Global Intermodal Tank Container Management for the Chemical Industry

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Abstract

The scale of the global chemical industry is enormous: in 2003, the total value of global production exceeded US$1.7 trillion. International logistics is especially crucial to the high-value chemicals industry, since raw materials sources, production facilities, and consumer markets are distributed globally. Fluctuating demand, imbalanced trade flows, and expensive transportation equipment necessitate dynamic asset management. This paper focuses on asset management problems faced by tank container operators, and formulates an operational tank container management problem as a large-scale multi-commodity flow problem on a time-discretized network. By integrating container routing and repositioning decisions in a single model, total operating costs and fleet sizes can be reduced. A computational study verifies this hypothesis.

Keywords: Empty repositioning, intermodal containers, multi-commodity network flow
1 Introduction

The chemical industry is growing steadily, especially in China, where chemical consumption is growing at a rate of 8% annually (China is projected to become the third largest consumer by 2010). The value of global chemical production exceeded US$1.7 trillion in 2003. World trade in chemicals continues to surge as well. In 2002, chemicals led all product groups in global trade growth at over 10%, with total world export value reaching US$660 billion. As a consequence, transport of chemicals represents a significant portion of worldwide transport of goods.

Long-distance, international transportation of liquid chemicals is conducted using one of five modes: pipeline, bulk tankers, parcel tankers, tank containers, or drums. Pipeline and bulk tankers are used primarily in the petrochemical industry for the transport of large quantities of a single product. Parcel tankers are smaller vessels with up to 42 tank compartments and are used to simultaneously transport multiple cargoes. Tank containers, also referred to as ISO tanks, intermodal tanks, or IMO portable tanks, are designed for intermodal transportation by road, rail, and ship. Tank containers have many advantages for the international transport of liquid chemicals:

- They are environment-friendly, since they are less prone to spillage during filling and unloading, as well as leakage during transportation.
- They permit a higher payload when compared to drums stowed in dry containers (43% more volume).
- They can be handled mechanically, which results in cost savings, but also ensures safety when handling hazardous commodities.
- They provide secure door-to-door multi-modal transportation (by road, rail, sea or inland waterways), and do not require specialized port-side infrastructure.
• They are safe and durable, with a design life of 20-30 years.

• They can be cleaned and placed into alternate commodity service with minimum downtime.

• They can be used as temporary storage for customers with limited space or high-cost permanent storage.

A tank container operator manages a fleet of tanks to transport liquid cargo for a variety of customers between essentially any two points in the world. Typically, 60% to 70% of the fleet is owned by the operator; the remaining tanks are leased, usually for periods of 5 to 10 years. To serve a standard customer order, a tank container operator would provide a tank (or multiple tanks) at the customer’s origin plant and arrange transportation for the tank across multiple modes to the destination plant. Transportation will usually include a truck leg at origin and destination and a steamship leg between a port near the origin to another port close to the destination. It may also include rail or barge legs at each end. Operators use depots for temporary storage, cleaning, and repair of empty containers.

In this paper, we consider the management problems faced by tank container operators. Specifically, we are interested in the difficult task of cost-effectively managing a fleet of tank containers, given imbalanced global trade flows. Given the high cost of tanks, high loaded container utilization is very important in this industry.

The remainder of this paper is organized as follows. In Section 2, we discuss tank container management in more detail. In Section 3, we develop an optimization model for integrated tank container management, where loaded and empty movements are planned simultaneously. In Section 4, we present the results of a computational study demonstrating the value of optimization-based tank container management. Finally, in Section 5, we outline our plans for extending and enhancing the presented model.
2 Tank container management

Tank container operators do not typically own or manage any of the underlying transportation services used to move a container from origin to destination. Instead, they enter into contracts for transportation service with a number of providers. Tank container operators maintain contracts with trucking companies, railroads, and port drayage companies for inland transportation, and with container steamship lines and nonvessel operating common carriers (NVOCCs) for port-to-port ocean transportation. Each transport service contract specifies transport legs that are available to the operator, and their costs. Operators combine these legs into itineraries to provide origin-to-destination service for customers.

