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Drayage Routing Problems: A Comprehensive Survey and a New Compact Model

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ABSTRACT

Drayage involves short-distance container trucking, a crucial part of intermodal transportation that fills the gap between long-haul transportation modes and inland facilities. Because of its high costs, drayage has been increasingly drawing the attention of researchers and practitioners from different disciplines, who have been exploring opportunities to improve the performance of drayage operations. In particular, operations researchers have traditionally contributed to these efforts by mathematically formulating drayage problems and by developing exact or heuristic approaches to solve them. We note that, in such problems, the modelling of trucks and containers has generally been limited to considering homogeneous containers and single-container trucks. However, recently introduced problems, such as the drayage routing problem with heterogeneous fleet, compatibility constraints and truck load configurations (DRP-HCL), enable richer fleet modelling, by allowing the consideration of containers of any type and trucks with specific load configurations, as well as truck–container and container–container compatibility constraints. In this paper, we review the literature on drayage, discussing how fleet modelling has evolved over the years until the introduction of DRP-HCL. Based on our review, we provide an outlook on the modelling of trucks and containers in upcoming drayage problems. This paper also presents a compact mixed-integer programming (MIP) formulation for DRP-HCL, which can outperform a previously proposed formulation and can be useful for researchers and practitioners who aim to solve small- or medium-sized instances using black-box MIP solvers.

1 | Introduction

Drayage involves trucking containers over short distances between various facilities, including intermodal terminals, distribution centres, storage yards and shipper/consignee locations. It plays a crucial role in intermodal transportation by bridging the gaps between long-haul modes—such as rail and maritime transport—and inland facilities.

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Efficiently planning drayage operations is crucial for achieving cost-effective intermodal cargo movement, given that drayage is recognised for its significant expenses compared to the overall intermodal costs. For example, conservative estimates reveal that, in the case of rail-truck intermodal services in the United States, drayage expenses range from 50% to 75% of the total intermodal costs (Resor et al. 2004).

Erera and Smilowitz (2008) remark that, to address the high costs of drayage, drayage carriers can capitalise on opportunities for enhancing their routing and scheduling. This has been recognised by researchers from diverse fields such as transportation, operations research, civil engineering and economics, who have progressively delved into exploring research possibilities within drayage operations. This trend is evident in the growing number of publications on drayage, which has witnessed a consistent rise since 2010 (Chen et al. 2022).

Traditionally, the research on drayage has focused on situations where full containers are delivered to importers, who unpack their cargoes and request the collection of the resulting empty containers. Furthermore, empty containers are delivered to exporters, who pack their cargoes and request the delivery of their full containers to facilities such as intermodal terminals or ports for further transportation. Empty containers collected at importers' premises are delivered to container storage yards, from where empty containers are delivered to exporters. Alternatively, in the so-called street turns, empty containers are delivered directly from importers' premises to exporters.

In view of the above, we can identify some issues that have been intensively considered in the drayage literature, such as empty container repositioning—which entails deciding the origins/destinations of empty containers, in order to match supply and demand—and the separation of trucks and containers—that is, deciding if trucks must stay with containers or can leave them during packing/unpacking operations. On the other hand, issues such as fleet modelling have received less attention, as it is commonly assumed that drayage movements involve a single container type and that trucks move a single container at a time. It has been only recently that researchers have begun to take more interest in drayage problems involving richer modelling of fleets, for example, considering 20/40-ft containers and double-container trucks.

Recent contributions that advanced the modelling of trucks and containers in drayage problems were made by Bustos-Coral and Costa (2022) and Bustos-Coral and Costa (2025), who introduced the drayage routing problem with heterogeneous fleet, compatibility constraints and truck load configurations (DRP-HCL), a problem that allows for richer fleet modelling than previously proposed problems. DRP-HCL involves the planning of container pickup and delivery services considering truck and container fleets with the following characteristics:

- Containers of any size (e.g., 20/40/45/48/53 ft) and cargo category (e.g., dry, reefer, tank);
- Trucks with different cargo capacities, which depend on the containers' sizes and contents (e.g., a truck may be able to carry up to two empty 20-ft containers but only one full 20-ft container);
- Standard trucks, that is, rigid trucks or semi-trucks pulling a single trailer/chassis, and longer combination vehicles (LCVs), that is, semi-trucks pulling two or more trailers/chassis;
- Container–container and truck–container compatibility constraints. Container–container compatibility constraints arise when, for example, containers carrying incompatible hazmat loads cannot be moved together. Truck–container compatibility constraints arise when, for example, only trucks with special permits can move out-of-gauge loads.

The objective of DRP-HCL is to determine a fleet composition and a routing plan that minimise fixed costs, for example, truck acquisition or chassis rental costs, and routing costs, for example, per-mile fuel costs.

Bustos-Coral and Costa (2022) developed a compact three-index mixed-integer programming (MIP) formulation and a tailored branch-and-cut algorithm for DRP-HCL. These developments were used to solve instances involving only standard trucks. Meanwhile, Bustos-Coral and Costa (2025) developed an adaptive large neighbourhood search heuristic (ALNS) for DRP-HCL aimed at solving harder instances, especially those involving LCVs.

This paper complements the studies of Bustos-Coral and Costa (2022) and Bustos-Coral and Costa (2025) with two main contributions. Firstly, we review the literature on drayage problems, classifying surveyed problems according to the level of detail with which truck and container fleets are modelled. We discuss how fleet modelling in drayage problems has evolved since the pioneering papers in the early 2000s, which considered only homogeneous containers and single-container trucks, until the proposal of DRP-HCL. We also provide an outlook on fleet modelling in future drayage problems. Secondly, we describe an alternative compact MIP formulation for DRP-HCL, which can outperform the three-index

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formulation of Bustos-Coral and Costa (2022). The proposed formulation may be of interest for operations research practitioners who want to solve small- and medium-sized instances (involving standard trucks) using black-box MIP solvers.

The rest of this paper is organised as follows: Section 2 reviews the drayage literature discussing the evolution of fleet modelling over the years. Section 3 presents our alternative compact MIP formulation. Section 4 presents computational results that show the performance of the proposed formulation. Finally, Section 5 concludes the paper.

2 | A Review of Fleet Modelling in Drayage Problems

This section summarises the literature on drayage problems, providing a detailed account of several surveyed studies and discussing how authors have modelled trucks and containers. To organise our review, we have classified the surveyed studies based on their fleet characterisation, that is, the level of detail with which trucks and containers are modelled. Based on this classification, we discuss how the modelling of fleets in drayage problems has evolved over the years until the proposal of DRP-HCL, which allows for the most detailed modelling of fleets relative to the problems addressed in other studies.

The proposed classification uses the characteristics of DRP-HCL as a guide: The surveyed studies are classified based on the consideration of heterogeneous containers (or cargoes), truck load configurations and compatibility constraints. (Note that the consideration of heterogeneous containers/cargoes paves the way for the consideration of compatibility constraints.) By truck load configurations we mean the explicit definition of the trucks' load capacities when they can carry two or more containers at a time. Depending on the trucks' load capacities, we distinguish between two types of load configurations, namely standard and non-standard. Standard load configurations are associated with standard trucks, that is, rigid trucks or semi-trucks pulling a single trailer/chassis. Non-standard load configurations are associated with non-standard trucks, which have increased cargo capacity. In this case, as non-standard trucks we consider LCVs and semi-autonomous platoons. The former consist of a semi-truck pulling two or more trailers/chassis. The latter consist of a crewed truck leading a group of wirelessly connected semi-autonomous trucks. (Note that LCVs are commonly used in Australia and we want to identify which studies can cater to the needs of the Australian drayage industry.)

Sections 2.1 to 2.9 group the reviewed articles according to the proposed classification; for each article, we outline the problem considered and the proposed solution method, as well as the experiments conducted to assess the latter. Finally, Section 2.10 presents a summary of our review and discusses how the modelling of fleets in drayage problems has evolved over time until the introduction of DRP-HCL.

2.1 | Homogeneous Containers, No Load Configurations

Wang and Regan (2002) addressed a full-truckload pickup and delivery problem with time windows (PDPTW) modelled as a multiple travelling salesman problem with time-window constraints (m-TSPTW). The problem's objective was to serve as many requests as possible. The authors proposed an iterative solution approach based on time-window partitioning. At each iteration, this approach solves an over-constrained and an under-constrained version of the problem, which provide primal and dual bounds on the optimal solution, respectively. The gap between these bounds serves as a stopping criterion for the solution method. The authors conducted computational experiments using real-world data and evaluated the performance of alternative approaches for obtaining the dual objective bound.

Gronalt et al. (2003) also considered a full-truckload PDPTW, with the objective of minimising empty vehicle movements. The authors developed an MIP formulation for the problem and four different savings-based heuristics. The linear programming relaxation of the formulation generates dual objective bounds used in assessing the quality of the heuristic solutions. The authors conducted computational experiments where they compared the performances of their heuristics and analysed the impact of time-window tightness on solution quality.

Jula et al. (2005) considered a drayage problem represented as an m-TSPTW with social constraints limiting the number of hours drivers could work per shift. The problem's objective was to minimise the total travel cost. The authors proposed three solution approaches: an exact two-phase dynamic programming (DP) method; a hybrid approach combining DP with a genetic algorithm (GA); and an insertion heuristic. Results of computational experiments indicated that the two-phase DP algorithm outperformed the insertion heuristic on small- and medium-sized instances, while the hybrid DP–GA method was best suited for larger instances.

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Ileri et al. (2006) tackled a drayage problem involving a heterogeneous (in-house and third-party) crew of drivers. The drivers had an earliest and latest start time, starting and ending locations, maximum work hours and minimum daily wage. The problem's objective was to minimise driver-associated costs. The authors presented a set-partitioning formulation for the problem and developed a column generation–based solution approach. Computational experiments on data provided by an American truckload carrier showed a high runtime efficiency of the proposed solution approach.

Smilowitz (2006) addressed a drayage problem referred to as the multi-resource routing problem (MRRP). In this problem, some tasks are well-defined and have only one possible way to be executed—for example, a truck must move a trailer from one location to another. In contrast, other tasks are flexible and allow for alternative decisions—for example, an empty trailer can be moved from (or to) several possible locations. The main objective of the MRRP is to minimise fleet size and the secondary objective is to minimise travel time. The author proposed a set-partitioning formulation for the MRRP and developed a branch-and-price algorithm to solve it. She implemented two versions of the algorithm: a hybrid exact-heuristic approach and a pure heuristic approach. To test them, she considered instances based on real data from the Chicago area and larger instances generated randomly. The hybrid exact-heuristic approach could solve only small instances, while the pure heuristic approach could tackle all instances, obtaining good primal bounds.

Francis et al. (2007) addressed the MRRP building upon the approach of Smilowitz (2006). However, while Smilowitz (2006) used a fixed radius around the flexible tasks' locations to find their possible assignments, Francis et al. (2007) proposed a variable radius (VR) method that finds different numbers of possible assignments, depending on the density of locations on the area being considered. The authors also presented a greedy randomised procedure (GRP) to generate routes. The combined GRP–VR method was tested on instances based on real data from the Chicago area, central Illinois, Wisconsin and Indiana. The results indicated that the GRP–VR method could improve the results obtained by a fixed radius, purely greedy method.

Imai et al. (2007) studied a drayage problem where trucks moved containers from/to an intermodal terminal. The trucks could be company-owned or contracted, thus having different costs and working times. The problem's objective was to minimise fuel expenses for company-owned trucks and renting expenses for contracted trucks. The authors developed a subgradient heuristic based on Lagrangian relaxation that solves several assignment problems. Results of computational experiments indicated that the proposed heuristic could consistently find high-quality solutions in short runtimes.

Namboothiri and Erera (2008) considered a drayage problem where containers were transported between a port and several customer locations. The problem involved a port access system, which imposed fixed time windows (called slots) for trucks to access the port. During each slot, there was a limit on the number of trucks that could access the port. The problem's objective was to serve as many drayage requests as possible while minimising costs. The authors developed a column generation–based heuristic to solve the problem. Using it, they analysed the productivity impacts of factors such as the port access capacity, the slot duration and the geographical distribution of customers.

Caris and Janssens (2009) addressed a drayage problem modelled as a full-truckload PDPTW. The problem's objective was to minimise fixed truck costs and travel time–dependent routing costs. To solve the problem, the authors developed a two-phase heuristic approach. In this approach, an initial solution is created by pairing pickups and deliveries and inserting those pairs into routes. Then, a local search procedure is used to improve the quality of the initial solution. The authors also described an exact formulation for the problem and a relaxation used to obtain dual objective bounds. Results of computational experiments showed that the proposed heuristic could consistently find primal solutions with small gaps relative to the dual bounds.

Zhang et al. (2009) considered a drayage problem involving an intermodal terminal, where containers were transshipped; several depots, where empty containers were stored and trucks were parked; and several customer locations, where containers were transported to and from. The problem's objective was to minimise the time trucks travelled empty or carrying empty containers. The authors tackled this problem as an m-TSPTW with multiple depots, proposing an MIP formulation based on a graph of tasks, where each vertex/arc could involve several tasks. For example, a vertex could entail picking up a container at the terminal, delivering it to a customer location and unpacking it. Meanwhile, an arc could entail picking up a recently unpacked container, delivering it to a depot and travelling back to the terminal. The authors developed two solution methods: a clustering-based method and a reactive tabu search (RTS) heuristic. They conducted computational experiments comparing the solutions of both methods against the solutions obtained by solving the MIP formulation. The results indicated that the RTS heuristic could find better solutions than the clustering-based method. However, the latter was capable of solving larger instances much faster.

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Máhr et al. (2010) studied a dynamic drayage problem inspired by a real case arising in the Port of Rotterdam, the Netherlands. This problem involved drayage movements between port facilities and customer locations, considering time-window constraints and two sources of dynamism: varying service times and job arrivals. The authors developed two solution approaches to solve the problem: a decentralised multiagent system, where agents participate in auctions using locally perceived information, and a centralised approach, which solves an MIP model at 30-s intervals considering all available information about the problem. These approaches were evaluated based on the number of deadhead miles, missed revenue from declined jobs and delays in serving the jobs. Results of computational experiments indicated that neither approach was dominant, with their performances being highly dependent on the sources and levels of dynamism.

Zhang et al. (2010) studied a problem similar to that of Zhang et al. (2009). In this case, the problem involved multiple intermodal terminals, depots and customer locations. The problem's objective was to minimise the trucks' operating time. The authors modelled the problem as an m-TSPTW with multiple depots and multiple terminals. They proposed a mathematical model based on a graph of tasks and a window partition–based (WPB) solution method based on the time-window partitioning approach of Wang and Regan (2002). The authors showed that the WPB method could find good-quality solutions and could outperform an RTS heuristic.

Zhang et al. (2011) addressed a drayage problem where there was a limited supply of empty containers that had to be delivered to customers. The problem's objective was to minimise the trucks' operating time. The authors tackled the problem as an m-TSPTW with resource constraints. They proposed a mathematical formulation based on a graph of tasks and an RTS heuristic. To ascertain the quality of the heuristic solutions, the authors considered dual objective bounds found by solving a relaxed formulation for the problem. Results of computational experiments indicated that the RTS heuristic could rapidly find solutions with a small gap relative to the dual objective bounds.

Braekers et al. (2013) considered a drayage problem involving a depot and several terminals, with the latter being used as storage places for empty containers. The problem involved movements of full and empty containers, with the latter having flexible origins/destinations—similar to the problem dealt by Smilowitz (2006). The problem's objective was to minimise both fleet size and total travelled distance (in lexicographic order). The authors formulated the problem as an asymmetric m-TSPTW and proposed two approaches based on deterministic annealing (DA): one sequential, the other integrated. The sequential approach allocates empty containers before establishing a routing plan, while the integrated approach conducts assignment and routing operations simultaneously. The integrated approach was shown to be better than its sequential counterpart.

Nossack and Pesch (2013) addressed a full-truckload PDPTW where full and empty containers were moved between a terminal and customer locations, with empty containers having flexible origins/destinations. The problem's objective was to minimise the trucks' operating time. The authors presented a two-stage heuristic approach that first creates sequences of pickups and deliveries and then applies an improvement heuristic. Results of computational experiments indicated that the two-stage heuristic could outperform the WPB method of Zhang et al. (2010).

