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Enhancing Container Handling Operations in Maritime Terminals Using the Ant Colony Optimization

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ABSTRACT: Numerous studies have underscored the significance of scheduling and optimization challenges within maritime terminals. This dissertation examines how to optimize container movements specifically for export operations, simultaneously taking into account the operating sequences of yard cranes and trucks. It also considers any potential interference that may arise among yard cranes. A survey of existing literature on yard crane scheduling indicates a lack of work addressing both unproductive crane moves and possible crane-to-crane interferences at the same time, which constitutes an innovative element in our study. Initially, the container loading scheduling task is formulated as a mixed-integer linear program, where the objective function aims to minimize the overall handling time required by the yard cranes. The mathematical model incorporates various assumptions that address interference effects and non-productive movements. In order to tackle this problem, an Adaptive Large Neighborhood Search (ALNS) heuristic is introduced. This strategy proves effective in managing optimization issues in container terminals, regardless of the size of the problem—whether it involves 10, 20, or even 100 containers. The data utilized for validating the method are intentionally generated, allowing for differences in both the number of containers and the amount of accessible handling equipment. Extensive testing verified the ALNS algorithm's usefulness. Various situations were tested by combining various removal and insertion strategies, and the results demonstrated the ALNS method's robustness.

1 INTRODUCTION

The increasing complexity of global trade has significantly altered the role of container terminals, which have evolved into crucial nodes in the international logistics network. These infrastructures, far beyond their initial purpose as transfer points, now serve a crucial role in enhancing the fluidity, speed, and reliability of global goods flows.

Contemporary container terminals function as intricate, well-integrated systems, merging different logistical, technological, and operational processes. The handling of container movements depends on accurate synchronization among various kinds of specialized machinery. Key components include quayside cranes, which transfer containers to and from ships and the terminal; yard cranes (or yard gantry cranes), utilized for organizing and accessing containers from storage zones; and internal transport vehicles, like port tractors or Automatic Guided Vehicles (AGVs), which move containers horizontally between the yard and quayside. Figure 1 shows the operational and spatial arrangement of this apparatus within a terminal.

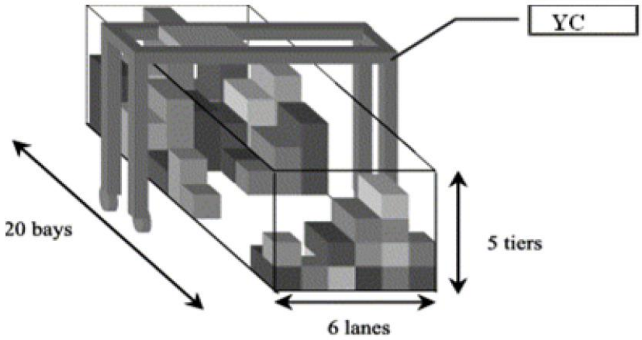

Figure 1. The different constituents of a block (Zhang et al., 2002)

The effectiveness of port activities relies on the seamless and strict synchronization of all the human and material resources involved. In a container terminal, this coordination is crucial to ensure a steady and efficient flow of goods, while reducing waiting periods and operational expenses. A minor error in the sequence of operations can lead to significant delays, influence the logistics chain downstream, and negatively affect the port's competitiveness.

In general, a container terminal is divided into two primary functional zones, with the connections between them influencing the system's overall efficiency: the quay side and the yardside.

The quay side serves as the direct connection between the vessels and the terminal. Here is where quay gantry cranes are utilized for loading and unloading containers. This region faces significant time limitations because of the requirement to shorten the duration of ship calls.

Conversely, the yard area is essential for the temporary storage, arrangement, and readiness of containers for their journey, whether it's transportation to another port or land delivery (by truck or train). It includes different kinds of handling machinery, like gantry cranes and forklifts.

Figure 2 demonstrates the functional separation between the two regions and emphasizes the significance of their dynamic interaction. Effective handling of container movement between the quay and the yard is crucial to prevent bottlenecks, enhance productivity, and maintain the flow of port activities in an environment frequently faced with intricate logistical challenges.