The typical service offering provided by a tank operator to a shipper customer is a one-way trip. To obtain service, customers first place a request for a price quote for a given origin-destination pair, and then subsequently make a booking or multiple bookings under the quote. We will call these steps the quotation and booking processes respectively. With the exception of certain ancillary charges, the tank container operator charges the customer a fixed price for transportation, and pays the transportation service providers directly out of this fee. Therefore, it is in the operator’s interest to minimize the transportation costs for most shipments. However, there must be a level of “reasonableness” in transit times, and some customers may be willing to pay a premium for faster service.

To develop price quotes for customers, container operators currently rely on a port-to-port methodology for developing and pricing itineraries. In this process, the operator associates both the origin and destination customer locations with an appropriate export port and import port. Then, using a database of available ocean carrier contracts and the scheduled sailings for each carrier, at most two or three potential ocean carrier services between these ports are selected. Each such service forms the basis for an itinerary. The price of each itinerary is then determined by adding an inland transportation cost (if necessary), a profit component, and possibly an overhead cost allocation (for example, to account for
asset repositioning costs) to the ocean service cost. The itinerary transit time is computed by adding inland transport times if necessary and schedule delays to the transit time of the scheduled ocean service. These identified itineraries now likely provide different combinations of price and transit time. Typically, the low-price itinerary is first presented to the customer, and if the transit time is unacceptable a higher-price shorter-duration option is presented. Once the customer selects an itinerary, the quote is formalized.

Price quotes to customers are usually valid anywhere from 30 to 90 days (and sometimes longer), and one or many bookings may be made over the duration of the quote. When booking, the customer specifies the number and type of tank containers needed, and service time windows at the origin and destination. Minimally, the time window information will include the earliest time containers may be loaded at the origin, and the latest time containers should be delivered to the destination. Given these requirements, the tank operator must verify that the quoted itinerary is feasible. Since ocean sailings are scheduled and service is not provided each day, the sailing used to generate the quote may or may not allow a feasible routing satisfying the time windows. The operator must also verify that the quoted sailings have available space. If all components of the quoted service offering are not available, the operator must determine an alternative best itinerary that meets customer requirements.

**Empty repositioning** is a critical component of tank container management. Since fleet operators provide global service and loaded flow patterns are not balanced geographically, some regions tend to be net sources of empty tanks and others net sinks. Additionally, loaded flow demands exhibit seasonal patterns. Operators correct geographic and temporal imbalances in container supply and demand by repositioning empty containers between depots.

Some tank container operators have recently begun using decision support tools based on mathematical programming for dynamic operational planning of reposition moves. One method that we are aware of determines weekly repositioning moves using a deterministic
multi-commodity network flow model to minimize empty move cost given forecasts of loaded arrivals and departures in each port area. Such models typically use a planning horizon of several months discretized into weeks, and are solved each week with only the first week’s decisions implemented in the standard rolling-horizon approach. Empty container repositioning has received a fair amount of research attention since it is an integral part of many freight transportation problems (see, e.g., Crainic et al., 1993; Shen and Khoong, 1995; Cheung and Chen, 1998; Choong et al., 2002). Repositioning decisions have also been treated directly in large-scale tactical planning models. Recent work by Bourbeau et al. (2000), for example, develops parallel solution techniques for large-scale static container network design problems that explicitly consider repositioning decisions.

Many opportunities exist to provide improved operational decision support technology to tank container operators. However, we believe that the most significant opportunity lies in integrating container booking and routing decisions with repositioning decisions. When a tank container is booked, an appropriate empty is assigned to the load, moved from its depot to the customer, loaded and transported via multiple modes to the destination meeting customer requirements, moved back to a depot for cleaning, and then stored or repositioned for future use. An operator making these decisions centrally for a global system via an integrated management model may indeed be able to reduce costs and improve equipment utilization. Such an integrated approach would differ substantially from current practice. Although optimization models are used for repositioning, the inputs to current models are forecasts of weekly loaded flow imbalances at depots; thus, container routings that may improve flow balance without repositioning are ignored. This approach to container management, i.e., breaking up the problem into an empty container allocation phase and a container booking and routing phase, resembles the one proposed about a decade ago by Crainic et al. (1993). They argue that “one would like to develop a single mathematical model to optimize short-term land operations of the company to fully account for the interaction between the various

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decisions to be made, but given the intrinsic complexity of the problem at-hand and the current state-of-the-art in OR, this is not feasible.” We will show that even though such integrated models will indeed be substantially larger than existing repositioning models, recent advances in linear and integer programming technology and in computer hardware technology are able to absorb the increased computational requirements.