Sterzik and Kopfer (2013) tackled a drayage problem involving empty containers with flexible origins and destinations and trucks that could finish their routes at different locations. The problem's objective was to minimise the trucks' operating time. The authors presented an MIP formulation for the problem and proposed a tabu search (TS) heuristic. Results of computational experiments showed that the TS heuristic could outperform the WPB method of Zhang et al. (2010) in terms of both solution quality and computation times.

Wang and Yun (2013) studied a multimodal transportation problem with time windows involving trucks and trains, with the latter operating according to scheduled timetables. The problem's objective was to minimise rail and drayage costs. The authors presented an MIP formulation for the problem and developed a hybrid greedy—TS heuristic to solve it. Results of computational experiments indicated that the MIP formulation could be solved for small instances in practical runtimes. However, for large instances, the use of the greedy–TS heuristic was required.

Braekers et al. (2014) considered a bi-objective version of the problem studied in Braekers et al. (2013). In this new problem, the objective was to minimise both fleet size and the total travelled distance simultaneously, rather than in lexicographic order. The authors proposed three approaches to the problem: an iterative method, which uses a hierarchical objective function; a two-phase DA algorithm, which explicitly considers the dual objectives of the problem; and a two-phase hybrid DA–TS algorithm, which incorporates improvements over the two-phase DA algorithm. The DA–TS algorithm showed better results than the other methods, being particularly suitable to solve large instances.

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Xue et al. (2014) considered a drayage problem in which semi-trucks could be uncoupled from trailers so that a trailer carrying a container could stay at a customer location while the container was packed or unpacked. The problem's objective was to minimise both the fixed costs of using the semis and travel costs. The authors presented an MIP formulation for the problem and proposed a TS heuristic to solve it. Through computational experiments, the authors assessed the performance of the TS heuristic considering instances with different geographical distributions of locations. Furthermore, they analysed the cost savings that could be obtained by operating semis and trailers that could be uncoupled, as opposed to the operation of semis and trailers that could not be uncoupled.

Zhang et al. (2014) addressed a dynamic drayage problem with flexible orders (similar to the flexible tasks described by Smilowitz 2006). New requests for drayage movements could arrive dynamically. The problem's objective was to minimise the trucks' operating time. The authors formulated the problem as a graph of tasks with temporary vertices describing the status of the trucks. Based on this graph, the authors proposed a mixed-integer nonlinear programming (MINLP) model, which turns out to be an extension of the asymmetric m-TSPTW. The authors proposed four strategies to solve the problem: a simple appending method, solving the MINLP model, solving a pure-integer nonlinear programming model (derived from the MINLP model) and a WPB method. The WPB method proved to be more robust in comparison to the other strategies.

Xue et al. (2015) tackled a problem where semi-trucks could be uncoupled from trailers, similar to the problem of Xue et al. (2014). In this case, the objective was to minimise waiting costs in addition to travel costs and the costs of using semi-trucks. The authors presented an MIP formulation for the problem and an ant colony optimisation (ACO) solution algorithm. Results of computational experiments indicated that the latter could obtain good-quality solutions in short runtimes, which is particularly useful for solving large instances. The authors also analysed how the times required to pack/unpack the containers could affect the obtained results, comparing situations where semi-trucks and trailers could be uncoupled or not.

Shiri and Huynh (2016) considered a problem involving drayage movements of empty and full containers between a terminal, an empty container depot and customer locations. Empty containers could be moved between customer locations or between the empty container depot and customer locations. Meanwhile, full containers were moved between the terminal and customer locations. An important aspect of this problem was that trucks required an appointment to access the terminal. Moreover, the trucks could be divided into sub-fleets located in different truck depots. The problem was modelled as an extension of the m-TSPTW where the objective was to minimise the drayage operation time. The authors proposed a mixed-integer quadratic programming (MIQP) model (based on a graph of tasks) and developed an RTS heuristic. Results of computational experiments showed that the RTS heuristic could rapidly find high-quality solutions and scaled much better than solving the MIQP model. The authors also analysed how different appointment quotas and truck depot locations affected drayage operation times.

Schulte et al. (2017) addressed a problem involving a truck appointment system (TAS) and emission costs. TAS enabled cooperation among drayage companies, for example, a trucker belonging to a group of collaborative truckers could undertake a task not assigned to them if this ultimately increased the overall profit of the group. The problem's objective was to maximise the overall profits of a group of truckers, determined by the summation of their earnings minus the combined costs of transit and emission costs. The authors presented a mathematical formulation for the problem, which is an extension of the m-TSPTW. By solving instances generated from real-world data, the authors showed that their formulation would allow the generation of collaborative truck appointments that would help reduce emissions and costs.

Song et al. (2017) studied a drayage problem where semi-trucks could leave containers during packing/unpacking operations. The problem was a variant of the asymmetric vehicle routing problem (VRP) with time windows where the objective was to minimise the total completion time of the trucks in operation. The authors presented an MIP formulation for the problem based on a graph of tasks. In addition, they developed a branch-and-price-and-cut algorithm that uses two-path cuts to strengthen the lower bound of the master problem and uses TS and a heuristic label setting to solve the sub-problems. The authors showed that their algorithm could solve instances with up to 35 requests in short runtimes. Furthermore, they analysed the benefits that could be obtained when semis could be uncoupled from trailers and discussed how the geographical distribution of locations could impact the obtained solutions.

Escudero-Santana et al. (2020) developed a generalised formulation for drayage problems involving a terminal, a container depot, a truck depot and customer locations. This problem involved trucks that carried only one container at a time, soft

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time windows (which could be violated at a penalty cost) and tasks with flexible origins/destinations. The problem's objective was to minimise travel distance, fixed costs of using the trucks and time-window violations. Through computational experiments, the authors analysed the impacts of policies concerning flexible tasks and time-window lengths. In this regard, the authors stated that flexibility in the repositioning of empty containers could lead to cost savings for all parties involved. However, there were conflicting interests regarding the lengths of the time windows because long time windows could reduce costs for drayage companies, but could also hinder the management of terminal operations.

Zhang et al. (2020) addressed a drayage problem involving a limited supply of empty containers and flexible orders. The problem had two objectives: minimising the number of trucks used and minimising the trucks' operating time. The authors formulated the problem as a nonlinear bi-objective model based on a graph of tasks. Then, they linearised the model and converted it into a single-objective MIP by defining weights for each objective. To solve the problem, the authors developed a large neighbourhood search (LNS) algorithm capable of outperforming the RTS heuristic of Zhang et al. (2011).

Song et al. (2023) addressed a drayage problem involving a terminal, a depot and customer locations. The problem considered empty container repositioning, with a limited supply of empty containers being available at the depot. A fleet of homogeneous single-container trucks was available, with trucks being able to leave or stay with containers during packing/unpacking operations. Services were subject to time-window constraints. The objective was to minimise the trucks' fixed costs as well as travel costs. The authors presented a graphical representation of the problem that allowed them to reduce it to a VRP variant. They developed an MIP formulation for the problem based on the said representation. The authors also developed a branch-and-price algorithm aimed at solving larger instances. Results of computational experiments showed that the branch-and-price algorithm outperformed the MIP formulation, being able to solve problems with 40 requests within an hour. The authors noted that significant cost savings could be achieved when trucks were allowed to leave containers instead of staying with them during packing/unpacking operations, especially when customers were densely located near the terminal and when fixed costs were high.

Chen et al. (2023) considered a dynamic drayage problem where new service requests arrived over the planning horizon. Each request involved the pickup and delivery of a container and was associated with a specific profit. The time horizon was split into several time periods, and, for each period, probabilities of the arrival of new requests were known (such probabilities were estimated from historical data). An e-commerce drayage platform had to decide which requests were accepted and rejected, and the periods when the accepted requests were delivered. The objective was to maximise profits, while minimising travel costs, truck usage and penalties for rejecting requests. The authors presented a multi-stage stochastic programming model for the problem and developed a multi-scenario approach heuristic, which creates routing plans considering both known and potential future requests. Considering data from a drayage operator, the authors conducted computational experiments that revealed that highly flexible delivery time windows did not necessarily increase profits when the arrivals of new requests were highly dynamic. In addition, the heuristic was shown to perform better when pickup and delivery locations were clustered nearby.

Fazi et al. (2023) studied a problem involving drayage moves between an inland terminal, a seaport, an empty container depot and several customer locations, with a key component of this problem being the repositioning of empty containers. A fleet composed of single-container trucks was available to perform the drayage moves, with the trucks being able to perform multiple trips starting and ending at the terminal. The main constraints of this problem included the presence of time windows, a limited number of trucks and a limited stock of empty containers at the inland terminal. The objective was to minimise the total routing cost. The authors proposed an MIP formulation for the problem and developed a branch-and-price algorithm in two versions: the first one creates multi-trip routes in the pricing stage, while the second one does so in the master problem. Results of computational experiments showed the superiority of both versions of the branch-and-price algorithm against the MIP formulation. In addition, it was shown that the creation of multi-trips in the master problem yielded better results than the creation of multi-trips in the pricing stage. The authors remarked that the combination of multiple requests in single trips could significantly reduce costs. In addition, they noted that the control of containers by shipping lines hindered container re-usage, emphasising the need for greater visibility of available containers and improved coordination between shippers and transport operators.

Wang et al. (2023) tackled a drayage problem involving semi-trucks and container chassis that could be coupled and uncoupled. However, there were several fleets, and semis and chassis could be coupled only if they belonged to the same fleet. Furthermore, it was said that there was 'interference' between two semis (belonging to the same fleet) when

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a semi-truck was coupled with a chassis previously uncoupled from another semi-truck. The objective was to minimise the total cost, which involved the number of semis used, the total travel time and the total completion time. The authors presented an MIP formulation for the problem and developed a branch-and-price-and-cut algorithm in which the pricing sub-problem considers route interferences. Results of computational experiments showed that the authors' branch-and-price-and-cut algorithm could significantly outperform the MIP formulation in terms of both solution quality and solving time, being also able to handle larger instances. The authors remarked that allowing interferences between up to two semis was the most convenient alternative in terms of computing efficiency.

Wang et al. (2024) addressed the drop-and-pull container drayage problem with work-breaks (DPCD-WB). This problem involves semi-trucks that pull a container chassis, with the semis being able to leave their chassis during packing/unpacking operations. In addition, driver work-breaks can be flexibly scheduled at any customer site. The objective of the DPCD-WB is to minimise fixed costs associated with truck utilisation and the completion time of the routes. The authors proposed an MIP formulation and introduced three families of valid inequalities to strengthen it. Additionally, to solve larger instances, they developed a heuristic approach based on an adaptive threshold acceptance criterion with backtracking, with an MIP component used to assign work-breaks. Through computational experiments, the authors assessed their formulation and heuristic, quantifying the extent to which the latter outperformed the former. In addition, they studied the impact of implementing work-breaks of different durations, concluding that the presence of work-breaks could reduce waiting times and improve truck utilisation.

Huang et al. (2024) tackled a drayage problem involving a terminal, a truck depot, an empty container depot and several customer locations. The problem also considered empty container repositioning and single-container 40-ft trucks that could stay with or leave containers during packing/unpacking operations. The problem also involved customer time windows and an appointment system at the terminal, which allowed trucks to access the terminal only within pre-booked time slots. There were several time slots, each with its own quota that could not be exceeded. The problem's objective was to minimise the trucks' operating time. The authors proposed an MIP formulation for the problem based on a graph of tasks and developed a GA aimed at solving larger instances. The authors conducted computational experiments, which showed that instances with up to 20 tasks could be solved with the MIP formulation within 2 h, while the GA could solve instances with up to 200 tasks in a few seconds. From their experiments, the authors also concluded that shorter operating times resulted when trucks were allowed to leave containers during packing/unpacking operations, especially when the number of tasks increased. In addition, they noted that the trucks' operating time was reduced when the size of the appointment quotas increased. Adding to this, the authors noted that very large quotas could result in congestion at terminals, while very small quotas limited decision-making flexibility for drayage carriers.

Song and Zhang (2024a) considered a drayage problem involving repositioning of empty containers, which were limited in supply and could be kept at a depot with limited storage capacity. The problem assumed a fleet of homogeneous trucks that carried a single container at a time. Drayage moves were subject to time-window constraints. The objective was to minimise the trucks' fixed costs and the total travel cost. The authors presented an MIP formulation for the problem and a branch-and-price-and-cut algorithm incorporating strategies such as heuristic label setting and decremental state-space relaxation. Results of computational experiments showed that the authors' branch-and-price-and-cut algorithm could optimally solve instances involving up to 75 requests in 1 h, thus outperforming the MIP formulation as well as meta-heuristics such as GA, TS, LNS and simulated annealing (SA). The authors concluded by analysing the cost savings resulting from considering a larger stock of empty containers, a larger depot capacity and longer time windows.

Zhang et al. (2024) tackled a drayage problem involving import and export orders. Import orders involved the delivery of a full container to a customer who unpacked it and requested the pickup of the resulting empty container. Export orders involved the delivery of an empty container to a customer, who packed it and requested the transportation of the resulting full container to a terminal. The problem involved a fleet of semi-trucks pulling container chassis, with the semis being able to stay with or leave their chassis during packing/unpacking operations. The objective was to minimise the number of trucks used and the total travel time. The authors proposed MINLP and MIP formulations for the problem and developed a time-window partitioning heuristic that uses the MINLP formulation to refine the obtained solutions. In benchmark tests against the MIP formulation of Xue et al. (2015), the authors' MIP formulation and heuristic method showed competitive performance. In addition, the heuristic method was shown to outperform meta-heuristics such as GA, TS, SA and variable neighbourhood search (VNS).

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2.2 | Homogeneous Containers With Load Configurations

Lai et al. (2013) tackled a problem involving single- and double-container trucks that moved containers between customer locations and a port. In each route, all importers—who received full containers and unpacked them—had to be served before the exporters—who received empty containers and packed them. In this problem, a truck had to stay with a container during packing/unpacking operations. The problem's objective was to minimise costs associated with container handling at the port and truck operation costs. The authors presented an MIP formulation for the problem and developed a solution method based on local search. Results of computational experiments indicated that, for small instances, it was possible to solve the MIP formulation in practical runtimes. Nevertheless, to solve larger instances, representing realistic situations, it was necessary to use the local search approach.

Daham et al. (2017) considered a problem encompassing movements of 20-ft containers between a port and customer locations. The problem involved single- and double-container trucks and containers with one or several possible destinations. The problem required checking the ready times of containers at the port, time windows, maximum vehicle weights and drivers' working hours. The objective was to minimise a combination of routing costs and penalty costs incurred due to extra driving hours. The authors presented an MIP formulation for the problem. Through computational experiments, they showed that their formulation could be solved for instances with up to 350 drayage requests in about 30 min, which enabled it to tackle realistic scenarios.

Ghezelsoflu et al. (2018) tackled a problem based on the case of a real carrier specialising in the movement of 24.5-ft containers. The problem involved two truck types, with some trucks being capable of accommodating one container and others two. The problem's objective was to minimise routing costs. A particularity of this problem was that each route could contain up to four customers; this characteristic of the routes allowed the authors to develop a set covering formulation that could be solved by explicitly enumerating all feasible routes. Through computational experiments, the authors showed that their formulation outperformed a previously proposed formulation and could be used to optimally solve instances of realistic size—indeed, exceeding the requirements of the carrier.

Zhang et al. (2018) studied a problem involving the movement of foldable containers, which can be folded down and stacked over one another, making it possible for a truck to carry two or more folded containers at once. This problem also considered the repositioning of empty containers. The problem's objective was to minimise the trucks' operating time, which included travel and waiting times. To model the problem, the authors established truck states—representing the location and load of a truck—with transitions between them. Considering such states and transitions, the authors formulated the problem as an extension of the sequence-dependent m-TSPTW. The authors proposed an RTS approach to the problem, remarking that the sequence-dependent aspect of the problem made the use of commercial MIP solvers infeasible. Through computational experiments, the authors showed that their RTS approach could outperform a previously proposed solution method. In addition, they analysed the cost savings that could be realised with the use of foldable containers, as well as the impact of fleet size and truck cargo capacity on the solutions.

