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Review

Truck Appointment Scheduling: A Review of Models and Algorithms

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Abstract: This paper provides a comprehensive review of truck appointment scheduling models and algorithms that support truck appointment systems (TASs) at container terminals. TASs have become essential tools for minimizing congestion, reducing wait times, and improving operational efficiency at the port and maritime industry. This review systematically categorizes and evaluates existing models and optimization algorithms, highlighting their strengths, limitations, and applicability in various operational contexts. We explore deterministic, stochastic, and hybrid models, as well as exact, heuristic, and metaheuristic algorithms. By synthesizing the latest advancements and identifying research gaps, this paper offers valuable insights for academics and practitioners aiming to enhance TAS efficiency and effectiveness. Future research directions and potential improvements in model formulation are also discussed.

Keywords: truck appointment systems; port logistics; optimization models and algorithms; truck appointment scheduling; port capacity planning and scheduling

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1. Introduction

In the mid-2000s, Truck Appointment Systems (TASs) emerged as a prevalent strategy for reducing congestion and truck turnaround times at container terminals [1]. A TAS aims to regulate truck arrivals throughout the day to minimize gate congestion, improve operational planning, and reduce waiting times, thereby promoting efficiency and reliability in container drayage. A well-designed TAS benefits both carriers, through shorter waiting times, and container terminals, by enabling better resource planning. The benefits, particularly in reducing waiting times and gate congestion, have been quantified (see the work of Zhao and Goodchild [2]).

From a practical perspective, TASs are technological platforms designed to coordinate and balance truck flows at ports and container terminals by planning and scheduling truck arrivals. This ensures that truck arrival patterns are evenly distributed, reducing peak-hour congestion [3]. The implementation of a TAS varies based on the specific conditions of each container terminal, particularly in terms of flexibility and the role of truck carriers. Consequently, tailoring TAS designs to the unique operational context of terminals is crucial to achieving tangible benefits [4].

From early studies that examined the advantages and disadvantages of TASs [4] to recent research addressing disruptions [5] and collaborative schemes [6,7], TAS design has been widely studied. Modern TAS platforms incorporate several advanced features, such as appointment scheduling systems that allow trucking companies to book specific time

slots for container pickups or drop-offs. This smooths gate operations and prevents sudden spikes in arrivals. These systems also integrate real-time data from terminal operations, trucking schedules, and traffic conditions, enabling dynamic schedule adjustments. Additionally, a TAS enhances communication and collaboration among stakeholders, including terminal operators, trucking companies, and shippers, by employing optimization algorithms to allocate time slots efficiently and balance truck arrivals with terminal capacity. The reader is referred to Huynh et al. [1] and Abdelmagid et al. [8] for previous reviews of truck appointment systems.

In practice, port environments utilizing TASs require consignees to book specific time slots in advance for picking up inbound containers. Similarly, customers delivering outbound containers must schedule appointments ahead of time. From a mathematical perspective, a critical aspect of TAS design involves determining the appointment quota, which refers to the number of truck appointments to schedule per time slot [9]. Objective functions in existing models often aim to minimize truck turnaround time, delays, emissions, and energy consumption while maximizing yard equipment utilization [8]. Modeling approaches such as queuing theory, mathematical programming, and computer-aided simulations are frequently employed.

This review focuses on modeling TASs, with particular attention to the components of analytical models. This paper makes three key contributions to the literature: (i) it conducts a comprehensive review, analyzing and discussing TAS features, objective functions, decisions, constraints, and solution methods; (ii) it introduces a taxonomy that classifies various aspects of TASs, offering a deeper understanding of the current state of the problem; and (iii) it examines recent trends to provide guidance for future research directions.

The remainder of this paper is organized as follows: Section 2 outlines the formulation of a basic TAS model. Section 3 details the methodology employed in this study. Section 4 examines TAS modeling approaches and variants in solution algorithms. Section 5 discusses the findings and highlights potential directions for future research. Finally, Section 6 presents the conclusions of this study.

2. A Basic TAS Model

In this section, we present the formulation of a baseline problem representing the simplest variant of a TAS. The optimization model is designed to identify the optimal assignment of arriving trucks to time slots at a container terminal, with the objective of minimizing congestion.

Indices:

- t: time slots ($t = 1, 2, \ldots, T$).
- i: trucks ($i = 1, 2, \ldots, N$).

Parameters

- d_i: demand (number of trucks) from trucking company i.
- c_t: capacity of the container terminal during time slot t.
- p_t: penalty cost for exceeding terminal capacity at time slot t.

Decision variables

- $x_{it} \in \{0, 1\}$: 1 if truck i is assigned to time slot t, 0 otherwise.
- $y_t \geq 0$: congestion (number of trucks in operation) at time slot t.

Objective function

$$\min \sum_{t=1}^{T} p_t \cdot \max(0, y_t - c_t) \tag{1}$$

Subject to:

$$\sum_{t=1}^{T} x_{it} = 1 \quad \forall\, i = 1, \ldots, N \tag{2}$$

$$\sum_{i=1}^{N} x_{it} \leq c_t \quad \forall\, t = 1, \ldots, T \tag{3}$$

$$y_t = \sum_{i=1}^{N} x_{it} \quad \forall\, t = 1, \ldots, T \tag{4}$$

$$x_{it} \in \{0, 1\} \quad \forall\, i = 1, \ldots, N;\ t = 1, \ldots, T \tag{5}$$

$$y_t \geq 0 \quad \forall\, t = 1, \ldots, T \tag{6}$$

The objective function (1) minimizes congestion, where $\max(0, y_t - c_t)$ represents the exceeding terminal capacity at time slot t. Constraint (2) ensures that each truck is assigned to exactly one time slot. Constraint (3) imposes a terminal capacity limit, stipulating that the number of trucks assigned to any time slot cannot exceed the terminal's capacity. Constraint (4) defines the congestion term, which measures the total number of trucks scheduled for a given time slot. Finally, constraints (5) and (6) specify the nature of the decision variables.

3. Methodological Framework

This study conducts a literature review to summarize the existing research on modeling and solution approaches for TASs and to provide a comprehensive understanding of the state of the art and research needs in this area. This research adopts a content analysis methodology [10,11], guided by the following steps:

Material collection: To gather relevant publications related to TAS models and algorithms in ports and container terminals, an extensive search was conducted across digital resources, including databases and publishers such as Google Scholar, ScienceDirect, Emerald, Inderscience, Springer, Hindawi, and Taylor & Francis. The search utilized keywords such as truck appointment systems, truck appointment scheduling, gate appointment system, truck scheduling, vehicle booking systems, and time slot assignment. To enhance the reliability of the review process, the full text of each paper was screened and included in this review only if it met the following criteria: (i) papers published in 2008–2024; (ii) papers written in English; (iii) exclusive focus on TASs in ports and container terminals; (iv) papers including a mathematical models for TASs; and (v) exclusion of "grey" literature items, such as textbooks, conference papers, monographs, doctoral dissertations, and book chapters.

Category selection and material evaluation: To define the formal aspects of the materials for evaluation and summarize the review findings, a set of questions was developed (as presented in Table 1) across four structural dimensions: (1) journals and publication trends; (2) context and scope; (3) modeling and solution approach; and (4) data integration and validation. The collected papers were systematically analyzed according to these structural dimensions, enabling the identification of relevant insights and trends in the literature.

Table 1. Category and selection of structural dimensions.