It is interesting to note that in a recent article discussing the successful implementation of an optimization-based decision support system for the operational management of Danzas Euronet, the typical decomposition approach, in which repositioning decisions are considered separately from customer order planning, is followed (Jansen et al. (2004)). One reason a decomposition approach is used for this application may be due to the fact that Danzas manages 2,000-6,000 customer container orders daily, and would like to handle a planning horizon of up to three days for order decisions.

3 An integrated container management model

This section describes an integrated operational model for tank container operators providing decision support for routing booked containers and repositioning empties. For simplicity of exposition, we assume that the operator manages a homogeneous fleet of containers. The problem is formulated as a deterministic multicommodity network flow over a time-expanded network. This type of formulation is often used to model freight transportation problems (see, e.g., Crainic and Laporte, 1997; Crainic, 2000).

3.1 Problem Definition

Consider an operator managing a global tank fleet. Let $D$ represent the set of container depots used to store and clean containers, and let $P$ be the set of seaports through which the operator maintains ocean transportation service contracts.
Suppose that the operator is making decisions at time $t = 0$ by planning movements for a fixed horizon $[0, t_{\text{max}}]$. In a rolling horizon approach, container movement decisions in some subinterval $[0, t_R]$, $t_R \leq t_{\text{max}}$ are implemented. Let $T$ be the ordered set of time periods to be considered, $T = \{0, ..., t_{\text{max}}\}$.

At time $t = 0$, a set of containers are empty, clean, and available (ECA) for assignment at depot locations. Other containers are in transit and will become ECA at specific depots at future time periods. Additionally, new purchased or leased containers may come into the system at depots at future times, and existing containers may leave the system in the future due to retires or lease returns. If we assume homogeneity, container availabilities can be summarized by net ECA container inflows at depots at specific points in time. For each depot $d \in D$ and time $t \in T$, let $b_{dt}$ be the net ECA container inflow, where a negative number indicates a net outflow. Of course, this modeling convention does not track specific individual container numbers which may be important if modeling lease returns.

During $T$, the operator must serve a set of origin-destination customer demands $\Delta$ which we assume to be known with certainty. Let $L$ be the set of all customer locations (origin and destination). Each demand $\delta \in \Delta$ may represent booked containers or forecasted future container bookings, and minimally has the following characteristics:

- $o_\delta \in L$ origin customer location
- $d_\delta \in L$ destination customer location
- $n_\delta$ number of containers to be transported
- $e_\delta \in T$ earliest time empty containers can be delivered to origin
- $l_\delta \in T$ latest time loaded containers can begin unloading at destination
- $\tau^L_\delta$ time required to load all containers at origin
- $\tau^U_\delta$ time required to unload all containers at destination

This representation simplifies the customer time windows. If more detailed information such as the latest time loaded containers can depart the origin customer or the earliest time loaded
containers can be delivered to the destination were available, it could be used to restrict the problem further.

Operators contract with providers for two types of transportation service. *Scheduled service* is provided by ocean carriers between seaport pairs in $P \times P$. Let $\Phi$ be the set of scheduled service contracts, where $\phi \in \Phi$ minimally has the following attributes:

- $o_\phi \in P$ origin port of the service
- $d_\phi \in P$ destination port
- $\tau_\phi$ total sailing time
- $T^D_\phi \subseteq T$ time periods at which service departs origin port
- $T^A_\phi \subseteq T$ time periods at which service arrives destination port
- $c_\phi$ cost per container

Sets $T^D_\phi$ and $T^A_\phi$ describe the schedule of any service over the planning horizon. For now, we ignore service commitments or capacities.