Ghezelsoflu et al. (2021) addressed a drayage problem where the planning horizon comprised several periods (e.g., several days). This problem involved single- and double-container trucks that hauled 20-ft containers. Similar to the problem of Ghezelsoflu et al. (2018), each route could visit up to four customers in each period. The problem's objective was to minimise routing costs and penalties associated with off-schedule services. The authors proposed three exact approaches to the problem: a path-based formulation, which adapts the set covering formulation of Ghezelsoflu et al. (2018) to the multi-period case; a column generation method; and an arc-flow formulation. The authors conducted computational experiments where they showed that the arc-flow formulation outperformed the other approaches, allowing them to solve even large instances. The authors also discussed cost savings that could be obtained when there was flexibility in the penalties associated with off-schedule services.

2.3 | Homogeneous Containers With Non-Standard Load Configurations

Lai et al. (2015) addressed a problem inspired by the operations of an Italian carrier. The problem resembles that of Lai et al. (2013), but in this case, the trucks were identical and hauled specialised 24.5-ft containers. The authors considered different fleets of trucks, with carrying capacities varying from one container to six containers. The problem's objective was to minimise routing costs. The authors proposed an MIP formulation for the problem and developed an adaptive

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guidance (AG) heuristic, which uses rules to assess solution quality and identify potential enhancements. Results of computational experiments indicated that solving the MIP formulation could be suitable for small instances. However, on larger instances, the AG heuristic performed better, being capable of finding good-quality solutions in short runtimes.

You et al. (2020) studied a drayage pickup and delivery problem (PDP) involving semi-autonomous truck platoons. The problem's objective was to minimise costs related to driver wages, truck utilisation and fuel consumption. The authors presented a mathematical formulation for the problem, analysing similarities with other problems involving the following features: trucks that stay with containers during packing/unpacking operations; repositioning of empty containers between customer locations; and semi-trucks that can be uncoupled from trailers. The authors further proposed an ACO-based heuristic to solve the problem. Results of computational experiments indicated that solving the formulation, even for small instances, could prove to be impractical. On the other hand, the ACO-based heuristic could solve both small and large instances, finding high-quality solutions in short runtimes.

Zhang et al. (2021) considered a problem comprising a homogeneous fleet of semi-trucks and trailers used to haul dry containers. The semis travelled without trailers or pulled two or more trailers, with each trailer being capable of carrying one container at a time. Furthermore, the semis could leave customer locations during packing/unpacking operations. The problem's objective was to minimise the trucks' operating time. The authors presented MINLP and MIP formulations for the problem and proposed a heuristic based on an adaptive threshold acceptance criterion with backtracking. Results of computational experiments showed that the heuristic approach could obtain better solutions than those found by solving the MIP formulation. In addition, the heuristic approach required shorter computation times. The authors also analysed the reductions in operating times obtained when double-trailer trucks were used instead of single-trailer trucks and when semis were allowed to leave customer locations during packing/unpacking operations. The authors also discussed the impacts of packing/unpacking times and the geographical distribution of customers.

Xue et al. (2021) considered a drayage problem entailing the management of drivers, trucks and containers, with trucks being capable of forming semi-autonomous platoons. In this case, the problem also considered the fuel savings achievable by trucks when they followed the lead truck in a platoon, primarily attributed to reduced air drag. The problem's objective was to minimise costs related to driver wages and fuel consumption. The authors provided a mathematical model for the problem and developed a TS algorithm. Through computational experiments, the authors identified that optimal platoons consisted of three trucks, as longer platoons achieved only marginal savings. In addition, the authors noted that, when compared with standard trucks, semi-autonomous platoons could reduce the number of drivers required but might travel longer distances. Semi-autonomous platoons were also found to be more fuel-efficient, but only on large instances.

Peng and Xue (2023) tackled a drayage problem considering semi-autonomous truck platoons. This problem involved delivery customers who requested the delivery of a full container and the subsequent pickup of the container after being emptied, and pickup customers who requested the delivery of an empty container and the subsequent pickup of the container after being packed. The objective was to minimise driver labour costs and fuel costs, with the latter being dependent on the load of the trucks. The authors proposed an MIP formulation for the problem and developed an SA algorithm aimed at solving larger scale instances. From experiments on a set of random instances, the authors concluded that consideration of the truck load when calculating fuel costs could lead to more efficient routing. In addition, the authors noted that, for practical applications, an optimal platoon should be composed of three trucks.

Yan et al. (2023) tackled a drayage problem involving semi-autonomous truck platoons where drivers (of lead trucks) could switch trucks instead of waiting during packing/unpacking operations. To this aim, drivers could travel between customer locations (e.g., by motorcycle or taxi) to find another truck to drive. In addition, trucks could leave their platoons and form new ones. The objective was to minimise driver labour costs, truck deployment costs and fuel costs (considering platooning fuel savings). The authors presented an MIP formulation for the problem and proposed an SA-based heuristic. Results of computational experiments showed that the SA-based heuristic could yield solutions of equal or similar quality as the ones found with the MIP formulation, while requiring much shorter runtimes. Moreover, the SA-based heuristic was shown to outperform a GA and a swarm optimisation algorithm. The authors used their SA-based heuristic to analyse the cost impacts of labour expenses, platoon size and the type of vehicle the drivers used when switching trucks.

You et al. (2023) studied a drayage problem involving semi-autonomous truck platoons where trucks could perform multiple trips starting and ending at a terminal. Furthermore, the cost a truck incurred when travelling between two locations depended on its load. The objective was to minimise the total travel cost. The authors proposed two

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set-partitioning models for the problem, along with several sets of valid inequalities. To solve this problem, the authors developed a branch-and-price-and-cut algorithm that uses an ACO-based heuristic to generate an initial solution and a pulse propagation algorithm to solve the subproblem. Computational results showed that the authors' algorithm could efficiently solve instances with up to 100 tasks. The authors used their algorithm to derive managerial insights into the operation of truck platoons, compared to single-container trucks. They found that platoons could realise important savings regarding labour costs and total operation time, although their fuel consumption could be slightly higher. They also remarked that two-truck platoons should be the best fit for most real-world applications.

2.4 | Heterogeneous Containers, No Load Configurations or Compatibility Constraints

Reinhardt et al. (2016) tackled a problem involving several terminals and depots, time-window constraints, empty container repositioning and trucks that carried a single container at a time. The authors addressed issues related to empty container movements, such as selecting storage depots and managing imbalances in availability. Customers specified the type of container they required, which had to be taken into account when repositioning the empty containers. The problem, however, did not explicitly state compatibility constraints between container types and trucks. The authors proposed a set covering formulation for the problem solvable by column enumeration. In addition, they conducted computational experiments considering alternative objectives, namely minimisation of routing costs, balancing of empty container stocks at depots and minimisation of fleet size.

Stoop et al. (2024) tackled a dynamic and stochastic drayage problem based on real-life drayage operations at the port of Antwerp, Belgium. In this problem, there were several depots, container terminals and customer locations, with each terminal operating a TAS to avoid congestion. The problem involved stochastic (un)loading times and travel times, dynamic arrival of new requests, empty container repositioning and a fleet of trucks that could accommodate a single 20/40-ft container. The problem's objective was to minimise the trucks' operating time. The authors formulated the problem as an MINLP problem, which they then linearised using a time-window partitioning approach, obtaining an integer linear programming (ILP) formulation that can efficiently be solved by MIP solvers (and re-solved if necessary to include dynamic requests). Results of computational experiments showed that the ILP formulation was suitable to solve instances with up to 300 requests and could be re-solved fast enough to deal with dynamic requests. The solutions obtained showed to be robust with respect to the stochastic operating times. Furthermore, it was shown that an important increase in the probability for a solution to be valid could be obtained with only a small increase in operating times. The results also indicated that variations to the time-window discretisation width could have an important impact on solving times while having a minimal impact on the resulting objective.

2.5 | Heterogeneous Containers With Compatibility Constraints, No Load Configurations

Tan et al. (2006) tackled a multi-objective truck and trailer VRP arising in drayage operations. In this problem, a company operated its own fleet of semi-trucks and trailers but could subcontract more vehicles when necessary. There were several types of tasks that required specific types of trailers. This problem also involved trailer exchange points, where trucks could drop off their trailers and pick up new ones for their next tasks. The problem's objectives were to minimise both the number of trucks used and their routing costs. The authors developed a multi-objective memetic algorithm to solve this problem. Through computational experiments, the authors analysed relationships between factors such as the number of trucks and trailers, the number and locations of the trailer exchange points and truck usage.

Meisel and Kopfer (2014) tackled the active–passive vehicle-routing problem (APVRP), which serves as a generic representation of drayage routing. In the APVRP, there are two types of vehicles: passive vehicles and active vehicles. Passive vehicles have the capacity to carry cargo but lack autonomous movement, whereas active vehicles can move passive vehicles. Each passive vehicle is capable of carrying a single cargo unit at a time and each active vehicle can transport one passive vehicle at a time. Compatibility constraints are an important aspect of the APVRP, as passive vehicles can only carry specific types of cargo and active vehicles are limited to moving certain passive vehicles. Furthermore, an active vehicle has the option to leave a passive vehicle during the loading or unloading process. So, within the domain of drayage, a container is a cargo unit, container chassis are passive vehicles and semi-trucks are active vehicles. The objective of the APVRP is to minimise a weighted sum of the travelled distance, the total finish time of all routes and the number of unfulfilled requests. The authors formulated the APVRP as an MIP problem and proposed a set of construction/improvement heuristics and an ALNS heuristic. Results of computational experiments indicated that the best results could be obtained by combining ALNS with the proposed heuristics.

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Regnier-Coudert et al. (2016) studied a dynamic real-world problem arising in the daily operations of a major trucking company based in Aberdeen, UK. The problem consisted of routing a fleet of semi-trucks (which could pull trailers), straight trucks and vans. Only some vehicles and trailers were compatible with specific tasks. For example, large-sized cargoes required high-capacity vehicles and dangerous loads required vehicles operated by drivers with specialised training. The company might outsource some tasks, but this entailed higher costs. Therefore, the objective was to minimise the number of subcontracted tasks. The authors proposed a constructive heuristic based on hill climbing and SA to solve the problem. The heuristic first creates sequences of compatible tasks and then assigns such sequences to compatible vehicles. Results of computational experiments showed that the proposed heuristic could help the company achieve enhanced performance with respect to vehicle utilisation and outsourced tasks.

Pérez Rivera and Mes (2017) considered a drayage problem arising in a synchromodal network—here, synchromodality entails the repositioning of empty containers between terminals and customer locations, and the selection of terminals where full containers are to be delivered for transshipment to long-haul vehicles. In this problem, there were several types of containers and only certain types of trucks were suitable for hauling a given container. The objective was to minimise routing costs and the costs of using terminals. The authors proposed an MIP model of the problem where requests were represented as arcs instead of nodes, although this representation led to larger graphs. To counter this disadvantage, the authors proposed a set of valid inequalities for their model. In addition, they developed two matheuristics, one static and one dynamic. The static matheuristic uses different kinds of cutting planes that force the routes to connect customers located close to each other. The dynamic matheuristic can deal with dynamic instances of the problem; it uses strategies to fix some routes and uses the static matheuristic to replan the remaining routes. The authors conducted computational experiments where they analysed how the performances of their solution approaches varied depending on customer dispersion, time-window lengths and dynamic re-planning.

Ritzinger et al. (2017) studied a variant of the MRRP involving the movement of containers by tractor-trailers that could be uncoupled. This problem assumed a limited fleet of semi-trucks and trailers. While the semis could pull any trailer, the trailers were compatible only with specific containers. When necessary, a semi could leave its trailer loaded with a container during packing/unpacking operations. The problem's objective was to minimise the number of unfulfilled requests, the overall travel time and the total cost incurred by trucks when travelling on toll roads. The authors proposed a VNS heuristic to solve the problem and conducted computational experiments considering the case of a real drayage company. The results indicated that the implementation of the VNS heuristic for operational planning could enable the company to handle more drayage movements without requiring additional resources.

Shiri and Huynh (2018) considered a drayage problem involving a terminal, an empty container depot, a chassis yard, truck depots and customer locations. This problem considered movements of 20/40-ft containers and semi-trucks operated by a drayage company and by owner-operators. As in the problem of Shiri and Huynh (2016), empty containers were moved between customer locations or between the empty container depot and customer locations. Meanwhile, full containers were moved between the terminal and customer locations. However, in this problem, the semis had to head to the chassis yard to find a chassis suitable for their next task, respecting compatibility constraints between the containers to be transported and the selected chassis. In addition, the trucks were based in different depots, depending on whether they were driven by company drivers or owner-operators. The problem's objective was to minimise the total drayage operation time. The authors considered a graph of tasks to develop an MIQP model of the problem, which is an extension of the m-TSPTW. They also modelled the emissions of the trucks. To solve the problem, the authors developed an RTS algorithm. Results of computational experiments indicated that the RTS algorithm could find high-quality solutions and was much more scalable than solving the MIQP formulation. The authors also concluded that the best performance in terms of operation time, deadhead miles and emissions could be obtained when the chassis yard was inside the terminal, with the chassis belonging to a cooperative pool of chassis, a third party that rented them or the terminal.

Tilk et al. (2018) developed a branch-and-price-and-cut algorithm to solve the APVRP. This algorithm utilises a complex network representation that models logical relationships between transport tasks and the synchronisation of movements of active and passive vehicles, and was the first branch-and-price-and-cut algorithm to explicitly consider temporal interdependencies between active and passive vehicles. This branch-and-price-and-cut algorithm was also the first to solve an ng-path relaxation of a pricing problem with linear vertex costs using a bidirectional labelling approach. The authors conducted computational experiments with their algorithm and found improved bounds and solutions for several APVRP instances. The algorithm could find optimal solutions for instances with up to 76 tasks, four active vehicles and eight passive vehicles in up to 2 h of computational time.

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Heggen et al. (2019) studied an intermodal routing problem involving two regions. Within each region, trucks moved containers between customer locations and rail terminals. These terminals were part of a long-haul rail network that transported containers between the two regions. The problem involved heterogeneous trucks and containers of different sizes, which could be moved only by suitable trucks. The problem's objective was to minimise the total transportation costs, encompassing rail and trucking costs. The authors proposed an LNS heuristic to solve the problem. Results of computational experiments indicated that increased performance could be achieved by the integrated planning of drayage and long-haul transportation. When customers were randomly located, the capacity of long-haul transportation was utilised better, although no cost savings were obtained. On the other hand, cost savings in drayage operations could be obtained when the customers were clustered. The authors also identified a trade-off between increasing capacity utilisation and reducing vehicle routing costs.

Cui et al. (2022) tackled a drayage PDP involving 20/40-ft containers. The problem assumed a fleet of semi-trucks that pulled two types of chassis, with one chassis type being compatible with 20-ft containers and the other with 40-ft containers. Each truck could pull one chassis at a time and each chassis could carry one container. The problem considered depots where semis and chassis could be coupled and uncoupled. In addition, semis and chassis could be coupled at some pickup locations and uncoupled at some delivery locations. The authors addressed the problem in two stages: The first stage sought to determine optimal routing strategies, disregarding potential chassis shortages at depots. The objective of this stage was to maximise profits. The authors developed an MIP formulation and a hybrid LNS–TS heuristic to tackle this stage. The second stage comprised an MIP formulation to address chassis shortages through repositioning. The objective of this stage was to minimise chassis repositioning costs. Through computational experiments, the authors showed that the LNS-TS heuristic could find similar or better solutions than the first-stage MIP formulation, requiring shorter runtimes. The authors also analysed how the solutions of the second-stage MIP formulation were impacted by factors such as the number of requests, time windows and chassis distribution across depots.

Rist et al. (2024) presented a novel combinatorial Benders decomposition formulation for the APVRP. This formulation is based on a network of tasks (a task represents the movement of an active vehicle coupled with a passive vehicle) and was solved by a branch-and-cut algorithm. The authors also introduced a novel delayed disaggregation principle in their Benders decomposition approach, which allows for the construction of disaggregated Benders cuts from a single subproblem. Through computational experiments, the authors showed that their solution approach could outperform the algorithm of Tilk et al. (2018) by reducing solution times and tightening optimality gaps across several instances. In addition, the authors implemented valid inequalities, a simple heuristic and passive vehicle route enumeration to improve the performance of their approach.

