Mathematical Modeling and Simulation for Optimizing Truck Dispatch in Bulk Unloading Operations: A Case Study at the Port of Itaqui

Victor José Beltrão Almajano Martinez[a], Carlos Eduardo V. Gomes[b],
João Augusto F. N. de Carvalho[c], Francisco Glaubos Nunes Clímaco[d],
João Dallyson Sousa de Almeida[e], Geraldo Braz Júnior[f] and Tiago Bonini Borchatt[g]

Núcleo de Computacão Aplicada, Universidade Federal do Maranhão (UFMA), São Luís, MA, Brazil
{victor.martinez, carlos.evg, augusto.joao}@discente.ufma.br,
{fra a.br

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Abstract: This paper addresses the optimization of truck pulling for bulk unloading operations at the Port of Itaqui, a critical logistics hub in Brazil. The current manual process often leads to inefficiencies such as congestion, delays, and increased emissions. To tackle these challenges, we propose a mathematical model for responsive truck pulling to minimize queue imbalances considering emissions while maintaining operational efficiency. A port activity simulator was developed to evaluate the model under various demand and supply scenarios, comparing its performance against a benchmark algorithm replicating operator behavior. Results demonstrate that the proposed model reduces truck congestion in the primary area by up to 50% without increasing unloading times, offering a more balanced and sustainable approach. The findings enhance port logistics and provide a framework for automating truck dispatch processes in bulk cargo operations. Future work involves integrating the model into real-world applications and extending its capabilities to multi-terminal environments.

1 INTRODUCTION

Maritime transport is the main means of transportation for global trade. It is the basis of international trade due to its cost-effectiveness for moving large amounts of goods over long distances. In fact, according to the Review of Maritime Transport, 2024 (United Nations Conference on Trade and Development, 2024), more than 80% of global trade by volume and approximately 70% by value is carried by sea. According to projections by the International Transport Forum 2023 (ITF, 2023), maritime freight demand will double by 2050. Thus, the growth in demand, together with larger vessel sizes, intensifies the complexity of the operation, driving the need to improve port infrastructure, logistics performance, and efficient cargo handling.

[a] https://orcid.org/0009-0001-8759-8927
[b] https://orcid.org/0009-0007-0273-4373
[c] https://orcid.org/0009-0004-1165-1228
[d] https://orcid.org/0000-0002-1357-1318
[e] https://orcid.org/0000-0001-7013-9700
[f] https://orcid.org/0000-0003-3731-6431
[g] https://orcid.org/0000-0002-3709-8385

The intensification in the complexity of port operations, without proper planning, can lead to port congestion, especially when unloading and reloading cargo. This results in longer dwell times and creates bottlenecks that disrupt the flow of goods, leading to increased costs, delays, and inefficiencies throughout the supply chain. Furthermore, congestion in ports can drive up shipping freight rates, as observed in the case of maritime trade in liquefied petroleum gas, where supply and demand dynamics were strongly influenced by port efficiency (Xiwen Bai and Xu, 2022).

Real-time analysis of port congestion using vessel tracking information reveals that congestion can extend port response times, affecting economic implications for stakeholders and necessitating better network design (Xiwen Bai and Xu, 2024). The spatial computable general equilibrium (CGE) model (Haddad et al., 2010) highlights that port costs act as trade barriers, spreading the impact of congestion across space and time and impacting regional growth and inequality.

The congestion of multiple services in container ports, where different services interfere, can propagate delays through port nodes and links, exacerbating the problem (Talley and Ng, 2016). The growth

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in container traffic and the COVID-19 pandemic have intensified congestion, making cargo transit times uncertain and increasing freight rates, which requires predictive models to help shipping companies adjust their schedules (Talley and Ng, 2016).

Efficient cargo handling and coordination with the interior are crucial, as congestion at port gates due to high variability in truck arrivals can lead to uneven resource utilization, which truck appointment systems (TAS) aim to mitigate (Ramírez-Nafarrate et al., 2017).

The Port of Itaqui serves as a central logistics hub for the export of bulk solids and liquids. As one of Brazil's largest and most strategic ports, it faces substantial operational challenges (see Figure 1). In 2022, the port achieved a historic milestone by handling a record cargo volume of 33.61 million tons. Of this total, 23 million tons were solid bulk, which marked a significant increase of 19% compared to the previous year. This substantial growth in cargo throughput has added to the operational complexity of the port, especially in managing the efficient flow of trucks involved in the unloading process.

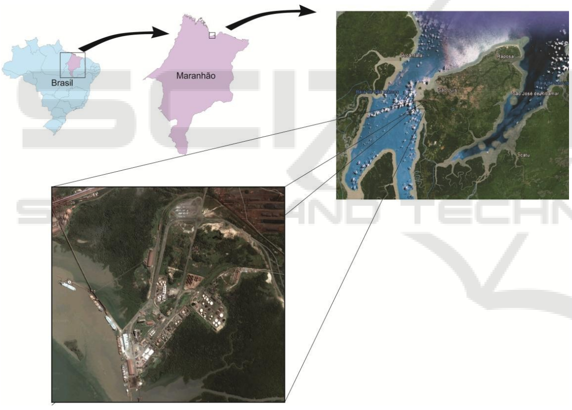

Figure 1: Port of Itaqui, on the west coast of the island (São Marcos Bay), 11 km from São Luís (EMAP, 2024).

In the port of Itaqui, the current operation is managed manually by a human operator who controls the number of trucks to pull based on real-time observations of port conditions. Although this method has been in place for years, the rapid growth in cargo volume has exposed its limitations. The manual nature of the process can lead to inefficiencies such as delayed responses, improper queue balancing, and periods of under-utilization and overcrowding. These inefficiencies often result in bottlenecks, increased congestion, and disruption of the smooth flow of trucks through the port, ultimately affecting the overall productivity of unloading operations.

