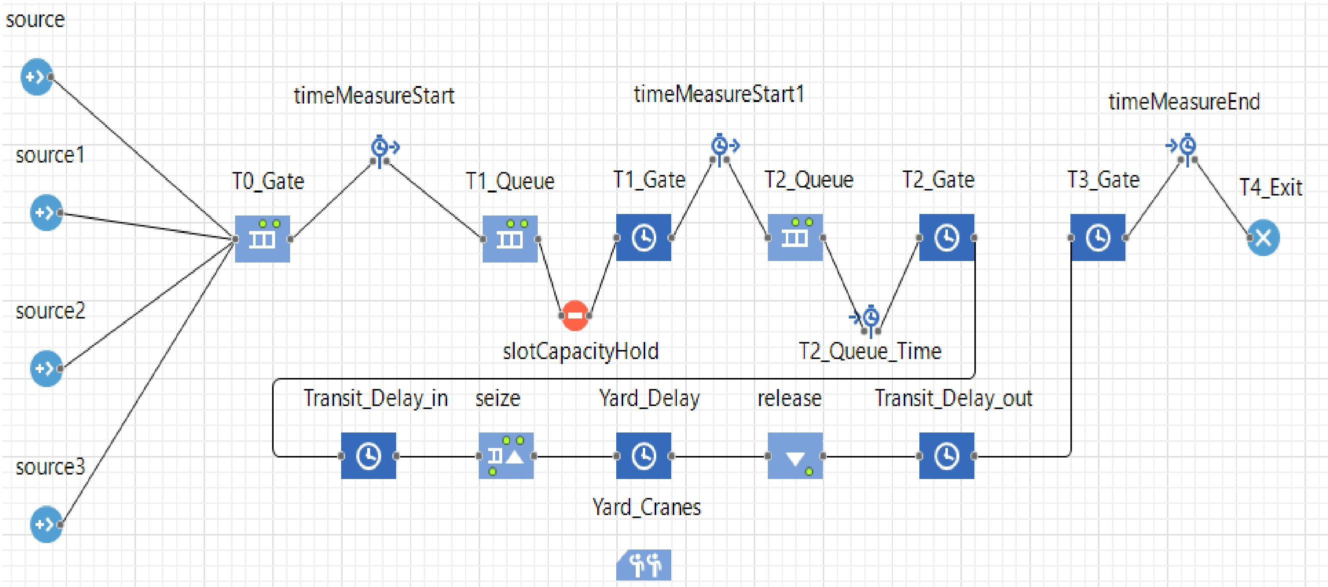

Figure 32 Scenario-2 model

In order to ensure the slot-based arrival is accurately implemented, truck arrivals in this scenario are no longer solely controlled by Source agents. There are 'injectTruck' events defined per source to inject tucks into sources according to arrival schedule by switching to deterministic interarrival time that maintains the same total arrival rate. There are four of these events implemented in this scenario as shown in figure 33.

