Proceedings of the 2025 Winter Simulation Conference
E. Azar, A. Djanatliev, A. Harper, C. Kogler, V. Ramamohan, A. Anagnostou, and S. J. E. Taylor, eds.

OPTIMIZATION OF OPERATIONS IN SOLID BULK PORT TERMINALS USING DIGITAL TWIN

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ABSTRACT

This article presents the development of a Digital Twin (DT)-based tool for optimizing scheduling in solid bulk export port terminals. The approach integrates agent-based simulation with the Ant Colony System (ACS) metaheuristic to efficiently plan railway unloading, stockyard storage, and maritime shipping. The model interacts with operational data, anticipating issues and aiding decision-making. Validation was performed using real data from a port terminal in Brazil, yielding compatible results and reducing port stay duration. Tests were based on a Baseline Scenario, aligned with a mineral export terminal, for ACS parameter calibration, along with three additional scenarios: direct shipment, preventive maintenance, and a simultaneous route from stockyard to ships. This study highlights DT's potential to modernize port operations, offering practical support in large-scale logistics environments.

1 INTRODUCTION

The increasing digitalization of industries has driven the development of advanced technologies to optimize complex processes. Among these, Digital Twin (DT) stands out, enabling real-time monitoring, simulation, and optimization. The origin of the DT concept was first used in NASA's Apollo project, where twin spacecraft were created on the ground for training and critical scenario simulation (van der Valk et al. 2020). This concept evolved and was formally introduced by Michael Grieves in 2002 in the context of product lifecycle management (Grieves 2016). DT creates a highly detailed virtual representation of a physical system, integrating real-world data for analysis and informed decision-making.

DT applications span various fields, including manufacturing, healthcare, energy, and logistics. In industrial settings, it enhances failure prediction, operational efficiency, and cost reduction. In logistics, particularly in supply chain and transportation management, DT improves resource coordination and workflow optimization (Tao et al. 2019).

Bulk commodity exports rely on complex logistics networks connecting production sites to ports. This chain includes transportation, storage, and port operations, where inefficiencies and fragmented management increase costs. Currently, there are no commercial tools that focus on optimizing bulk transport networks in an integrated manner.

This DT-based tool is intended to support decision-making and optimize the short-and medium-term scheduling of dispatch, unloading, storage, and loading of bulk cargo at port terminals. The approach adopted for the development of this tool combines computational simulation and optimization algorithms. Optimization and simulation are two of the most widely used techniques worldwide to analyze complex systems, regardless of their existing or non-existing nature (Law 2015). The tool will use real-time data to update the digital simulation of the system, enabling dynamic adjustments in the scheduling of logistics operations. Additionally, scheduling strategies will be evaluated to maximize the efficient use of available resources, minimize operational costs, and improve the predictability of port operations. Therefore, the

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research question guiding this study is: Can a DT-based tool optimize the scheduling of dispatch, transport, storage, and loading operations for bulk cargo at port terminals?

This article is structured as follows. Section 2 reviews related works on DT applications in port operations. Section 3 describes the case study and methodology, including simulation and optimization techniques. Section 4 discusses expected results and DT's impact on port logistics. Finally, Section 5 presents conclusions and future research directions.

2 RELATED WORK

This section presents studies that support the development of digital models and DT-based solutions. The goal is to improve the simulation and optimization of processes at port terminals. These studies demonstrate how these approaches enhance scheduling, transportation, storage, and loading operations for bulk cargo. As a result, port operations become more efficient and reliable. Table 1 summarizes the aspects covered in each study, indicating whether they considered Port Operation (Port Op.), Berth (B), Yard (Y), Ship (N), and Optimization (OPT).

(Ouhaman et al. 2020) address storage space allocation in solid bulk export terminals, emphasizing material segregation to prevent contamination and reduce delays. They propose a MILP model and a heuristic to manage large datasets efficiently. Similarly, (Lopes et al. 2023) optimize stockyard and port operations in iron ore chains using deterministic simulation and metaheuristics to reduce ship berthing times. Their approach supports real-time decision-making and aligns with Industry 4.0 goals.

DT technology technologies are emerging as key tools for improving energy efficiency and reducing emissions in ports (dos Santos et al. 2025). In manufacturing and logistics, DTs support better decisions through simulation and process optimization (Lu et al. 2020).