To address these challenges, this work proposes solutions that include:

1. **A Novel Mathematical Model** Developed to automate the truck-pulling process for bulk unloading operations at the Port of Itaqui, optimizing truck allocation to minimize queues while considering dock capacities and operational constraints and incorporating the reduction of greenhouse gas emissions into the optimization process.
2. **A Real-Time Simulation Environment.** Designed to test the model under various operational scenarios dynamically, ensuring robustness and adaptability.
3. **First Evaluation of the Manual Truck-Pulling Process in a Simulated Environment.** The manual truck-pulling strategy, provided by EMAP (Maranhão Port Administration Company), was analyzed in a controlled simulation for the first time.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on port congestion and the mathematical models used in logistics optimization, providing the foundation to understand this work. Section 3 provides a detailed description of the problem, defining its key aspects. Section 4 describes the methodology employed in the study, including the definition of the object of study and the data analysis conducted to develop the proposed mathematical model (Section 5) and its validation environment (Section 6). Finally, Section 7 presents the results and discussion, while Section 8 concludes the paper by summarizing key findings and highlighting potential directions for future research.

2 RELATED WORK

Mathematical modeling is essential to optimize the distribution of trucks for unloading ships, address operational challenges to increase efficiency, and minimize polluting emissions. For example, Integer Linear Programming models can ensure that trucks are loaded within their dimensional and weight capacities, considering factors such as the center of gravity and minimizing the number of pallets. This is crucial for practical applications in distribution companies (Alonso et al., 2017).

Other approaches focus on reducing greenhouse gas emissions by optimizing berth allocation yard block assignment, internal truck operations, and berth allocation in container terminals (Karakas et al., 2021). Furthermore, models such as cyclic queuing and Markov decision processes can be used to optimize the size of transport fleets, including cranes and trucks, to maintain stable port productivity and dynamic operational policies, as demonstrated with empirical data from the Port of Balboa (Kang et al., 2008).

The routing and scheduling of yard trucks between quay cranes and yard cranes have been optimized using binary integer programming models, minimizing total operational costs and determining the optimal number of yard trucks, thus improving the efficiency of container terminals (Tsai et al., 2016). Furthermore, the spatial behavior of carriers, particularly in repositioning empty trucks due to trade imbalances, is modeled probabilistically to increase transparency and operational planning, which is vital for sustaining business in low-demand zones (Boumahdaf et al., 2023). The truck sector optimization (TSO) model evaluates the impact of investments in fuel-saving technologies on life cycle greenhouse gas emissions, highlighting the importance of comprehensive modeling in reducing environmental impacts (Guerrero et al., 2013).

Ensuring load balance throughout the distribution route is another critical aspect addressed by the Multi-Drop Load Balancing Recovery Algorithm, which adjusts load arrangements to maintain compliance with safety regulations and operational efficiency (Silva et al., 2018). Integrated optimization problems involving quay cranes and yard truck scheduling are solved using mixed-integer programming models and particle swarm optimization methods, which significantly reduce computational complexity and improve solution efficiency (Zhen et al., 2019).

Queuing models for unloading operations, considering different probability distributions, help determine the optimal number of trailers, ensuring robustness and cost-effectiveness in unloading processes. The interaction between strategic location and tactical inventory/transport decisions is modeled using nonlinear mixed-integer models, which explicitly detail load costs and demonstrate significant savings when inventory decisions are integrated into facility location planning (Sıla Çetinkaya and Üster, 2014).

Although various mathematical models have been developed to optimize truck distribution in port operations, most existing approaches focus on general aspects such as routing, scheduling, or load balancing, often designed for container terminals or specific transportation scenarios. Thus, there is a notable gap in the literature regarding the automation of truck-pulling processes for unloading bulk solids in ports. Specifically, no studies have been identified that address truck-pulling optimization considering the unique operational characteristics of bulk unloading, such as responsive queue management, dock-specific constraints, and environmental impacts.

This work addresses this gap by proposing a novel mathematical model tailored to automate truck-pulling for bulk unloading operations. Unlike existing approaches, our model integrates real-time queue balancing with reducing carbon emissions. By focusing on the specific context of the Port of Itaqui, the proposed model offers a practical solution to improve efficiency and sustainability in bulk port operations.

3 PROBLEM DESCRIPTION

At the Port of Itaqui, trucks unload cargo from ships with the assistance of mobile cranes and hoppers. When new empty trucks arrive for unloading, they first proceed to an External Yard located outside the port, where they wait to be called in for unloading. Once the operator registers a dispatch signal (or pull signal), the selected trucks move from the External Yard to the Truck Retention Yard within the port area. In this yard, they undergo preparations for the next stage, which includes activities such as weighing and verifying their readiness for unloading.

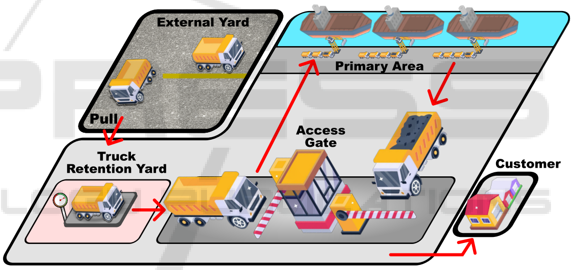

Figure 2: Illustration of Port Unloading Operation.

Once ready, the trucks pass through the Access Gate, entering the Primary Area of the port, where they line up to unload the cargo from the ships. After receiving the cargo, the trucks leave the Primary Area and head toward the Customer, where the cargo is delivered. This process repeats as new trucks are scheduled from the External Yard, ensuring continuous unloading and cargo delivery operations. Figure 2 shows the main stages of this process, from the External Yard to Customer Delivery.

Since the External Yard cannot be relocated inside the port due to the high value of the land for other uses, there needs to be a more consistent approach to the decision to "pull" trucks. This is important, given the current operational circumstances. A longer response time for trucks arriving at the port after being dispatched means that underestimating the number of trucks to call could disrupt the flow of trucks in the main area, affecting the unloading operations. On the other hand, overestimating could lead to congestion.

The current truck-pulling system is operated manually, with an operator determining the number of trucks to dispatch for each Modal Window — a combination of customer, product, and shipment—based on real-time observations of port conditions. While this method has been in place for years, the rapid growth in cargo volume has revealed its limitations. The manual nature of this process can lead to delayed responses, improper queue balancing, and periods of under-utilization and overcrowding. These inefficiencies often result in bottlenecks, increased congestion, and disruptions to the smooth flow of trucks through the port, ultimately impacting the overall productivity of unloading operations.