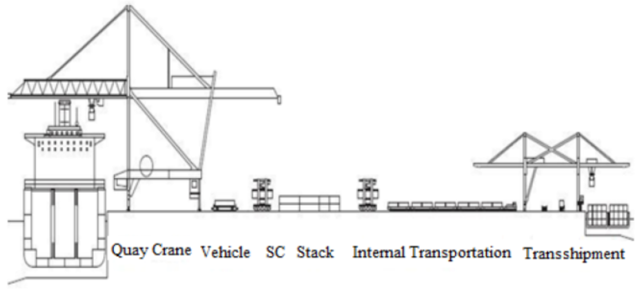

Figure 2. Schematic view of a terminal (Vis and Koster, 2003)

Vehicles serve as shuttles between these zones. The containers are stored in structured blocks made up of bays, rows, and tiers, where the location of each container is precisely defined (see Figure 3).

Figure 3. Container handling equipment (yard and quay cranes)

The stack height is constrained by the type of handling equipment available at the terminal (Steenken et al., 2004; Chen & Langevin, 2011). Despite technological advances, terminals face persistent challenges such as congestion, high operational costs, and the need for continuous reorganization of containers. These issues arise mainly due to the inefficient coordination between handling equipment, especially between yard cranes and transport vehicles. Traditional planning methods are often inadequate in addressing the dynamic nature of terminal operations. Interference, idle movements, and excessive waiting times all contribute to performance degradation. Each container handling operation can be viewed as a task with a total completion time known as the makespan (see Figure 4).

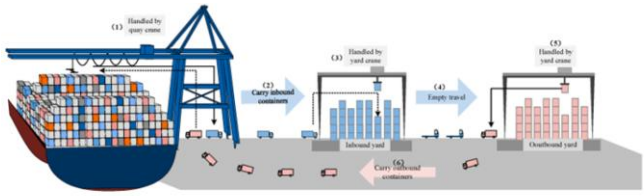

Figure 4. The container unloading process cycle (Lee et al. 2009a)

In the case of imports, tasks involve a sequence of actions including waiting, transferring, unloading, and empty returns. The export process mirrors this flow. The role of transport vehicles, including Automated Guided Vehicles (AGVs) and Straddle Carriers (SCs), is essential to shuttle containers between quay and yard zones (see Figure 5).

Figure 5. Means of transport (AGV LGV) in a terminal (Steenken et al., 2004)

These vehicles differ significantly in terms of flexibility, automation, and cost. This study proposes an integrated optimization model for jointly scheduling yard cranes and transport vehicles. We use mixedinteger linear programming (MILP) formulation combined with an adaptive large neighborhood search (ALNS) heuristic to solve large problem instances efficiently. The goal is to minimize the makespan of export operations while mitigating crane interference and reducing non-productive container movements.

The article is organized into three major sections. The first section describes the operating background of maritime container terminals, including critical equipment and coordination requirements. The second component is a literature study that focuses on scheduling concerns with yard cranes and transport vehicles, as well as crane interference and container re-handling. The final section provides a comprehensive optimization strategy that combines a Mixed-Integer Linear Programming (MILP) model with an Ant Colony Optimization (ACO) metaheuristic, and validates the model by implementing it in AMPL Studio with a genuine case study.

2 LITERATURE REVIEW

Container terminals possess numerous operational issues, particularly in handling equipment planning and scheduling, such as quay cranes, yard cranes, and transportation trucks. These terminals are efficient, depending largely on the careful planning of these resources within a constraint set and minimizing delays and redundant operations.

A substantial amount of literature has been devoted to the scheduling of yard cranes. Early contributions by Young & Hwan(1997 and 1999) introduced optimization techniques and mixed-integer programming models for determining crane routing and bay visitation orders for export operations. Additional research conducted by Linn & Zhang (2003) introduced methods aimed at enhancing crane efficiency using Lagrangian relaxation and heuristic approaches. Ng et al.(2005) and Horng et al. (2007) developed mathematical models to reduce crane interference and container loading activities, while Gu et al. (2008) demonstrated how real-time information may improve yard crane productivity. These findings highlight the complexities of crane operations and the importance of flexible and speedy scheduling choices.

At the same time, research on the scheduling of transport vehicles has highlighted the significance of AGVs and ALVs in enabling smooth container movement between the yard and the quay. Evers et al. (1996) were among the first to model AGV traffic using control systems grounded in simulation. Ebru (2003) proposed two-stage vehicle assignment and container allocation by using list scheduling heuristics. Other researchers, such as those conducted by Vis and Harika(2004) and Kim and Bae(2004), experimented on the effect of equipment selection and traffic control on terminal capacity.Huynh(2009) also addressed truck scheduling and fleet management with genetic algorithms and hybrid mathematical-simulation approaches in pursuit of higher utilization and shorter turnaround time. Aside from crane or truck management on its own, coordinated scheduling has recently gained popularity. Huynh et al.(2004) and Ng and Ge (2006) proposed detailed models for yard crane operations and truck scheduling to reduce overall service time and vessel delays. These models usually employ tabu search or fuzzy heuristics to handle the complexity of resource interactions. Zhang and Jiang (2008) designed multi-device coordination techniques, focusing on equipment synchronization to improve overall terminal performance. Cao et al.(2010) conducted further studies by providing a decomposition-based optimization platform for the simultaneous scheduling of yard cranes and trucks, with encouraging performance results for export activities. Another significant cause of inefficiency is rehandling, or pointless container moves. To solve increasingly complicated optimization challenges, academics have used a wide range of innovative techniques.