I. Journals and Publication Trends	II. Context and Scope
(1) Trend: How is the distribution of publications across the period 2008–2024? (2) Journals: In which journals are such articles mainly published?	(3) Research topics: Which are the main research topics within the TAS literature? (4) Scope: Is the focus on terminal operators, trucking companies, port authority, or collaborative? (5) Context: Does the study focus on a single terminal, multiple terminals, or a broader port area? (6) Contribution of the paper: Which is the main contribution of the paper?
III. Modeling and Solution Approach	**IV. Data Integration and Validation**
(7) Modeling: What type of modeling approach is proposed (e.g., mixed-integer programming, stochastic programming, dynamic programming, simulation–optimization framework)? (8) Aims and Objectives: What is being optimized (e.g., minimizing waiting times, maximizing resource utilization, reducing emissions)? (9) Decisions: Which are the main decisions to make (e.g., assign trucks to time slots, reschedule truck appointments)? (10) Constraints: What operational and regulatory constraints are incorporated (e.g., time windows, resource availability, truck capacities)? (11) Algorithms: Which exact, metaheuristic, or hybrid method is used to solve the problem?	(12) Data Sources: Are real-world data or simulated data used for validation? (13) Validation: Is the model validated using simulations, real-world case studies, or both? (14) Dynamic Features: Are the data deterministic or uncertain? Is the model static or dynamic? Does the model account for real-time data (e.g., live traffic conditions, truck GPS updates)?

4. TAS Models and Algorithms: State of the Art

The implementation of TASs to mitigate hinterland delays and enhance terminal velocity was adopted by ports in Asia, the United States, and Europe around 2005 [12]. However, to the best of our knowledge, the first formal formulation of the truck appointment scheduling problem was introduced by Rashidi and Tsang in 2006 [13]. The earliest formal publications on TASs appeared in 2007, notably, the work of Giuliano and O'Brien [4], who analyzed the outcomes of legislation enabling terminals to adopt gate appointments as a strategy to reduce truck queues at the gates of the Ports of Los Angeles and Long Beach. The publication of research articles presenting mathematical models for the truck appointment scheduling problem began in 2008. A comprehensive review of the literature identified 65 articles published between 2008 and 2024.

The literature database is shown in Table A1 of Appendix A.

4.1. Descriptive Analysis of Published Literature

The study of TASs has presented a considerable increase in the number of research works in the last 17 years (see Figure 1). This resulted in several models, algorithms and solution approaches in multiple TAS variants.

The reviewed literature indicates that most contributions are journal articles spanning various fields, including transportation, operation research and management science, engineering, environmental studies, decision science, and computer science. The journals with the highest volume of TAS-related works include *Transportation Research Part E*, *Computers and Industrial Engineering*, *Flexible Services and Manufacturing Journal*, *Sustainability*, *Annals of Operations Research*, *European Journal of Operational Research*, *International Journal of Produc-*

tion Economics, *Logistics*, *Maritime Economics and Logistics*, and *The Asian Journal of Shipping and Logistics*.

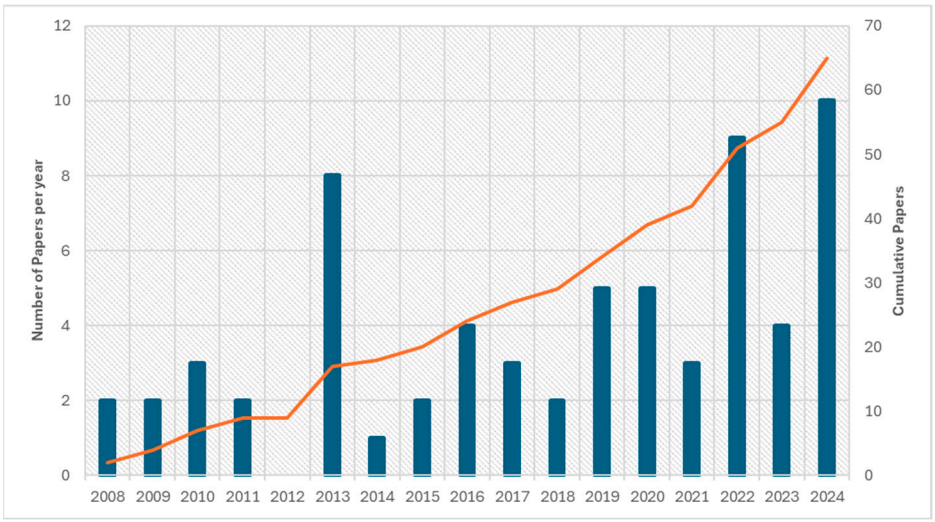


Figure 1. Trend in the publication of articles proposing truck appointment scheduling models.

Figure 2 illustrates the annual volume of TAS-related research published in these journals. The width of the horizontal bars represents the number of papers published per year and journal, while the total number of papers published in each journal between 2008 and 2024 is displayed on the right side of the figure. Additionally, 25 papers were published across 20 other journals, including the *Journal of Marine Science and Engineering*, *International Journal of Modelling and Simulation*, *Transportation Research Part B and D*, *Transportation Research Records*, and *Maritime Policy and Management*. Notably, the past two years have seen an expansion in the range of journals publishing TAS-related research, reflecting a growing diversification in the dissemination of studies within this field.

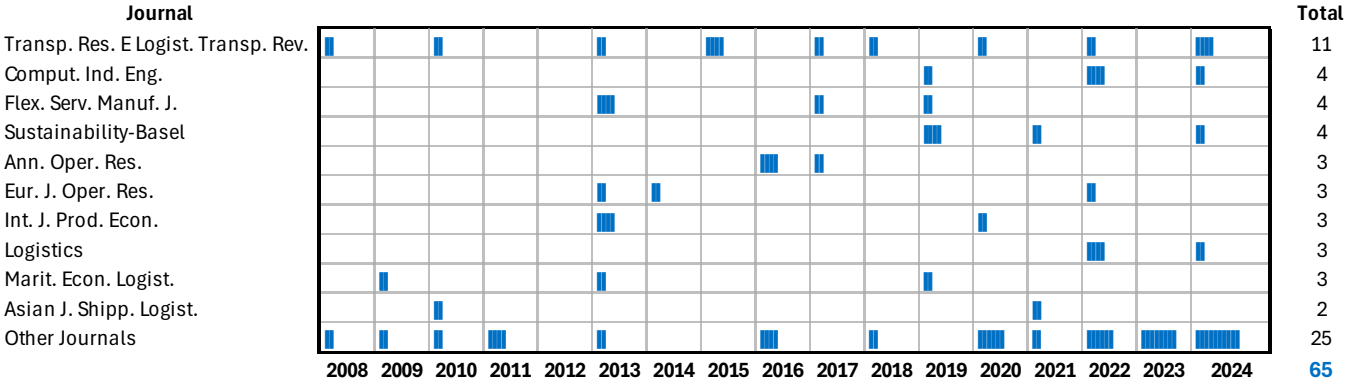


Figure 2. Distribution of articles per journal.

4.2. Modeling and Solution Approaches

The various methods used in the literature to handle the truck appointment scheduling problem can be grouped into four large categories: the queueing models, the optimization models, the simulation-based models, and the hybrid models (see Figure 3).

Traditional queuing and mathematical programming approaches focus on gate and yard optimization. Queuing models are used to model gate and yard congestion dynamics and aim to minimize truck waiting times and service delays [14–17]. These models are usually integrated with cost optimization models. Optimization models are used to minimize

waiting times, emissions, or operational costs, and to balance yard workloads and optimize crane scheduling [9,18,19]. Simulation-based models are used to evaluate system performance under real-world variability, and to test the robustness of TAS designs [3,20–24]. Hybrid models combining queuing, simulation, and optimization techniques between them and with data analytics techniques, have been proposed to handle complex constraints, uncertainty, and multi-objective scenarios [25–29]. Collaborative systems are modeled as decentralized and agent-based frameworks accommodating multiple actors [30]. Emerging trends include AI-driven and IoT-enabled solutions for real-time and predictive scheduling.