4 METHODOLOGY

The methodology applied in this study begins with the definition of the object of study, followed by the analysis of port data, the development of a mathematical truck-dispatching model, and finally, the implementation of a simulator for validation and comparison of the model, as seen in Figure 3. Each step is detailed in the following sections.

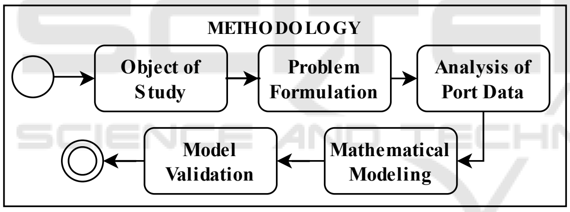

Figure 3: Methodology Diagram.

4.1 Object of Study and Formulation

To gain a comprehensive understanding of the bulk unloading operations at the Port of Itaqui, extensive interactions were undertaken with key stakeholders. Meetings with managers and operators provided valuable insights into the behavior of vehicle flows under various scenarios. Additionally, field visits were conducted to observe real unloading operations, ensuring that the analysis reflects practical realities. Based on these observations, key concepts were identified and defined:

- **Truck Flow.** The movement of trucks throughout the stages of the process, starting with their arrival at the External Yard and ending with the delivery of the cargo to the client's location. The smoothness of this flow ensures the continuity of unloading operations without creating bottlenecks.
- **Modal Window.** Refers to a record in the port's system associated with a client contract. Each window is linked to a ship, a product type, a client, and a set of trucks authorized to unload within that window. Typically, the client hires a company to deliver their product. In that case, the trucks belonging to that company/client only unload within the designated window for which they were contracted.
- **Dispatch (or Pull).** Denotes authorization for a truck in the External Yard to begin the unloading process at its designated modal window. The unloading process follows a First In, First Out (FIFO) strategy, meaning that the truck that has been waiting the longest is prioritized, provided it is aligned with the designated modal window.

Thus, the dispatching problem can be defined as determining the optimal number of trucks to be pulled at this moment to ensure the smoothness of truck flow across all windows until the next pull. The port operates with a set of active ships $(\mathbf{S})$, where each ship is linked to a set of modal windows $(\mathbf{W}_s)$. Each modal window, in turn, stores the real-time quantity of trucks at each process step.

4.2 Analysis of Port Data

A detailed analysis was conducted using data provided by EMAP (Maranhão Port Administration Company). These data included comprehensive records of truck flow within the port and the pulling strategy currently employed to address varying demand scenarios. Key documents reviewed contained historical data on truck movements, as well as suggested strategies for different operational contexts. The dispatching suggestions are summarized in Table 1.

In addition to the dispatch strategies, the historical data provided by EMAP included detailed records of truck movements at each stage of the unloading process. This data highlighted the number of trucks at various points in the flow, the average time spent in each phase, and an overview of the pulling operations performed by human operators.

These data sets were critical for developing the proposed model and for constructing benchmark algorithms (Section 5). Furthermore, they served as the foundation for refining the model validation environment (Section 6), ensuring that the proposed solutions were well-aligned with real-world operational scenarios at the Port of Itaqui.

Table 1: Pulling suggestions across various scenarios.

Ships	Open windows	Suggested	Maximum
1	1	15	60
	2	9	30
	3	6	20
	4	5	15
	5	5	12
2	1	15	30
	2	6	15
	3	5	10
	4	5	8
	5	3	6
3	1	8	20
	2	6	10
	3	5	7
	4	5	5
	5	3	4

5 MATHEMATICAL MODELING

The problem of dispatching trucks for unloading solid bulk materials can be modeled as an integer programming problem, as it is well-suited for handling discrete search spaces and complex constraints. In this context, a mathematical decision model for truck dispatch was developed to balance queue sizes responsively in the primary area while minimizing total truck emissions.

This model aims to coordinate the pulling of trucks from the External Yard to the primary area, considering the status of each modal window. The objective is to ensure that all active windows are served balanced, considering their respective truck flows, preventing equipment idleness and bottlenecks while minimizing congestion in the primary area and reducing the volume of pollutants released into the environment.

5.1 Responsive Truck Dispatching Model

Consider the decision variable $x_{sw} \in \mathbb{Z}_0^+$ representing the number of trucks to be dispatched to a window $w \in \mathbf{W}$ of ship $n \in \mathbf{N}$. The objective function is defined as shown in Equation 1.

$$\min \sum_{s=1}^{|S|} \sum_{w=1}^{|W_n|} P\, x_{sw} + Q \sum_{s=1}^{|S|} \sum_{w=1}^{|W_n|} L_{sw} \frac{|x_{sw} + T_{sw} - F_{sw}\, Min_{Queue}|}{W_{active}} \tag{1}$$

The first term of the objective function aims to minimize the total carbon emissions of trucks. The second term seeks to minimize the imbalance in queue sizes for each window by reducing the difference between the actual and ideal queue sizes based on the current truck flow.

The parameter P represents the average expected emissions for a vehicle to complete the cycle, while Q is the penalty factor associated with the imbalance of the queues. Thus, P and Q are, respectively, proportional to the penalty related to carbon emissions and the lack of responsiveness in queue balancing.

Furthermore, L_{sw}, calculated as the number of trucks available for pulling in the External Yard for that window divided by Min_{Queue}, represents the reduction of the penalty associated with a window having reduced truck availability for pulling in the External Yard. Thus, the queue size is dynamically adjusted by considering truck availability in the External Yard and the vehicle flow F_{sw} in the primary area for that specific window. These factors ensure the model's responsiveness. Other parameters of the model are summarized in Table 2.