Metaheuristic methods such as reinforcement learning and ant colony optimization (ACO) have gained fast momentum over the past couple of years because they are readily adaptable to dynamic and unpredictable scenarios. For example, ACO has been successfully utilized to optimize energy-efficient scheduling in smart manufacturing systems and recorded dramatic increases in performance and resource consumption (Eswaran et al., 2015). Similarly, Tabu Search has also shown satisfactory performance in proactive scheduling of projects, particularly under flexible resource allocation and skill matching conditions(Kellenbrink & Helber,2023). Hybrid heuristics that combine greedy and insertion-based approaches have also demonstrated robustness in tough scheduling settings. The majority of current research assumes static environments, limiting its application in real-world scenarios where equipment availability and task priorities can change unexpectedly.

3 METHODOLOGY

The process of handling containers in maritime terminals is a complex and highly dynamic operation, comprising various interacting elements like yard cranes (YCs), trucks (YTs), and quay cranes (QCs). In this research, we aim to enhance the loading operations of export containers by optimizing the coordination of yard cranes and trucks while considering interference and rehandling limitations. This part outlines the approach used to model and enhance these operations through an Ant Colony Optimization (ACO) metaheuristic.

First, we represent the export container loading issue by integrating multiple operational assumptions and limitations. Every container has an established location in the yard and a specified endpoint on the quay. Yard cranes can only shift once between blocks and might experience interference when several cranes function in neighboring bays within the same block. Trucks are expected to transport a single container at a time and adhere to fixed travel durations between the yard and quay. Additionally, container handling encompasses not just the loading duration but also extra time for any unproductive rehandling operations necessary to reach containers that are situated under others in the stack. The issue is illustrated as a directed graph, with each node representing a container handling task, while edges indicate possible transitions between tasks for trucks and cranes. The goal is to identify the best sequences and assignments that reduce the total makespan.

To address this scheduling issue, we employ a customized ACO framework, modeled after the foraging habits of ants, where artificial agents (ants) construct solutions progressively using pheromone trails and heuristic data. The amount of pheromone deposited corresponds to the quality of the solutions: superior schedules result in increased pheromone concentrations. During every iteration, ants make probabilistic choices for the next task, weighing the use of acquired pheromone insights against the discovery of new routes. To avoid premature convergence, pheromone evaporation diminishes the intensity of once-attractive routes, enabling the colony to adjust fluidly to shifting circumstances.

In our adjustment to port operations, every ant creates a complete timetable by allocating tasks to yard cranes and trucks while adhering to limitations like interference, block assignments, and priority handling sequences. The heuristic element prefers tasks that have reduced travel and handling durations, with penalties added for routes that incur high rehandling expenses or possible crane conflicts. The phase of solution construction is directed by a transition probability function that combines pheromone intensity with heuristic attractiveness, which is updated dynamically throughout the iterations.

A significant advantage of the suggested ACO framework is its adaptability in integrating dynamic disturbances. In actual terminal operations, unforeseen events like crane failures or unexpected ship arrivals can interrupt the scheduled plan. Our model incorporates dynamic event management by adjusting the solution space in real time. Upon detecting a disruption, pheromone concentrations on the impacted transitions are lowered or reset, urging the ants to reassess paths and create alternative viable solutions. This enables the system to stay agile and robust in fluctuating circumstances.

The suggested methodology provides a robust and adaptable tool for enhancing container handling operations in maritime terminals by combining modeling and metaheuristic optimization approaches. The ACO-based scheduler excels in settings with high complexity and variability, exceeding standard static or greedy algorithms through continual learning and adaptation to operational reality.

4 MATHEMATICAL MODEL AND SOLUTION

4.1 *Mathematical Formulation*

The mathematical formulation of the export container handling problem integrates container positions, crane interferences, and rehandling operations into a comprehensive mixed-integer linear programming (MILP) model. This formulation aims to minimize the makespan while satisfying operational constraints related to equipment coordination and terminal layout.