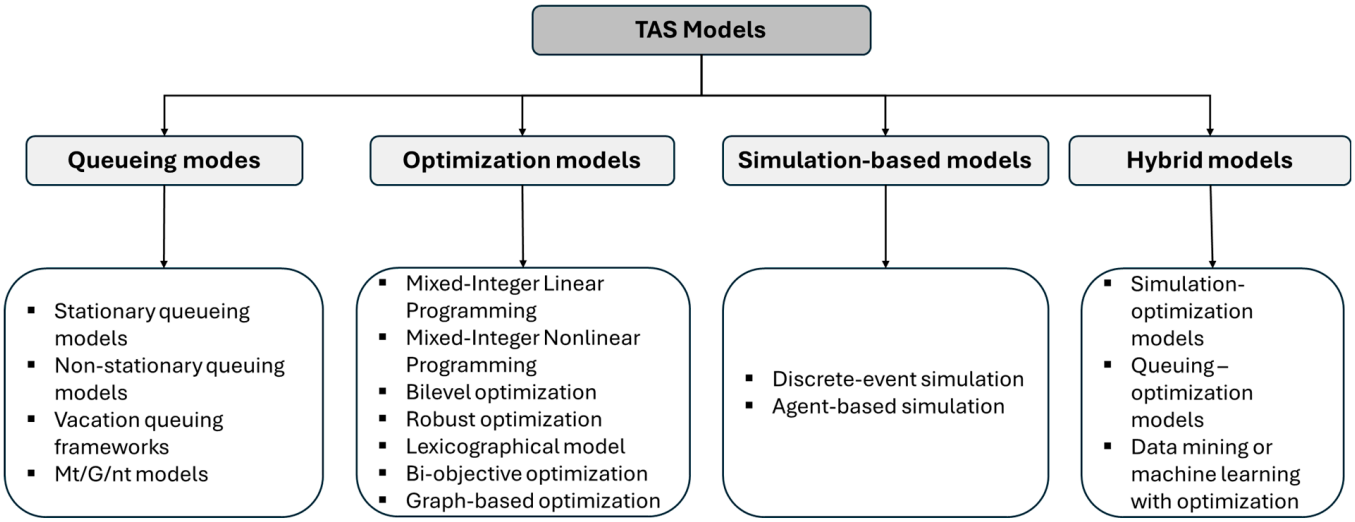


Figure 3. TAS models.

From the analysis of the collected papers, 23 types of objective functions, 19 types of decision, and 20 types of constraints were identified (see Figure 4), on which the complexity of the TAS problem depends. These elements are explicitly analyzed in the following sections.

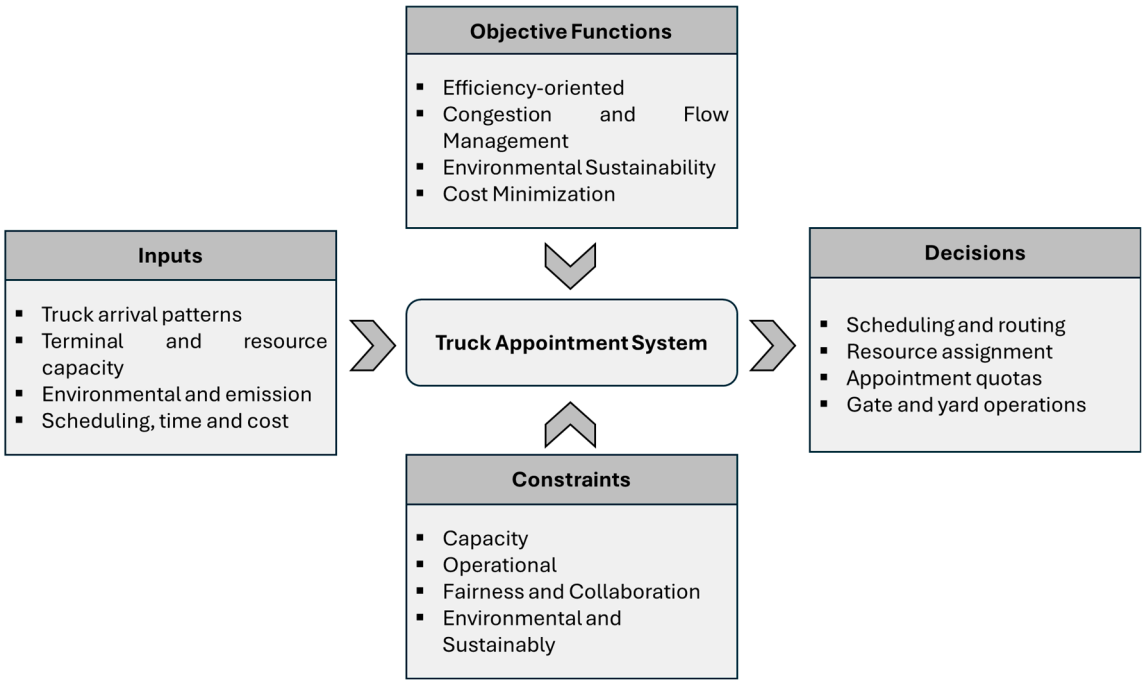


Figure 4. Characteristics of TAS models.

4.2.1. Decisions

The decision variables for scheduling truck appointments can be categorized into four primary groups (see Figure 5): (i) scheduling and routing, (ii) appointment quotas, (iii) resource utilization, and (iv) gate and yard operations.

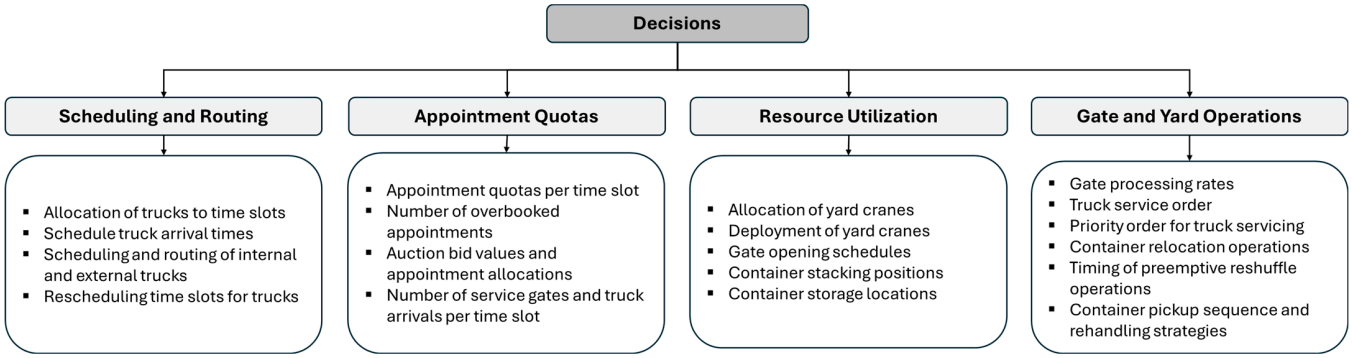


Figure 5. Decisions of TAS models.

Scheduling and routing decisions focus on allocating truck and container operations to time slots to optimize arrivals and departures, reduce gate congestion, and minimize idle times [31–33]. By balancing workloads across time windows, these decisions aim to enhance service rates. Rescheduling often requires dynamic updates and real-time data integration [31]. Additionally, integrating scheduling and routing decisions improves network-wide efficiency by minimizing empty runs, maximizing resource utilization, and coordinating internal and external movements across terminals and hinterlands.

Appointment quota decisions focus on regulating truck appointments through quotas to manage demand and prevent overloading [34,35]. By balancing truck flow and capacity across time periods, these decisions aim to avoid bottlenecks and implement demand-side control mechanisms, such as auction-based quotas.

Resource utilization decisions involve the allocation and efficient use of terminal resources such as gates, equipment, and yard cranes [36–38]. The primary objective is to maximize equipment throughput while minimizing operational costs and energy consumption. Gate and yard operation decisions address operational priorities at terminal gates and yards, with the aim of minimizing processing delays [5,35,39]. They focus on streamlining operations at entry and exit points of the terminal and within the yard, reducing truck idle time and container rehandling costs. These decisions typically involve sequencing and priority-based rules to enhance efficiency.

4.2.2. Objective Functions

The objective functions for scheduling truck appointments can be categorized into four main groups (see Figure 6): (i) efficiency-oriented objectives, (ii) congestion and flow management objectives, (iii) environmental sustainability objectives, and (iv) cost minimization objectives.