Extending this concept to seaports, (Neugebauer et al. 2024) explore DTs for resource optimization (e.g., cranes, berths, AGVs), highlighting their use in monitoring, simulation, and predictive maintenance, while also noting the need for standardized models. At the Port of Santos, a DT project simulates the navigation channel and infrastructure to support predictive monitoring and operational efficiency (Portos e Navios 2025).

In line with this, (Gao et al. 2022) propose a DT-based scheduling system for stockyards, optimizing storage, ASCs, and AGVs. Case studies show that ASC reprogramming improves responsiveness to cargo variability, while sensitivity analyses guide system configuration.

Building on these insights, (Gao et al. 2023) focus on real-time congestion monitoring and proactive management in terminals. Together, these studies underscore DT's role in enhancing port efficiency, sustainability, and alignment with smart port initiatives.

Table 1: Summary of Bibliographic References by Author.

Author	Research objective	Port Op.			Approach	
		B	Y	S	DT	OPT
(Wang et al. 2018)	Column Generation-based heuristic with different solution strategies and apply dual stabilization techniques to accelerate the algorithm to solve integrated optimization problem	X	X			X
(Ouhaman et al. 2020)	Formulated the storage allocation problem at an export bulk terminal as a MILP and solve large scale data sets with a heuristic method		X			X
(VanDerHorn and Mahadevan 2021)	Provide a consolidated definition of a DT, and presented a case study to explore the process of DT, the key design decisions and implementation strategies				X	
(Yao et al. 2021)	Focus on the needs of port digitalization and integrated management, including infrastructure development, data integration, information modeling, and platform expansion.				X	
(Xu 2021)	Establish an agent-based intelligent port ship dispatch model to solve planning and dispatching ship operations.			X		

Author	Research objective	Port Op.			Approach	
		B	Y	S	DT	OPT
(Gao et al. 2022)	Optimization of key resources—storage area, ASCs, and AGVs—demonstrates how DT implementation can bridge the gap between optimization results and actual terminal operations.		X		X	
(Gao et al. 2023)	Minimizes the total energy consumption of completing all tasks, and the Q-learning algorithm is adapted to optimize a solution based on the operating data from the ACT DT system.				X	
(Bouzekri et al. 2023)	Proposed Integer Programming Model for the integrated tactical Laycan Allocation Problem and the dynamic hybrid case of the operational Berth Allocation Problem	X				X
(Lopes et al. 2023)	Use deterministic simulation and a meta-heuristic algorithm to address the stockyard–port planning problem, with the aim of reducing the time that ships spend in berths. The stockyard-port terminal is represented by a graph and VND meta-heuristic is used to improve the initial solution		X			X
(Lv 2023)	Provide a systematic overview of DT for the intelligent development of industrial manufacting, automated real-time process, speeding up error detection and correction. Improvement and cost reductions to industrial manufacturing.				X	
(Neugebauer et al. 2023)	The paper examines digital twin adoption in seaports, highlighting use cases, challenges, and insights from global examples, including the EUROGATE terminal in Hamburg.			X		
(Neugebauer et al. 2024)	Use DT in seaports, focusing on optimizing resource allocation, including cranes, berths, and AGVs. Additionally, it identifies gaps in research, highlighting the need to develop more accurate models and establish common standards for their efficient implementation.	X			X	
(Jiang et al. 2024)	Built a multi-objective optimization model for the global scheduling of waterways, berths, and restricted yards in bulk cargo ports in low-carbon environments, and the feasibility of combining this model with onshore scheduling is studied.	X				X
(Zhen et al. 2024)	Propose to optimize the berth planning problem by considering berth allocation, quay crane assignment, fairway traffic control and berthing safety requirements.	X				X
(Lin et al. 2024)	Uses container visualization technology to create a hierarchical model through the search, matching, and integration of container images, along with a mathematical optimization model for resource management and scheduling.	X				X
(Li et al. 2024)	Introduces a DT-driven proactive-reactive scheduling system to address uncertainties (e.g., operating time fluctuations, equipment failures, IGV route conflicts) and provide transparent operational information visualization.				X	
(Li et al. 2025)	Integrates graph structure for yard mapping with MIP and reinforcement learning, using Dueling and Double Deep Q-Networks to optimize performance and accelerate learning, improving solution efficiency.		X			X
(Cao et al. 2025)	Introduce a DT based Automated Container Terminals data management system that consists of 4 components: data storage, data interaction, data visualization and data security.				X	
(Li et al. 2025)	MILP model solving integrated load reduction, berth shifting, and allocation problems, using an innovative hybrid meta-heuristic algorithm (AGA-ASA) solver.	X				X
(Wang et al. 2025)	Propose a stockyard allocation model to minimize total costs, including delay penalties and electricity and water costs for spraying operations.		X			X
This paper	Propose to optimize the scheduling of dispatch, transport, storage and loading operation for bulk cargo in port terminals.	X	X	X	X	X