To ensure the integrity of the model regarding truck pulling, the model must respect the following constraints:

$$x_{sw} \leq SUPPLY_{sw} \quad \forall s \in \mathbf{S},\ \forall w \in \mathbf{W}_s \tag{2}$$

Constraint (2) ensures that the number of trucks dispatched does not exceed the available trucks in the External Yard ($SUPPLY_{sw}$) for a given window w of ship s.

$$x_{sw} \leq Max_{queue} - T_{sw} \qquad \forall s \in \mathbf{S},\ \forall w \in \mathbf{W}_s \tag{3}$$

Constraint (3) ensures that the number of trucks dispatched to a window w remains below the maximum queue size to prevent congestion. The dispatch value is restricted to the difference between the maximum queue size (Max_{queue}) and the number of trucks (T_{sw}) that have already been called but have not yet completed the cargo collection.

$$\sum_{w=1}^{|W_s|} x_{sw} \leq Max_{berth} - \sum_{w=1}^{|W_s|} T_{sw} \qquad \forall s \in \mathbf{S} \tag{4}$$

Constraint (4) ensures that the total number of trucks assigned for the unloading of a ship s does not exceed the maximum vehicle capacity of the ship (Max_{berth}), considering the number of vehicles already in operation (T_{sw}). This prevents the over-allocation of trucks to a single ship, avoiding congestion at the berths.

$$\sum_{s=1}^{|S|} \sum_{w=1}^{|W_s|} x_{sw} \leq Max_{port} - \sum_{s=1}^{|S|} \sum_{w=1}^{|W_s|} T_{sw} \tag{5}$$

Constraint (5) ensures that the total number of trucks dispatched for all operations does not exceed the port's capacity limit (Max_{port}).

Table 2: Summary of Objective Function Model Parameters.

Parameter	Description
P	Constant associated to the Expected Emissions for a truck to complete a cycle
Q	Constant associated with the General Penalty attributed to queue imbalance
R	Sufficiently Large Constant associated with slack variables
L_{sw}	Penalty reduction factor associated with a window having vehicle unavailability for pull
F_{sw}	Balancing factor proportional to the truck flow.
T_{sw}	Number of Trucks in transit to the port or waiting for collection in the Primary Area
W_{active}	Number of Active Windows across all ships
$SUPPLY_{sw}$	Number of Trucks available at External Yard to window **w** of ship **s**
Min_{queue}	Minimum number of trucks that must be queued to ensure uninterrupted unloading
Max_{queue}	Maximum number of trucks that can be allocated to attend to the unloading of a window
Max_{berth}	Maximum number of trucks that can be allocated to a berth
Max_{port}	Maximum number of trucks that can be in operation within the Port Area.

$$x_{sw} + T_{sw} + g_{sw} \geq Min_{queue} \quad \forall s \in \mathbf{S},\ \forall w \in \mathbf{W}_s \quad (6)$$

Constraint (6) ensures that each window maintains a minimum number of trucks in the queue in the primary area (Min_{queue}), aiming to ensure that trucks are constantly being loaded, preventing unloading interruptions and equipment idleness. A slack variable g_{sw} is also introduced for cases where there are not enough trucks in the External Yard to be dispatched, allowing the model to adjust without violating the minimum queue size constraint. This avoids conflicts with the vehicle availability constraint while enabling the continuity of operations.

$$x_{sw} + T_{sw} - F_{sw} Min_{queue} + \theta_{sw} \geq 0 \quad \forall s \in \mathbf{S},\ \forall w \in \mathbf{W}_s \quad (7)$$

Constraint (7) ensures the maintenance of the model within the linear programming domain, justifying the inclusion of the variable θ, representing the deviation from the average queue size. However, an adjustment is needed in the equilibrium term of the objective function (Eq. 1) to guarantee the attainment of absolute equilibrium values. The objective function becomes as follows:

$$\min \sum_{s=1}^{|S|} \sum_{w=1}^{|W_s|} P\, x_{sw} + R \sum_{s=1}^{|S|} \sum_{w=1}^{|W_s|} g_{sw} + Q \sum_{s=1}^{|S|} \sum_{w=1}^{|W_s|} L_{sw} \frac{(x_{sw} + T_{sw} - F_{sw}\, Min_{queue} + 2\theta_{sw})}{W_{atv}} \quad (8)$$

Additionally, in linear programming, slack variables must be included in the objective function to ensure consistency in cases where constraints cannot be fully satisfied. Thus, a term was added to the objective function that introduces the slack variables (g_{sw}) multiplied by a sufficiently large constant R.

These slack variables ensure that the model remains feasible even when some constraints — such as the minimum queue size — cannot be strictly satisfied. The constant R is a sufficiently large positive value that penalizes the use of slack variables, ensuring they are only used when necessary.

5.2 Benchmark Algorithm

To perform a comparative evaluation of the Responsive model, a solution algorithm was also developed for the dispatch problem to represent the port operator directly executing the pull based on the dispatch suggestions presented in Table 1. Since the dispatch suggestions are limited to the described scenarios, we assume that new scenarios will be treated as the most similar described scenarios. The pseudocode is presented below.

Algorithm 1: Benchmark Algorithm based on data provided by EMAP.

```
Data: Vetor of Ships, Windows and Trucks;
      Matrix of Scenario Sugestion
Result: Pull Matrix
for s in Ships do
    for w in s.Windows do
        Pull[s][w] = Sugest[s][w] - T_sw;
        Pull[s][w] = max(0, Pull[s][w]);
        Pull[s][w] = min(Supply, Pull[s][w]);
        if w is inactive then
            Pull[s][w] = 0;
        end
    end
end
```

The algorithm's operation replicates the dispatch from the tabulated scenario. It performs consistency tests to verify the integrity of the dispatch value and the availability of vehicles in the External Yard. If the window is inactive, no dispatch is assigned. This algorithm will be used in the results section to benchmark the proposed model, to compare it with solutions manually implemented at the Port of Itaqui.

6 MODEL VALIDATION ENVIRONMENT

To evaluate the proposed model, a simulator of port activities focused on bulk unloading was implemented, covering the main stages of the process. The simulator generates an initial scenario based on information about ships, unloading windows, trucks, load capacities, and average time intervals for each stage. Then, the simulator initializes the model by reading the current scenario, which includes the distribution of trucks across the stages of the operation.

The model performs a linear optimization process to evaluate potential dispatching decisions and returns the numerical decision for the number of trucks that should be dispatched at that moment to fulfill the unloading demands of each modal window. The scenario is then updated to incorporate these results, and the process is repeated at small regular intervals of one minute (timeslices), continuously simulating the port's unloading operations. The described process is illustrated in Figure 4.