Efficiency-oriented objectives focus on reducing waiting queue times, improving turnaround times, maximizing resource utilization to enhance operational flow, enhance efficiency by reducing operational bottlenecks, and improve customer satisfaction by minimizing delays [35,40]. Congestion and flow management aims to minimize traffic congestion and deviations from preferred arrival times, ensuring smoother operations [9,40,41]. Environmental sustainability targets reducing truck emissions, energy consumption, and empty trips, emphasizing eco-friendly practices, reducing the environmental impact of port operations, and supporting compliance with emission regulations and sustainability

targets [42,43]. Lastly, cost minimization seeks to lower transportation costs and eliminate unnecessary travel, aligning financial efficiency with environmental benefits, achieving cost efficiency while maintaining service quality, and addressing economic impacts on both terminals and external stakeholders [7,30,40]. Multi-objective functions often integrate environmental, economic, and operational goals [36,44]. These classifications align with terminal goals to improve efficiency, sustainability, and cost effectiveness.

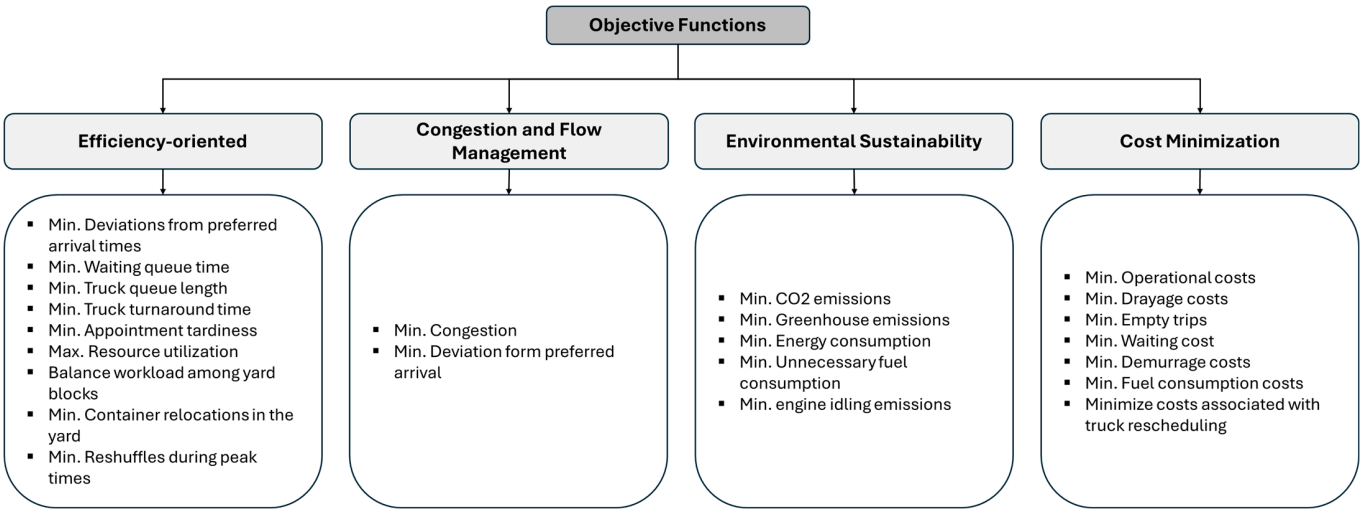


Figure 6. Objective functions of TAS models.

4.2.3. Constraints

The constraints for scheduling truck appointments can be categorized into four primary groups: (i) capacity constraints, (ii) operational constraints, (iii) fairness and collaboration constraints, and (iv) environmental and sustainability objectives (see Figure 7).

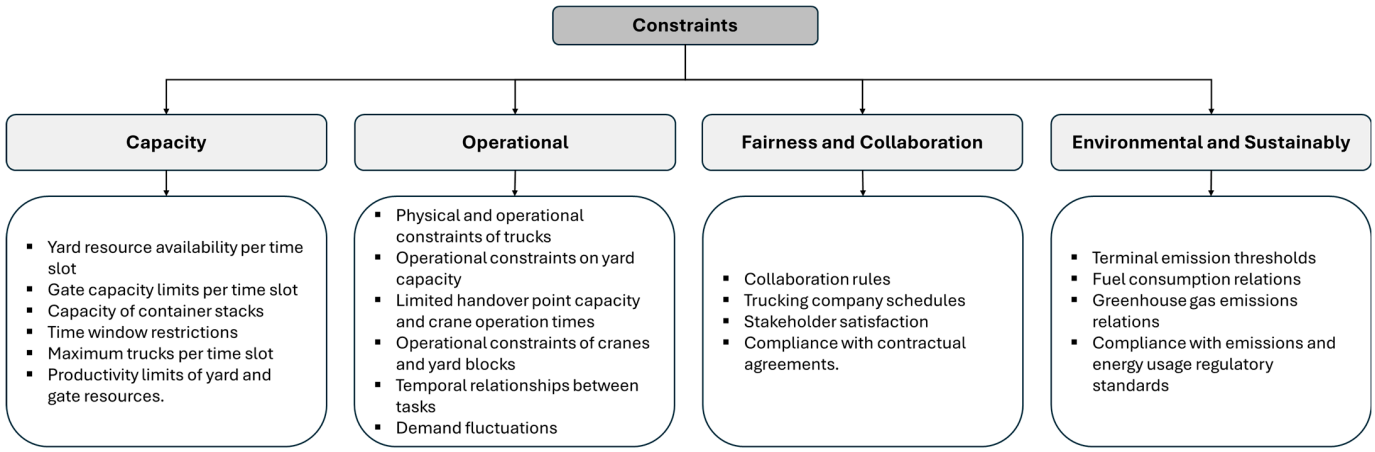


Figure 7. Constraints of TAS models.

Capacity constraints ensure that terminal operations remain within the physical and operational limits of available resources [45,46]. Their primary aim is to prevent resource overutilization, manage demand fluctuations, and maintain system stability. Typically modeled as upper-bound constraints, they play a critical role in maintaining operational efficiency. Operational constraints address the physical feasibility, resource limitations, temporal alignment, and coordination requirements of truck appointment systems [47,48]. The objective is to optimize terminal performance while ensuring operations are practical, equitable, and efficient. Fairness and collaboration constraints focus on equitable resource

allocation and scheduling across stakeholders, including terminals, trucking companies, and drayage firms [49,50]. The aim is to foster collaboration and ensure a fair distribution of appointment slots and other resources. Environmental and sustainability constraints align terminal operations with environmental goals and regulatory standards [43,51,52]. The aim is to minimize the environmental footprint of terminal activities by reducing emissions and ensuring compliance with sustainability regulations.

4.2.4. Input Parameters

The input parameters for scheduling truck appointments can be classified into four main categories: (i) truck arrival parameters, (ii) terminal and resource capacity parameters, (iii) environmental and emission parameters, and (iv) scheduling, time and cost parameters (see Figure 8).

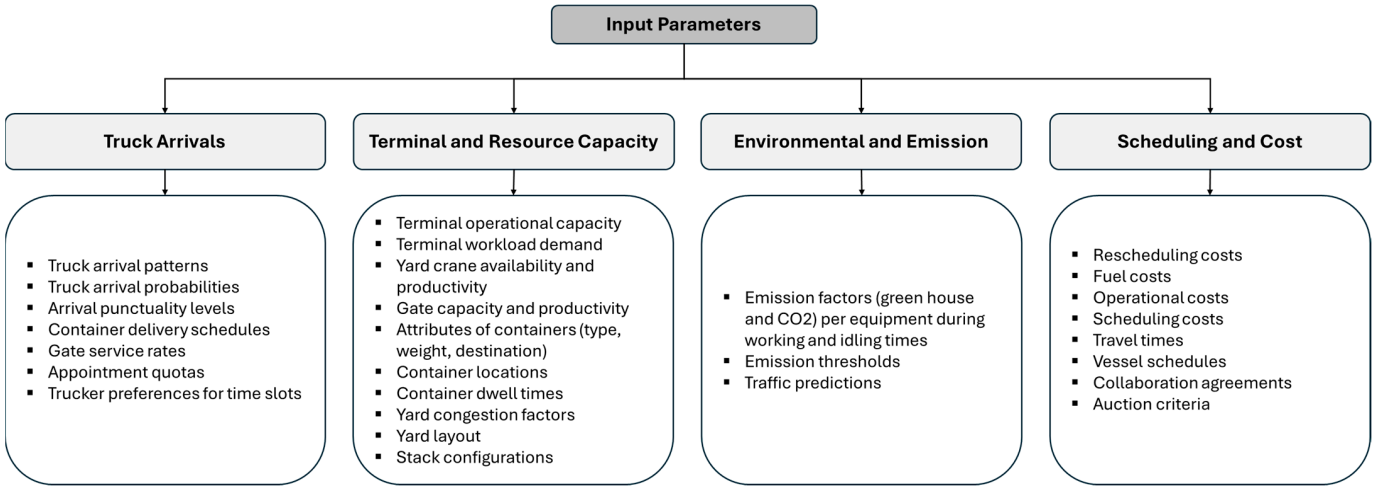


Figure 8. Input parameters of TAS models.