Decision Variables and Objective Function

Let:

- x_{ij}^{m} : binary variable equal to 1 if yard crane m handles container j immediately after i.
- y_{ij}^{n} : binary variable equal to 1 if truck n carries container j immediately after i.
- $z_{bb'}^{m}$: binary variable equal to 1 if crane m moves from block b to b'.
- s_i : starting time for handling container i.
- d_i : departure time of truck carrying container i.
- H_i : total handling time of container i (including rehandling).

The objective is:

$$\min \max_{i} \left(d_i \right) \tag{1}$$

This objective minimizes the makespan, i.e., the total completion time, which is a critical performance metric in port operations.

Constraints

The MILP model is subject to the following constraints:

- Assignment constraints: Ensure each container is processed by exactly one yard crane and transported by one truck.
- Flow conservation constraints: Maintain consistency in crane and truck assignments by balancing incoming and outgoing operations.
- Handling time constraints: Integrate rehandling delays based on container stack configuration.
- Interference constraints: Prevent two cranes from operating in adjacent bays of the same block simultaneously.
- Safety and operational limits: Yard cranes are restricted to a maximum number per block, and travel times are capped.
- Priority constraints: Enforce sequencing based on predefined priority groups; if container i has higher priority than j, then $s_i < s_j$.

This formulation guarantees the feasibility of crane schedules, respects terminal structure, and accounts for real-world logistical challenges.

4.2 *Implementation of the ACO Algorithm*

To tackle the NP-hard nature of this optimization problem, we implement an Ant Colony Optimization (ACO) metaheuristic, adapted to the specificities of maritime terminal operations. The algorithm uses the collective behavior of ants to discover near-optimal sequences of equipment operations.

ACO Components

- Pheromone trails (τ): Quantify the historical quality of paths taken by ants.
- Heuristic information (η): Represents real-time desirability, incorporating factors like crane travel distance and container urgency.
- Transition probability:(Dorigo and Gambardella 1997)

$$p_{ij}^{m} = \frac{\left(\tau_{ij}^{m}\right)^{\alpha} \left(\eta_{ij}^{m}\right)^{\beta}}{\sum_{k} \left(\tau_{ik}^{m}\right)^{\alpha} \left(\eta_{ik}^{m}\right)^{\beta}} \tag{2}$$

- Evaporation rate (ρ): Controls the decay of pheromone levels to avoid premature convergence.
- Pheromone update rule:

$$\tau_{ij}^{m} \leftarrow (1-\rho)\tau_{ij}^{m} + \Delta\tau_{ij}^{m} \quad (3)$$

where:
- τ_{ij}^{m} is the pheromone value on edge (*i, j*) at iteration *m*
- $\rho \in (0,1]$
- $\Delta\tau_{ij}^{m}$ is the amount of pheromone deposited by the ants on edge (*i, j*) during iteration *m*.

ACO Process
- Initialization: Define the problem graph, set τ_{ij}^{m} to a small constant, and initialize ACO parameters (α, β, ϱ).
- Solution Construction: Each ant constructs a valid sequence of container handling and transportation decisions, using p_{ij}^{m}.
- Evaluation: The fitness of each ant's solution is computed based on makespan and constraint penalties.
- Pheromone Update: The best ants deposit additional pheromones on high-quality paths to reinforce efficient sequences.
- Termination: The algorithm halts upon convergence or after reaching a predefined number of iterations.

This algorithm achieves a trade-off between exploration of new solutions and exploitation of promising ones, adapting well to dynamic changes such as crane breakdowns or unexpected container arrivals.

4.3 *Illustrative Case Study*

To demonstrate the efficacy of our MILP model and ACO implementation, we analyze a realistic use case involving a medium-sized maritime terminal managing 50 export containers.

Scenario Assumptions

The case study assumes the following parameters:
- Terminal layout: 2 yard blocks, each with 5 bays, 3 rows, and 3 tiers.
- Resources: 3 yard cranes (YC1, YC2, YC3), 5 trucks (T1 to T5), and 2 quay cranes (QC1, QC2).
- Container classification: Grouped by export priority, with known destination quay cranes.
- Equipment constraints: No more than 2 yard cranes per block; fixed crane speed and truck travel times.

Execution and Results

A Python-based simulation integrating the ACO algorithm was executed for 100 iterations. Simplified parameters included:
- Handling time per container: 20 seconds.
- Rehandling time: 40 seconds per obstructing container.
- Travel time matrix generated using Euclidean distance approximation.