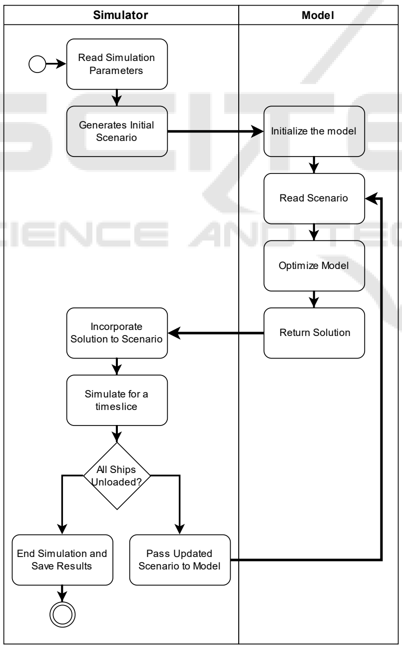

Figure 4: Model implementation within the Simulation.

All parameters are based on data provided by EMAP (Section 4.2), ensuring that the simulation reflects real-world operations. The simulator periodically assigns new trucks to active modal windows, which then pass through the following stages (see Figure 5):

1. **External Yard.** Trucks wait in the External Yard until the operator issues a pull signal for the respective modal window, dispatching the informed quantity of trucks using the FIFO strategy.
2. **In Transit to Port.** This phase covers the journey to the port, starting from the confirmation of the pull, followed by the weighing of the empty truck at the weighbridge, and ending with the truck's arrival at the Access Gate.
3. **Primary Area.** Internal port area designated for the loading/unloading operations. Here, trucks proceed to their ship's berth and wait in line for their turn to collect the cargo at the modal window's hopper.
4. **In Transit to Costumer.** The last phase, extending from the collection of the cargo to the delivery at the customer's location. After delivery, trucks are removed from the flow of vehicles.

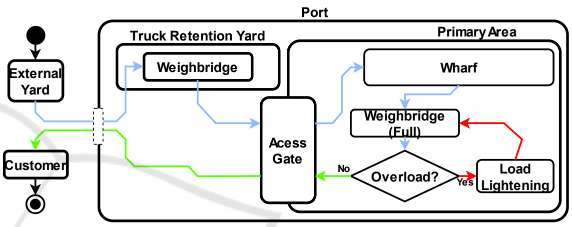

Figure 5: Stages from port gate to customer delivery.

6.1 Supply Scenarios

To control the periodic assignment of new trucks across the modal windows, renewing the supply of trucks in the External Yard, a variable ρ is introduced to determine the frequency of new truck arrivals. For example, if $\rho = 0.5$, the simulation assumes that the probability that a truck arrives at the External Yard is 50% in each time slice. Thus, three supply scenarios were defined:

1. Affluent ($\rho \geq 0.5$): Truck supply exceeds demand, allowing flexible pulls.
2. Standard ($0.1 < \rho < 0.5$): Truck availability fluctuates, representing typical port conditions.
3. Scarcity ($0 \leq \rho \leq 0.1$): Truck supply cannot meet demand, restricting pulls and limiting operational capacity.

In addition, a Gaussian variation was applied to the variable ρ, to avoid uniform and repetitive simulations. This variation adds small fluctuations around the value of ρ in each operating window. This simulates natural variability in operations, such as truck arrival times. Furthermore, a random walk-inspired variation was introduced through a variable ω. This technique randomly alters the frequency of truck arrivals over time, creating unpredictable variations that mimic real fluctuations in port operations, such as possible delays or busy periods. The simulation continues until all vessels and their respective operating windows have completed the unloading process.

6.2 Vehicle Emissions Control

Vehicle emissions control was also implemented throughout the simulation to evaluate the model concerning pollutant emissions. Therefore, for each truck, the exhaust emissions of greenhouse gases were considered: carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), as well as carbon monoxide gases(CO), nitrogen oxides (NO_x), non-methane hydrocarbons ($NMHC$), and particulate matter (PM). Evaporative, refueling, specific sulfate, and aldehyde emissions were not considered because of the lack of available data.

Thus, it is necessary to estimate emissions at each phase of the flow (External Yard, In Transit to Port, Primary Area, and In Transit to Customer). To calculate the emissions related to the transit to the port/customer, the emission factors provided in the latest national vehicle inventory were used (Brasil, 2013), summarized in Table 3.

Table 3: Emission Factors for Greenhouse gases (GHGs) and Non-Greenhouse gases on Heavy Duty Vehicles (Diesel Engines) in $g_{pollutant}/km$ and their Global Warming Potential (GWP). Adapted from (Brasil, 2013).

Type	Pollutant	Em. Factor	GWP (CO_2eq)
GHG	CO_2	765.58	1
	CH_4	0.06	21
	N_2O	0.03	310
Non GHG	CO	0.111	-
	NO_x	1.544	-
	$NMHC$	0.011	-
Other	PM	0.014	-

On the other hand, calculating the emissions in the primary area is slightly different, as the trucks are lined up waiting for collection, with the engine primarily idle. Although studies are mapping the performance of diesel engines, such as (Barth et al., 2005), the lack of data on truck conditions prevents their use.

Thus, to calculate idle emissions, data on diesel engine consumption in idle mode and pollutant emissions per liter of diesel consumed were used, as available in (Brasil, 2013). Finally, the trucks' emissions can be calculated using Equation 9, adapted from (de Araújo, 2016):

$$E_p = \sum^{|Truck|} \left(f_p d_{ph} + e_{idle} c_{idle} t_{idle} \right) \quad (9)$$

Where:

- E_p represents the total emissions for pollutant p.
- f_p is the emission factor for the pollutant during each phase, in $g_{pollutant}/km$.
- d_{ph} denotes the distance, in kilometers, traveled in each phase.
- e_{idle} is the pollutant's emission rate per liter of fuel during idle periods.
- c_{idle} represents the fuel consumption factor during idle time.
- t_{idle} is the time the vehicle idles, predominantly in the primary area.