2.6 | Heterogeneous Containers With Load Configurations, No Compatibility Constraints

Vidović et al. (2011) considered a problem involving movements of 20/40-ft containers between customer locations and a terminal. Trucks could carry one 40-ft container or up to two 20-ft containers, and their routes could include up to four stops. The problem's objective was to minimise routing costs. The authors formulated the problem as a multiple matching problem and proposed a savings-based solution algorithm which showed promising performance in preliminary tests.

Popović et al. (2014) extended the problem of Vidović et al. (2011) by including time windows. The authors presented an MIP formulation for the problem and proposed a VNS heuristic to solve it. Results of computational experiments indicated that the proposed VNS heuristic could find good-quality solutions in short runtimes, being particularly useful to solve medium-sized instances, which could not be solved with the MIP formulation in practical runtimes.

Zhang et al. (2015) studied a drayage problem in which a fleet of homogeneous trucks moved containers between customers, a terminal and a depot. Trucks could haul one 40-ft container or up to two 20-ft containers, and their operation was subject to working time limits. The problem required dealing with the repositioning of empty containers. The authors established truck states that specified a truck's location, current load, load details and the customer who requested the service (when applicable). Based on the truck states and transitions between them, the authors modelled the problem as a sequence-dependent m-TSPTW with social constraints, with the objective of minimising the trucks' operating time. As in Zhang et al. (2018), the authors mentioned that the use of commercial solvers was not possible because of the sequence-dependent aspect of the problem. Thus, they developed three tree search–based procedures, which were able to solve small instances to optimality, and an RTS algorithm to obtain feasible solutions for larger instances. The RTS algorithm was also used to solve an instance based on real data.

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Funke and Kopfer (2016) tackled a problem involving the movements of 20/40-ft containers between customer locations, terminals and a depot. Trucks could haul one 40-ft container or up to two 20-ft containers, and their operation adhered to limited working shifts. This problem required deciding whether the trucks had to stay with containers during packing/unpacking operations. The authors proposed an MIP model of the problem. To formulate the model, they considered two main issues: the assignment of empty containers to requests and truck routing. To assign empty containers to requests, the authors formulated a multicommodity flow problem. For the routing part, they formulated an asymmetric m-TSPTW. The authors conducted computational experiments where they solved their MIP formulation for small instances, considering two objectives: minimisation of total distance and minimisation of the trucks' operating time. Their experiments showed that the formulation could be solved faster when considering distance minimisation.

Popović et al. (2018) considered a problem where trucks and container handlers had to synchronise their routes so that their arrival times at the customer locations matched. The trucks could carry one 40-ft container or up to two 20-ft containers. The problem's objective was to minimise the routing costs of both trucks and the handlers. The authors developed a MIP formulation for the problem and conducted computational experiments where they assessed the impacts of synchronising the routes of container handlers and trucks, comparing with a scenario in which all customers had their own container handling equipment and hence routing of container handlers was not required.

Bruglieri et al. (2021) addressed a drayage problem involving a planning horizon of several days and limited working hours for drivers. This problem considered trucks that could carry one 40-ft container or two 20-ft containers. The objective was to minimise the total travelled distance. The authors developed two mathematical formulations for the problem: one based on arcs and the other on trips. To solve the latter for large instances, the authors developed six combinatorial Benders decomposition approaches. Through computational experiments, the authors assessed the performances of their formulations and decomposition approaches across instances with different numbers of customers.

2.7 | Heterogeneous Containers With Load Configurations and Compatibility Constraints

Chung et al. (2007) studied three drayage problems. The first problem considered a single type of container, a homogeneous fleet of trucks with capacity for a single container and limited operation time. Optionally, this problem could consider time windows. The objective of this first problem was to minimise the fleet size. The second problem considered movements of 20/40-ft containers by trucks equipped with three types of container chassis: 20 ft, 40 ft and combo 20/40 ft, with the combo 20/40 ft chassis being capable of carrying one 40-ft container or two 20-ft containers. The objective of this second problem was to minimise the trucks' routing costs. Finally, the third problem extended the second one by incorporating company-owned and subcontracted trucks. The objective was to minimise the trucks' routing costs, which differed between company-owned and subcontracted trucks. The authors solved an instance of the second problem, derived from data provided by a Korean drayage company.

Bomboi (2020) considered a problem in which trucks could carry up to two 20-ft containers. However, some containers carried special cargoes, for example, flammable or very heavy goods, and had to be moved individually. Trucks could stay with or leave the containers during packing/unpacking operations. The problem's objective was to minimise routing costs. The author proposed a node-arc formulation, a set partitioning formulation with heuristics to limit the number of routes, and a branch-and-price algorithm with exact and heuristic pricing methods. Through computational experiments, the author compared the performances obtained with her formulations and with the branch-and-price algorithm.

Yang and Daham (2020) addressed a problem involving a fleet of heterogeneous trucks, with some trucks being capable of carrying one 20-ft container and others one 40-ft container or up to two 20-ft containers. The trucks could be company-owned or contracted. The problem further considered regulations of working hours and explicitly considered the payload weight of containers. The problem's objective was to minimise the total operation cost, consisting of travel costs and expenses for contracted trucks. The authors presented an MIP model of the problem and developed a heuristic approach based on decomposition and aggregation. The heuristic approach divides orders into subgroups, solves them using the MIP model and then uses column generation to balance the fleet size among all subgroups. Results of computational experiments indicated that the MIP model could be solved for instances with up to 120 requests, while the heuristic approach was highly scalable and could solve instances with up to 500 requests.

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Yang et al. (2021) tackled a problem where containers were moved between customer locations, a port and inland depots. The problem also considered the repositioning of empty containers, which could be stored at inland depots. The problem assumed a fleet of trucks akin to that of Yang and Daham (2020). The trucks could stay with or leave the containers during packing/unpacking operations. The problem's objective was to minimise the overall travel costs and penalties for exceeding working time limits. The authors presented an MIP formulation for the problem and developed a GA. Through computational experiments, the authors noted that solving the MIP formulation was suitable only for small instances, with the GA being required to solve larger instances. The authors also analysed the cost savings that could be obtained when inland depots were available and when trucks were allowed to both leave and stay with containers during packing/unpacking operations.

Song and Zhang (2024b) studied a drayage problem involving 20/40-ft containers and repositioning of empty containers (which were limited in supply). There were two types of trucks: 20-ft trucks, which could move a single 20-ft container, and 40-ft trucks, which could move up to two 20-ft containers or a single 40-ft container. Drayage moves were subject to time-window constraints. The objective was to minimise the trucks' fixed costs, fuel consumption and carbon emissions. The authors proposed a graphical representation of the problem where each request was associated with either an origin or destination location. Based on said representation, the authors proposed a mathematical formulation for the problem and developed an exact branch-and-price algorithm, as well as a heuristic version of it. Results of computational experiments showed that the exact branch-and-price algorithm could solve instances with up to 60 drayage requests in 1 h. Meanwhile, its heuristic counterpart was better suited for larger instances and could outperform a GA and a TS heuristic. The authors also analysed how a larger stock of empty containers and longer time windows could reduce costs, and studied the cost impact of different fleet compositions.

2.8 | Heterogeneous Containers With Non-Standard Load Configurations, No Compatibility Constraints

Vidović et al. (2017) tackled a drayage PDP involving movements of 20/40-ft containers between a terminal and several customer locations. Three different truck fleets were considered. The first fleet was composed of standard trucks, which could accommodate one full 20/40-ft container and could make up to two stops along their routes. The second fleet was composed of European modular system (EMS) trucks, which could accommodate up to two full 20-ft containers and could make up to four stops along their routes. The third fleet was composed of LCVs, which could accommodate up to two 40-ft, four 20-ft or even three 40-ft containers and could make up to eight stops along their routes. The problem's objective was to minimise the total routing costs. The authors proposed an MIP formulation for the problem and a VNS heuristic. Through computational experiments, the authors analysed how the fleet type could affect the performance of their VNS heuristic. In addition, they quantified the cost savings that could be realised by EMS trucks and LCVs with respect to standard trucks.

Chen, Wang, and Meng (2021) considered a drayage problem where semi-autonomous truck platoons moved containers between two terminals. As in Xue et al. (2021), fuel consumption was modelled explicitly, with the trucks following the lead truck of a platoon being capable of saving fuel due to reduced air drag. The problem's objective was to minimise the costs of in-terminal travel and freeway travel, as well as penalties incurred from rejecting requests. The authors presented a mixed-integer second-order-cone programming (MISOCP) formulation for the problem and developed a column generation–based heuristic. Through computational experiments, the authors compared the solutions found with the MISOCP formulation and with the heuristic, finding that the latter could find near-optimal solutions for small instances. Meanwhile, for larger instances, the heuristic was shown to outperform the MISOCP formulation in both runtime and solution quality. The authors also analysed the cost impacts of factors such as platoon capacity, air drag reduction and speed.

Bjelić et al. (2022) addressed a dynamic drayage PDP where trucks moved containers between customer locations and a central depot. The sources of dynamism in this problem included the arrival of new service requests, the cancellation of existing requests, fluctuations in travel times caused by traffic conditions and modifications to time windows or service durations. The problem's objective was to minimise the time required to serve all requests and violations to time-window constraints. The authors developed a VNS-based heuristic that solves static versions of the problem at different time points, considering any new information available. To test their approach, the authors conducted experiments on instances involving 20/40-ft containers and fleets of single-trailer and multi-trailer trucks. The results showed that multi-trailer trucks could reduce travel distances and the number of trips by 30% and 40%, respectively.

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2.9 | Heterogeneous Containers With Non-Standard Load Configurations and Compatibility Constraints

Moghaddam et al. (2020) tackled a problem involving heterogeneous trucks that picked up and delivered 20/40-ft containers between different locations, with the trucks' cargo capacities varying from 20 to 80 ft. The trucks could stay with or leave a container during packing/unpacking operations. Furthermore, it was necessary to reposition empty containers. Some requests might not be fulfilled; hence, the objective was to maximise the number of served requests while minimising the required travel time. The authors developed an MIP formulation based on a request layer and a transportation layer. The request layer handles time constraints, ensuring that pickup and delivery locations are visited in the correct order. The transportation layer handles capacity constraints, ensuring the delivery of previously picked-up containers. Through computational experiments, the authors analysed how the instance size could impact the number of served requests and fleet utilisation. They also analysed the performances of different fleets, composed of trucks with different cargo capacities. In this regard, the authors noted that trucks with larger cargo capacity could be more cost effective. However, instances involving such trucks could be more difficult to solve. The authors also showed that the two-layer MIP formulation could be better than an alternative formulation based on PDP constraints.

Chen et al. (2021) considered a drayage problem involving movements of containers of various sizes. The containers were transported between a container terminal and customer locations, both for inbound requests (to customers) and outbound requests (from customers). The problem assumed trucks with different load capacities—the authors considered trucks capable of accommodating up to six 20-ft containers. This problem further involved compatibility constraints due to the inability of small trucks to transport large containers. The objective was to minimise fixed and routing costs, with the latter being dependent on the types and the loads of the trucks. The authors developed an MIP formulation for the problem, with two associated relaxations, and a VNS-based heuristic. Results of computational experiments indicated that the relaxations could find optimal solutions in short runtimes for some small instances. Meanwhile, the VNS-based heuristic was shown to be highly scalable and able to solve realistic-sized instances. The authors noted that the complexity of the problem could significantly depend on the number of truck types involved.

2.10 | Discussion

Table 1 lists all the reviewed studies, grouping them according to the proposed classification and comparing them with the studies of Bustos-Coral and Costa (2022) and Bustos-Coral and Costa (2025), who introduced DRP-HCL. For each surveyed study, the table specifies the type of container or cargo considered, indicating the presence of heterogeneous or non-standard trucks, as well as the inclusion of compatibility and time-window constraints. The table also indicates the type of solution approach used (exact or heuristic) and the size of the largest instances solved. Furthermore, Figure 1 shows the temporal distribution of reviewed studies, allowing us to easily see the evolution of truck and container modelling in drayage problems.

As Table 1 and Figure 1 show, nearly half of the reviewed studies involve simplified modelling of trucks and containers, assuming homogeneous containers with neither explicit truck load configurations nor compatibility constraints. Moreover, studies that consider heterogeneous containers are generally limited to the 20/40-ft sizes. The focus of the reviewed studies is on modelling other issues related to drayage, such as empty container repositioning, multiple depots/terminals, port schedules, drivers' working conditions, subcontracted tasks and decisions on whether trucks and containers should be separated during packing/unpacking operations. However, we can also note that, over the years, the research on drayage problems has intensified, and more detailed models of trucks and containers have been proposed while preserving the interest in other issues related to drayage (as those previously mentioned). Indeed, Chen et al. (2022) note that the research on drayage has intensified since 2010, leading to the exploration of new directions of research. We can argue that the modelling of more detailed trucks and containers is one of such directions—note that most of the problems featuring heterogeneous containers, trucks with explicit load configurations or compatibility constraints have been proposed after 2010, while all the problems involving non-standard trucks have been proposed over the last decade.

Despite all the progress made concerning the characterisation of trucks and containers, we can see that, among the surveyed studies, a research gap persists, as very few articles address drayage problems involving arbitrary container types (of any size and cargo category), trucks with specific load configurations (possibly considering LCVs) and compatibility constraints regarding container size and cargo. The studies of Bustos-Coral and Costa (2022) and Bustos-Coral and

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TABLE 1 | Comparison of studies on drayage based on fleet characterisation.

Study	Container/cargo types	Het. trucks	Non-std trucks	Compatibility	T. windows	Approach	Size of largest instance
Section 2.1: homogeneous containers, no load configurations							
Wang and Regan (2002)	Unspecified loads				✓	E/H	150 loads
Gronalt et al. (2003)	Full truckloads				✓	E/H	512 orders
Jula et al. (2005)	Unspecified container type				✓	E/H	100 nodes
Ileri et al. (2006)	Trailers (l&e)	✓			✓	E/H	130 orders
Smilowitz (2006)	Trailers and containers				✓	E/H	1638 tasks
Francis et al. (2007)	Trailers and containers				✓	H	200 tasks
Imai et al. (2007)	Unspecified container type	✓				E/H	200 nodes (100 orders)
Namboothiri and Erera (2008)	Unspecified container type				✓	H	100 customer requests
Caris and Janssens (2009)	Unspecified container type				✓	E/H	200 customers
Zhang et al. (2009)	Unspecified container type (f&e)				✓	E/H	200 containers
Máhr et al. (2010)	Reefer containers				✓	H	65 jobs a day, 33 days
Zhang et al. (2010)	40-ft containers (f&e)				✓	E/H	75 loads
Zhang et al. (2011)	40ft containers (f&e)				✓	E/H	75 containers
Braekers et al. (2013)	Unspecified container type (f&e)				✓	E/H	200 nodes
Nossack and Pesch (2013)	Unspecified container type (f&e)				✓	E/H	75 requests
Sterzik and Kopfer (2013)	40-ft containers (f&e)				✓	E/H	75 requests
Wang and Yun (2013)	40-ft containers (f&e)				✓	E/H	40 containers
Braekers et al. (2014)	Unspecified container type (f&e)				✓	E/H	400 nodes
Xue et al. (2014)	Unspecified container type (f&e)				✓	E/H	100 pickups/100 deliveries
Zhang et al. (2014)	Unspecified container type (f&e)				✓	E/H	75 orders
Xue et al. (2015)	Unspecified container type (f&e)				✓	E/H	100 pickups/100 deliveries
Shiri and Huynh (2016)	40-ft dry containers (f&e)				✓	E/H	200 nodes
Schulte et al. (2017)	Standard containers (f&e)				✓	E	80 vertices
Song et al. (2017)	Unspecified container type (f&e)				✓	E	35 requests
Escudero-Santana et al. (2020)	Unspecified container type (f&e)				✓	E	200 orders

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TABLE 1 | (Continued)