3 USE CASE: PORT

This section introduces the real-world use case of a solid bulk port terminal and presents the proposed approach to address its scheduling challenges. We describe the terminal's operational context, formalize the scheduling problem, and propose a hybrid solution that combines a constructive heuristic, an ACS algorithm, and a simulation model. Finally, we explain how these components are integrated into a DT for decision support.

3.1 Data Sources

The simulated port terminal operates by receiving cargo via railway and exporting it by sea. The flow of materials and its interface with external systems follow a well-defined structure, encompassing three main operational flows. The railway unloading flow involves receiving and stacking ore. The maritime loading flow consists of recovering and loading ore onto ships. Direct loading flow allows cargo to be unloaded from railcars and sent directly to the ship loader, which may or may not occur simultaneously with the recovery of cargo from stockyards.

To enable these operations, the terminal has an infrastructure composed of three stockyards designated for ore (stockyards 1, 2, and 3), which are divided into stacks. Additionally, it has two stacker-reclaimers (SR-1 and SR-2), two stackers (S-1 and S-2), and one reclaimer (R-4). Railway unloading is carried out by three car dumpers (CD-1, CD-2, and CD-3). Maritime loading is performed by a ship loader (SL-1). The structure is completed with a berth for loading the ships. Figure 1 represents this port terminal.

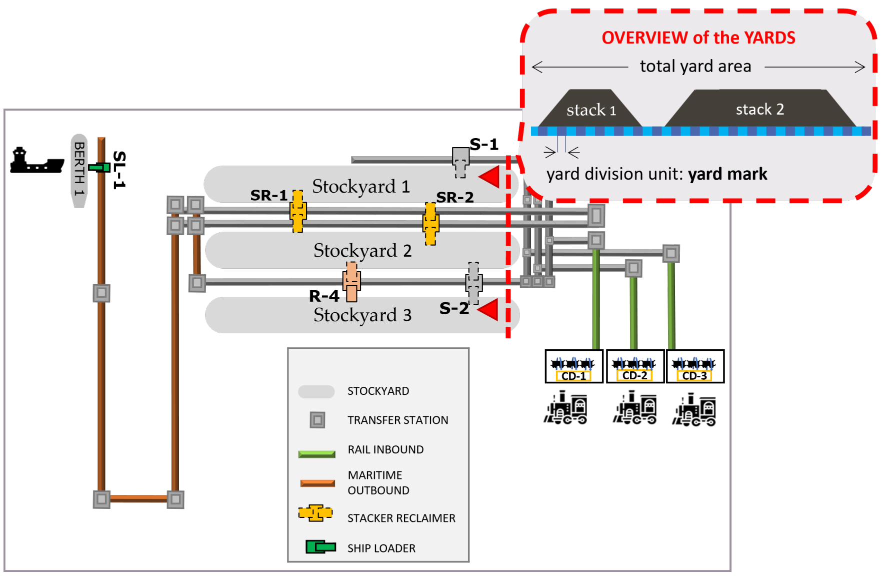

Figure 1: Representation of the Simulated Port Terminal.

The input data was constructed with values and characteristics compatible with this port terminal. The operational routes for executing these flows will be input parameters for the model and can be configured through the tool's interface, along with information such as export demand and the capacity/productivity of machines, considering effective operational rates, as well as preventive, corrective, and operational downtime.

3.2 Conceptual Model

The port terminal performs the processes of railway unloading, maritime loading, and direct loading. This terminal is based on two real Brazilian ore export terminals, where the cargo arrives by train, is unloaded at the stockyard, and, when the time comes, is loaded onto ships.

The railway unloading is the first process in which trains arrive at the terminal and are unloaded at the tipplers. The unloaded ore is then transported to the stockyard, where it can be either piled or sent directly to the ships. The train arrival schedule takes into account the arrival time in the port, the time required for unloading operations, the allocation of stacks in the stockyard, and the routes used to transfer the cargo.