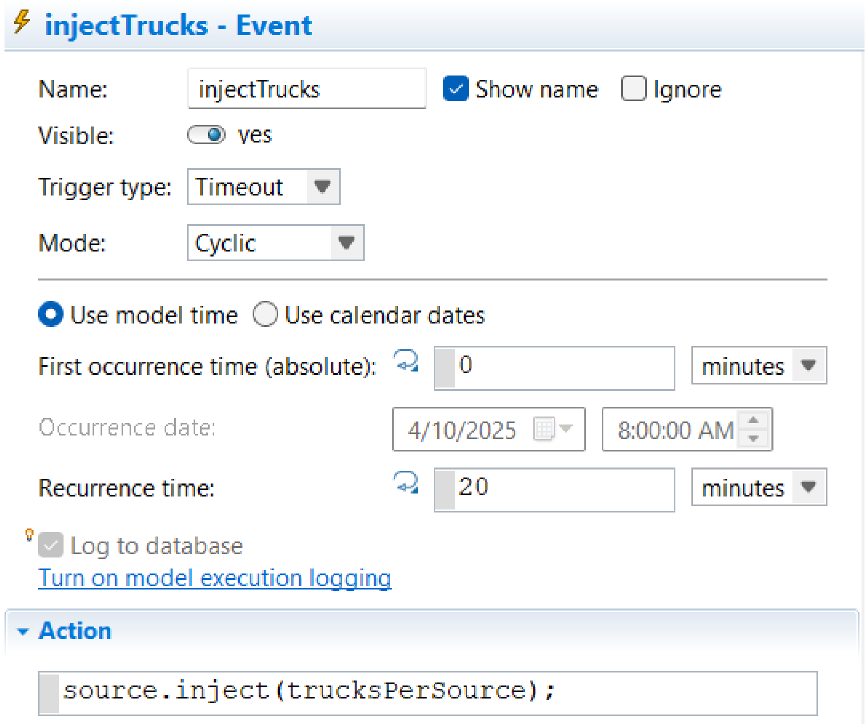

Figure 33 Inject events in scenario-2

Some TAS systems use real-time data, for example gate wait times and yard occupancy, to adjust slot availability. To replicate this dynamic adjustment that TAS systems offer, we use AnyLogic's "Dynamic Event" as an inject function to adjust slot availability based on T2_Queue length. If T2-Queue length (staging before yard) gets longer than 12, a slot adjustment event will be triggered to reduce the arrival rate of the agents. The java codes used to implement this dynamic event are shown in figure 34.