Truck arrival parameters provide data on the timing, patterns, and preferences associated with truck operations [53]. Their primary aim is to model and predict truck arrival behaviors to optimize scheduling and balance truck inflow, thereby minimizing congestion and waiting times. Terminal and resource capacity parameters reflect the physical and operational capabilities of terminals [5,39]. Their objectives include assessing resource limits, ensuring efficient alignment of resource allocation with demand, optimizing yard operations and container handling, and enhancing stacking, retrieval, and container movement efficiency. Environmental and emission parameters quantify the environmental impact of terminal and truck operations [54–56]. The aim is to evaluate and minimize the environmental footprint of terminal activities while supporting compliance with sustainability and regulatory requirements. Scheduling, time, and cost parameters focus on optimizing cost efficiency while meeting operational constraints [29,57,58]. They aim to ensure fair and balanced appointment slot allocation, support equitable decision-making, enhance stakeholder satisfaction, and foster collaboration among terminals, trucking companies, and other stakeholders.

Additionally, to enhance model robustness and improve resilience against disruptions, published TAS models incorporate variability and uncertainty related to yard capacity, travel and loading times, no-show probabilities, and truck arrival patterns.

4.2.5. Solution Approaches

Initially, TAS models were predominantly solved using commercial optimization solvers, and priority rule-based heuristics. However, the increasing complexity of these

problems and advancements in solution techniques led to the adoption of a broader range of methodologies. Notable approaches include queuing-theory-based models for dynamic arrival patterns [44], exact algorithms, and heuristic or metaheuristic solutions such as genetic algorithms and auction-based mechanisms to handle dynamic and complex scenarios [59–61]. The integration of mathematical programming with non-stationary and vacation queuing models has significantly improved the estimation of truck waiting times and service rates, facilitating more responsive TAS designs [62]. Additionally, decentralized systems utilizing agent-based approaches enable realistic simulations of interactions between drayage and terminal operators [61,63,64].

Optimization models in TAS can be classified into exact and metaheuristic approaches. Exact methods include techniques such as the Frank–Wolfe method and branch-and-price heuristics. Metaheuristic algorithms encompass Genetic Algorithms (GAs), hybrid GA-Simulated Annealing, Tabu Search (TS), Variable Neighborhood Search (VNS), improved VNS (IVNS), and Hybrid GA-VNS combinations. Robust and stochastic optimization models are tackled using two-stage robust optimization with column-and-row generation algorithms or stochastic assignment heuristics integrated with discrete choice modeling. Simulation-based optimization approaches embed simulation within heuristic methods or combine discrete-event simulation with optimization algorithms like GA. Furthermore, agent-based models employ auction-based mechanisms for decentralized scheduling or simulate collaborative systems to evaluate interactions and performance.

5. Discussion and Further Research Directions

From the analysis of the reviewed literature, we observe that the modeling approaches for TAS optimization have evolved over the years, reflecting the increasing complexity of port operations, the growing emphasis on environmental and operational efficiency, and advancements in emerging technologies aimed at enhancing data integration and automation. To provide a clearer understanding of these developments and their progression, we classify the TAS models into four distinct generations (see Table 2).

The earlier contributions, categorized as the first generation of TAS models, present foundational approaches focused on optimizing truck turn times and crane utilization using deterministic and queuing-based formulations. These formulations are characterized by deterministic inputs, such as fixed arrival rates and static service times, with limited consideration of variability. The models predominantly employed linear programming, integer programming [14], and queuing theory [15,18] to minimize operational bottlenecks and utilize simulations to validate and evaluate the impacts of appointment systems [24,25,44]. These early models were relatively simple, often assuming static or deterministic inputs and exhibiting limited ability to handle real-world uncertainties, such as late arrivals or no-shows.

The second generation of TAS models demonstrates greater attention to integrating environmental objectives [28,57], such as emission reduction, with traditional operational goals; proposing collaborative frameworks [48,49] to promote coordination between terminals and trucking companies for optimized scheduling; and expanding the scope of TAS decisions to consider yard and drayage operations to coordinate truck arrivals with container relocations and retrievals [65–67] and matching inbound and outbound contains to facilitate double moves and minimize empty trips [19]. The complexity of the models necessitated an increased use of heuristics and metaheuristics to solve complex problems. However, the increased model complexity posed challenges for real-world implementation. These models often lacked the ability to dynamically adapt to real-time changes in truck arrivals or terminal operations. Furthermore, while collaboration was introduced, models typically addressed yard and gate operations separately rather than holistically.

The third generation of TAS models addresses uncertainty in operational conditions, such as dynamic truck arrivals, stochastic travel times, and real-time disruptions. These models are characterized by the introduction of dynamic and stochastic approaches [68], the use of agent-based simulations to explore decentralized and centralized scheduling [30], and the incorporation of real-time decision-making capabilities [51]. This generation accounted for uncertainties in truck arrivals, travel times, and service times, making the models more realistic. Agent-based simulations enabled the exploration of decentralized and centralized scheduling approaches, offering valuable new insights. Additionally, this generation began to cohesively integrate yard operations, gate operations, and truck appointment systems. Despite these advances, challenges persisted; for example, dynamic and stochastic models required significant computational resources, limiting their scalability. Furthermore, real-time deployment remained difficult due to the need for high-quality, real-time data and advanced infrastructure, and the complexity of these models made them less accessible to terminal operators without specialized expertise.

The fourth generation of TAS models leverages artificial intelligence, multi-agent systems, and advanced optimization algorithms to handle large-scale, real-time, and decentralized scenarios. These models capitalize on auction-based mechanisms and decentralized coordination [61], the integration of machine learning algorithms for predictive and adaptive optimization [31,69], and advanced algorithms such as branch-and-price heuristics [70] and robust optimization frameworks to handle uncertainty [35,43,61,71]. These models achieve fully integrated gate, yard, and crane operations, addressing congestion, emissions, and resource utilization simultaneously. However, these models rely heavily on high-quality, real-time data, which may not be available in all terminal settings, and require advanced technological infrastructure, such as IoT devices and cloud-based systems, for successful implementation. Additionally, the integration of intelligent systems and decentralized approaches posed considerable challenges for practical deployment, and the adoption of advanced technologies and infrastructure upgrades incurred high initial costs.

Table 2. Classification of TAS models.

Generation	Characteristics	Advantages	Limitations	Related Papers
First Generation	Deterministic, foundational models for gate optimization.	Simple, foundational models; computationally efficient; introduced TAS concepts.	Deterministic; limited scope; no real-time or stochastic considerations; scalability issues.	Guan and Liu [14], Namboothiri and Erera [18], Huynh [20], Zhao and Goodchild [21], Esmemr et al. [22], Huynh and Walton [25].
Second Generation	Emphasis on environmental and collaborative optimization.	Integrated environmental and collaborative objectives; advanced heuristics; expanded scope.	Computational complexity; limited real-time adaptability; partial yard–gate integration.	Schulte et al. [7], Do et al. [28], Zhang et al. [44], Phan and Kim [49], Chen and Jiang [57], Torkjazi et al. [63], Azab and Morita [65].
Third Generation	Dynamic and stochastic models with real-time decision-making.	Dynamic and stochastic models; real-time adaptability; agent-based simulations; synchronization.	High computational demand; implementation barriers; complexity for practitioners.	Li et al. [5], Riaventin et al. [30], Xu et al. [51], Stoop et al. [68].
Fourth Generation	Intelligent systems leveraging AI, IoT, and robust optimization.	Intelligent systems; decentralized coordination; robust and holistic integration; sustainability.	Data dependency; high infrastructure requirements; cost and implementation complexity.	da Silva et al. [31], Li et al. [35], Hoxha et al. [43], Wang et al. [70], Wasesa et al. [71].