During stacking, the stacks are formed on the basis of the ore's characteristics, such as granulometry and moisture content. The movement of cargo within the stockyard is managed to serve both the ships and direct loading.

The storage scheduling of the cargo, which involves forming the stacks and their use over time, includes: the start and end markers of each stack, the material stored, the capacity of each stack, the identification of the rail lot that originated the cargo (including the stacking date) and the determination of the maritime lot to which the cargo is destined (including the scheduled recovery date). The allocation of stacks must also consider that the more different types of products there are, the more space is required between the stacks, due to the spacing required for product compatibility.

The maritime loading process begins with the arrival of the ships at the terminal and docking at the berths. Ships are generated according to the arriving trains, that is, the type of product being transported. The available ore stacks in the stockyard are selected based on proximity, priority order, and availability of transport routes. The cargo is then transferred to the ship until the loading process is complete and the ship begins the undocking process. The ship loading queue is organized efficiently, reserving cargo in the stockyard to ensure that each ship has the material needed for its operation.

The maritime loading schedule defines the allocation of stockyard stacks for each vessel and includes several key decision variables, such as the start and end times of loading activities, the total volume of cargo to be handled, the specific stacks assigned to serve each ship, and the routes selected for cargo transfer, that is, the sequence of equipment to be used, including conveyors and reclaimers. These variables will be determined by the optimization process and depend on the dynamic interaction between ship demand, resource availability, and operational constraints. The objective function guiding this model is to minimize the total vessel stay time in the port, measured from the moment of berthing to the time of departure upon the completion of loading operations. In addition, the operating rates of the equipment, such as wagon tipplers and conveyor belts, can be dynamically adjusted based on current operating conditions and the characteristics of the material being handled.

As a particular case, direct loading refers to the process in which the ore is transferred directly from the train to the ship, bypassing intermediate storage at the stockyard. When direct loading is allowed, the model prioritizes the unloading of trains carrying the appropriate product and coordinates this activity concurrently with the stockyard loading process.

3.3 Optimization

Given the inherent complexity of the port planning problem, which involves the integrated coordination of train unloading, stockyard allocation, and ship loading operations, we propose a hybrid optimization approach based on a constructive heuristic followed by refinement using the Ant Colony System (ACS) metaheuristic. The core objective is to minimize the total stay time of ships at the terminal, which includes waiting and loading times. This metric directly impacts demurrage costs and the overall efficiency of port operations. The scheduling must consider: a set of ships, each with a required cargo demand and time window; a set of trains, each carrying a specific product type, arriving over time; a stockyard, partitioned into stacks where products are temporarily stored; a limited number of wagon tipplers (used for unloading trains) and ship loaders (used for loading ships). An initial feasible solution is generated using a greedy constructive heuristic:

1. Ships are ordered for scheduling.
2. For each ship, the algorithm checks to see if there is sufficient cargo in existing stacks.
3. If not, it identifies the first unloaded train capable of supplying the missing cargo.
4. It then assigns: a route (from train to stack), a stack (existing or new), start and end times for unloading.
5. Once the ship's demand is fulfilled, the ship is scheduled for loading.

6. The total time associated with the solution, considering unloading and loading, is computed and serves as the initial objective value.

To improve this initial solution, the ACS is applied. In the port operations scheduling problem, each ant constructs a complete schedule, alternating between

- Unloading task: The ant selects the pair <route, stack>, where a stack can be an existing one or a yard region where a new stack will be created.
- Loading task: The ant selects the pair <route, stack> that serves the ship. In this case, all stacks are preexisting.

At each construction step, the ants probabilistically choose their next movement based on pheromone trails and heuristic attractiveness. The transition probability from location i to location j for ant k is defined as:

$$p_{ij}^k = \begin{cases} \dfrac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum\limits_{iv \notin tabu_k} \tau_{iv}^{\alpha}\eta_{iv}^{\beta}}, & \text{if } (i,j) \notin tabu_k, \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

where τ_{ij} is the amount of pheromone associated with the movement from i to j, η_{ij} is the attractiveness associated with this movement (in this case chosen as the inverse of the expected completion time of the respective task), and α and β are user-defined parameters that balance the importance of pheromone in relation to attractiveness.