Performance Metrics:
- Best makespan achieved: 1075 seconds.
- Average makespan across 10 runs: 1120 seconds.
- Standard deviation: 22.3 seconds.

Observed Benefits:
- Effective load balancing between yard cranes.
- Minimized crane interference through intelligent task sequencing.
- Consistent prioritization of urgent containers.

Visualization and Dynamic Adjustments

Simulation outputs generated visual timelines and a Gantt chart representing:
- Crane activity over time (color-coded per resource).
- Truck dispatch loops and idle times.
- Rehandling impacts visualized via stacked bar segments.

Additionally, robustness was tested under dynamic disruptions:
- Crane unavailability: One crane taken offline mid-schedule.
- Late container arrival: 5 containers added during runtime.

The ACO algorithm responded by reallocating tasks dynamically, maintaining solution quality with a marginal increase in makespan (approximately +6.5%). This illustrates the adaptability and practical value of the proposed method in real-time port operations.

5 MATHEMATICAL FORMULATION

This section presents the mathematical framework adopted for optimizing container handling operations within a terminal yard. It begins by outlining the modeling assumptions and proceeds to a rigorous description of the model, including the parameters, decision variables, constraints, and the objective function. A simplified example using fictitious data is also provided to demonstrate the model's functionality. The model is solved using AMPL Studio, and the resulting operational paths of the equipment are visualized.

5.1 *Model Assumptions*

The following assumptions are adopted for the proposed model:
- Only loading operations for export containers are considered.
- Container positions in the yard are known and fixed.
- The yard comprises multiple adjacent blocks.
- A block can accommodate up to two yard cranes.
- Yard cranes can switch blocks, but only once per crane.
- Each container is assigned to a specific quay crane.
- Yard cranes and trucks can operate simultaneously.
- All containers in a single bay are destined for the same vessel.
- Interference between yard cranes within the same block is considered.
- Containers are grouped by handling priority.
- Non-productive movements (rehandles) are accounted for.
- Truck unloading is assumed to be instantaneous.
- Yard crane speed is fixed at 36 km/h.
- Only 40-foot containers are modeled.

5.2 *Mathematical Model*

5.2.1 *Indices and Parameters*

Indices:.

- $i, j \in C$: Container indices, $i = 0$ denotes a dummy container
- $m \in M$: Yard cranes
- $n \in N$: Trucks
- $q \in Q$: Quay cranes
- $b \in B$: Yard blocks

Sets and Parameters:.

- M_0^b : Initial number of cranes in block b
- L: Storage locations defined by block, bay, row, tier
- l_i: Location of container i
- a_i, b_i, e_i, r_i: Bay, block, tier, and row of container i
- h_1: Time to handle one container
- $h_2 = 2h_1$: Time to rehandle a container
- P: Priority pair set
- U: Set of pairs with potential interference
- T: Large constant
- k_{ij}: Travel time between containers i and j
- t_i: Truck travel time for container i
- tv_{qa}: Return time of truck from quay q to bay a

5.2.2 *Decision Variables*

- d_i^{YC} : Start time for crane handling container i
- d_i^{YT} : Truck departure time with container i
- $X_{ijm} \in \{0,1\}$: Crane m handles j after i
- $Y_{ijm} \in \{0,1\}$: Truck n loads j after i
- $Z_{bb'm} \in \{0,1\}$: Crane m moves from b to b'
- $V_{ij} \in \{0,1\}$: Container j starts after i
- $u_{iji'j'} \in \{0,1\}$: Interference indicator
- $p_i = p_i^1 + p_i^2$: Total handling time

$$p_i^1 = h_1 + \sum_{\substack{j \in C \\ a_i = a_j \\ r_i = r_j \\ e_i < e_j}} h_1 \cdot V_{ij} \tag{3}$$

$$p_i^2 = \sum_{\substack{j \in C \\ a_i = a_j \\ r_i = r_j \\ e_i < e_j}} h_1 \cdot V_{ij} \tag{4}$$

5.2.3 *Objective Function*

$$\min \max_i d_i^{YT} \tag{5}$$

5.2.4 *Constraints*

$$p_i^1 = h_1 + \sum_{\substack{j \in C \\ a_i = a_j \\ r_i = r_j \\ e_i < e_j}} h_1 \cdot V_{ij} \qquad \forall i \in C \tag{6}$$

$$p_i^2 = \sum_{\substack{j \in C \\ a_i = a_j \\ r_i = r_j \\ e_i < e_j}} h_1 \cdot V_{ij} \qquad \forall i \in C \tag{7}$$

All variables satisfy:

$$d_i^{YC}, d_i^{YT}, p_i^1, p_i^2 \geq 0$$

$$X_{ijm}, Y_{ijn}, Z_{bb'}, V_{ij}, u_{iji'j'} \in \{0,1\}$$

6 NUMERICAL RESULTS AND DISCUSSION

We consider a simplified yard consisting of:

- 2 blocks, each with 4 bays, 3 rows, 3 tiers
- 2 yard cranes: YC1, YC2
- 3 trucks: YT1, YT2, YT3
- 10 containers located as follows:

Table 1.