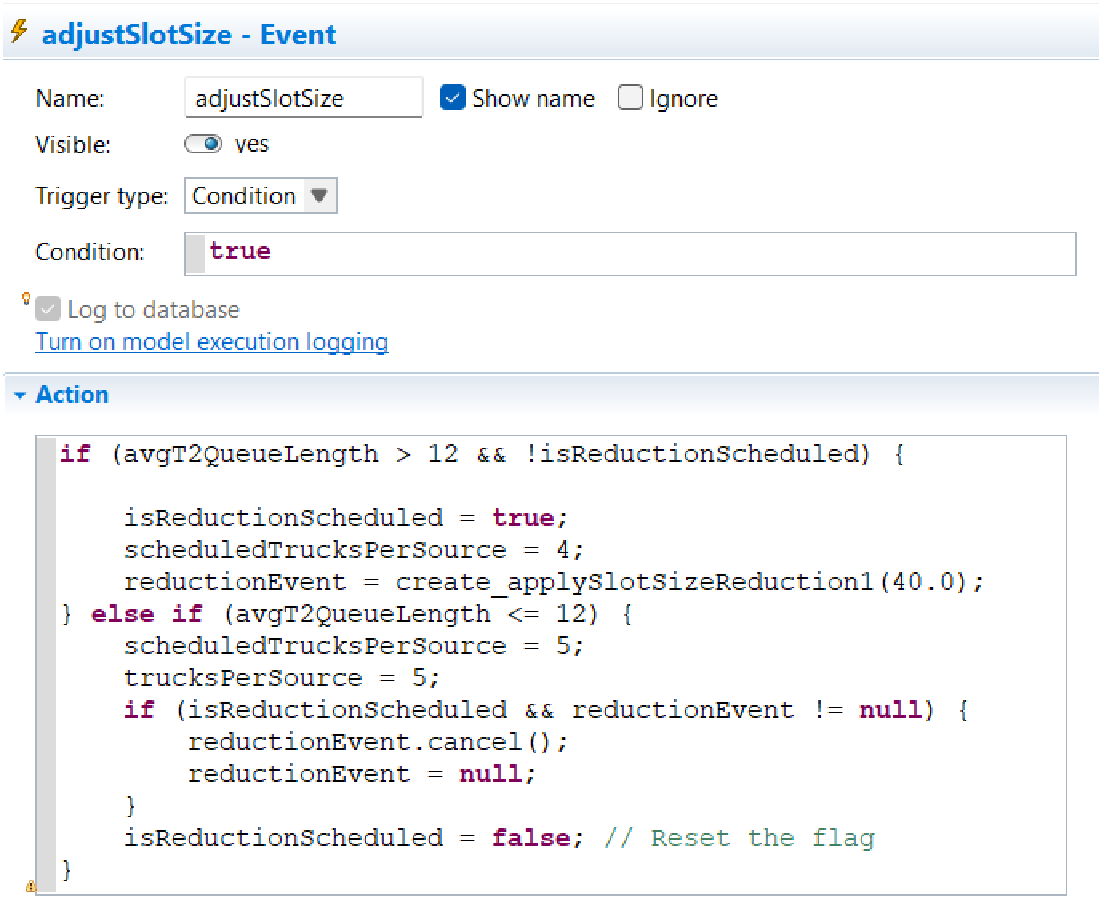

Figure 34 Adjusting slot-based arrivals in scenario-2

Due to limitation of Personal Learning Edition of AnyLogic, some basic parameters such as queue length could not be retrieved directly. To overcome these limitation variables, events and functions were used to ensure that the simulation model is implemented correctly. The list of variables and events used apart from the ones from the baseline scenarios are explained in Table 24.

Table 24 List of variables and events, Scenario-2

Variables	Type	Events	Type
SlotCount	Integer	injectTrucks1,2,3,4	Event
ReductionEvent	Boolean	calculateAvgT2Queue	Cyclic Event

AvgT2QueueLength	Double	resetSlotCount	Cyclic Event
TrucksPerSource	Integer	adjustSlotSize	Event
isReductionScheduled	Boolean	applySlotSizeReduction	Dynamic Event
scheduledTrucksPerSource	Integer	collectT2QueueLength	Event
queueLengthMeasurements	LinkedList	-	-

5.3.3 Scenario 3 – Autonomous Vehicle (AV) Integration

This scenario introduces autonomous vehicles into the terminal environment while maintaining the TAS from Scenario 2 and the existing shared resource structure. It aims to evaluate the performance improvements achieved by AVs when they operate within the same infrastructure as HDVs. As seen in figure 35, there is no infrastructure change in the layout of the terminal. What differentiate this scenario is that starting from this stage, the is no longer one single type of agent as 'Tucks' and the agents are assigned two different sets of characteristics according to being an autonomous truck or a humane driven one.