Each ant, after each step in constructing the solution, updates the pheromone of the last chosen $< i, j >$ pair using $\tau_{ij} = (1-\varphi)\tau_{ij} + \varphi\tau_0$, where $0 \leq \varphi \leq 1$ is the pheromone decay coefficient, and τ_0 is the initial amount of pheromone.

When locally reducing the pheromone of a previously visited location, the objective is to stimulate the following ants of the colony to search for alternative routes, exploring alternative solutions. At the end of each iteration, the pheromone is updated for all paths by a single ant, which could be the best of the iteration or the best so far, making the equation

$$\tau_{ij} = \begin{cases} (1-\rho)\tau_{ij} + \rho\frac{1}{L_{best}}, & \text{if } (i,j) \text{ belongs to the best solution,} \\ \tau_{ij}, & \text{otherwise.} \end{cases}$$

where L_{best} represents the total stay time of the best solution. Thus, the more ants choose a particular movement, the higher the probability that in the next iteration that movement will be chosen. The ACS metaheuristic is particularly suitable for this problem, due to its ability to balance intensification (exploiting good solutions) and diversification (exploring alternative schedules). By updating the pheromone trail both locally and globally, the algorithm avoids premature convergence and encourages the discovery of improved scheduling combinations.

This problem solving technique has been shown to be more efficient in finding the solution, demonstrating the ability to improve the solution within a feasible computational time (Dorigo et al. 2006).

In summary (see Figure 2), the ants iteratively construct alternative schedules–loading or unloading tasks–updating the routes/solutions that generate the best total stay time (the stay time in loading or unloading or even a weighting between the two parameters) up to the moment. The ACS metaheuristic efficiently supports the search for improved port operation plans by minimizing demurrage costs (fees associated with the waiting time of ships at the port) and optimizing resource utilization, such as equipment and storage space.

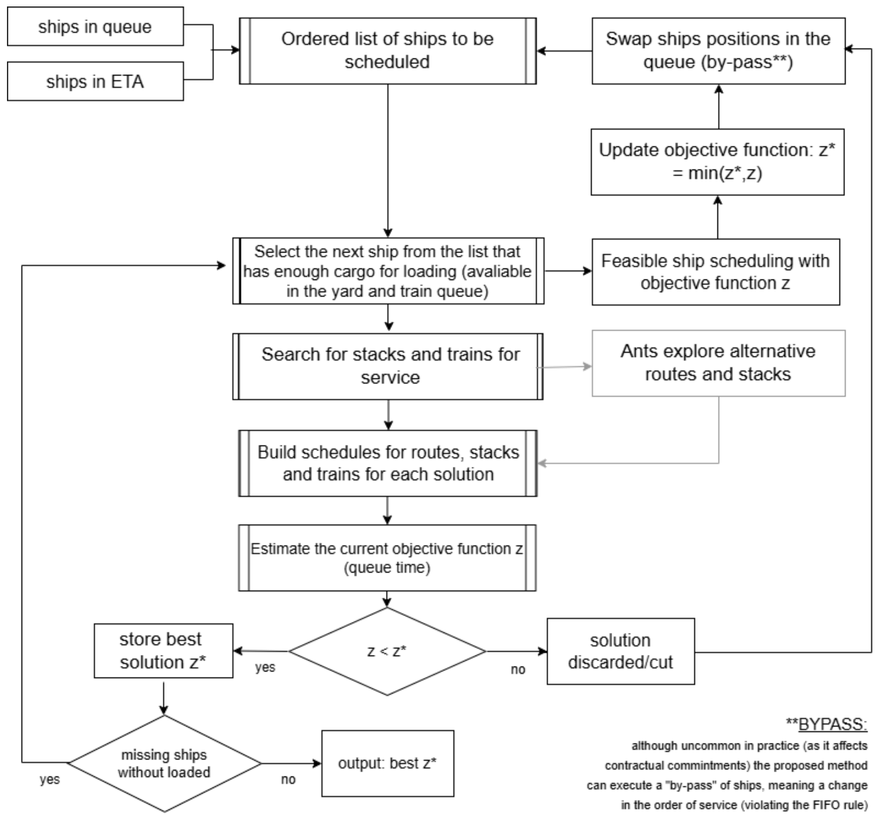

Figure 2: Port Operations Scheduler.

3.4 Simulation Model

The simulation model was developed in AnyLogic Professional software, version 8.9.3, chosen for its features. AnyLogic allows for hybrid simulation, combining discrete events, dynamic systems, and agent-based simulation in a single model. It also allows for exporting the model as an executable file and facilitates integration with the developed optimizer due to its communication library with Python programs.