Study	Container/cargo types	Het. trucks	Non-std trucks	Compatibility	T. windows	Approach	Size of largest instance
Zhang et al. (2020)	Unspecified container type (f&e)				✓	E/H	80 tasks
Song et al. (2023)	Unspecified container type (f&e)				✓	E	40 requests
Chen et al. (2023)	Unspecified container type				✓	H	200 requests
Fazi et al. (2023)	Unspecified container type (f&e)				✓	E	100 nodes
Wang et al. (2023)	Unspecified container type (f&e)	✓			✓	E	100 requests
Wang et al. (2024)	Unspecified container type (f&e)					E/H	200 orders
Huang et al. (2024)	40ft containers (f&e)				✓	E/H	200 tasks
Song and Zhang (2024a)	Unspecified container type (f&e)				✓	E	75 requests
Zhang et al. (2024)	Unspecified container type (f&e)				✓	E/H	100 tasks
Section 2.2: homogeneous containers with load configurations							
Lai et al. (2013)	Unspecified container type (f&e)	✓				E/H	50 customers
Daham et al. (2017)	20-ft containers (f&e)	✓			✓	E	350 orders
Ghezelsoflu et al. (2018)	24.5ft containers (f&e)	✓			✓	E	50 customers/141 containers
Zhang et al. (2018)	Foldable containers (f&e)				✓	H	75 orders
Ghezelsoflu et al. (2021)	20-ft containers (f&e)	✓			✓	E	1000 customers/6000 requests
Section 2.3: homogeneous containers with non-standard load configurations							
Lai et al. (2015)	24.5-ft containers (f&e)		LCVs			E/H	50 customers
You et al. (2020)	Unspecified containers (f&e)		platoons		✓	E/H	200 customers
Zhang et al. (2021)	Dry containers (f&e), trailers		LCVs			E/H	100 orders
Xue et al. (2021)	Unspecified container type (f&e)		platoons			E/H	100 customers
Peng and Xue (2023)	Unspecified container type (f&e)		platoons			E/H	100 customers
Yan et al. (2023)	Unspecified container type (f&e)		platoons			E/H	400 customers
You et al. (2023)	Unspecified container type (f&e)		platoons		✓	E	50 customers
Section 2.4: heterogeneous containers, no load configurations or compatibility constraints							
Reinhardt et al. (2016)	Dry 20/40-ft containers, normal and high cube (f&e)				✓	E	308 orders
Stoop et al. (2024)	20/40-ft containers (f&e)				✓	E	300 requests

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TABLE 1 | (Continued)

Study	Container/cargo types	Het. trucks	Non-std trucks	Compatibility	T. windows	Approach	Size of largest instance
Section 2.5: heterogeneous containers with compatibility constraints, no load configurations							
Tan et al. (2006)	20/40-ft containers (f&e)	✓		size	✓	H	132 tasks
Meisel and Kopfer (2014)	Unspecified requests	✓		size & cargo	✓	E/H	500 requests
Regnier-Coudert et al. (2016)	General freight	✓		size & cargo	✓	H	203 jobs
Pérez Rivera and Mes (2017)	Any container (f&e)	✓		size & cargo	✓	E/H	50 jobs
Ritzinger et al. (2017)	Any container (f&e)	✓		size & cargo	✓	H	50 orders
Shiri and Huynh (2018)	20/40-ft containers (f&e), chassis	✓		size	✓	E/H	150 job nodes
Tilk et al. (2018)	Loading units	✓		size & cargo	✓	E	76 tasks
Heggen et al. (2019)	Any container (f&e)	✓		size	✓	H	Up to 470 requests
Cui et al. (2022)	20/40-ft containers (f&e)	✓		size	✓	E/H	400 requests
Rist et al. (2024)	Unspecified requests	✓		size & cargo	✓	E	20 requests
Section 2.6: heterogeneous containers with load configurations, no compatibility constraints							
Vidović et al. (2011)	20/40-ft containers					E/H	76 requests
Popović et al. (2014)	20/40-ft containers				✓	E/H	100 nodes
Zhang et al. (2015)	20/40-ft containers (f&e)					E/H	500 orders
Funke and Kopfer (2016)	20/40-ft containers (f&e)				✓	E	11 requests
Popović et al. (2018)	20/40-ft containers				✓	E	25 tasks
Bruglieri et al. (2021)	20/40-ft containers					E	200 customers
Section 2.7: heterogeneous containers with load configurations and compatibility constraints							
Chung et al. (2007)	20/40-ft containers	✓		size	✓	H	1093 orders
Bomboi (2020)	20-ft containers, ordinary and special (f&e)			cargo		E	60 customers
Yang and Daham (2020)	20/40-ft containers (f&e)	✓		size	✓	E/H	500 orders
Yang et al. (2021)	20/40-ft containers (f&e)	✓		size	✓	E/H	500 orders
Song and Zhang (2024b)	20/40-ft containers (f&e)	✓		size	✓	E/H	160 requests

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TABLE 1 | (Continued)

Study	Container/cargo types	Het. trucks	Non-std trucks	Compatibility	T. windows	Approach	Size of largest instance
Section 2.8: heterogeneous containers with non-standard load configurations, no compatibility constraints							
Vidović et al. (2017)	20/40-ft containers		LCVs		✓	E/H	193 tasks
Chen, Wang, and Meng (2021)	Containers with different weights		platoons		✓	E/H	50 requests
Bjelić et al. (2022)	20/40-ft containers (f&e)		LCVs		✓	E/H	96 tasks
Section 2.9: heterogeneous containers with non-standard load configurations and compatibility constraints							
Moghaddam et al. (2020)	20/40-ft containers (f&e)	✓	LCVs	size	✓	E	89 requests
Chen, Wang, and Meng (2021)	Any container	✓	LCVs	size		E/H	300 requests
Bustos-Coral and Costa (2022) and Bustos-Coral and Costa (2025)	Any container (f&e)	✓	LCVs	size & cargo	✓	E/H	1000 requests

Note: (f&e): full and empty (l&e): loaded and empty E: exact H: heuristic.

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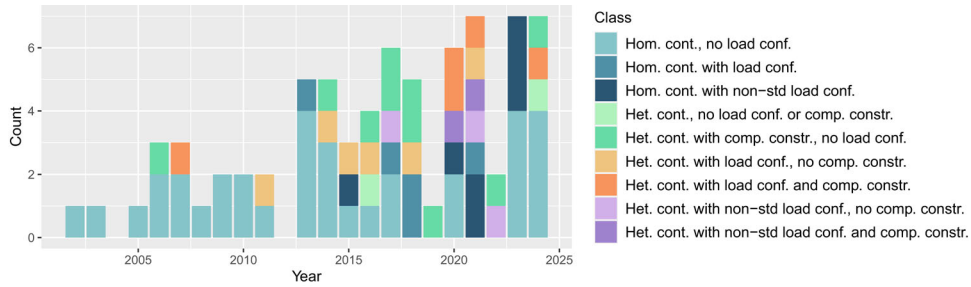


FIGURE 1 | Annual publication count.

Costa (2025) fill such a research gap, as they touch all these issues simultaneously—DRP-HCL allows for considering all the mentioned features in an integrated and flexible framework (as highlighted in Table 1).

We expect DRP-HCL to serve as a basis for modelling richer drayage problems in the future. Particularly, a promising direction for further research consists of the formulation of a drayage problem combining the rich fleet modelling of DRP-HCL with two of the main concerns identified in our review: that is, the repositioning of empty containers and the separation of trucks and containers during packing/unpacking operations. A problem combining all those elements would certainly be a powerful analytical tool, able to represent most real-life scenarios with unmatched accuracy.

Considering that DRP-HCL allows for modelling pickup and delivery tasks involving both full and empty containers, a richer drayage problem, involving empty container repositioning and truck-container separation during packing/unpacking operations, can be formulated proceeding as follows:

- Tasks involving packing/unpacking operations can be modelled by establishing precedence relationships between two pickup and delivery tasks, with the first task involving the delivery of a full (empty) container to a given customer and the second task involving the delivery of an empty (full) container from the customer's location to another site. It is necessary to consider a time gap between the delivery of the first task and the pickup of the second task, to represent unpacking (packing) operations.
- Empty container repositioning tasks can be created by defining sets of pickup and delivery tasks such that, in each set, tasks have a common pickup (delivery) location and different delivery (pickup) locations and, for each set, only one of its tasks must be performed.
- The separation of trucks and containers during packing/unpacking operations—maybe the most challenging aspect to model—can be implemented by planning the routes of semi-trucks and container chassis separately, such that the movements of the latter are always synchronised with the movements of the former, as was done in the APVRP (Meisel and Kopfer 2014).

One can argue that a first step aligned with the mentioned direction of research consists of developing improved formulations for DRP-HCL; such formulations can later serve as a basis for formulations for richer drayage problems. With this in mind, in the next sections, we present a new, compact MIP formulation for DRP-HCL, and show that it can outperform the compact MIP formulation proposed by Bustos-Coral and Costa (2022).

3 | An Alternative Compact MIP Formulation for DRP-HCL

This section introduces an alternative compact MIP formulation for DRP-HCL. First, Section 3.1 formally describes DRP-HCL and introduces the required notation. Then, Section 3.2 describes a state transition logic used to model the trucks' load capacities and compatibility constraints. Finally, considering the concepts introduced in Sections 3.1, 3.2 and 3.3 presents the alternative formulation.

3.1 | Problem Statement and Notation

We assume n requests for container pickup and delivery services. Let $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ be a directed graph of requests, with $\mathcal{N} = \{0, 1, \ldots, 2n, 2n+1\}$ and $\mathcal{A} = \{(i, j) : i, j \in \mathcal{N}\}$. Node 0 is the start depot and node $2n+1$ is the end depot.

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$\mathcal{P} = \{1, \ldots, n\}$ is the subset of pickup nodes and $\mathcal{D} = \{n+1, \ldots, 2n\}$ is the subset of delivery nodes. Each service request i, $1 \leq i \leq n$, must be picked up at node $i \in \mathcal{P}$ and delivered at node $n+i \in \mathcal{D}$.

Each node in $\mathcal{N}$ has an activity description that specifies the service to perform at such a node. Let $\mathcal{U} = \{+, -\}$ be the set of service types: + for pickup and − for delivery. Also, let $\mathcal{V}$ be the set of container types. For example, $\mathcal{V} = \{\texttt{e20}', \texttt{f20}', \texttt{e40}', \texttt{f40}', \texttt{e45}', \texttt{f45}'\}$ indicates that the problem involves 20/40/45-ft containers (empty and full).

Each node $i \in \mathcal{P} \cup \mathcal{D}$ has a service description $r_i = (u_i, v_i) \in \mathcal{U} \times \mathcal{V}$. For each request j, $1 \leq j \leq n$, the service descriptions of its corresponding pickup and delivery nodes have the following pattern: $u_j = +$, $u_{n+j} = -$ and $v_j = v_{n+j}$; that is, the same container that is picked up at node j is delivered at node $n+j$. For example, if $r_j = (+, \texttt{e20}')$, then $r_{n+j} = (-, \texttt{e20}')$. The start and end depots have service descriptions given by $r_0 = \texttt{start}$ and $r_{2n+1} = \texttt{end}$, respectively. $\mathcal{R} = (\mathcal{U} \times \mathcal{V}) \cup \{\texttt{start}, \texttt{end}\}$ is the set of all service descriptions.

Each node $i \in \mathcal{N}$ has a service duration s_i and a time window $[e_i, l_i]$, with e_i and l_i indicating the earliest and latest times for starting service at the node, respectively. The depot nodes' time windows, $[e_0, l_0] = [e_{2n+1}, l_{2n+1}]$, represent the planning horizon. In addition, $s_0 = s_{2n+1} = 0$.

Let $\mathcal{F} = \{1, \ldots, F\}$ be a set of truck types. Each truck type $f \in \mathcal{F}$ has a fixed cost E^f and a routing cost $c^f_{i,j}$, for an arc $(i, j) \in \mathcal{A}$. Let $\tau_{i,j}$ be the travel time a truck of type $f \in \mathcal{F}$ spends in traversing an arc $(i, j) \in \mathcal{A}$—this time is assumed to be truck-independent. We assume that costs $c^f_{i,j}$ depend on the travel times $\tau_{i,j}$, for $(i, j) \in \mathcal{A}$, and on the truck type $f \in \mathcal{F}$.

Each truck type $f \in \mathcal{F}$ is compatible with specific containers and has a load capacity that depends on the containers' sizes/contents (e.g., a truck may carry up to two empty 20-ft containers, one full 20-ft container or one full/empty 40/45-ft container).

The objective of DRP-HCL is to define a routing plan for a fleet of trucks (of types $f \in \mathcal{F}$) to serve the requests of graph $\mathcal{G}$ while minimising all fixed and routing costs. All trucks must depart from the start depot and return to the end depot, all requests must be served exactly once and all services must be performed meeting all time-window constraints.

3.2 | State Transition Logic to Model the Trucks' Load Capacities and Compatibility Constraints

Bustos-Coral and Costa (2022) proposed a state transition logic to model the trucks' load capacities and compatibility constraints. For each truck type $f \in \mathcal{F}$, such logic defines a state transition graph with nodes (states) representing truck load configurations and arcs (state transitions) representing the transitions a truck makes between load configurations as it performs services along its route. Below, we describe this logic.

Formally, let $\Theta_f = \{0, 1, \ldots, m_f - 1, m_f\}$ be the set of possible states for a type f truck. States $1, \ldots, m_f - 1$ represent the load configurations supported by the truck. Meanwhile, states 0 and m_f represent the truck's start and final states, respectively. Let $\Sigma_f \subset (\Theta_f \times \mathcal{R})$ be the subset of ordered pairs $(h, r) \in (\Theta_f \times \mathcal{R})$ such that the service described by r can be undertaken by a type f truck in state h. The state transitions for a type f truck are defined by a transition function $q_f : \Sigma_f \to \Theta_f$; $(h, r) \mapsto q_f(h, r)$. The state transition graph for a type f truck is composed of nodes representing truck states $h \in \Theta_f$ and arcs representing transitions $(h,\ h')$ such that $q_f(h, r) = h'$, with $(h, r) \in \Sigma_f$ and $h' \in \Theta_f$.

For example, consider heavy-duty trucks, say $f = 1$, that can carry one empty/full 20/40/45-ft dry container or two empty 20-ft dry containers. Let $\Theta_1 = \{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$ be the set of states for these trucks. States $1, \ldots, 8$ represent load configurations, as follows:

1. empty truck,
2. truck carrying one empty 20-ft dry container,
3. truck carrying two empty 20-ft dry containers,
4. truck carrying one full 20-ft dry container,

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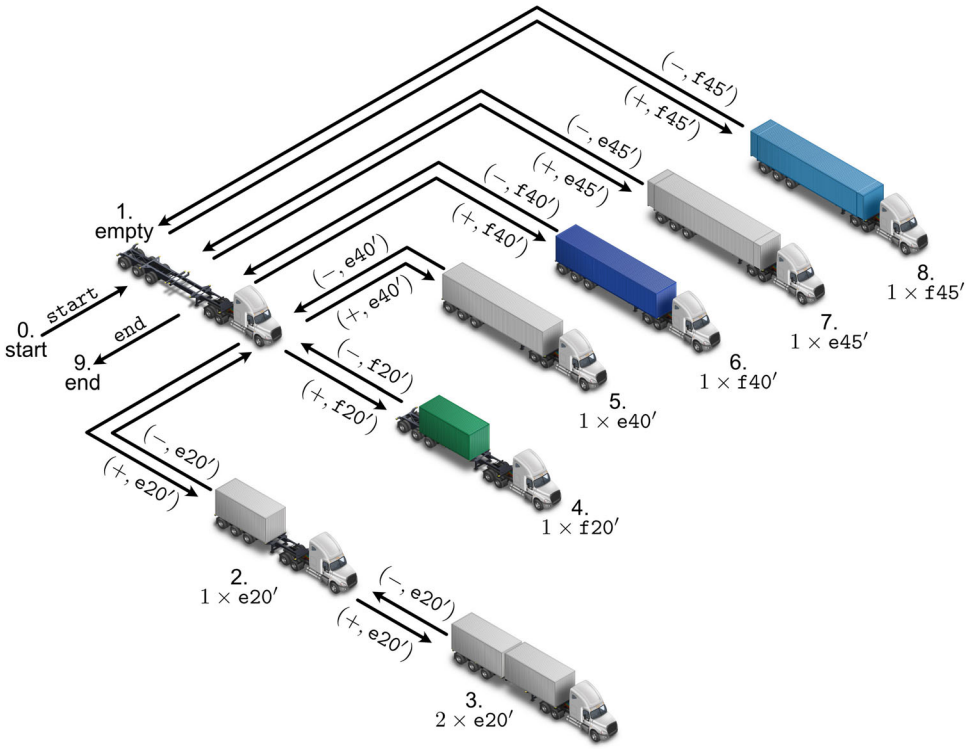


FIGURE 2 | State transition graph for heavy-duty trucks that haul 20/40/45-ft dry containers.