This formulation accounts for both the distance traveled during active phases and the emissions from idling time, ensuring a comprehensive emission estimate. However, it does not consider the emissions generated during the truck's travel to reach the External Yard. Additionally, it is valid to consider that vehicles in the Heavy-duty and Medium-duty truck categories predominantly operate on highways, and their contribution to air quality degradation in urban areas should be relativized.

7 RESULTS AND DISCUSSION

This section presents the results of the computational experiments to validate the proposed truck-dispatching model. The experiments were designed to evaluate the models' performance across distinct operational scenarios. All parameters were based on real data provided by EMAP (section 4.2), reflecting actual operations at the Port of Itaqui.

The models were implemented in Python 3.12 and executed in a Windows 10 (64-bit) environment, utilizing the PuLP Mixed-Integer Programming solver (Dunning et al., 2011), running on an Intel® Core™ i7-11700 processor with 16 GB of RAM.

7.1 Simulation Visualization

As the first experiment, a simulation was conducted using parameters reflecting the most frequent operations at the Port of Itaqui, representing a typical scenario, referred to as the *standard* scenario ($\rho = 0.2$). The simulation, initialized from an "empty" stage in which no unloading operations have yet been performed, considers bulk cargo unloading for two ships, each with two windows, with an average load of $10kt$ per window and a standard deviation of $2.5kt$.

Figure 6 displays the simulation results for the Responsive Model and the Benchmark Algorithm. It shows the total number of trucks at the different stages

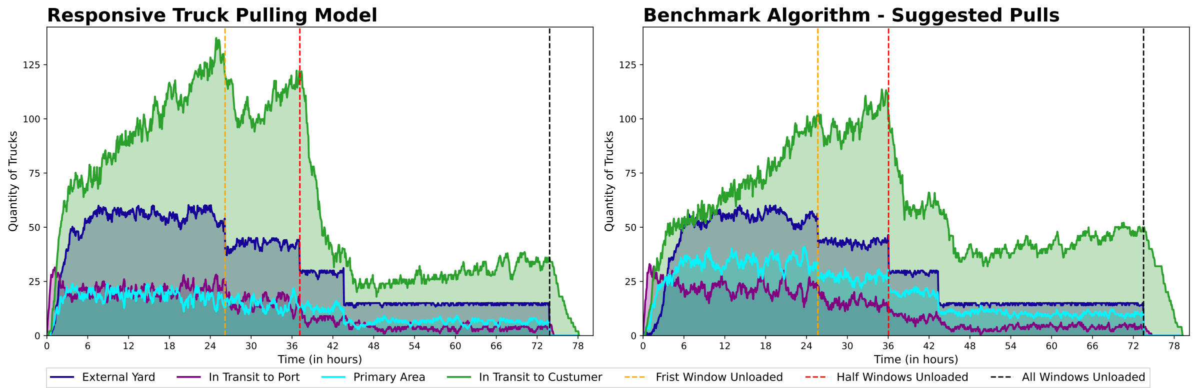

Figure 6: Simulation in standard port unloading processes.

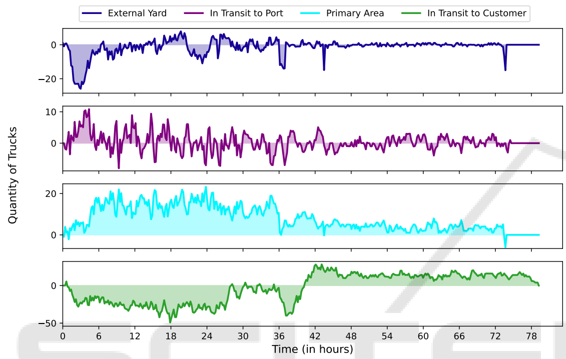

Figure 7: Difference in the number of trucks across flow phases between the benchmark algorithm and the responsive truck dispatching model in a standard scenario.

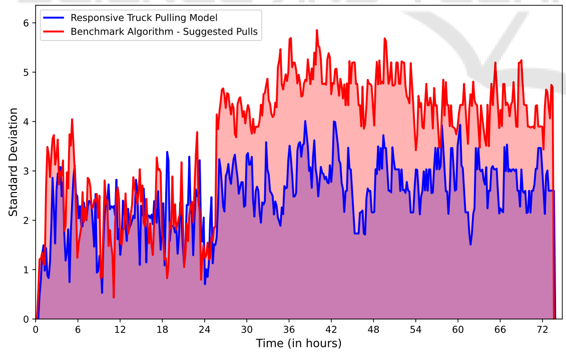

Figure 8: Comparison of the queue size balance in the primary area between the benchmark algorithm and the responsive truck dispatching model in a standard scenario.

of the unloading process: External Yard, In Transit to Port, Primary Area, and In Transit to Customer. Once the simulation starts, both implementations immediately increase the number of trucks In Transit to Port. As the simulation progresses, trucks move through the different stages of the process and eventually reach a balanced state between the number of trucks in the Primary Area and those In Transit to Port after approximately four hours. This indicates that many trucks are waiting for dispatch, which signals that the system has reached a steady state. At this point, the unloading process can continue smoothly, even in a temporary shortage of new trucks.

Once the simulation reaches a state of balance, with no decrease in the supply frequency to the External Yard, this balance is maintained until the first window is fully unloaded. At this point, adjustments in the number of trucks can be observed, reflecting variations in the dispatch decisions made by both the model and the benchmark algorithm transitioning to a new situation, leading to a new equilibrium. This shift becomes more noticeable toward the end of the simulation when fewer windows remain active. As each window completes unloading and the model stops pulling trucks for it, a new equilibrium is established, creating visible "steps" in the graph. The unloading process concludes around the 73-hour mark, with an additional 5 hours to complete the simulation fully.

The main difference between the model and benchmark algorithm lies in the number of vehicles reaching equilibrium in truck flow. The number of vehicles at each stage varies depending on the dispatch strategy. This is shown in Figure 7, which displays the absolute difference in the number of trucks between the Algorithm and the Model across the four key stages. Each subplot illustrates how truck numbers differ throughout the simulation.