*Unscheduled services* are available every time period. Unscheduled service may represent local or long-haul trucking, rail service, and barge feeder service. Let $\Theta$ be the set of unscheduled service contracts, where $\theta \in \Theta$ minimally has the following attributes:

- $o_\theta \in D \cup L \cup P$ origin depot, customer, or port
- $d_\theta \in D \cup L \cup P$ destination depot, customer, or port
- $\tau_\theta$ total transport time
- $c_\theta$ cost per container

Containers may be repositioned empty between all depot pairs using both scheduled services $\Phi$ and unscheduled services $\Theta$. Suppose that all depot-to-depot repositioning options are specified by set $\Gamma$. Each $\gamma \in \Gamma$ specifies:
$o_\gamma \in D$ origin depot

$d_\gamma \in D$ destination depot

$T_D^D \subseteq T$ time periods at which option departs origin depot

$T_A^A \subseteq T$ time periods at which option arrives destination depot

$\tau_\gamma$ total travel time

$c_\gamma$ total cost per container

We assume that each $\gamma \in \Gamma$ is generated by transportation service contracts. When repositioning for a depot-depot pair can be conducted directly via an unscheduled service $\theta \in \Theta$, we create a repositioning option which departs the origin depot at all time periods. When repositioning between depots $i$ and $j$ uses a scheduled service $\phi \in \Phi$ (i.e., needs to be routed through a seaport), we create an option combining the costs and times of an unscheduled service to connect $i$ to $o_\phi$, the scheduled service connecting $o_\phi$ to $d_\phi$, and then an unscheduled service to connect $d_\phi$ to $j$. Such composite options depart the origin depot at time periods appropriate for the container to meet the scheduled service sailings without delay.

Finally, we consider important container processing steps at depots and customers. It is assumed that customers return containers to the depot that is closest in distance to the customer location, and that this transportation requires only unscheduled transportation service. After a container is returned to a depot, it must undergo cleaning before it can be stored or reused. Let $\tau^C_d$ represent the duration of the cleaning process at depot $d \in D$, which may vary due to available equipment; in fact, some depots must send containers out for cleaning. In this initial problem, however, we assume that depot cleaning times are independent of the previous commodity transported. Let $c_d$ represent the per container cleaning cost at $d$. Furthermore, we assume that there are no capacity restrictions for cleaning or storage at the depots.

At customer locations, arriving empty containers must immediately begin loading and must depart once loaded. On the other end of the move, we assume that loaded containers
arriving at a destination customer must immediately begin unloading, and once unloaded must be immediately dispatched to a depot.

Given this description, the goal of the tank container operator is to route loaded containers and reposition empty containers to serve all customer demands according to time window requirements, while minimizing total transportation and depot costs incurred.

3.2 Multi-commodity network flow model

The optimization problem outlined in the previous section can be formulated as a deterministic multi-commodity network flow on a time-expanded network. For simplicity of exposition, suppose that $T$ is a uniform discretization, where each time period represents a day: $T = \{0, 1, 2, ..., t_{\text{max}}\}$.

**Decision variables** Each variable represents integer flows of containers, both loaded and empty, through different stages of routing.

**Container flow variables**

- $x_\delta^\phi(t) = \text{containers of demand } \delta \text{ transported by scheduled option } \phi \text{ at time } t$
- $y_\delta^\theta(t) = \text{containers transported by unscheduled option } \theta \text{ at time } t \text{ associated with demand } \delta$, either empty or loaded
- $u_\delta(t) = \text{containers of demand } \delta \text{ beginning unloading at time } t$
- $v_\delta(t) = \text{containers of demand } \delta \text{ beginning loading at time } t$
- $z_\gamma(t) = \text{containers transported with repositioning option } \gamma \text{ at time } t$
- $s_d(t) = \text{inventory of ECA containers carried at depot } d \text{ from time } t \text{ to } t + 1$
- $w_d(t) = \text{containers beginning cleaning at depot } d \text{ at time } t$

Of course, each of these flow variables need not be present at each time period of the model. For example, we can exclude loaded flows $x_\delta^\phi$ and $y_\delta^\theta$ for time periods $t < e_\delta + \tau_\delta^L$ and $t > l_\delta$. Instance-specific preprocessing may be able to further tighten the time windows for which
certain flow variables require definition.

The model description to follow does not prevent a customer demand of more than one container to be split as it is routed through the network, as long as each container in the demand reaches the destination by the customer deadline. If demands are unsplittable in the sense that they should be loaded and unloaded simultaneously and use the same transportation options, an alternative formulation is required.