Container	Block	Bay	Row	Tier
C1	1	1	1	1
C2	1	2	2	1
C3	1	3	3	1
C4	1	4	2	2
C5	1	4	2	1
C6	2	5	3	1
C7	2	7	2	1
C8	2	7	1	1
C9	2	8	3	1
C10	2	8	2	1

This instance is modeled and solved using AMPL Studio. The solution minimizes the makespan and provides an optimized schedule for container handling. A graphical illustration of equipment movements is derived from the solution and supports operational planning within the yard.

Container Placement and Handling in the Yard

Table 2 below visualizes the placement of containers in the yard's storage area using a grid system.

Table 2. Locations of containers in the storage area (using grid system)

B1				
	a1	a2	a3	a4
r3			(3)	
r2		(2)		(4) (5)
r1	(1)			

B2				
	a5	a6	a7	a8
r3	(6)			(9)
r2			(7)	(10)
r1			(8)	

We assume that containers are grouped, and each group follows a specific priority sequence. The groups are defined as follows:

- Group A: C1, C4, C5, C8
- Group B: C2, C7
- Group C: C9, C10
- Group D: C3, C6

Groups A and B will be serviced by quay crane 2 and are bound for containership 2. Groups C and D will be handled by quay crane 1, destined for containership 1 (see Table 3).

When quay cranes load containers, a particular order must be respected for reasons such as simplifying unloading or aligning with cargo characteristics:

- Group B must be processed before Group A
- Group C must be processed before Group D

Group-level priorities can also transfer to individual containers. In this model, the destination quay crane for each container is known in advance.

Table 3. Container Quay Destinations

Ci	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
QC	2	2	1	2	2	1	2	2	1	1

Table 4.: General Parameters

Parameter	Value
Total containers	10
Total yard cranes	2
Total quay cranes	2
Total trucks	3
Bays per block	4
Rows per block	3
Maximum tiers	3

Table 5. Yard Crane Handling Times

Parameter	Value (in sec)
Container handling time (h_1)	20
Time to move and re-place a container (h_2)	40

Table 6. Transport Times (t_i) for Containers to the Quay (by Truck)

Container	Quay Crane	t_i (min)	t_i (sec)
C1	QC 2	3	180
C2	QC 2	3	180
C3	QC 1	2	120
C4	QC 2	3	180
C5	QC 2	3	180
C6	QC 1	2	120
C7	QC 2	2	120
C8	QC 2	2	120
C9	QC 1	3	180
C10	QC 1	3	180

Table 7. Truck Empty Return Times (tv_{qa}) from a Quay Crane to a Yard Bay

Quay Crane	Bay	tv_{qa} (sec)
QC1	a1	60
QC1	a2	60
QC1	a3	60
QC1	a4	60
QC1	a5	90
QC1	a6	90
QC1	a7	90
QC1	a8	90
QC2	a1	90
QC2	a2	90
QC2	a3	90
QC2	a4	90
QC2	a5	60
QC2	a6	60
QC2	a7	60
QC2	a8	60

6.1 *Solution*

Following the detailed presentation of each data category, we turned to AMPL Studio to encode the mathematical model and generate a solution. First, we entered the model itself into a .mod file. Afterward, we compiled the data described earlier into a .dat file. Finally, we utilized CPLEX to solve this model.

From the solution produced by the AMPL software (depicted in Figure 6), we gathered substantial information about the problem, including the makespan and the operating sequence of each yard crane and truck. The cumulative time required to process 10 containers was found to be 560 seconds.