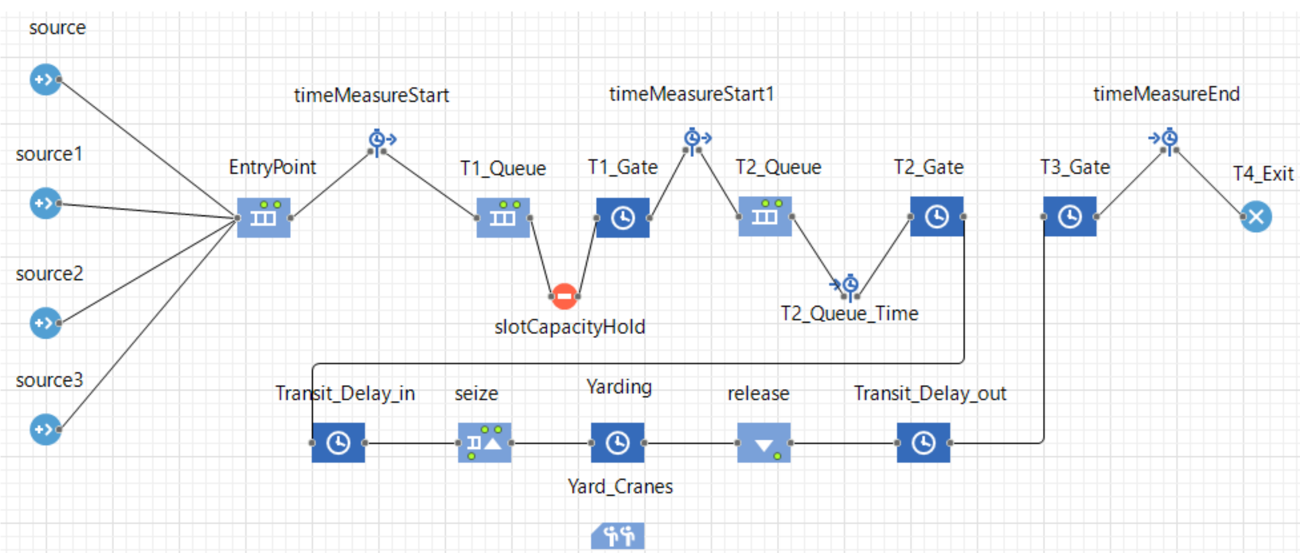

Figure 35 Scenario-3 model

Autonomous vehicles constitute 35% of the total truck arrivals, with the remaining 75% being HDVs. AVs are modeled with distinct efficiency attributes: they are assigned lower reaction times, reflecting their automated and consistent response capabilities, which translates to less idle time during internal movements and quicker maneuvering. Additionally, AVs experience more consistent and typically shorter yard delay durations due to optimized automated processing. The model incorporates a plausible 20% delay reduction for AVs in yard operations, based on relevant literature. Despite the presence of AVs, both HDVs and AVs continue to share the same pool of 15 yard cranes. No dedicated infrastructure or resource allocation is provided for AVs in this scenario. While the TAS provides overall flow management, the inherent efficiencies of AVs (reduced reaction times, consistent yard delays, faster acceleration rate and speed) are expected to contribute to further reductions in overall average TTT. However, the benefits might be somewhat diluted due to resource contention with HDVs and the lack of optimized AV-specific infrastructure.

To assign different parameters to Avs and HDVs, in each Source block in the model and before the agents exit the block, a new entity from Truck agent pool is created. Then the probability of this truck to be AV is assigned randomly. Subsequently, different parameters of AVs and HDVs are assigned by calling an intializeTruck() function which is a function defined in Truck agent section. These steps are shown in figure 36.

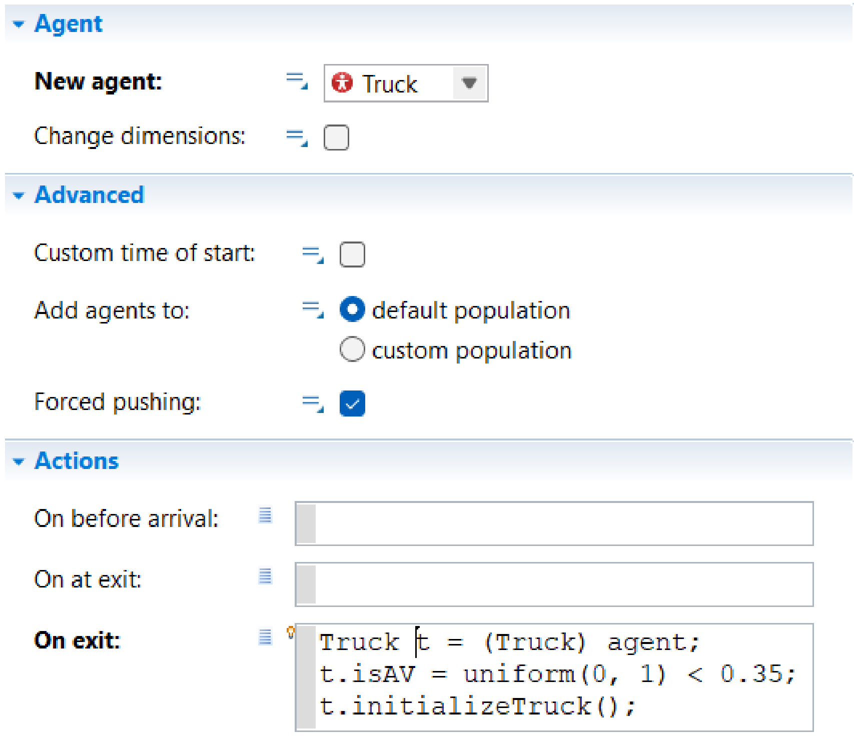

Figure 36 Assigning truck agent parameters in AnyLogic

The list of variables and functions used, apart from the ones from the baseline scenario, is shown in Table 25.