**Constraints** The decision variables must satisfy constraints of three general types: (a) flow balance, (b) time-window demand satisfaction, and (c) integrality and non-negativity.

**Port nodes**

In the model, each port \( p \in P \) only explicitly handles loaded container flows, strictly assigned to some demand \( \delta \). (Empty repositioning flows between depots that require the use of scheduled services through ports are handled independently using set \( \Gamma \), as explained in the previous section.) We require flow balance constraints for both containers to be loaded onto scheduled services (export), and containers to be unloaded from scheduled services (import):

**Port export flow balance**

\[
\sum_{\phi \in \Phi|\alpha_\phi = p, \, t \in T^D_\phi} x^\delta_{\phi}(t) - \sum_{\theta \in \Theta|\alpha_\theta = \alpha_\delta, \, d_\theta = p} y^\delta_{\theta}(t - \tau_\theta) = 0 \quad \forall \, p \in P, \, t, \, \delta \quad (1)
\]

**Port import flow balance**

\[
\sum_{\theta \in \Theta|\alpha_\theta = p, \, d_\theta = d_\delta} y^\delta_{\theta}(t) - \sum_{\phi \in \Phi|d_\phi = p, \, t \in T^A_\phi} x^\delta_{\phi}(t - \tau_\phi) = 0 \quad \forall \, p \in P, \, t, \, \delta \quad (2)
\]

**Depot nodes**

Each depot \( d \in D \) is treated as two nodes at each point in time. One node allows for the
consolidation of arrivals of dirty empty containers from destination customer locations, while
the other models flow balance of ECA containers. Thus, we need two sets of flow balance
constraints for each depot at each point in time.

**Depot dirty flow balance**

\[
w_d(t) - \sum_{\theta \in \Theta | d_\theta = d} \sum_{\delta \in \Delta | d_\delta = o_\theta} g_\theta^\delta(t - \tau_\theta) = 0 \quad \forall \ d \in D, \ t \quad (3)
\]

**Depot ECA flow balance**

\[
\sum_{\theta \in \Theta | o_\theta = d} \sum_{\delta \in \Delta | o_\delta = d_\theta} y_\theta^\delta(t) + \sum_{\gamma \in \Gamma | o_\gamma = d, \ t \in T^p_d} z_\gamma(t) + s_d(t) - \sum_{\gamma \in \Gamma | d_\gamma = d, \ t \in T^f_d} z_\gamma(t - \tau_\gamma) - w_d(t - \tau_d^C) - s_d(t - 1) = b_d t \quad \forall \ d \in D, \ t \quad (4)
\]

**Customer locations**

Customer locations \( \ell \in L \) during the planning horizon may be origins of freight, destinations of freight, or both. In the absence of capacity restrictions on loading and unloading demands, constraints at customers can be separated by demand. Constraints (5) and (6) model loading operations, where arriving empty containers begin loading and upon loading completion are immediately dispatched.

**Demand loading flow balance**

\[
v^\delta(t) - \sum_{\theta \in \Theta | d_\theta = o_\delta} g_\theta^\delta(t - \tau_\theta) = 0 \quad \forall \ \delta \in \Delta, \ e_\delta \leq t \leq l_\delta \quad (5)
\]

**Demand outbound flow balance**

\[
\sum_{\theta \in \Theta | o_\theta = o_\delta} y_\theta^\delta(t) - v^\delta(t - \tau^L_\delta) = 0 \quad \forall \ \delta \in \Delta, \ e_\delta + \tau^L_\delta \leq t \leq l_\delta \quad (6)
\]
Similarly, constraints (7) and (8) model the arrival of loaded containers to their destination. These tanks are immediately unloaded, and then dispatched dirty to a container depot:

**Demand inbound flow balance**

\[ u^\delta(t) - \sum_{\theta \in \Theta | d_\theta = d_\delta} y^\delta_{\theta}(t - \tau_\theta) = 0 \quad \forall \ \delta \in \Delta, \ e_\delta + \tau^L_\delta \leq t \leq l_\delta \]  

(7)

**Demand unloading flow balance**

\[ \sum_{\theta \in \Theta | o_\theta = d_\delta} y^\delta_{\theta}(t) - u^\delta(t - \tau^U_\delta) = 0 \quad \forall \ \delta \in \Delta, \ e_\delta + \tau^U_\delta \leq t \leq l_\delta + \tau^U_\delta \]  