The key elements that define the contribution and scope of a TAS model include quotas and time slot considerations, yard and drayage operations, sustainability and environmental objectives, uncertainty handling, collaborative and real-time decision-making capabilities, appointment rescheduling, and the integration of advanced technologies.

The primary aim of TAS models is to optimize the allocation of time slots for external trucks to alleviate gate congestion [3,40]. Additionally, TAS models may consider yard [53,72] and drayage operations [16,36,70], synchronizing external truck arrivals with yard crane schedules to minimize truck delays and streamline terminal operations. Sustainability is another feature considered in TAS models [37,71]. These models integrate emission reduction a core objective, targeting CO_2 and other pollutants associated with idling trucks and inefficient yard operations. Uncertainty handling is also a modeling feature of TAS models [35]. These models address stochastic elements, including early arrivals, no-shows, travel delays, and operational disruptions, to enhance scheduling robustness. Methods such as overbooking mechanisms and robust optimization approaches are often employed to mitigate these uncertainties [41,68,71]. The option of collaborative decision-making and the optimization of multiple objectives, such as minimizing costs, emissions, and congestion while maximizing throughput and efficiency, are special features considered in some TAS models. Finally, the integration of advanced technologies to predict emissions, gather real-time data, and facilitate the dynamic rescheduling of appointments and disruption management [31,61,69,73] represents a recent advancement in TAS modeling. Table 3 provides a comparison of these specific modeling features, highlighting the progression from foundational deterministic models to advanced intelligent systems.

Table 3. Comparison of modeling features within the four generations of TAS models.

Modeling Feature	First Generation	Second Generation	Third Generation	Fourth Generation
Quotas and Time Slot	Focused primarily on static quotas and deterministic time slots. Early models lacked flexibility in adjusting quotas dynamically.	Introduced time-window adjustments for improved scheduling but remained mostly static. Collaborative quota adjustments began emerging.	Time slots became dynamic, with models incorporating demand variability and operational constraints. Quota adjustments linked to real-time conditions.	Fully dynamic quota and time slot management with adaptive allocation using AI and machine learning for optimization. Auction-based systems emerged.
Yard Operations	Minimal focus on yard operations. Models were limited to gate optimization and truck turn times.	Began integrating yard operations, such as crane scheduling, but often addressed yard and gate operations separately.	Comprehensive integration of yard and gate operations, including synchronization of yard crane and truck movements.	Holistic yard and gate integration. Advanced algorithms handle crane scheduling, container relocations, and yard throughput optimization. IoT enables real-time updates.
Drayage Operations	Limited consideration of drayage operations. Focused on truck turn times at the gate.	Introduced basic collaboration between terminals and trucking companies to optimize drayage schedules.	Significant focus on drayage operations with dynamic routing, real-time truck scheduling, and decentralized systems.	Full integration of drayage operations with TAS, utilizing multi-agent systems, AI, and predictive analytics for efficient scheduling.

Table 3. *Cont.*

Modeling Feature	First Generation	Second Generation	Third Generation	Fourth Generation
Sustainability and Environment	No explicit focus on sustainability or emissions reduction.	Introduced sustainability objectives, such as emissions reduction, alongside operational goals.	Strong emphasis on sustainability, with models optimizing truck arrival patterns to reduce emissions and idle times.	Sustainability is a central focus, with advanced systems optimizing emissions, energy consumption, and overall environmental impact.
Uncertainty	Deterministic models with limited ability to handle uncertainties such as late arrivals or no-shows.	Began addressing uncertainty with stochastic elements in a few models, though still limited in scope.	Comprehensive treatment of uncertainty in truck arrivals, travel times, and operational disruptions using stochastic and dynamic models.	Advanced uncertainty handling with robust optimization, predictive analytics, and real-time adjustments for dynamic scenarios.
Collaborative Decisions	Models focused on individual terminal optimization.	Collaboration between terminals and trucking companies emerged, focusing on schedule coordination.	Enhanced collaboration, with agent-based systems allowing for decentralized decision-making among stakeholders.	Decentralized collaboration is supported by multi-agent systems and auction-based frameworks, enabling stakeholder alignment and flexibility.
Real-Time Decisions	No real-time capabilities.	Limited real-time adaptability. Few models included dynamic adjustments based on near-term data.	Real-time decision-making became a key feature, enabled by dynamic models and agent-based systems.	Advanced real-time capabilities using IoT, cloud computing, and AI for continuous optimization and decision-making.
Appointment Rescheduling	No rescheduling capabilities. Appointments were static and fixed once scheduled.	Basic rescheduling capabilities began to emerge, often requiring manual intervention.	Rescheduling became dynamic, accounting for real-time disruptions and delays using advanced algorithms.	Fully dynamic rescheduling based on real-time data, leveraging AI and IoT to optimize changes and minimize disruptions.
Technology integration	Limited use of technology. Relied on traditional optimization methods (e.g., linear and integer programming).	Early use of heuristics and metaheuristics (e.g., Genetic Algorithms).	Adoption of agent-based simulations and predictive analytics.	Advanced integration of AI, machine learning, IoT, and auction-based systems. Real-time data feeds and predictive algorithms optimize operations.

Despite significant progress, future research should address several critical areas. Stakeholder integration is needed to create holistic frameworks that unify the perspectives of terminal operators, drayage firms, and port authorities. Models must also enhance scalability and real-time adaptability to manage high-traffic terminals and dynamic demand conditions. The digital transformation of TASs using IoT, AI, and blockchain technologies presents opportunities to enhance data integration and automation. Lastly, the exploration of sustainability beyond emissions, such as noise pollution and community well-being, remains an underexplored yet vital area for future work.

6. Conclusions

The development of advanced optimization models for truck appointment scheduling has significantly enhanced container terminal operations by addressing efficiency, revenue maximization, and risk management. Employing methodologies like robust optimization, stochastic dynamic programming, mixed-integer programming, and hybrid heuristics, these models effectively manage uncertainty and interdependent operational decisions. Through real-world case studies and simulation-based evaluations, researchers have provided practical insights for terminal managers, demonstrating the potential to improve operational efficiency, reduce costs, and mitigate risks. These efforts underscore the importance of combining mathematical modeling with empirical validation to meet the complex demands of modern terminal operations.

Collectively, the state-of-the-art TAS models reflect substantial progress in addressing challenges such as disruptions, uncertainty, emissions, and dynamic scheduling. By integrating truck scheduling with yard equipment allocation and employing innovative frameworks, such as vessel-dependent time windows and advisory-based systems, recent studies highlight strategies to optimize terminal performance. Furthermore, advancements in TAS models emphasize multi-stakeholder collaboration, robust optimization techniques, and sustainability-focused approaches to reduce congestion, emissions, and operational costs while enhancing overall terminal efficiency.

The evolution of TAS modeling approaches reveals a clear progression in sophistication, scope, and technological integration. Early generations laid the foundation for operational efficiency but lacked considerations such as uncertainty, real-time adaptability, and environmental sustainability. Subsequent generations progressively addressed these limitations by incorporating advanced features, including dynamic scheduling, collaborative decision-making, and sustainability objectives. The fourth generation represents the pinnacle of current advancements, leveraging artificial intelligence, the IoT, and robust optimization frameworks to achieve holistic and sustainable terminal operations.