Significant differences in truck allocation are observed when comparing the strategies, particularly in the Primary Area. The Benchmark Algorithm quickly exhausts trucks from the External Yard at the beginning of the simulation. In contrast, the Responsive Model adopts a more balanced approach, maintaining a steadier truck supply. The model consistently operates in the Primary Area with fewer trucks, averaging 3.03 trucks per window compared to the algorithm's 5.19. This results in shorter waiting times for the model (45.26 minutes) compared to the pull suggestion (76.58 minutes), reducing congestion and ensuring smoother operations.

Despite the Responsive Model's more moderate strategy, both approaches achieve similar overall unloading efficiency. However, using the model also results in a greater queue balance than the Benchmark Algorithm during the simulation's progression, as seen in Figure 8. A greater balance in the queue size in the Primary Area is a positive factor, as the port management company also aims to serve all clients equitably.

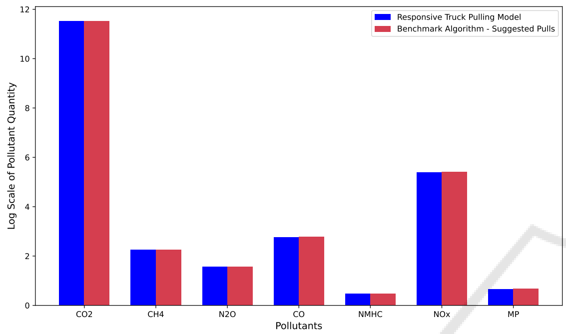

Figure 9: Pollutant Emissions between the Benchmark Algorithm and the Responsive Truck Pulling Model in a Standard Scenario, using a Logarithmic Scale to Highlight Differences Across Pollutants with Varying Magnitudes.

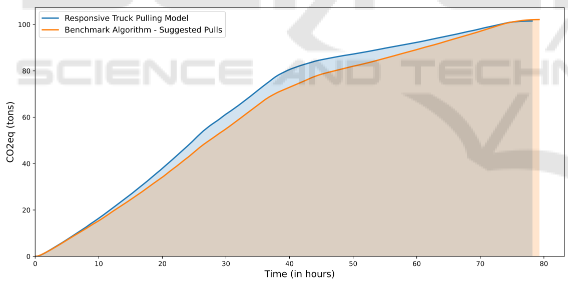

Figure 10: Comparison of CO2-equivalent Emissions between the Benchmark Algorithm and the Responsive Truck Pulling Model throughout the Simulation.

Additionally, regarding vehicle emissions, it is observed that there was no significant variation in the total amount of pollutants released into the atmosphere. Both implementations yielded similar results for both individual emissions and total CO_2 Equivalent emissions, as shown in Figures 9 and 10. This occurs because, although there is a reduction in congestion in the primary area, a higher accumulation of vehicles is observed in the first half of the simulation during the transit phases to the port and the customer, generating higher transit emissions that balance out the total emissions of both approaches. This outcome is also influenced by the choice of weight parameters in the model, as prioritizing queue balance may reduce congestion but lead to increased transit emissions.

7.2 Exhaustive Comparison Across Demand Scenarios

To conduct a more thorough analysis, we conducted simulations for three scenarios of external yard supply — Standard, Scarce, and Affluent — with varying truck demand levels — low, medium, and high. In the low-demand scenario, we considered one ship with two windows, while medium demand involved two ships with two windows each, and high demand consisted of three ships with four windows each. Each window had an average load of 10,000 tons, with a standard deviation of 2,500 tons. For each combination of supply and demand, 100 simulation runs were performed for both approaches. The key results for the Standard, Scarcity, and Affluent scenarios are shown in Tables 4, 5, and 6.

Table 4 summarizes key simulation metrics. It shows the average queue size at each stage of the unloading process (External Yard, Transit to Port, Primary Area, Transit to Customer) and the average time trucks spent in each stage. Additionally, it presents the average standard deviation of queue sizes in the primary area and the average equivalent $CO2$ emissions at the end of the simulation. Furthermore, it provides the total time required to complete unloading for all time windows and finalize customer deliveries, thus concluding the simulation. Similar information is provided in Tables 5 and 6 for the Standard and Affluent scenarios.

The results reveal key trends, such as the increase in unloading and simulation time proportional to the port's demand and inversely proportional to the frequency of truck arrivals at the External Yard. As port demand rises, there is a gradual reduction in queue sizes at all stages of the process, suggesting that both model and benchmark algorithm are effectively adjusting their dispatch values to suit the situation.

The responsive truck dispatching model significantly reduced truck queue sizes, waiting times, and balance discrepancies in all three scenarios — Scarcity, Standard, and Affluent — achieving reductions ranging from 20% to 60%. However, in the Scarcity scenario, the reductions were the smallest, limited to the range of 20% to 30%, due to the decision limitations of the model caused by the restricted supply in the external yard. In contrast, the Standard and Affluent scenarios, where truck availability was less restrictive, allowed the models greater flexibility. The primary difference between the models was observed in the Primary Area, where the Responsive

Table 4: Simulations Comparison For the Responsive Model and the Benchmark Algorithm in 100 scarce scenarios.

Scarcity External Yard Supply	Low Demand				Medium Demand				High Demand			
	Pull Suggestion		Responsive Model		Pull Suggestion		Responsive Model		Pull Suggestion		Responsive Model	
	Queue	Time	Queue	Time	Queue	Time	Queue	Time	Queue	Time	Queue	Time
Avg. External Yard	0.63	0:07:56	1.47	0:21:15	1.31	0:14:22	1.43	0:15:03	1.08	0:14:08	1.24	0:17:07
Avg. In Transit to Port	3.92	0:43:44	3.85	0:43:57	3.43	0:43:52	3.39	0:43:57	3.10	0:43:55	3.09	0:43:54
Avg. Primary Area	2.58	0:36:01	1.76	0:23:39	2.27	0:28:32	1.65	0:21:09	1.82	0:27:30	1.44	0:21:58
Avg. In Transit to Customer	16.10	3:10:23	14.47	3:06:47	13.60	2:56:14	13.34	2:56:14	12.76	3:09:01	12.55	3:05:33
Avg. Queue Size Standard Deviation	1.97		1.21		2.39		1.62		2.49		1.80	
Avg. CO2 Equivalent Emissions (tons)	72.28		66.96		143.81		141.09		435.12		427.05	
Avg. All Windows Unloaded	2 days, 13:04:30		2 days, 14:03:50		3 days, 0:33:55		3 days, 0:47:53		3 days, 7:10:36		3 days, 7:03:31	
Avg. End of Simulation	2 days, 18:05:53		2 days, 18:51:50		3 days, 6:17:52		3 days, 6:33:25		3 days, 13:37:17		3 days, 13:20:14	

Table 5: Simulations Comparison For the Responsive Model and the Benchmark Algorithm in 100 standard scenarios.