Table 25 Variables and function, Scenario-3

Variables and Functions	**Type**
AVTurnTimes	LinkedList
HDVTurnTimes	LinkedList
isAV	Boolean
ReactionTime	Double
Acceleration	Double
Speed	Double
InitializeTruck	Function

5.3.4 Autonomous Vehicle (AV) Staging and Dedicated Cranes

This final scenario represents a more advanced stage of AV integration, where dedicated infrastructure and resource allocation are provided to maximize the benefits of autonomous operations. It explores the potential for significant TTT reduction through specialized handling of AVs.

Similar to Scenario 3, AVs comprise 35% of the total truck arrivals. A crucial operational change is that AVs are no longer routed through the general staging area (T2_Queue) but instead through a dedicated staging area. In this dedicated area, AVs are held and released based on the real-time availability of their reserved cranes, optimizing their entry into the yard processing stage and bypassing congestion-prone segments. A key feature of this scenario is the partitioning of yard crane resources: out of the total 15 cranes, 4 cranes (approximately one-third) are reserved exclusively for AV processing. The remaining 11 cranes continue to serve HDVs. This setup simulates a future infrastructure investment strategy. The efficiency parameters for AVs (reduced reaction times, consistent yard delays) from Scenario 3 are maintained. This scenario is hypothesized to yield the most significant reductions in both system-wide and per-vehicle truck turn times. The combination of dedicated staging, precise release based on resource availability, and guaranteed access to dedicated cranes for AVs is expected to virtually eliminate AV-related queuing and significantly improve their throughput, while also potentially alleviating some pressure on HDV-served resources.