5. truck carrying one empty 40-ft dry container,
6. truck carrying one full 40-ft dry container,
7. truck carrying one empty 45-ft dry container and
8. truck carrying one full 45-ft dry container.

Meanwhile, states 0 and 9 are the start and final states, respectively. The transition function is given by

$$
\begin{aligned}
&q_1(0, \texttt{start}) = 1, \quad q_1(1, (+, \texttt{e20}')) = 2, \quad q_1(2, (+, \texttt{e20}')) = 3, \quad q_1(3, (-, \texttt{e20}')) = 2,\\
&q_1(2, (-, \texttt{e20}')) = 1, \quad q_1(1, (+, \texttt{f20}')) = 4, \quad q_1(4, (-, \texttt{f20}')) = 1, \quad q_1(1, (+, \texttt{e40}')) = 5,\\
&q_1(5, (-, \texttt{e40}')) = 1, \quad q_1(1, (+, \texttt{f40}')) = 6, \quad q_1(6, (-, \texttt{f40}')) = 1, \quad q_1(1, (+, \texttt{e45}')) = 7,\\
&q_1(7, (-, \texttt{e45}')) = 1 \quad q_1(1, (+, \texttt{f45}')) = 8 \quad q_1(8, (-, \texttt{f45}')) = 1 \qquad q_1(1, \texttt{end}) = 9
\end{aligned}
$$

Figure 2 shows the state transition graph for the example under consideration. In this figure, each node is labelled with a load configuration, for example, node 3, labelled as $2 \times \texttt{e20}'$, indicates that the truck is carrying two empty 20-ft dry containers, and each arc is associated with a service description $r \in \mathcal{R}$.

Note that each truck's state transition graph inherently incorporates load capacity and compatibility constraints. Capacity limitations are implemented by restricting states and transitions that would permit a truck to transport additional containers when there is no available load capacity. Furthermore, there cannot be states and transitions that would enable an empty truck to perform deliveries. Truck–container and container–container compatibility constraints can also be considered by defining adequate states and transitions.

Proceeding as in the example above, it is possible to model different truck types, for example, Bustos-Coral and Costa (2022) model different types of standard trucks, while Bustos-Coral and Costa (2025) show how to model different types of LCVs.

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3.3 | Formulation

Let $\mathcal{T} = \{1, \ldots, T\}$ be a set of trucks and let $f : \mathcal{T} \to \mathcal{F}; t \mapsto f(t)$ be a function mapping each truck to its corresponding type. In addition, define the following sets:

- $\Delta_i^f = \{h' \in \Theta_f : q_f(h, r) = h',\ (h, r) \in \Sigma_f \text{ and } r = r_i\}$, which contains *the possible states in which a truck of type f can be after visiting node i*;
- $\Omega_{i,j}^f = \{(h,\ h') \in \Theta_f^2 : q_f(h, r) = h',\ (h, r) \in \Sigma_f,\ h \in \Delta_i^f \text{ and } r = r_j\}$, which contains *the transitions (state at node i, state at node j) that a truck of type f can perform in traversing arc (i, j)*;
- $\Phi_{i,j}^{f,\ h,\cdot} = \{g' \in \Theta_f : (g, g') \in \Omega_{i,j}^f \text{ and } g = h\}$, which contains *the state in which a truck of type f can be after visiting node j when travelling arc (i, j), given that the truck is in state h after visiting node i*; and
- $\Phi_{i,j}^{f,\cdot,\ h'} = \{g \in \Theta_f : (g, g') \in \Omega_{i,j}^f \text{ and } g' = h'\}$, which contains *the state in which a truck of type f can be after visiting node i when travelling arc (i, j), given that the truck is in state h' after visiting node j*.

For each arc $(i, j) \in \mathcal{A}$, truck $t \in \mathcal{T}$ and state transition $(h,\ h') \in \Omega_{i,j}^{f(t)}$, let $z_{i,j}^{t,h,h'}$ be a binary variable equal to 1 if and only if truck t travels arc (i, j) making state transition $(h,\ h')$ and 0 otherwise. For each node $i \in \mathcal{P} \cup \mathcal{D}$, denote its start of service time by B_i. For each truck $t \in \mathcal{T}$, let B_0^t and B_{2n+1}^t denote, respectively, the times at which the truck leaves the start depot and arrives at the end depot.

Our alternative compact MIP formulation for DRP-HCL is given by Equations (1–19). A summary of the used notation is provided in Table A1.

$$\text{minimise} \sum_{t\in\mathcal{T}} E^{f(t)} \sum_{j\in\mathcal{P}} \sum_{(h,h')\in\Omega_{0,j}^{f(t)}} z_{0,j}^{t,h,h'} + \sum_{t\in\mathcal{T}} \sum_{(i,j)\in\mathcal{A}} \sum_{(h,h')\in\Omega_{i,j}^{f(t)}} c_{i,j}^{f(t)} z_{i,j}^{t,h,h'} \tag{1}$$

$$\text{subject to:} \sum_{t\in\mathcal{T}} \sum_{j\in\mathcal{N}} \sum_{(h,h')\in\Omega_{i,j}^{f(t)}} z_{i,j}^{t,h,h'} = 1, \quad \forall i \in \mathcal{P} \tag{2}$$

$$\sum_{j\in\mathcal{N}} \sum_{(h,h')\in\Omega_{i,j}^{f(t)}} z_{i,j}^{t,h,h'} - \sum_{j\in\mathcal{N}} \sum_{(h,h')\in\Omega_{n+i,j}^{f(t)}} z_{n+i,j}^{t,h,h'} = 0, \quad \forall i \in \mathcal{P}, t \in \mathcal{T} \tag{3}$$

$$\sum_{j\in\mathcal{N}} \sum_{(h,h')\in\Omega_{0,j}^{f(t)}} z_{0,j}^{t,h,h'} = 1, \quad \forall t \in \mathcal{T} \tag{4}$$

$$\sum_{i\in\mathcal{N}} \sum_{(h,h')\in\Omega_{i,2n+1}^{f(t)}} z_{i,2n+1}^{t,h,h'} = 1, \quad \forall t \in \mathcal{T} \tag{5}$$

$$\sum_{j\in\mathcal{N}} \sum_{h'\in\Phi_{j,i}^{f(t),\cdot,h}} z_{j,i}^{t,h',h} - \sum_{j\in\mathcal{N}} \sum_{h'\in\Phi_{i,j}^{f(t),h,\cdot}} z_{i,j}^{t,h,h'} = 0, \quad \forall i \in \mathcal{P} \cup \mathcal{D}, t \in \mathcal{T},\ h \in \Delta_i^{f(t)} \tag{6}$$

$$\sum_{j\in\mathcal{N}} \sum_{h'\in\Phi_{0,j}^{f(t),h,\cdot}} z_{0,j}^{t,h,h'} = 1, \quad \forall t \in \mathcal{T},\ h \in \Delta_0^{f(t)} \tag{7}$$

$$\sum_{i\in\mathcal{N}} \sum_{h\in\Phi_{i,2n+1}^{f(t),\cdot,h'}} z_{i,2n+1}^{t,h,h'} = 1, \quad \forall t \in \mathcal{T},\ h' \in \Delta_{2n+1}^{f(t)} \tag{8}$$

$$B_j \geq (B_0^t + s_0 + \tau_{0,j}) \sum_{(h,h')\in\Omega_{0,j}^{f(t)}} z_{0,j}^{t,h,h'}, \quad \forall j \in \mathcal{P}, t \in \mathcal{T} \tag{9}$$

$$B_j \geq (B_i + s_i + \tau_{i,j}) \sum_{t\in\mathcal{T}} \sum_{(h,h')\in\Omega_{i,j}^{f(t)}} z_{i,j}^{t,h,h'}, \quad \forall i, j \in \mathcal{P} \cup \mathcal{D} \tag{10}$$

$$B_{2n+1}^t \geq (B_i + s_i + \tau_{i,2n+1}) \sum_{(h,h')\in\Omega_{i,2n+1}^{f(t)}} z_{i,2n+1}^{t,h,h'}, \quad \forall i \in \mathcal{D}, t \in \mathcal{T} \tag{11}$$

$$e_0 \leq B_0^t \leq l_0, \quad \forall t \in \mathcal{T} \tag{12}$$

$$e_i \leq B_i \leq l_i, \quad \forall i \in \mathcal{P} \cup \mathcal{D} \tag{13}$$

$$e_{2n+1} \leq B_{2n+1}^t \leq l_{2n+1}, \quad \forall t \in \mathcal{T} \tag{14}$$

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$$B_{n+i} \geq B_i + s_i + \tau_{i,n+i}, \quad \forall i \in \mathcal{P} \tag{15}$$

$$z_{i,j}^{t,\ h,h'} \in \{0,1\}, \quad \forall (i,j) \in \mathcal{A}, t \in \mathcal{T}, (h,\ h') \in \Omega_{i,j}^{f(t)} \tag{16}$$

$$B_0^t \geq 0, \quad \forall t \in \mathcal{T} \tag{17}$$

$$B_i \geq 0, \quad \forall i \in \mathcal{P} \cup \mathcal{D} \tag{18}$$

$$B_{2n+1}^t \geq 0, \quad \forall t \in \mathcal{T} \tag{19}$$

The objective of the formulation (1) is to minimise the fixed and routing costs. Constraints (2) and (3) check that each request is served exactly once and that, for each request, the pickup and delivery nodes are visited by the same truck. Constraints (4) and (5) check, respectively, that each truck departs the start depot and arrives to the end depot (trucks going straight from the start depot to the end depot incur no cost). Constraints (6) check that the truck entering a pickup/delivery node also leaves it, and that there is a single state associated with such a node. Constraints (7) and (8) explicitly set the trucks' initial and final states, respectively (note that constraints (4) and (5) achieve this as well, although implicitly). Time-window constraints are given by constraints (9–14). Constraints (15) ensure that, for each request, the pickup location is visited before the corresponding delivery location. Constraints (16–19) define the variables. The formulation is nonlinear because of constraints (9–11). These constraints are linearised, as shown by Cordeau (2006).

Finally, we perform the following trivial variable fixations: $z_{i,i}^{t,h,h'} = 0,\ \forall i \in \mathcal{N}, t \in \mathcal{T}, (h,\ h') \in \Omega_{i,i}^{f(t)}$ and $z_{n+i,i}^{t,h,h'} = 0,\ \forall i \in \mathcal{P}, t \in \mathcal{T}, (h,\ h') \in \Omega_{n+i,i}^{f(t)}$.

4 | Performance of the Proposed Alternative Formulation

4.1 | Experiments Setup

We conducted a set of computational experiments to assess our alternative compact MIP formulation, considering as baseline the results of the three-index MIP formulation proposed by Bustos-Coral and Costa (2022). We used both formulations to solve a set of benchmark instances. For both formulations, we set a maximum runtime limit of 1 h per instance. In addition, we limited the number of trucks available in the instances according to the solutions found by the fragment-based approach of Bustos-Coral and Costa (2022), aiming to speed up the solution process.

To implement both formulations, we used Python 3.9 with the Gurobi 10.0 API. We conducted all experiments on The University of Melbourne's Spartan high-performance computing system, which has a physical partition with 14 nodes featuring Intel Xeon Gold 6154 CPUs@3.00 GHz, with 1519-GB RAM per node and 79 nodes featuring Intel Xeon Gold 6254 CPUs@3.10 GHz, with 710-GB RAM per node.

4.2 | Problem Instances

We used the proposed compact MIP formulation and the three-index MIP formulation of Bustos-Coral and Costa (2022) to solve the 25-, 50- and 75-request instances introduced by Bustos-Coral and Costa (2022). There are 225 instances in total. The instances are characterised by different geographical distributions of locations, truck fleets and time-window lengths.

Concerning the geographical distributions of locations, the instances are categorised into the following classes:

- C1, where requests have distant pickup and delivery locations;
- C2, where requests have pickup and delivery locations clustered nearby;
- R, where requests have randomly distributed pickup and delivery locations;
- RC1, a hybrid class combining characteristics of both C1 and R; and
- RC2, a hybrid class combining characteristics of both C2 and R.

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As to the truck fleets, the instances involve containers that can either be transported individually, limiting routing possibilities, or in a $2 \times 20'$ load configuration, offering more flexible routing options. Additionally, various levels of truck–container compatibility exist. Considering these factors, the instances are categorised into the following classes:

- F1, with very high truck–container compatibility, and where all containers must be moved individually;
- F2, with very high truck–container compatibility and a high percentage of containers that can be transported in a $2 \times 20'$ load configuration;
- F3, with high truck–container compatibility and a moderate percentage of containers that can be moved in a $2 \times 20'$ load configuration;
- F4, with medium truck–container compatibility and a small percentage of containers suitable for a $2 \times 20'$ load configuration; and
- F5, with low truck–container compatibility and a very small percentage of containers that can be transported in a $2 \times 20'$ load configuration.

Regarding the time-window constraints, the instances are categorised into the following classes:

- W1, where the requests' time windows are short;
- W2, where the requests' time windows are long; and
- W3, where some requests have short time windows and others have long time windows.

4.3 | Results

The summarised results are presented in Table 2, which groups the instances by their number of requests (columns with headers 25, 50 and 75), as well as by their geographical distribution of locations, fleet and time-window setting (across rows). The results across all instances are summarised at the bottom of the table. For each group of instances, the table displays the counts of proven optimal solutions, instances for which the solution process timed out with a solution and instances for which the solution process timed out without solution. The table also shows average runtimes in seconds for each group of instances. The detailed solutions are available in Tables A2–A4.

In terms of the effectiveness in finding solutions, the alternative compact MIP formulation generally performed better than the three-index MIP formulation. With the former, we could find a solution for 175 out of 225 instances (146 proven optimal solutions), while with the latter we could solve 163 out of 225 instances (138 proven optimal solutions). In addition, there were 12 instances solved to proven optimality with the alternative compact MIP formulation and not with the three-index MIP formulation, while only 4 instances were solved to proven optimality with the three-index MIP formulation and not with the alternative compact MIP formulation. Generally, the alternative compact MIP formulation showed a better time performance as well: there were 131 instances where this formulation was solved faster than the three-index MIP formulation, the opposite occurred only in 19 instances, and there were 75 instances where the solution process timed out for both formulations. Note that the alternative compact MIP formulation achieved evident reductions in runtime mainly on 25-request instances. On 50- and 75-request instances, the reductions were generally more subtle.

Figure 3 compares the gaps between the best dual bounds provided by the formulations and the optimal solutions found by the fragment-based approach of Bustos-Coral and Costa (2022). For each formulation and instance, the gap is given by $100 \cdot (S^* - S)/S^*$, where S^* is the cost of the optimal solution found by the fragment-based approach and S is the best dual bound provided by the formulation.

The alternative compact MIP formulation produced better dual bounds for 71 instances. The largest improvements in the dual bounds occurred mainly across 75- and 50-request instances, with the largest gap reductions being of around 20 percentage points for 75-request instances and 13 percentage points for 50-request instances. Across 25-request instances, the improvements were commonly of less than 10 percentage points, except for one instance where the improvement was of almost 17 percentage points. On the other hand, the three-index MIP formulation produced better dual bounds

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TABLE 2 | Summary of results of the compact MIP formulations.