Standard External Yard Supply	Low Demand				Medium Demand				High Demand			
	Pull Suggestion		Responsive Model		Pull Suggestion		Responsive Model		Pull Suggestion		Responsive Model	
	Queue	Time	Queue	Time	Queue	Time	Queue	Time	Queue	Time	Queue	Time
Avg. External Yard	8.57	1:09:33	10.50	1:26:25	7.93	1:14:51	9.16	1:26:49	6.68	1:17:51	7.57	1:29:29
Avg. In Transit to Port	5.53	0:43:43	5.27	0:43:41	4.75	0:43:55	4.64	0:43:52	3.70	0:43:55	3.67	0:43:59
Avg. Primary Area	7.98	1:09:29	3.11	0:27:55	5.13	0:52:06	2.72	0:28:21	3.77	0:46:51	2.30	0:28:54
Avg. In Transit to Customer	17.93	2:31:12	17.92	2:29:40	15.75	2:37:18	15.51	2:36:35	12.14	2:33:09	12.21	2:33:12
Avg. Queue Size Standard Deviation	2.78		1.38		3.02		1.90		2.98		2.06	
Avg. CO2 Equivalent Emissions (tons)	68.58		66.38		133.79		129.79		386.47		380.43	
Avg. All Windows Unloaded	2 days, 5:31:40		2 days, 6:31:56		2 days, 7:32:09		2 days, 8:01:47		3 days, 2:16:04		3 days, 2:05:48	
Avg. End of Simulation	2 days, 6:45:39		2 days, 7:36:56		2 days, 12:08:48		2 days, 12:36:34		3 days, 2:16:04		3 days, 2:05:48	

Table 6: Simulations Comparison For the Responsive Model and the Benchmark Algorithm in 100 affluent scenarios.

Affluent External Yard Supply	Low Demand				Medium Demand				High Demand			
	Pull Suggestion		Responsive Model		Pull Suggestion		Responsive Model		Pull Suggestion		Responsive Model	
	Queue	Time	Queue	Time	Queue	Time	Queue	Time	Queue	Time	Queue	Time
Avg. External Yard	12.11	1:35:42	12.36	1:42:40	10.25	1:37:12	10.53	1:42:23	8.47	1:40:21	8.74	1:44:49
Avg. In Transit to Port	5.64	0:43:41	5.34	0:43:44	4.59	0:43:37	4.47	0:43:41	3.64	0:43:52	3.59	0:43:43
Avg. Primary Area	8.44	1:14:04	3.04	0:28:28	5.18	0:53:08	2.66	0:28:03	3.84	0:48:43	2.33	0:29:46
Avg. In Transit to Customer	17.18	2:31:38	17.20	2:29:38	14.05	2:28:04	14.61	2:35:24	11.78	2:31:15	12.15	2:35:05
Avg. Queue Size Standard Deviation	2.70		1.42		2.97		1.89		2.92		2.06	
Avg. CO2 Equivalent Emissions (tons)	61.80		60.15		126.31		126.49		383.86		383.61	
Avg. All Windows Unloaded	1 day, 21:17:36		1 day, 22:13:05		2 days, 10:49:37		2 days, 10:49:37		2 days, 22:24:20		2 days, 22:27:38	
Avg. End of Simulation	2 days, 1:07:46		2 days, 2:21:55		2 days, 15:23:03		2 days, 15:23:03		3 days, 3:55:00		3 days, 4:02:04	

Model reduced truck queue sizes and waiting times between 40% and 60% compared to the Benchmark Algorithm. There was a slight increase in queue sizes in the External Yard, but this did not result in delays: both approaches exhibited maximum differences in average unloading times of less than 1 hour.

The significant reduction in truck congestion and waiting time in the Primary Area has broader implications for port logistics, as it enhances operational efficiency and increases queue balancing. On the other hand, the average reduction of total CO_2 Equivalent emissions was approximately 2.5%, considering all supply demands. This can be attributed to the selection of P and Q parameters of the Responsive Model. When the parameter Q is significantly larger than P, it results in a greater focus on responsive queue balancing, potentially at the expense of minimizing total truck emissions. These weights are selected at the operator's discretion using the model and the institution adopting it. This choice depends on factors such as operational priorities, cost considerations, infrastructure constraints, regulatory requirements, internal policies, safety regulations, and environmental laws.

8 CONCLUSIONS

This study proposed one mathematical model, the Responsive Truck Dispatching Model, to automate the decision-making process for truck dispatch in the unloading operations at the Port of Itaqui, soughing to optimize operations by minimizing queue formation in the unloading area without compromising overall operation time. Furthermore, a benchmark algorithm based on data provided by the port administration was implemented to replicate the current behavior of port operators.

A detailed evaluation of the models was conducted using a port activity simulator designed to replicate bulk unloading processes, covering key stages such as the External Yard, Transit to Port, Primary Area, and Transit to Customer. The simulation results, derived from comprehensive tests across varying levels of demand and truck arrival frequencies, demonstrated that both approaches were responsive to dynamic operational conditions. However, it was observed that the model reduced queue sizes in the primary area by 20% to 60% compared to pull suggestions or operator recommendations. Notably, in scenarios where truck supply was not a limiting factor, the model demonstrated a significant advantage by reducing queue lengths and waiting times in the primary area by up to 60%, without extending the total unloading time or increasing overall truck emissions.

Future work will focus on integrating these models into real-world operations at the Port of Itaqui and exploring additional optimization strategies prioritizing queue balancing, throughput maximization, and ideal occupancy levels in different windows. This research contributes to the literature on port logistics, specifically in bulk cargo handling. It provides tools that can support operators in optimizing the flow of trucks, reducing congestion, and potentially automating the decision-making process for truck pull.

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