The simulator was based on agents representative of the terminal (Borshchev and Filippov 2004). The model includes the following agents: Train, Ship, Yard, Stack, Route, Equipment and Berth. The agent-based simulation approach has two advantages: flexibility in representing different configurations of the number and layout of equipment, stacks, yards, among others; and ease of evolutionary maintenance of the model. For example, if it is necessary to implement equipment breakdowns, this can be done directly in the states of the Equipment agent without causing a significant impact on the processes already implemented.

3.5 Digital Twin Integration

A DT is a virtual representation of a physical system that allows the monitoring, simulation and optimization of real-world operations (Tao et al. 2019). In the context of ore export terminals, the DT enables testing of scheduling strategies in a virtual environment before they are applied to the real system. This contributes to more informed and robust decision making.

In the optimization process, an ACS-based heuristic was applied to plan the various activities of the terminal. The simulation phase follows the optimization and is essential to validate the operational plan obtained by the heuristic. The simulation provides a detailed view of the operation, allowing risk analysis, real-time visualization of operations, and comparison of different scenarios. Additionally, the tool generates an analysis report with the main problems encountered during the simulation, allowing the user to identify opportunities for system improvement. Figure 3 illustrates the structure of the proposed DT, showing the interaction between the optimization engine and the simulation environment.

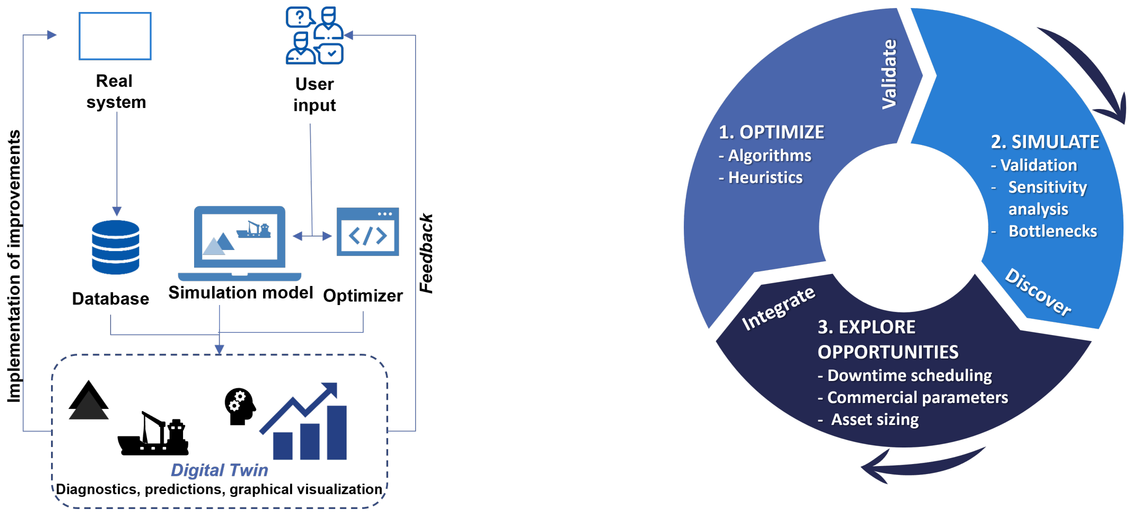

Figure 3: Integration of optimization and simulation components within the Digital Twin.

4 RESULTS

The tool is highly customizable, so, for example, solutions can be sought that only improve the stay time in loading or unloading, or even the weighting between the two parameters. As results, in addition to the fully optimized operations schedule, with times and descriptions of resources and routes used, the tool provides results in a graphical and visual format, such as the timelines for loading and routes. Various tests were conducted on the simulator not only to verify the quality of the response but also to identify the best input parameters for the metaheuristic (number of ants, attractiveness exponents, etc.).

4.1 Simulation Verification

The validation stage in a simulation project is crucial, as it aims to eliminate errors in the simulator that could compromise its use (verification) and ensure that the results obtained are comparable to the real system (validation). This process begins with the analysis of consistent data from the real system, from which parameters such as process times, distributions, and representative Key Performance Indicators (KPIs) are extracted. The main goal is that, by inputting real data into the model, the simulator's outputs are compatible with the KPIs observed in the real system.