Looking ahead, the TAS literature presents significant opportunities for further innovation. Incorporating cutting-edge technologies such as AI, IoT, and blockchain could enable real-time decision-making, enhance scalability, and improve system resilience. Future research should prioritize the integration of multi-modal operations and adaptive systems to address the growing complexity of port ecosystems. This paper provides a solid foundation for a comprehensive understanding of TAS models, identifying critical gaps and highlighting opportunities to expand the scope of TAS applications. Ultimately, these advancements aim to foster efficiency, resilience, and environmental sustainability in global terminal operations.

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Appendix A

Table A1. Selected research articles on truck appointment scheduling literature.

Author	Year	Model *	Data Source	Validation Framework	Main Contribution
Huynh and Walton [25]	2008	OPT + SIM	Not explicitly provided but references terminals like Evergreen Los Angeles Terminal and Long Beach	Simulations to test the effectiveness of the proposed system under various arrival scenarios, including late arrivals and no-shows	Introduces a methodology that combines a mathematical model and simulation to optimize truck appointment systems
Namboothiri and Erera [18]	2008	OPT	Simulated data based on U.S. port operations	Computational experiments using test instances designed to simulate realistic drayage operations. These tests explore the impact of slot capacity variations on fleet productivity and customer service levels	Develops an integer programming-based framework to optimize drayage fleet operations under appointment-based port access control systems. The study highlights how increased slot capacities improve fleet productivity, providing insights into the impact of appointment systems on drayage firms
Guan and Liu [14]	2009	QUE	U.S. marine terminal data	Case study using field data collected from marine terminal gate operations. Sensitivity analysis is conducted to assess the impact of appointment caps and arrival rates on system performance	Proposes a multi-server queuing model to optimize gate appointment systems, balancing terminal operating costs and truck waiting costs. The study demonstrates that appointment systems significantly reduce congestion and associated costs at terminal gates
Huynh [20]	2009	SIM	Simulated terminal data	Evaluates different scheduling rules under various operational scenarios, showing clear improvements in resource utilization and truck turn times	The study provides evidence that properly designed appointment systems improve yard crane utilization and reduce truck turn times in grounded operations
Zhao and Goodchild [21]	2010	SIM	Simulated data based on container yard setups	Simulation experiments to model different levels of truck arrival information and container bay configurations	Demonstrates how improved truck arrival information can reduce container rehandling in terminal yards, enhancing crane productivity
Esmemr et al. [22]	2010	SIM	Turkish port	Case study at a Turkish port to analyze how varying the number of terminal trucks impacts environmental and operational performance	Proposes a simulation-based approach to optimize the number of terminal trucks required for operations, integrating lean and green concepts

Table A1. *Cont.*

Author	Year	Model *	Data Source	Validation Framework	Main Contribution
Kiani et al. [15]	2010	QUE	Simulated data	Simulates various gate configurations and arrival patterns	Develops a queuing-based simulation methodology to address truck congestion and reduce turnaround times at marine terminal gates. The study provides practical insights into improving gate operations and mitigating queue lengths
Huynh and Walton [23]	2011	SIM	Simulated terminal data	Simulation experiments to evaluate the impact of appointment caps and scheduling rules on gate throughput and resource utilization	Analyze the effects of TAS on gate throughput and operational efficiency. The paper introduces scheduling rules and their impact on reducing resource idling and truck turn times
Sharif et al. [26]	2011	DAN + SIM	---	Simulates experiments with real-time data scenarios	Highlights how real-time information, coupled with predictive strategies by truck dispatchers, can stabilize truck arrivals and reduce gate queuing
van Asperen et al. [53]	2013	SIM	An automated container terminal	Testing different scenarios of truck arrival announcements, quantifying crane idle time and reshuffling efficiency	Demonstrates the TAS's ability to optimize yard crane utilization, albeit with challenges in implementation
Dekker et al. [72]	2013	QUE	Rotterdam Maasvlakte terminals	A case study quantifying waiting time and emission reductions	Proposes a Chassis Exchange Terminal concept that mitigates gate congestion and enhances throughput, focusing on operational off-peak hours
Zhao and Goodchild [2]	2013	SIM + QUE	---	Analytical framework demonstrating improved efficiency in yard crane productivity and reduced truck delays	Validates the operational benefits of using truck arrival information to optimize yard operations
Zhang et al., [55]	2013	OPT	Tianjin terminal	Case study demonstrating significant reductions in turnaround times	Validates TAS as a viable tool for congestion management and reduce truck turn time at container terminals using optimized appointment quotas
Chen et al. [59]	2013	OPT	Northern China terminal	Case study from a Northern China terminal	Implement vessel-dependent time windows to control truck arrivals and reduce congestion at terminal gates and highlight significant reductions in gate congestion and improved resource allocation
Chen et al. [62]	2013	QUE	Port of Vancouver	Case study	Demonstrates dynamic TAS improves flexibility and reduces congestion effectively

Table A1. *Cont.*

Author	Year	Model *	Data Source	Validation Framework	Main Contribution
Chen et al. [42]	2013	OPT + QUE	---	Validated through numerical examples	Proves that minor shifts in truck arrivals can significantly reduce emissions and congestion
Islam et al. [54]	2013	OPT	Port of New York and New Jersey	Case study using publicly available port operation data	Reengineers the truck hauling process at container terminals by introducing a truck-sharing arrangement to minimize empty trips and improve transport capacity
Nossack and Pesch [60]	2013	OPT	---	Computational experiments on synthetic datasets	Highlights efficient handling of pre- and end-haulage to reduce operational costs in intermodal transportation
Zehendner and Feillet [38]	2014	OPT	---	Real-world data demonstrate reductions in delays and improved multimodal service quality	Evaluates the benefits of a TAS on multimodal terminal service quality, gained by coordinating inland transport and yard resource allocation
Phan and Kim [6]	2015	OPT	---	Numerical simulations validating system efficiency under different scenarios	Develops a decentralized negotiation process for scheduling truck arrivals at container terminals
Phan and Kim [49]	2016	OPT	---	Numerical experiments to assess system robustness under operational uncertainties	Introduces a collaborative truck appointment system, integrating trucking company operations with terminal schedules
Chen and Jiang [57]	2016	OPT	Chinese container terminals	Numerical experiments with real-world scenarios	Demonstrates the effectiveness of vessel-dependent time windows in reducing gate congestion
Do et al. [28]	2016	SIM	Simulated terminal data	Numerical experiments to analyze emission reductions	Demonstrates the impact of operational control mechanisms on emission reduction and efficiency
Schulte et al. [7]	2017	OPT	---	A real-world scenario, demonstrating effective reductions in emissions and costs through collaboration	Advocates for collaborative TAS designs, showing significant environmental and economic benefits for ports and trucking companies
Ramírez-Nafarrate et al. [24]	2017	SIM	Port of Arica	Case study	Evaluates the impact of a truck appointment system (TAS) on yard efficiency in port terminals
Gracia et al. [3]	2017	SIM	Port of San Antonio	Case study	Demonstrates that lane segmentation and optimal booking levels significantly reduce congestion and emissions at the terminal gates

Table A1. *Cont.*

Author	Year	Model *	Data Source	Validation Framework	Main Contribution
Torkjazi et al. [63]	2018	OPT	U.S. container terminals	Numerical analysis of real-world scenarios	Proposes a TAS considering drayage truck tours to minimize costs for terminal and drayage operations
Li et al. [5]	2018	SIM	---	Sensitivity analysis of strategies under disruption scenarios at container terminals	Introduces practical resilience strategies to manage typical disruptions effectively, improving operational stability and sustainability
Zhang et al. [44]	2019	QUE	---	Numerical experiments with sensitivity analysis	Improves service efficiency by aligning truck arrivals with crane operations, reducing gate and yard congestion
Yi et al. [32]	2019	OPT	---	Empirical data from a port terminal are used for validation, demonstrating improved scheduling efficiency	Effective in balancing terminal workloads and minimizing congestion-related delays
Zeng et al. [39]	2019	OPT	---	Numerical experiments validate the model, showing significant reductions in container rehandling	Provides tools for terminals to enhance yard efficiency and reduce delays by optimizing container rehandling and pickup sequences using partial truck arrival information
Fan et al. [58]	2019	OPT	Chinese container terminals	Numerical examples	Addresses truck scheduling under TAS to minimize carbon emissions and operational and proves low-carbon scheduling improves operational efficiency and sustainability
Ma et al. [40]	2019	OPT	Tianjin Port	Numerical experiments demonstrating emission reductions	Demonstrates the effectiveness of vessel-dependent time windows in congestion and emission management
Caballini et al. [19]	2020	DAN + OPT	PSA—Genova, Italy and Altamira terminal, Mexico	Case studies on two real-world terminals, and an experimental design using factorial analysis to evaluate the impacts of various clustering and optimization configurations	Offers a robust TAS methodology combining clustering and optimization to minimize empty truck trips and congestion, applicable across terminals globally
Mar-Ortiz et al. [9]	2020	OPT	Mexican container terminal	Real case study at a Mexican container terminal	Proposes an optimization-based DSS to determine the appointment quota for each time slot on a one-day planning horizon, within a container terminal working on a TAS environment