		Proven optimal			Timeout (solution)			Timeout (unsolved)			Avg. runtime (s)		
Class	**Formulation**	**25**	**50**	**75**	**25**	**50**	**75**	**25**	**50**	**75**	**25**	**50**	**75**
Geographical distribution of locations													
C1	Alternative	14	10	7	1	2	2	0	3	6	311.58	1210.10	2113.55
	Three-index	13	10	8	1	1	2	1	4	5	497.34	1378.54	1821.54
C2	Alternative	15	7	5	0	6	3	0	2	7	53.01	2196.07	2436.58
	Three-index	14	5	5	1	4	1	0	6	9	372.58	2421.62	2575.05
R	Alternative	14	10	5	1	0	3	0	5	7	354.38	1461.69	2426.26
	Three-index	15	9	7	0	2	0	0	4	8	418.66	1537.28	2251.37
RC1	Alternative	15	10	7	0	2	2	0	3	6	188.43	1395.97	1950.02
	Three-index	12	10	7	3	2	2	0	3	6	809.45	1511.65	2068.88
RC2	Alternative	15	8	4	0	4	3	0	3	8	92.38	1892.17	2655.04
	Three-index	14	6	3	1	2	3	0	7	9	618.49	2175.66	2930.30
Container and truck types													
F1	Alternative	14	12	7	1	1	2	0	2	6	288.04	818.50	2165.15
	Three-index	15	12	9	0	2	2	0	1	4	153.79	1002.18	1994.93
F2	Alternative	14	0	0	1	6	0	0	9	15	599.41	3600.00	3600.00
	Three-index	10	0	0	4	0	0	1	15	15	1955.37	3600.00	3600.00
F3	Alternative	15	5	0	0	6	7	0	4	8	111.13	2744.36	3600.00
	Three-index	13	3	0	2	6	3	0	6	12	604.62	3087.10	3600.00
F4	Alternative	15	13	7	0	1	3	0	1	5	1.18	854.79	1948.95
	Three-index	15	11	8	0	2	1	0	2	6	2.26	1078.76	1880.96
F5	Alternative	15	15	14	0	0	1	0	0	0	0.04	138.36	267.35
	Three-index	15	14	13	0	1	2	0	0	0	0.49	256.71	571.24
Time windows													
W1	Alternative	25	19	14	0	5	6	0	1	5	14.45	980.07	1618.64
	Three-index	25	18	15	0	2	2	0	5	8	90.95	1149.21	1632.20
W2	Alternative	23	10	4	2	3	1	0	12	20	514.92	2328.51	3037.31
	Three-index	20	9	5	4	4	2	1	12	18	989.18	2501.77	2971.20
W3	Alternative	25	16	10	0	6	6	0	3	9	70.51	1585.02	2292.92
	Three-index	23	13	10	2	5	4	0	7	11	549.79	1763.87	2384.88
All	Alternative	73	45	28	2	14	13	0	16	34	199.96	1631.20	2316.29
	Three-index	68	40	30	6	11	8	1	24	37	543.31	1804.95	2329.43

for 19 instances, with all improvements being of less than 10 percentage points, and commonly less than 5 percentage points.

When analysing the counts of instances solved, the gaps with respect to the optimal solutions and the runtimes, we note that the instances' characteristics affected the performance of the alternative compact MIP formulation in a manner comparable to how they impacted the performance of the three-index MIP formulation of Bustos-Coral and Costa (2022): We can see that instances involving many $2 \times 20'$ loads, high truck–container compatibility, long time windows or more requests were generally harder to solve than instances involving few or no $2 \times 20'$ loads, low

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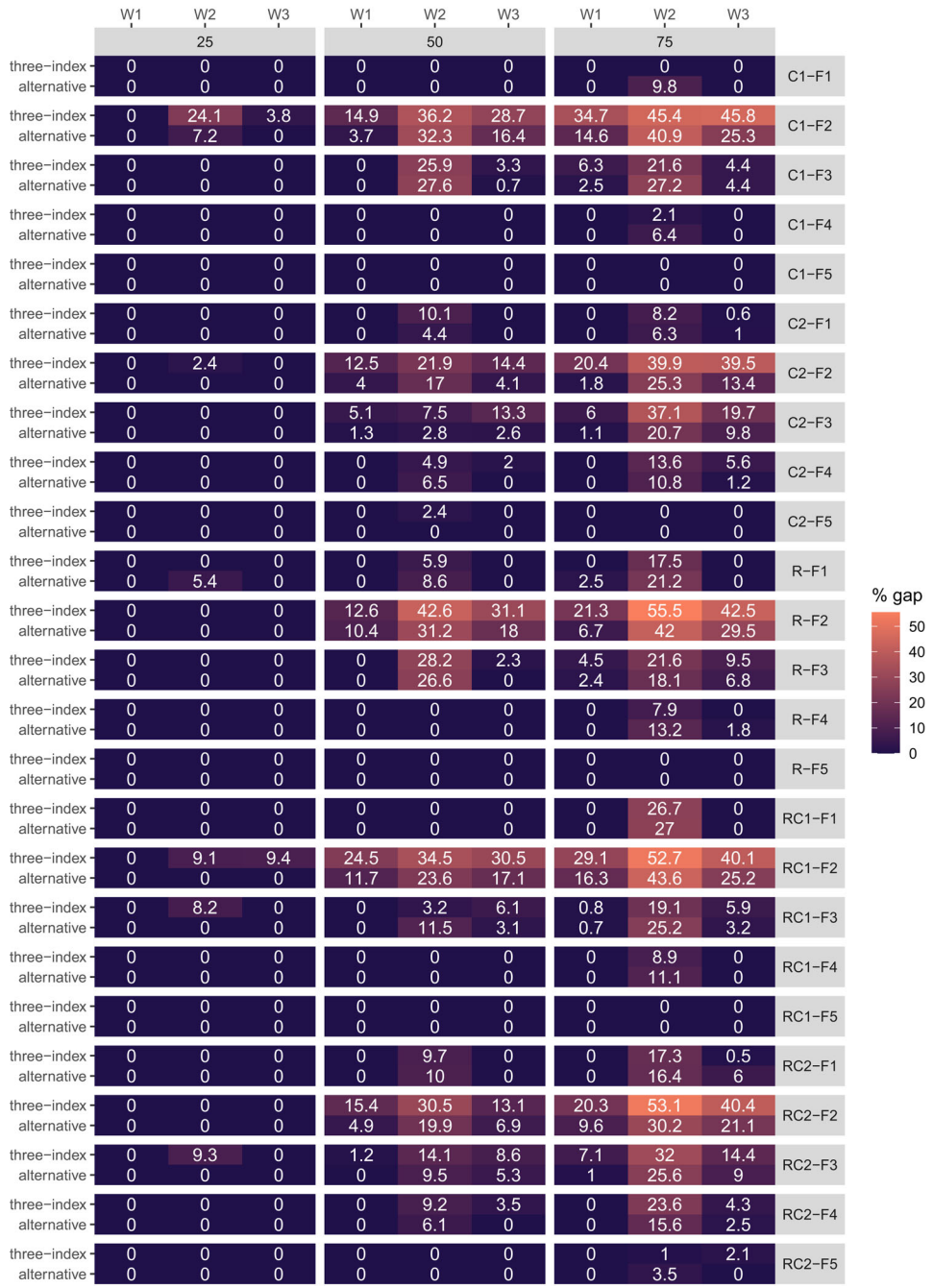


FIGURE 3 | Gaps between optimal solutions and the best dual bounds produced by the compact MIP formulations.

truck–container compatibility, short time windows or fewer requests. On the other hand, the geographical distributions of locations did not significantly affect the performance of the formulations.

5 | Conclusions

We have reviewed the literature on drayage problems analysing how the modelling of trucks and containers has evolved over the years, starting in the early 2000s with problems involving single-container trucks and homogeneous containers, continuing with problems featuring more detailed fleet modelling (e.g., problems involving 20/40-ft containers, heterogeneous trucks or compatibility constraints) and finishing with the introduction of the drayage routing problem with heterogeneous fleet, compatibility constraints and truck load configurations (DRP-HCL) by Bustos-Coral and Costa (2022) and Bustos-Coral and Costa (2025).

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We discussed how DRP-HCL enables more detailed modelling of trucks and containers than any of the reviewed problems, as DRP-HCL allows for considering the following aspects, which had not been considered simultaneously before: (1) containers of any size (e.g., 20/40/45/48/53 ft) and cargo category (e.g., dry, reefer, tank); (2) trucks of any type, considering both standard trucks (rigid trucks or semi-trucks pulling a single trailer/chassis) and longer combination vehicles (semi-trucks pulling two or more trailers/chassis); (3) trucks' cargo capacities depending on the containers' sizes and cargoes (e.g., a truck may carry up to two empty 20-ft containers but only one full 20-ft container); and (4) compatibility constraints between containers (e.g., containers carrying incompatible hazmat loads cannot be transported together) and between trucks and containers (e.g., only trucks with special permits can move out-of-gauge loads).

We also proposed an alternative compact MIP formulation for DRP-HCL which can yield better results than the three-index formulation of Bustos-Coral and Costa (2022). We showed that, with the proposed formulation, we can solve more instances from the benchmark set of Bustos-Coral and Costa (2022), while often requiring shorter runtimes. Our proposed formulation can be a compelling alternative for operations research practitioners who aim to solve small- or medium-sized instances and prefer the ease of use of a compact formulation that can readily be input into black-box MIP solvers.

While analysing the evolution of fleet modelling in drayage problems, we noted that many problems focus on aspects of drayage different from fleet modelling, such as empty container repositioning and decisions on the separation of trucks and containers during packing/unpacking operations. Fleet modelling has started to gain traction only in recent years. Thus, an interesting direction of research consists of addressing a drayage problem involving the rich fleet modelling of DRP-HCL plus other issues associated with drayage, such as empty container repositioning and decisions on the separation of trucks and containers. Such a problem would certainly be a very powerful analytical tool, capable of representing a wide range of situations with unrivalled level of detail. In particular, it would be possible to start modelling such a problem based on the alternative compact MIP formulation we have proposed.

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Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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Appendix A

Summary of Notations

Table A1 presents the notations used in our alternative compact MIP formulation for DRP-HCL.

Detailed Solutions

Tables A2, A3 and A4 report the detailed solutions obtained in the experiments reported in Section 4. Proven optimal solutions are shown in the following format: '*objective function value|runtime'. Solutions returned by the solver after reaching the runtime limit are displayed in the following format: 'upper bound|lower bound|gap|runtime limit'. The upper bound and gap are denoted by 'N/A' for the instances unsolved within the runtime limit. The tables present the solutions according to the instances' characteristics: the rows indicate the geographical distribution of nodes and fleet, while the columns indicate the type of time windows. The solutions found with the proposed alternative compact MIP formulation and with the three-index MIP formulation of Bustos-Coral and Costa (2022) are displayed in the rows marked as 'alternative' and 'three-index', respectively.

TABLE A1 | Summary of the Used Notations.

Symbol	Description
Sets	
$\mathcal{N}$	Node set, $\mathcal{N} = \{0, 1, \dots, 2n, 2n+1\}$.
$\mathcal{A}$	Arc set, $\mathcal{A} = \{(i,j) : i,j \in \mathcal{N}\}$.
$\mathcal{P}$	Set of pickup nodes, $\mathcal{P} = \{1, \dots, n\}$.
$\mathcal{D}$	Set of delivery nodes, $\mathcal{D} = \{n+1, \dots, 2n\}$.
$\mathcal{U}$	Set of service types, $\mathcal{U} = \{+, -\}$, where + indicates pickup and − delivery.
$\mathcal{V}$	Set of container types, for example, $\mathcal{V} = \{\texttt{e20'}, \texttt{f20'}, \texttt{e40'}, \texttt{f40'}, \texttt{e45'}, \texttt{f45'}\}$.
$\mathcal{R}$	Set of all service descriptions, $\mathcal{R} = (\mathcal{U} \times \mathcal{V}) \cup \{\texttt{start}, \texttt{end}\}$.
$\mathcal{F}$	Set of truck types, $\mathcal{F} = \{1, \dots, F\}$.
Θ_f	Set of possible states for a type f truck, $\Theta_f = \{0, 1, \dots, m_f - 1, m_f\}$.
Σ_f	Subset of ordered pairs $(h, r) \in (\Theta_f \times \mathcal{R})$ such that the service described by r can be undertaken by a type f truck in state h.
$\mathcal{T}$	Set of trucks, $\mathcal{T} = \{1, \dots, T\}$.
Δ_i^f	Set of possible states in which a type f truck can be after visiting node i, $\Delta_i^f = \{h' \in \Theta_f : q_f(h, r) = h',\ (h, r) \in \Sigma_f \text{ and } r = r_i\}$.
$\Omega_{i,j}^f$	Set of transitions (state at node i, state at node j) that a type f truck can perform in traversing an arc (i,j), $\Omega_{i,j}^f = \{(h,\ h') \in \Theta_f^2 : q_f(h, r) = h',\ (h, r) \in \Sigma_f,\ h \in \Delta_i^f \text{ and } r = r_j\}$.
$\Phi_{i,j}^{f,\ h,\cdot}$	Set containing the state in which a type f truck can be after visiting node j when travelling arc (i,j), given that the truck is in state h after visiting node i, $\Phi_{i,j}^{f,\ h,\cdot} = \{g' \in \Theta_f : (g, g') \in \Omega_{i,j}^f \text{ and } g = h\}$.
$\Phi_{i,j}^{f,\cdot,\ h'}$	Set containing the state in which a type f truck can be after visiting node i when travelling arc (i,j), given that the truck is in state h' after visiting node j, $\Phi_{i,j}^{f,\cdot,\ h'} = \{g \in \Theta_f : (g, g\prime) \in \Omega_{i,j}^f \text{ and } g\prime = h'\}$.
Parameters	
n	Number of requests.
$0, 2n+1$	Start and end depot, respectively.
r_i	Service description at node i, $r_i = (u_i, v_i) \in \mathcal{U} \times \mathcal{V}$.
s_i	Service duration at node i.
$[e_i, l_i]$	Time window at node i.
E^f	Fixed cost of a type f truck.
$c_{i,j}^f$	Routing cost incurred by a type f truck in travelling arc (i,j).
$\tau_{i,j}$	Travel time associated with arc (i,j).
q_f	Transition function for a type f truck, $q_f : \Sigma_f \to \Theta_f; (h, r) \mapsto q_f(h, r)$.
$f(t)$	Truck t's type.
Variables	
$z_{i,j}^{t,\ h,\ h'}$	Binary variable equal to 1 iff truck t travels arc (i,j) making state transition $(h,\ h')$ and 0 otherwise.
B_i	Start of service time at node $i \in \mathcal{P} \cup \mathcal{D}$.
B_0^t	Time at which truck t leaves the start depot.
B_{2n+1}^t	Time at which truck t arrives at the end depot.

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TABLE A2 | Compact MIP formulations: solutions to 25-request instances.