For the simulation, real operational data from the studied bulk port terminal were used, including routes, equipment, and the breakdown and blockage curves obtained from data analysis. The validation and calibration of the model considered the ships serviced between January and the following January, with the "ship queue" lasting 13 months, though the simulation was limited to 12 months, ensuring that rail batches were generated until the last day of the year. In the model, trains are automatically generated during the simulation, considering parameters such as the number of wagons, the weight per wagon for each product, and the maximum number of daily trains per product. During the analysis year, a long period of preventive maintenance for the VV-1 was recorded as corrective maintenance in the system. For simulation purposes, this downtime was treated as preventive, with the outputs adapted to reflect the corrective values, ensuring consistency with operational reports.

The input data for validating the scenario (Table 2) included information on the dates and durations of preventive maintenance carried out throughout the year, operational stoppages due to equipment breakdowns, with their probabilistic distributions, the effective loading rates by operation type and material, as well as unloading rates by equipment and operation. Data on ship arrivals and the routes adopted for transport were also considered. Additionally, the capacities and configurations of the yards and stacks were analyzed, considering the operational and logistical aspects for executing the loading process.

Table 2: Input data for validation.

Input Parameter	**Value**	**Input Parameter**	**Value**
Period of Analyse (months)	12	Train Capacity (t)	13,974
Materials	4	Nominal Rate (tph) ER-1	7,100
Stockyard	3	Nominal Rate (tph) ER-2	7,100
Total Capacity of yards (t)	913,500	Nominal Rate (tph) E-3	8,800
Berth	1	Nominal Rate (tph) E-4	10,560
Reclaimers	3	Nominal Rate (tph) R-4	8,800
Ships	167	Nominal Rate (tph) VVs	8,800
Types of ships	2	Nominal Rate (tph) CN-1	14,000

As a validation criterion, representative KPIs for the port were considered, such as:

- Loading: total cargo loaded, cargo loaded by direct loading, effective loading rate, productivity, utilization, preventive maintenance (total hours in the year), corrective maintenance (total hours in the year per turner), total effective operational hours in the year, hours of operational blockages in the year.
- Unloading: total cargo unloaded, effective unloading rate, productivity, utilization, preventive maintenance (total hours in the year), corrective maintenance, total effective operational hours in the year, and hours of operational blockages in the year.

In this process, the objective was to minimize the deviation between the real values and the simulated values for each selected KPI. As a criterion, a maximum deviation of 5% was established: $d = \frac{real - simulated}{real} \leq 5\%$.

In Table 3, a comparison is presented between the simulated and real values for the loading and unloading KPIs of the port terminal during validation. The table includes the following columns: 'Simulated', which shows the values generated by the simulation; 'Real', which presents the values observed at the port terminal; 'Abs. Dif.' (Absolute Difference), which calculates the difference between the simulated and real values; and 'Rel. Dif. (%)' (Relative Difference), which expresses the difference as a percentage of the real value.

Table 3: Validation between the simulated and real values.

	Parameter	**Simulated**	**Real**	**Dif. Abs.**	**Dif. Rel. (%)**
LOADING	Loading [Mtpy]	28.02	28.05	-0.03	0.11
	Direct Loading [Mtpy]	19.06	18.34	0.72	-3.93
	Effective Rate [tph]	6,425.89	6,463	-37.11	0.57
	Productivity [%]	36.51	36.69	-0.18	0.49
	Utilization [%]	66.41	67.27	-0.86	1.28
	Preventive [hpy]	775.62	775.62	0.00	0.00
	Corrective [hpy]	1,417.44	1,408.58	8.86	-0.63
	Operationals [hpy]	604.48	612.00	-7.52	1.23
	Parameter	**Simulated**	**Real**	**Abs. Dif.**	**Rel. Dif. (%)**
UNLOADING	Unloading [Mtpy]	28.08	28.10	-0.02	0.07
	Effective Rate [tph]	4,855.15	4,848.41	6.74	-0.14
	Productivity [%]	55.17	55.10	0.07	-0.13
	Utilization [%]	31.83	31.82	0.01	-0.03
	Preventive [hpy]	1,640.17	1,689.57	-49.40	2.92
	Corrective [hpy]	6,471.44	6,356.24	115.20	-1.81
	Operationals [hpy]	473.00	468.79	4.21	-0.90

In general, the differences between the simulated and real values are small, with most of the relative deviations being below 1%. The model validation was considered successful, as all the relative differences between the simulated and real data are within the 5% limit established as the acceptance criterion. This confirms that the model works correctly and produces results that reflect the reality of the system, ensuring its reliability for analysis and predictions of the performance of the port terminal. Since the terminal operates to maximize occupancy and, therefore, takes advantage of the formation of long queues, this indicator was not considered for validation (the longer the queue, the better for the terminal).