Table A1. *Cont.*

Author	Year	Model *	Data Source	Validation Framework	Main Contribution
Azab et al. [27]	2020	OPT + SIM	Alexandria Container Terminal	Validated against artificial instances inspired by real-world data	Develop a simulation-based optimization approach for collaborative scheduling of external trucks in container terminals and highlights the importance of collaborative scheduling and IoT-based frameworks for improved terminal performance
Li et al. [36]	2020	OPT	Dalian Maritime Terminal	Numerical experiments	Highlights the efficiency of integrated quota allocation and crane scheduling in reducing congestion
Im et al. [64]	2021	OPT	Generic large-scale container terminals	Simulated case study highlighting cooperative scenarios	Cooperation models between transport companies and terminal operators reduce congestion and improve scheduling efficiency
Xu et al. [51]	2021	OPT	---	Simulation-based experiments on real data validate the model, showing improved cost efficiency over traditional TAS approaches	Develops a multi-constraint truck appointment system considering truck companies and terminals to minimize operation costs while considering urban peak congestion and queuing costs
Neagoe et al. [52]	2021	SIM	Bulk cargo marine terminal	Simulated using empirical data from weighbridges and geo-positioning systems	Compares congestion management initiatives at bulk cargo marine terminals using discrete-event simulation to assess truck queuing and emissions
Wasesa et al. [71]	2021	SIM	---	Case studies focusing on operational performance under varying no-show rates	Proposes overbooking strategies to enhance terminal productivity and environmental performance
Azab and Morita [50]	2022	OPT	Japanese container terminal	A case study demonstrating significant reductions in container relocations while preserving scheduling preferences	Integrates truck appointments and yard operations decisions to reduce yard congestion and enhanced terminal efficiency
Xu et al. [66]	2022	OPT	---	Simulation experiments demonstrate cost reductions and improved adaptability to arrival uncertainties.	Addresses dynamic appointment rescheduling under truck arrival uncertainties to minimize operating costs and operational disruptions
Abdelmagid et al. [33]	2022	OPT	Port of Alexandria	Numerical experiments based on instances from literature	Improves workload distribution and reduces truck turnaround time, leading to cost minimization and enhanced terminal efficiency
Azab and Morita [65]	2022	OPT	Simulated terminal data	Solved using instances from literature	Highlights the benefits of integrating appointment scheduling with yard operations

Table A1. *Cont.*

Author	Year	Model *	Data Source	Validation Framework	Main Contribution
Li et al. [16]	2022	OTP + QUE	Shenzhen and Dalian terminals	Simulation-based experiments	Develops a queuing model to optimize truck appointments and yard equipment use for dual transaction systems
Ma et al. [37]	2022	OPT	Dalian Maritime Terminal	Numerical experiments	Enhances yard efficiency by integrating truck arrivals with crane operations
Nadi et al. [56]	2022	SIM	Port of Rotterdam	Experimental analysis	Introduces an advisory-based time slot management system to mitigate truck waiting times at terminal gates and highlights the benefits of behavioral modeling in time slot allocation for congestion reduction
Sun et al. [41]	2022	OPT + DAN	YT Port, China	Numerical experiments based on smart gate data	Reduces external truck turnaround times and emissions in ports using data-driven optimization of appointment quotas
Torkjazi et al. [45]	2022	OPT	U.S. container terminals	Simulated using multi-player game scenarios	Models TAS as a multi-player game between terminals and drayage firms, that outperform single-player models in balancing terminal and drayage firm interests
da Silva et al. [69]	2023	SIM + DAN	Brazilian port terminal	A case study achieving a 90.4% reduction in waiting times and reduced queue sizes	Demonstrates the effectiveness of integrating smart technologies in truck appointment systems to improve port logistics flexibility and visibility with real-time data
Zhou [34]	2023	OPT + QUE	---	Real-world data demonstrate reductions in no-show impacts and improved resource utilization	Highlights overbooking strategies to mitigate disruptions in TAS operations, and incorporate no-show behaviors into truck appointment scheduling to minimize terminal resource inefficiencies and carbon emissions
He et al. [47]	2023	OPT	Shanghai Maritime University's data	Sensitivity analysis on task appointment strategies	Demonstrates that balancing yard workload improves efficiency and reduces truck delays
Minh and Noi [46]	2023	OPT + QUE	Ho Chi Minh City Terminal	Case study validation with comparison to observed data	Develops a TAS to optimize arrival management and service gate allocation and demonstrate cost and congestion reductions through optimized gate management

Table A1. *Cont.*

Author	Year	Model *	Data Source	Validation Framework	Main Contribution
Abeysooriya et al. [17]	2024	QUE + OPT	A major Asian port	Data-driven analysis based on truck arrival and emission patterns	Proposes a gate queuing optimization model to minimize greenhouse gas emissions from idling trucks
Huang et al. [48]	2024	OPT	---	Extensive experiments showing a 29.4% reduction in total operating time compared to traditional approaches	Highlights the benefits of integrating appointment systems with efficient task scheduling to enhance operational efficiency in drayage operations
Li et al. [35]	2024	OPT	---	A case study on real-world terminal operation data, showing robust performance under uncertain scenarios	Provides a practical framework for gate appointment design, improving terminal efficiency and mitigating congestion under uncertainty
Bett et al. [29]	2024	SIM + OPT	Literature-derived scenarios.	Numerical experiments based on research data	Emphasizes the need for dynamic scheduling and resource optimization in the face of uncertainties. Optimize truck appointment systems using simulation-based methods to account for yard congestion and dynamic scheduling
da Silva et al. [31]	2024	DAN + OPT	Brazilian port terminal	A case study to anticipate disruptions and to actively manage hinterland port flows	Proposes a conceptual model for flexible truck appointment systems, able to consider a continuous stream of real-time data from smart technologies to identify disruptive events and to dynamically reschedule truck appointments
Duan et al. [67]	2024	OPT	Simulated data from Chinese terminals	Numerical experiments with sensitivity analysis	Integrates TAS with container relocation operations to enhance yard crane efficiency and reduce congestion while balancing operational workloads
Hoxha et al. [43]	2024	DAN + OPT	PSA Genova	Case study	Demonstrates effective emission reductions through optimized arrival scheduling
Riaventin et al. [30]	2024	SIM	---	Simulation with synthetic data reflecting real-world configurations	Investigates synchronization between truck arrival and yard crane scheduling under centralized and decentralized approaches to reduce emissions
Stoop et al. [68]	2024	OPT	Port of Antwerp	Case study	Demonstrates robust scheduling under uncertainties of drayage operations improve efficiency and reduce delays

Table A1. *Cont.*

Author	Year	Model *	Data Source	Validation Framework	Main Contribution
Wang et al. [70]	2024	OPT	Tianjin Port	Case study	Develops an optimization model for scheduling automated container terminal robots and external trucks in a parallel layout
Wasesa et al. [71]	2024	SIM	Port of Rotterdam	Case study	Designs an auction-based truck appointment system for automated container terminals and demonstrate enhanced operational efficiency and sustainability through market-driven appointment allocation

* (OPT) optimization model, (SIM) simulation model, (QUE) queueing model, (DAN) data analytics.

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