(8)

In addition to flow balance, we must also ensure that all containers in each demand are loaded and unloaded during the appropriate customer time window. The following constraints are used:

**Loading demand time windows**

\[ \sum_{e_\delta \leq t \leq l_\delta} v^\delta(t) = n_\delta \quad \forall \ \delta \in \Delta \]  

(9)

**Unloading demand time windows**

\[ \sum_{e_\delta \leq t \leq l_\delta} u^\delta(t) = n_\delta \quad \forall \ \delta \in \Delta \]  

(10)

We note that constraints (9) and (10) introduce difficulty into this model, since they bundle and constrain flow for multiple demands.

**Integrality and non-negativity**

\[ x^\phi_\phi(t), y^\delta_{\theta}(t), u^\delta(t), v^\delta(t), z_\gamma(t), s_d(t), w_d(t) \geq 0 \quad \text{and integer} \]  

(11)
**Objective Function** The objective is to minimize the total cost of all empty and loaded transportation, and depot costs:

$$\min EC + LC + DC$$ \hspace{1cm} (12)

where the empty cost is given by

$$EC = \sum_t \sum_{\delta \in \Delta} \sum_{\theta \in \Theta \{\theta_0 = \alpha_k\}, \{\theta_0 = \delta_k\}} c_{\theta} y_{\delta}^\theta(t) + \sum_t \sum_{\gamma \in \Gamma} c_{\gamma} z_{\gamma}(t),$$

the loaded cost by

$$LC = \sum_t \sum_{\delta \in \Delta} \sum_{\phi \in \Phi} c_{\phi} x_{\phi}^\delta(t) + \sum_t \sum_{\delta \in \Delta} \sum_{\theta \in \Theta \{\theta_0 = \alpha_k\}, \{\theta_0 = \delta_k\}} c_{\theta} y_{\delta}^\theta(t),$$

and the depot cost by

$$DC = \sum_t \sum_{d \in D} c_{d} w_d(t).$$

Each of the sums above is assumed to only include time periods $t \in T$ during which the corresponding variable is defined.

4 **A Computational Study**

As mentioned earlier, we believe that substantial benefits can be derived from integrating container booking and routing decisions with repositioning decisions. We have conducted a small computational study to (1) demonstrate that it is now computationally feasible to solve realistic instances of an integrated model using commercially available integer programming software on a high-end personal computer, and (2) assess the magnitude of the benefits of an integrated model in terms of reduced repositioning costs and increased asset utilization.
4.1 Instance Generation

We consider container management problems with a planning horizon of six months, discretized in days. To create representative global problems, we build instances around 10 ports of global importance: Singapore, Hong Kong, Shanghai, Kobe, Hamburg, Rotterdam, Southampton, Seattle, Los Angeles, and Savannah. Each port is paired with a nearby container depot. The ports are grouped together to form six regions as described in Table 1.

<table>
<thead>
<tr>
<th>Region</th>
<th>Ports</th>
<th># customer locations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Singapore</td>
<td>Singapore</td>
<td>5</td>
</tr>
<tr>
<td>Asia</td>
<td>Hong Kong, Shanghai</td>
<td>30</td>
</tr>
<tr>
<td>Japan</td>
<td>Kobe</td>
<td>5</td>
</tr>
<tr>
<td>UK</td>
<td>Southampton</td>
<td>5</td>
</tr>
<tr>
<td>Continental Europe</td>
<td>Hamburg, Rotterdam</td>
<td>25</td>
</tr>
<tr>
<td>America</td>
<td>Seattle, Los Angeles, Savannah</td>
<td>30</td>
</tr>
</tbody>
</table>

Table 1: Region characteristics for the computational study.

Fixed customer locations were generated within each region according to a uniform distribution on a rectangular geographical zone representing the region (see Figure 1 for a depiction of the instance geography).

Transportation between locations in the same region is assumed to be land-based and therefore available whenever desired. Transportation between locations in different regions involves at least one sea leg and therefore depends on available sailings between ports. To determine a representative set of sailings between the ports, we use a published schedule (available online) for a large ocean carrier. For the six-month planning period, over 8,000 port-to-port sailings are considered. The average port-to-port sail time is roughly 18 days.