4.2 Base Scenario

A base scenario was constructed, more appropriate to the Brazilian port reality, and tested with the heuristic method. This scenario includes: 19 ships (14 ships loading 1 product and 5 ships loading 2 different products) and 231 trains; Planning horizon: 30 days; 15 different products; 17 stacks at the beginning of planning, distributed across 3 yards; 13 possible cargo transfer routes, 20 unloading routes, 8 loading routes, and 8 direct loading routes (or 'train on board'), formed by the composition of 30 available equipment.

This scenario was used to calibrate the optimal parameters of the ACS metaheuristic and to assess the effectiveness of the approach in minimizing both the total queue time and the number of ships awaiting service. The evaluation was carried out through a series of experiments under the following scenarios:

- ID: 0 - Base Scenario;
- ID: 1 - Previous scenario + direct loading (without passing through the yard);
- ID: 2 - Previous scenario + preventive maintenance of the ship loader (CN) for 3 days;
- ID: 3 - Previous scenario + possibility of more than one simultaneous route from the yard to the ship (two reclaimers operating simultaneously from two stacks, which means an increase in the loading rate).

Table 4: Consolidated Results.

Scenario	**0**	**1**	**2**	**3**
Initial Solution (h)	199,6	175,0	228,1	116,3
Best Solution	194,3	160,0	215,0	84,8
Estimated Demurrage Reduction (USD)	130.750,00	375.870,00	325.425,44	788.969,36
Total time in Queue Ships (h)	158,8	123,7	174,3	59,5
Ships Serviced	19	19	19	19
Average Queue (days/ship)	8,3	6,5	9,2	3,1
Unloaded Cargo (Mt)	3,19	3,19	3,19	3,19
Loaded Cargo (Mt)	3,12	3,12	3,12	3,12
Total Processing Time (s)	340	287	289	271

In the base scenario, the heuristic method generated a feasible operational plan in just 0.1 seconds, resulting in a total ship stay time of 199.6 hours. After applying the improvement procedure, a better solution was obtained, reducing the total stay time to 194.3 hours—equivalent to a reduction of approximately 5.2 days in ship queue time. This reduction is operationally significant, especially when considering a daily demurrage cost of USD 25,000. The optimization process required 340 seconds of computation, executed on a Nitro AN515-51 laptop (Intel Core i7-7700HQ CPU @ 2.80GHz, 16.0GB RAM, Windows 10 x64, Python 3.8).

5 CONCLUSIONS AND FUTURE WORKS

This study demonstrated the application of a DT-based tool to optimize the unloading, transportation, storage, and loading operations of bulk cargo at port terminals. The combination of agent-based simulation and the Ant Colony System metaheuristic allowed for optimized results in viable computational times, resulting in a reduction in the ships' stay time and, consequently, the estimated reduction in demurrage. Additionally, there was an improvement in the use of logistic resources, such as equipment and storage yards.

The integration of the model with real operational data enabled adjustments and improvements in the scheduling of the bulk port terminal, providing relevant support for decision-making. The tool demonstrated the ability to optimize cargo flow and increase the overall efficiency of the operations performed. Thus, the research answered the proposed question by confirming that the use of DT, which combines optimization and simulation methods, generates benefits for decision making and operational performance in complex logistic environments.

As future work, it is proposed to incorporate new aspects, such as improving ship arrivals, considering the Transportable Moisture Limit (TML) of ores, and unplanned equipment unavailability, allowing for a more realistic modeling of port operations. Furthermore, the implementation and integration of other techniques, such as Greedy Randomized Adaptive Search Procedures (GRASP) and machine learning, are suggested, aiming for more effective strategies for dynamic and complex scenarios.

ACKNOWLEDGMENTS

This work was funded by the São Paulo Research Foundation - FAPESP, Brazil, under grants # 2023/09733-2, # 2024/07615-5, and # 2024/08129-7. The financial support provided was instrumental in the successful development of this research, allowing us to achieve the proposed objectives.

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