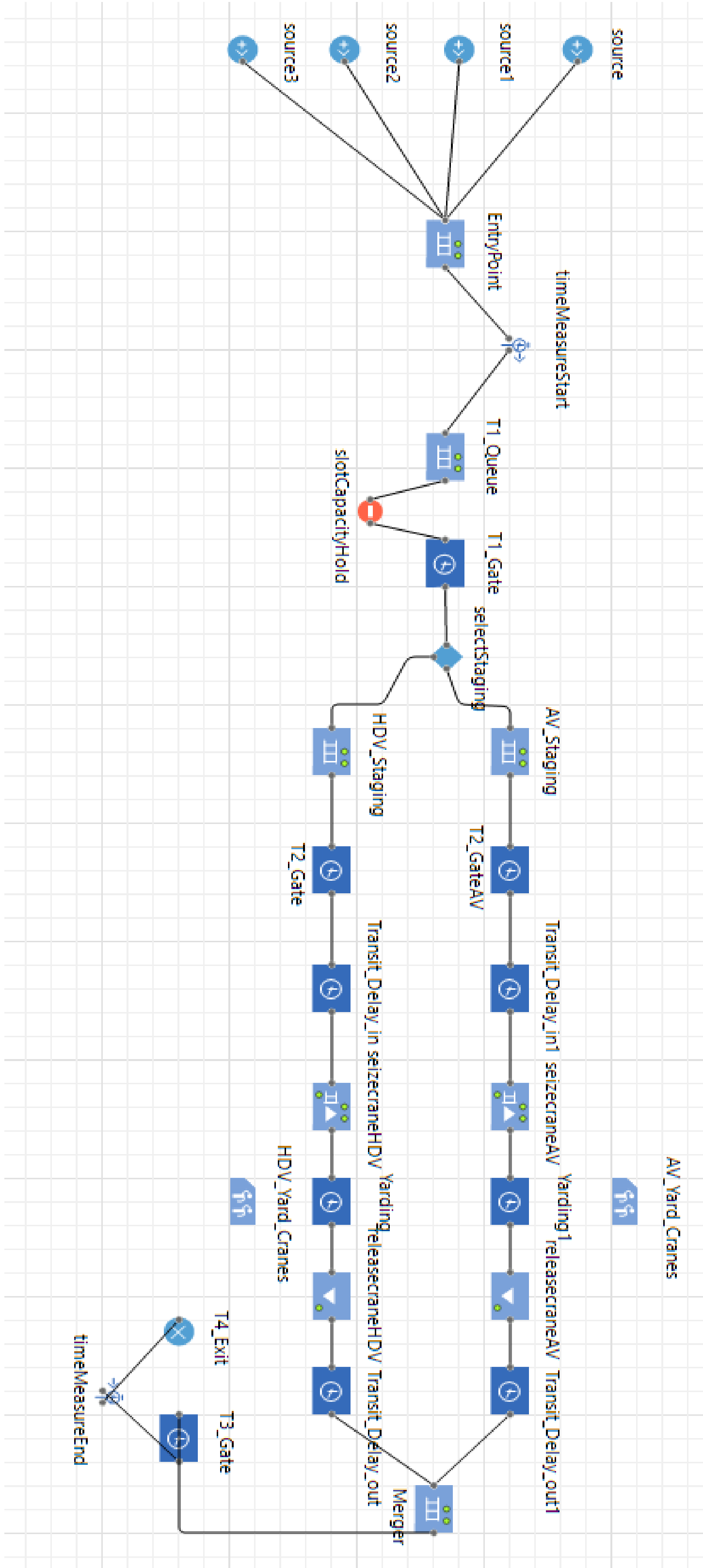

Figure 37 Scenario-4 model

The progression of these scenarios implicitly sets up a future cost-benefit analysis. Scenario 2 (TAS) represents a lower-cost, software-based intervention. Scenario 3 (partial AV) represents a moderate investment in vehicles. Scenario 4 (dedicated infrastructure) represents a significant capital expenditure. The simulation results will not only show TTT reduction but will also provide the basis for discussing the return on investment for each level of intervention, which is crucial for real-world decision-making and evaluating the practical issues with autonomous truck deployment. The summary of all the scenarios implemented is represented in table 26.

Table 26 Scenario summary and key characteristics

Scenario	**Truck Appointment System (TAS)**	**AV Integration (%)**	**Yard Crane Allocation**	**Key Operational Changes**	**Expected Impact on TTT**
1: Baseline	No	0%	All 15 shared (HDV)	FIFO processing, unmanaged arrivals	High TTT, significant congestion
2: TAS Only	Yes (Slot-based, 20-min slots, fixed capacity)	0%	All 15 shared (HDV)	Controlled arrivals, smoothed peaks	Moderate TTT reduction, improved predictability
3: Partial AV Integration	Yes (Slot-based)	35%	All 15 shared (HDV & AV)	AVs with reduced reaction times & yard delays; shared resources	TTT reduction, but potential contention
4: AV Staging & Dedicated Cranes	Yes (Slot-based)	35%	4 dedicated (AV), 11 shared (HDV)	Dedicated AV staging & reserved cranes for AVs	Most significant TTT reduction, optimized AV flow

Chapter 6:

Conclusion and Future Work

6.1 Conclusion

In this thesis we addressed the problem of high truck turn times in ports and investigated the feasibility of implementing autonomous vehicles to minimize truck turn time (TTT), port congestion and consecutively maximize operational efficiency. An application for Port of Montreal, Viau Terminal is conducted using DES. Four scenarios are investigated. These include, the baseline scenario, the Truck Appointment System (TAS) scenario, a scenario with partial integration of Avs, and finally, a scenario incorporating dedicated AV infrastructure.

The study was able to come up with a robust simulation model that accurately simulates the intricate operating activities influencing truck movements within the terminal from gate arrival to eventual departure. Through a systematic comparison of four scenarios, this research has established quantitative evidence robust enough to confirm the positive effect of strategic interventions on port congestion.