A set of 900 customer booking demands is generated for the six-month horizon, with each booking requesting between 1 and 5 containers. To reflect geographic trade imbalances, the origin region and destination region for each booking are selected according to the probabilities given in Table 2.

Within the origin and destination regions, the actual origin and destination customer locations are chosen from the set of available locations randomly with equal probability.
For this study, no demands are generated with origin and destination locations in the same region.

For each booking demand $\delta$, the earliest available day $e_\delta$ is generated using a discrete uniform distribution over the planning horizon days. To capture the possibility that different bookings may have varying travel time requirements, we determine the latest delivery day $l_\delta$ for booking $\delta$ as follows. Let $\tau_\delta$ be the average transportation time (in days) from the origin customer to the destination customer, where the average is computed over all itineraries in the planning horizon. Then,

$$l_\delta = e_\delta + \lceil \tau_\delta \rceil + DiscUniform([-0.2 \cdot \tau_\delta, [0.2 \cdot \tau_\delta]).$$

We further ensure that at least one feasible transport itinerary connects the origin customer to the destination customer by simply discarding any booking demand generated during the
Table 2: Distributions of origin-destination customer locations for computational study.

<table>
<thead>
<tr>
<th>Region</th>
<th>Probability of demand originating at region</th>
<th>Conditional probability destination Region 1</th>
<th>Conditional probability destination Region 2</th>
<th>Conditional probability destination Region 3</th>
<th>Conditional probability destination Region 4</th>
<th>Conditional probability destination Region 5</th>
<th>Conditional probability destination Region 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.15</td>
<td>0</td>
<td>0.10</td>
<td>0.05</td>
<td>0.10</td>
<td>0.25</td>
<td>0.50</td>
</tr>
<tr>
<td>2</td>
<td>0.40</td>
<td>0.10</td>
<td>0</td>
<td>0.05</td>
<td>0.10</td>
<td>0.25</td>
<td>0.50</td>
</tr>
<tr>
<td>3</td>
<td>0.10</td>
<td>0.05</td>
<td>0.10</td>
<td>0</td>
<td>0.10</td>
<td>0.25</td>
<td>0.50</td>
</tr>
<tr>
<td>4</td>
<td>0.05</td>
<td>0.15</td>
<td>0.30</td>
<td>0.15</td>
<td>0</td>
<td>0.25</td>
<td>0.50</td>
</tr>
<tr>
<td>5</td>
<td>0.15</td>
<td>0.15</td>
<td>0.30</td>
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<td>0.30</td>
<td>0</td>
<td>0.10</td>
</tr>
<tr>
<td>6</td>
<td>0.15</td>
<td>0.15</td>
<td>0.40</td>
<td>0.10</td>
<td>0.10</td>
<td>0.25</td>
<td>0</td>
</tr>
</tbody>
</table>

construction of the instance for which no feasible transport itinerary exist.

The final component of an instance is the number of available tank containers $\hat{b}$. For simplicity, we assume that the fleet is initially distributed over the depots according to the demand destination probabilities implied by Table 2. We consider three fleet scenarios in the computational experiments that follow. The first scenario models an excess capacity environment with $\hat{b} = 1000$; the system contains many more containers than necessary to handle all demand. The second scenario models an adequate capacity environment with $\hat{b} = 800$. Finally, the third scenario represents a tight capacity environment with $\hat{b} = 600$. In the tight environment, there are certain times during the planning horizon when nearly all containers are in use (either traveling loaded with a demand, repositioning, or traveling empty between a customer and a depot).

### 4.2 Repositioning Strategies

We model several repositioning strategies in this study, including a base strategy designed to emulate current state-of-the-practice in tank container management, and three strategies representing different options for deploying an integrated model.