The resulting sequence for each resource is as follows:

- YC1: C7 – C8
- YC2: C10 – C9 – C6 – C2 – C1 – C3 – C5 – C4
- YT1: C7 – C6 – C3 – C4
- YT2: C10 – C2 – C5
- YT3: C9 – C1 – C8

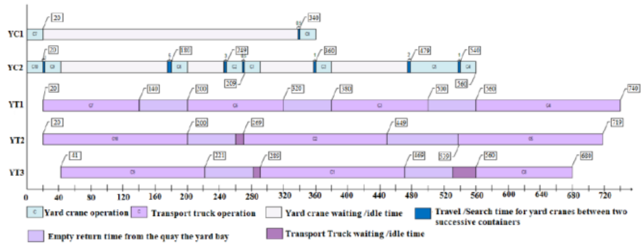

Figure 6. Presentation of the solution with AMPL

The AMPL solution indicates how each piece of equipment operates. The work sequences of yard cranes and trucks are shown graphically (Figures 7 and 8)

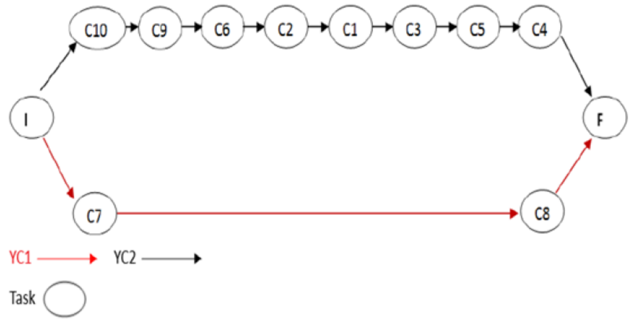

Figure 7. Yard Cranes' Operating Sequences

Figure 7 illustrates the operating sequences of two yard cranes (YC1 and YC2) assigned to handle container tasks within the yard. Each node represents a container task (C1 to C10), with directional arrows indicating the execution order.

YC1 is shown in red, handling a short and direct sequence: from the initial node (I) to container C7, and then moving directly to C8, before completing at the final node (F). This path suggests a minimal set of assignments for YC1, focusing on distant but isolated tasks that likely require minimal interference with the route of the other crane. YC2 is depicted in black, covering a significantly larger portion of the container set: C10 → C9 → C6 → C2 → C1 → C3 → C5 → C4. The sequencing of YC2 forms a continuous flow along the upper and right-hand side of the layout, reflecting a more intensive workload for this crane, optimized to follow a path with minimal backtracking.

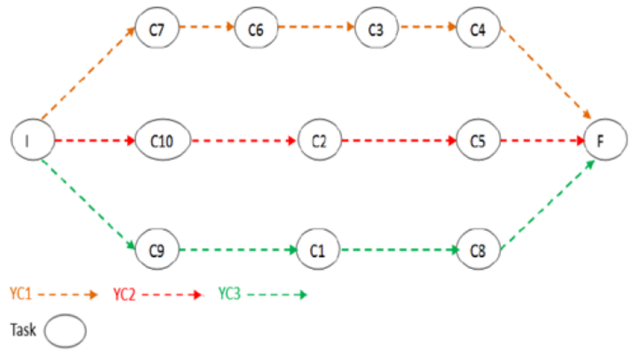

Figure 8. Trucks' Operating Sequences

Figure 8 displays the operating sequences of three yard trucks (YT1, YT2, and YT3) assigned to transport containers across the terminal. Each node in the diagram represents a container, with directional dashed arrows indicating the task execution order and color-coded paths for each truck.

YT1, illustrated in orange, follows the path: C7 → C6 → C3 → C4, starting from the initial node and proceeding along the upper left arc. This sequence indicates a relatively linear and upper-path operation with minimal detours.

YT2, represented in red, performs the sequence: C10 → C2 → C5, forming the central path between the initial and final nodes. This truck manages container tasks that are central in the yard layout, providing a balanced route between the upper and lower regions.

YT3, shown in green, moves through: C9 → C1 → C8. Its sequence runs along the lower path of the terminal layout, offering complementary coverage to the other two trucks.

The structure of the figure clearly separates the workload among the three trucks and illustrates how their routes are strategically defined to minimize overlap and ensure efficient transport of containers.