			W1	W2	W3
C1	F1	Alternative	*3822.73|0.48 s	*3213.59|4.62 s	*3310.17|2.57 s
		Three-index	*3822.73|0.78 s	*3213.59|7.71 s	*3310.17|2.71 s
	F2	Alternative	*3191.12|55.78 s	2847.48|2643.09|7.2%|1 h	*2749.36|968.36 s
		Three-index	*3191.12|29.61 s	N/A|2160.52|N/A|1 h	2749.36|2645.01|3.8%|1 h
	F3	Alternative	*2916.66|0.47 s	*2371.66|37.62 s	*3262.49|3.29 s
		Three-index	*2916.66|4.86 s	*2371.66|210.74 s	*3262.49|1.08 s
	F4	Alternative	*3074.82|0.11 s	*3481.05|0.14 s	*3148.65|0.19 s
		Three-index	*3074.82|0.43 s	*3481.05|0.66 s	*3148.65|0.47 s
	F5	Alternative	*3730.85|0.03 s	*3816.44|0.03 s	*4008.74|0.02 s
		Three-index	*3730.85|0.32 s	*3816.44|0.42 s	*4008.74|0.36 s
C2	F1	Alternative	*2249.83|0.45 s	*1381.32|312.17 s	*2087.49|13.69 s
		Three-index	*2249.83|1.49 s	*1381.32|482.83 s	*2087.49|7.39 s
	F2	Alternative	*1617.75|71.12 s	*1128.95|227.13 s	*1476.57|35.98 s
		Three-index	*1617.75|359.10 s	1128.95|1101.30|2.4%|1 h	*1476.57|602.45 s
	F3	Alternative	*1021.25|17.22 s	*866.57|102.91 s	*1348.23|4.14 s
		Three-index	*1021.25|46.75 s	*866.57|431.52 s	*1348.23|40.80 s
	F4	Alternative	*1345.67|2.63 s	*1254.44|4.61 s	*1685.85|3.03 s
		Three-index	*1345.67|1.42 s	*1254.44|10.64 s	*1685.85|3.41 s
	F5	Alternative	*1979.10|0.03 s	*1567.11|0.07 s	*1801.29|0.04 s
		Three-index	*1979.10|0.28 s	*1567.11|0.24 s	*1801.29|0.33 s
R	F1	Alternative	*2442.02|0.37 s	1867.33|1766.90|5.4%|1 h	*2525.41|0.48 s
		Three-index	*2442.02|0.85 s	*1867.33|909.14 s	*2525.41|1.09 s
	F2	Alternative	*2578.29|12.89 s	*1954.67|1319.03 s	*1945.18|232.49 s
		Three-index	*2578.29|113.48 s	*1954.67|1701.94 s	*1945.18|2893.89 s
	F3	Alternative	*2274.37|0.41 s	*1748.13|141.52 s	*2209.90|4.10 s
		Three-index	*2274.37|4.39 s	*1748.13|638.68 s	*2209.90|7.99 s
	F4	Alternative	*2413.87|2.19 s	*2022.11|0.17 s	*2575.47|1.99 s
		Three-index	*2413.87|6.44 s	*2022.11|0.42 s	*2575.47|0.74 s
	F5	Alternative	*2872.03|0.03 s	*2718.45|0.04 s	*2685.01|0.04 s
		Three-index	*2872.03|0.37 s	*2718.45|0.26 s	*2685.01|0.23 s
RC1	F1	Alternative	*2839.73|0.46 s	*2542.20|36.21 s	*3261.44|0.61 s
		Three-index	*2839.73|0.99 s	*2542.20|11.66 s	*3261.44|1.17 s
	F2	Alternative	*2680.55|16.02 s	*2388.00|1337.89 s	*2603.64|275.45 s
		Three-index	*2680.55|863.65 s	2388.00|2170.57|9.1%|1 h	2603.64|2360.02|9.4%|1 h
	F3	Alternative	*2418.69|0.34 s	*1907.49|1105.17 s	*2336.21|53.59 s
		Three-index	*2418.69|3.31 s	1907.87|1751.37|8.2%|1 h	*2336.21|451.26 s
	F4	Alternative	*3053.76|0.10 s	*2387.88|0.27 s	*2502.64|0.17 s
		Three-index	*3053.76|0.47 s	*2387.88|3.30 s	*2502.64|2.28 s
	F5	Alternative	*3036.11|0.04 s	*3291.84|0.03 s	*2808.28|0.09 s
		Three-index	*3036.11|0.72 s	*3291.84|0.86 s	*2808.28|2.15 s
RC2	F1	Alternative	*2211.47|0.39 s	*1577.14|345.43 s	*1690.89|2.64 s
		Three-index	*2211.47|1.06 s	*1577.14|874.58 s	*1690.89|3.38 s
	F2	Alternative	*1560.37|179.27 s	*1482.08|504.28 s	*1826.83|155.40 s
		Three-index	*1560.37|831.41 s	*1482.08|1443.23 s	*1826.83|2491.79 s
	F3	Alternative	*1977.97|0.24 s	*1352.75|193.37 s	*1882.28|2.55 s
		Three-index	*1977.97|0.76 s	1352.75|1227.44|9.3%|1 h	*1882.28|27.15 s
	F4	Alternative	*2025.23|0.14 s	*1759.51|0.13 s	*2568.22|1.81 s
		Three-index	*2025.23|0.45 s	*1759.51|0.49 s	*2568.22|2.32 s
	F5	Alternative	*2357.25|0.03 s	*2115.09|0.03 s	*2452.36|0.03 s
		Three-index	*2357.25|0.25 s	*2115.09|0.28 s	*2452.36|0.24 s

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TABLE A3 | Compact MIP formulations: solutions to 50-request instances.

			W1	W2	W3
C1	F1	Alternative	*7126.96|3.70 s	*5885.96|62.64 s	*6642.58|15.17 s
		Three-index	*7126.96|20.30 s	*5885.96|2467.16 s	*6642.58|34.41 s
	F2	Alternative	5183.97|4993.99|3.7%|1 h	N/A|3365.81|N/A|1 h	N/A|4417.63|N/A|1 h
		Three-index	N/A|4411.95|N/A|1 h	N/A|3170.39|N/A|1 h	N/A|3768.01|N/A|1 h
	F3	Alternative	*5659.12|14.41 s	N/A|3146.60|N/A|1 h	5339.69|5301.85|0.7%|1 h
		Three-index	*5659.12|59.23 s	N/A|3220.25|N/A|1 h	5339.69|5164.27|3.3%|1 h
	F4	Alternative	*6000.15|6.34 s	*5548.68|18.90 s	*6309.69|24.36 s
		Three-index	*6000.15|10.02 s	*5548.68|53.33 s	*6309.69|12.10 s
	F5	Alternative	*6896.80|5.24 s	*6524.63|0.57 s	*6965.38|0.13 s
		Three-index	*6896.80|10.93 s	*6524.63|7.43 s	*6965.38|3.11 s
C2	F1	Alternative	*3712.82|6.78 s	2650.20|2533.97|4.4%|1 h	*3709.76|158.72 s
		Three-index	*3712.82|39.45 s	2650.20|2383.44|10.07%|1 h	*3709.76|212.74 s
	F2	Alternative	2694.35|2583.30|4.1%|1 h	N/A|1993.22|N/A|1 h	2688.36|2577.82|4.1%|1 h
		Three-index	N/A|2354.21|N/A|1 h	N/A|1876.09|N/A|1 h	N/A|2300.89|N/A|1 h
	F3	Alternative	1957.43|1932.57|1.3%|1 h	2162.42|2102.00|2.8%|1 h	2070.43|2016.77|2.6%|1 h
		Three-index	1957.43|1856.65|5.1%|1 h	N/A|2001.26|N/A|1 h	N/A|1794.72|N/A|1 h
	F4	Alternative	*2726.05|17.20 s	N/A|1986.79|N/A|1 h	*3050.40|1917.08 s
		Three-index	*2726.05|66.70 s	N/A|2021.01|N/A|1 h	3050.40|2989.54|2.0%|1 h
	F5	Alternative	*3892.18|0.18 s	*2883.35|2040.66 s	*3883.98|0.47 s
		Three-index	*3892.18|2.62 s	2883.35|2814.21|2.4%|1 h	*3883.98|2.75 s
R	F1	Alternative	*4735.79|62.12 s	N/A|4131.86|N/A|1 h	*4577.26|47.64 s
		Three-index	*4735.79|49.96 s	4521.68|4253.88|5.9%|1 h	*4577.26|127.03 s
	F2	Alternative	N/A|3594.30|N/A|1 h	N/A|2332.85|N/A|1 h	N/A|2805.64|N/A|1 h
		Three-index	N/A|3504.62|N/A|1 h	N/A|1947.17|N/A|1 h	N/A|2354.78|N/A|1 h
	F3	Alternative	*3760.94|140.81 s	N/A|2601.75|N/A|1 h	*3816.21|2479.47 s
		Three-index	*3760.94|105.51 s	N/A|2543.78|N/A|1 h	3816.21|3728.33|2.3%|1 h
	F4	Alternative	*5021.79|33.69 s	*4069.09|1032.28 s	*3919.53|126.08 s
		Three-index	*5021.79|22.95 s	*4069.09|842.37 s	*3919.53|204.24 s
	F5	Alternative	*6097.80|0.16 s	*5158.57|2.67 s	*5534.97|0.41 s
		Three-index	*6097.80|2.95 s	*5158.57|81.99 s	*5534.97|22.17 s
RC1	F1	Alternative	*5905.51|26.92 s	*4865.30|924.37 s	*5155.86|59.58 s
		Three-index	*5905.51|58.06 s	*4865.30|972.45 s	*5155.86|89.29 s
	F2	Alternative	4872.51|4279.18|12.2%|1 h	N/A|2996.66|N/A|1 h	N/A|4090.26|N/A|1 h
		Three-index	N/A|3655.65|N/A|1 h	N/A|2569.00|N/A|1 h	N/A|3428.90|N/A|1 h
	F3	Alternative	*4290.70|1749.44 s	N/A|3878.56|N/A|1 h	4898.96|4734.36|3.4%|1 h
		Three-index	*4290.70|2941.70 s	4381.43|4239.59|3.2%|1 h	4898.96|4586.38|6.4%|1 h
	F4	Alternative	*5792.97|1.11 s	*5443.72|117.84 s	*5121.86|49.93 s
		Three-index	*5792.97|7.36 s	*5443.72|486.48 s	*5121.86|37.19 s
	F5	Alternative	*6133.80|0.22 s	*6188.12|3.19 s	*6145.94|6.98 s
		Three-index	*6133.80|2.97 s	*6188.12|23.88 s	*6145.94|55.44 s
RC2	F1	Alternative	*3338.58|46.11 s	N/A|2639.34|N/A|1 h	*3778.22|63.70 s
		Three-index	*3338.58|87.79 s	N/A|2648.21|N/A|1 h	*3778.22|74.04 s
	F2	Alternative	3728.45|3547.04|4.9%|1 h	N/A|2463.10|N/A|1 h	3466.96|3228.76|6.9%|1 h
		Three-index	N/A|3155.43|N/A|1 h	N/A|2137.28|N/A|1 h	N/A|3011.43|N/A|1 h
	F3	Alternative	*3019.86|781.27 s	N/A|2414.92|N/A|1 h	3143.39|2976.01|5.3%|1 h
		Three-index	3019.86|2982.49|1.2%|1 h	N/A|2294.11|N/A|1 h	N/A|2874.58|N/A|1 h
	F4	Alternative	*3899.26|5.86 s	3225.64|3028.60|6.1%|1 h	*3343.08|2271.19 s
		Three-index	*3899.26|38.69 s	N/A|2929.20|N/A|1 h	3343.08|3226.21|3.5%|1 h
	F5	Alternative	*4551.39|0.22 s	*4161.35|9.59 s	*4085.26|4.66 s
		Three-index	*4551.39|3.10 s	*4161.35|9.04 s	*4085.26|22.20 s

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TABLE A4 | Compact MIP formulations: solutions to 75-request instances.

			W1	W2	W3
C1	F1	Alternative	*9972.16|169.28 s	N/A|7738.23|N/A|1 h	*10,077.00|2568.54 s
		Three-index	*9972.16|241.89 s	*8574.80|1141.87 s	*10,077.00|433.42 s
	F2	Alternative	N/A|6908.11|N/A|1 h	N/A|4522.93|N/A|1 h	N/A|5605.27|N/A|1 h
		Three-index	N/A|5284.67|N/A|1 h	N/A|4173.09|N/A|1 h	N/A|4066.56|N/A|1 h
	F3	Alternative	8363.86|8154.07|2.5%|1 h	N/A|5305.10|N/A|1 h	8002.06|7648.37|4.4%|1 h
		Three-index	8400.56|7836.21|6.7%|1 h	N/A|5716.14|N/A|1 h	N/A|7648.23|N/A|1 h
	F4	Alternative	*9714.16|5.97 s	N/A|7442.80|N/A|1 h	*9170.22|149.41 s
		Three-index	*9714.16|73.29 s	7955.52|7785.33|2.1%|1 h	*9170.22|127.79 s
	F5	Alternative	*10,256.36|0.88 s	*9949.94|5.98 s	*10,320.45|3.16 s
		Three-index	*10,256.36|13.76 s	*9949.94|70.96 s	*10,320.45|20.06 s
C2	F1	Alternative	*5164.12|301.64 s	N/A|3516.37|N/A|1 h	5166.93|5117.75|1.0%|1 h
		Three-index	*5164.12|1137.19 s	N/A|3442.19|N/A|1 h	5166.93|5135.34|0.6%|1 h
	F2	Alternative	N/A|4226.24|N/A|1 h	N/A|2114.50|N/A|1 h	N/A|3040.56|N/A|1 h
		Three-index	N/A|3424.06|N/A|1 h	N/A|1702.02|N/A|1 h	N/A|2124.42|N/A|1 h
	F3	Alternative	3512.74|3475.71|1.05%|1 h	N/A|2304.67|N/A|1 h	N/A|3495.57|N/A|1 h
		Three-index	N/A|3303.47|N/A|1 h	N/A|1827.96|N/A|1 h	N/A|3112.05|N/A|1 h
	F4	Alternative	*4982.08|48.55 s	N/A|3077.37|N/A|1 h	4340.95|4290.78|1.2%|1 h
		Three-index	*4982.08|691.51 s	N/A|2982.65|N/A|1 h	N/A|4099.48|N/A|1 h
	F5	Alternative	*5139.03|0.91 s	*4515.02|182.59 s	*4451.20|15.00 s
		Three-index	*5139.03|9.13 s	*4515.02|766.09 s	*4451.20|21.79 s
R	F1	Alternative	7234.15|7056.21|2.5%|1 h	N/A|5036.45|N/A|1 h	*6990.10|226.04 s
		Three-index	*7234.15|319.80 s	N/A|5273.29|N/A|1 h	*6990.10|2482.76 s
	F2	Alternative	N/A|5254.76|N/A|1 h	N/A|2913.15|N/A|1 h	N/A|4001.86|N/A|1 h
		Three-index	N/A|4433.92|N/A|1 h	N/A|2236.91|N/A|1 h	N/A|3263.69|N/A|1 h
	F3	Alternative	5764.07|5623.86|2.4%|1 h	N/A|4738.76|N/A|1 h	N/A|5059.76|N/A|1 h
		Three-index	N/A|5502.60|N/A|1 h	N/A|4535.37|N/A|1 h	N/A|4913.70|N/A|1 h
	F4	Alternative	*7255.03|20.79 s	N/A|4873.80|N/A|1 h	6175.91|6067.48|1.8%|1 h
		Three-index	*7255.03|64.96 s	N/A|5170.61|N/A|1 h	*6175.91|1689.22 s
	F5	Alternative	*7051.56|6.58 s	*6479.30|133.98 s	*7551.07|6.48 s
		Three-index	*7051.56|30.59 s	*6479.30|283.58 s	*7551.07|99.65 s
RC1	F1	Alternative	*7894.95|96.29 s	N/A|5057.09|N/A|1 h	*7738.40|162.46 s
		Three-index	*7894.95|1390.06 s	N/A|5081.56|N/A|1 h	*7738.40|540.75 s
	F2	Alternative	N/A|5745.76|N/A|1 h	N/A|3316.79|N/A|1 h	N/A|5205.51|N/A|1 h
		Three-index	N/A|4870.18|N/A|1 h	N/A|2783.24|N/A|1 h	N/A|4170.49|N/A|1 h
	F3	Alternative	7448.88|7395.16|0.7%|1 h	N/A|4659.52|N/A|1 h	7445.36|7203.83|3.2%|1 h
		Three-index	7448.88|7388.03|0.8%|1 h	N/A|5038.91|N/A|1 h	7690.90|7007.64|8.9%|1 h
	F4	Alternative	*8346.91|26.56 s	N/A|6231.12|N/A|1 h	*8166.84|148.79 s
		Three-index	*8346.91|65.37 s	N/A|6390.22|N/A|1 h	*8166.84|195.73 s
	F5	Alternative	*9567.19|0.72 s	*7894.69|10.14 s	*8702.35|5.31 s
		Three-index	*9567.19|12.89 s	*7894.69|17.57 s	*8702.35|10.83 s
RC2	F1	Alternative	*5624.80|153.02 s	N/A|4074.88|N/A|1 h	N/A|5863.80|N/A|1 h
		Three-index	*5624.80|636.25 s	N/A|4031.24|N/A|1 h	6240.76|6207.64|0.5%|1 h
	F2	Alternative	N/A|4230.93|N/A|1 h	N/A|2562.45|N/A|1 h	N/A|3549.14|N/A|1 h
		Three-index	N/A|3733.87|N/A|1 h	N/A|1721.96|N/A|1 h	N/A|2681.89|N/A|1 h
	F3	Alternative	5399.58|5346.46|1.0%|1 h	N/A|3001.19|N/A|1 h	N/A|3849.10|N/A|1 h
		Three-index	N/A|5014.28|N/A|1 h	N/A|2744.04|N/A|1 h	N/A|3621.80|N/A|1 h
	F4	Alternative	*5700.68|34.13 s	N/A|3356.97|N/A|1 h	5104.52|4976.29|2.5%|1 h
		Three-index	*5700.68|106.48 s	N/A|3036.78|N/A|1 h	N/A|4885.35|N/A|1 h
	F5	Alternative	*7108.35|0.70 s	5340.85|5151.53|3.5%|1 h	*6164.23|37.80 s
		Three-index	*7108.35|11.73 s	5340.85|5288.00|1.0%|1 h	6164.23|6035.93|2.08%|1 h

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