The baseline scenario established the critical challenge of an average TTT of 88.2 minutes, which called for intervention. The sequential analysis demonstrated that a Truck Appointment System (TAS) on its own would lower TTT to 78.37 minutes, demonstrating the short-term gains from demand management. Adding Autonomous Vehicles (AVs) in a shared infrastructure later on, further optimized overall TTT to 55.91 minutes, uncovering the natural efficiencies of autonomous technology. Most significantly, even though Scenario 4 with dedicated AV infrastructure registered the least to-Top-of-the-line (TTT) in AV-specific terms (32.86 minutes), its system TTT of 57.13 minutes was ever so slightly higher than that of Scenario 3, as HDV TTT was increased (70.20

minutes). This subtlety proves to us that though dedicated resources are highly valuable to AVs, resource partitioning must be carried out carefully so that optimization at the systems level is achieved in a mixed fleet setup to an optimal level.

Sensitivity analysis also supported the interdependence among the critical operating parameters, with the percentage of AVs, crane capacity, and truck arrival rates all being significant drivers of terminal performance overall. These findings collectively support the thesis statement: that the use of autonomous vehicles, explored through DES, has potential to significantly lower truck turn time and enhance operational efficiency at the Port of Montreal, as long as issues related to them and strategic deployment, in the case of resource allocation in mixed fleets, are effectively addressed. This study enhances the body of knowledge by providing a concrete case study for the Port of Montreal, closing the gap between theoretical possibility and real-world application in an operational port environment.

6.2 Future Work

Though this study offers practical observations on the ability of autonomous vehicles and operational strategies for reducing truck turn time at the Port of Montreal, several avenues for further research can enhance the model's realism, scope, and applicability.

1. Using Real Data to Validate Findings:

The existing simulation model, although informed by publicly available data and prior studies, is still conceptual. One of the most important steps in the process would be to work closely with the Port of Montreal or Termont Montréal to obtain high-resolution, real-time operating data. This would include precise distributions for gate processing times, yard service times, actual truck arrival patterns, and detailed resource utilization logs. All these data would allow for closer calibration and validation of the model, going beyond qualitative fit and nearing quantitative accuracy. This additional verification would greatly increase the validity and applicability of the findings, so the port authorities would be more directly able to apply the recommendations.

2. Including Multi-Terminal Behavior:

The current model focuses exclusively on the Viau Terminal. The Port of Montreal possesses multiple container terminals, and truck traffic tends to cross among these terminals. Subsequent research could expand the model to accommodate multi-terminal behavior, representation of truck travel between terminals, inter-terminal transfer impacts, and potential spillover congestion. This would provide a more complete representation of port-wide logistics network and allow coordinated strategy to be tested on all terminals, such as a port-wide TAS or shared AV fleet.

3. Expanding Model to Account for Last-Mile Delivery

The scope of this study was intentionally confined to the internal landside operations of the Viau Terminal. The value addition would be to integrate the "last-mile" delivery feature, mirroring truck movement from port of departure right through to their ultimate destination in the urban or regional hinterland. Added would be including external road network conditions, city traffic, and last-mile logistics special features. This expansion would create the larger perspective on the overall drayage process to permit consideration of how port-side efficiencies are being translated into supply chain advantages more broadly and how AVs would affect the port-to-consignee trip overall. This can also enable consideration of the environmental advantages of less urban congestion and greater efficiency.

This thesis has demonstrated, through DES of the Port of Montreal's Viau Terminal, with rigor that autonomous vehicles can be revolutionary in reducing truck turn time to radically short periods but, for their optimal fit, need a multi-modal approach with well-developed truck appointment systems and appropriately planned dedicated infrastructure. The more detailed findings underscore that unless autonomous fleets are optimized to run at optimum efficiency it must be sacrificed for ensuring operational fluidity within human-operated vehicles and collectively embody the intricate dynamics of technology and infrastructure in ensuring an entirely maximized and sustainable port logistics environment. With this growing trend of global commerce, the findings from this study provide essential advice to port authorities in transitioning their operations towards a more automated and efficient future.

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