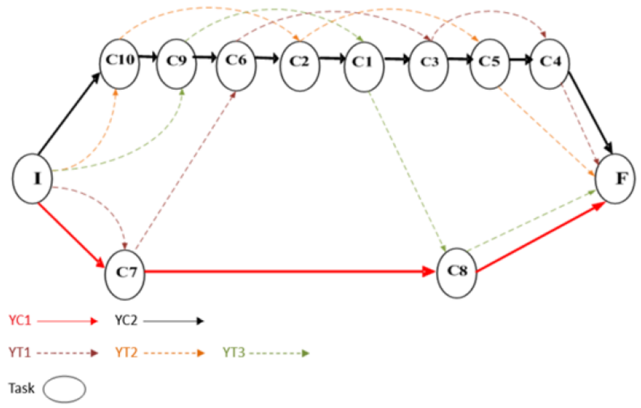

Figure 9. Overall Operating Sequences for Handling Equipment

Figure 9 illustrates the coordinated operations of two yard cranes (YC1 and YC2) and three yard trucks (YT1, YT2, and YT3) within the terminal. Each node corresponds to a container handling task, while the directed edges—color-coded by resource—represent the order of task execution for each piece of equipment.

YC1, depicted in red, handles a sequence starting from the initial node I, proceeding through C7 and C8, and concluding at the final node F. This route outlines a clear lower-path handling pattern with minimal interference.

YC2, shown in black, performs the upper-tier sequence: I → C10 → C9 → C6 → C2 → C1 → C3 → C5 → C4 → F. This sequence covers a more complex chain of tasks involving multiple yard blocks.

YT1, using dashed dark red arrows, operates through C10, C7, and C5, bridging tasks across both the upper and lower regions. Its trajectory helps facilitate crane coordination, especially at inter-block transitions.

YT2, indicated in orange, services the path: C9 → C3 → C4, assisting YC2 in upper yard deliveries while reducing idle crane times.

YT3, highlighted in green, ensures smooth container transfers along the route: C6 → C2 → C8, thereby covering inter-block transport along the central arc of the graph.

Overall, this figure visually encapsulates the effective division of labor among cranes and trucks, illustrating a synchronized scheduling solution aimed at minimizing interference and enhancing yard operational efficiency.

7 CONCLUSION

This research addressed the problem of optimizing container handling operations in maritime terminals, with a particular focus on the dynamic scheduling of yard cranes and transport vehicles. The main objective was to minimize the total processing time of export-bound containers, while accounting for real-world constraints such as yard-crane interference and container rehandling. A mixed-integer linear programming model was proposed and tested using fictitious data in the AMPL environment, producing operating sequences for 10 containers with a global completion time of 560 seconds. These sequences were visualized to analyze the cooperation between cranes and trucks, and to highlight the sources of efficiency or delay in the system.

One of the most significant contributions of this work lies in the validation of the Ant Colony Optimization (ACO) algorithm as a promising method for dynamic port logistics. Inspired by the behavior of natural ants, ACO allowed for adaptive decision-making in a complex and evolving environment, where static planning strategies may fail to respond efficiently to unforeseen events such as congestion, equipment breakdowns, or variations in container demand. Compared to conventional static approaches, ACO demonstrated greater flexibility, especially in minimizing non-productive moves and reducing interference between equipment. This adaptability positions ACO as a relevant and scalable solution for next-generation container terminals.

From a practical standpoint, the findings presented here have important implications for port managers and logistics operators. The dynamic scheduling framework proposed can serve as a foundation for real-time decision support systems. It is recommended that terminal operators consider a progressive integration of such intelligent algorithms into their operational workflows. A stepwise implementation—beginning with selected yards or during off-peak periods—can help mitigate deployment risks and build operator confidence. Additionally, the incorporation of Internet of Things (IoT) technologies can significantly enhance the model's effectiveness. Real-time data from connected cranes, trucks, and yard sensors would allow the system to react more accurately to the actual conditions on the ground, thereby improving the efficiency and robustness of container movement planning.

This work also opens several promising avenues for future research. First, the combination of ACO with machine learning techniques offers an exciting opportunity to enhance predictive capabilities. Machine learning models could anticipate demand fluctuations, identify recurring congestion patterns, and feed this information into the ACO algorithm to improve planning foresight. This hybrid approach would enable a more proactive and intelligent scheduling process. Second, the optimization methodology developed in this study could be extended beyond container handling to address other critical logistics challenges—such as energy management, maintenance scheduling, or berth allocation—thereby broadening the scope of its applicability. Finally, future investigations could explore multi-objective optimization strategies, which take into account not only completion time but also energy efficiency, emissions reduction, and equipment lifespan. This would align optimization efforts with the principles of sustainability and green port development.

In conclusion, the integration of bio-inspired algorithms such as ACO into port logistics systems represents a major step forward in addressing the increasing complexity and dynamism of terminal operations. When combined with real-time data and predictive analytics, these algorithms have the potential to significantly enhance decision-making, streamline resource allocation, and contribute to the development of smarter, more resilient, and more sustainable ports.

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