In the base strategy, we consider an environment in which a centralized decision maker determines repositioning decisions independently from routing decisions. We assume as in practice that these decisions are made once per week using estimates of weekly inflows and outflows of containers at depots. We call this the 2-phase strategy. To emulate this strategy
with our model for a given instance, we consider each booking demand $\delta$ and first label the closest container depot to the origin customer location as the origin depot, and the closest depot to the destination customer as the destination depot. Next, we consider all transportation itineraries (combinations of unscheduled and scheduled services) that can be used to feasibly cover $\delta$ within the time window defined by $e_\delta$ and $l_\delta$, and for each itinerary, determine the day that containers would depart the origin depot and be returned to the destination depot. We then assume that containers will depart the origin depot on its modal day, and be returned to the destination depot on its modal day. Aggregating across all bookings, we compute for each depot the expected weekly inflow and outflow of empty containers. These counts are converted to weekly external container inflows and outflows at depots by assuming that the inflow occurs on the final day of the week, and that the outflow occurs on the first day of the week. Next, the integrated model is solved without any demands to determine the weekly repositioning decisions. Finally, the external container inflows and outflows at depots are removed, the repositioning decisions are fixed, and the integrated model is solved with the booking demands to determine the routing decisions.

The three alternative strategies for deploying the integrated container management model also assume a centralized decision-maker, but determine routing and repositioning decisions simultaneously. The three strategies impose different restrictions on the availability of repositioning options, as follows:

- **Weekly Repositioning (WR):** Depot-to-depot repositioning is allowed only on the first day of each week. Further, for a given pair of depots, only the minimum cost repositioning option $\gamma$ is included in the model.

- **Bounded Daily Repositioning (BDR):** Depot-to-depot repositioning is allowed every day, and all repositioning options are included in the model. However, if a repositioning move is initiated on a given day, a lower bound on the number of containers repositioned is imposed to avoid repeatedly sending small numbers of containers.
• **Unbounded Daily Repositioning (UDR):** Depot-to-depot repositioning is allowed every day with all repositioning options. No lower bounds are imposed.

### 4.3 Computational Results

The integrated container management model was implemented using ILOG’s OPL Studio 3.6.1 and instances were solved using ILOG’s CPLEX 8.1. All computational experiments were conducted on a PC with a 1.6 GHz processor and 1 Gb of memory. Given a repositioning strategy and a container fleet size, we solved many instances representing different realizations of customer request demand over the six-month planning horizon. Since the variations between the results were relatively small for problems with the same characteristics, we have chosen to present results for a representative six-month demand realization generated with a particular seed rather than averaging results over many instances. The 900 customer requests in the representative instance require a total of 2,237 tank containers.

First, we compare the repositioning costs determined under the 2-phase strategy to those determined when using the integrated model with the unbounded daily repositioning (UDR) strategy. Table 3 presents the results.

<table>
<thead>
<tr>
<th>Container Fleet Size</th>
<th>Repositioning Costs: 2-phase</th>
<th>Repositioning Costs: Integrated UDR</th>
<th>Percent Improvement</th>
<th>CPU Time: Integrated UDR (seconds)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>125,969</td>
<td>113,286</td>
<td>10.0</td>
<td>81.46</td>
</tr>
<tr>
<td>800</td>
<td>152,174</td>
<td>131,489</td>
<td>13.5</td>
<td>68.42</td>
</tr>
<tr>
<td>600</td>
<td>-</td>
<td>165,546</td>
<td>-</td>
<td>174.53</td>
</tr>
</tbody>
</table>

Table 3: Comparison of repositioning costs between 2-phase approach and integrated UDR approach.

Note that all instances were solved within 3 minutes of CPU time and that no feasible solution was found by the 2-phase strategy in the tight capacity scenario.

The results in Table 3 demonstrate the value of integrated container management since empty repositioning costs are substantially reduced (by 10.0% in the overcapacity scenario).
and by 13.5% in the adequate capacity scenario). However, perhaps even more interesting is the fact that the integrated model is able to produce a feasible schedule in an environment with far fewer containers in the system (the 2-phase strategy was also unable to find a feasible solution with 700 containers in the system). The integrated container management model is able to fully exploit any routing flexibility offered by the service time windows for each booking. This indicates that it may be very beneficial for container operators to try to collaborate with their customers to obtain timely and accurate information about bookings, since it may allow the container operator to free up capital that is otherwise tied up in expensive tank containers.

In the next experiment, we investigate the relative performance of the three alternative deployment strategies for the integrated model. We first compare the costs determined by the UDR, BDR, and WR strategies in Table 4. Note that for the BDR strategy, we assume that a lower bound of 4 containers must be transported whenever a depot-to-depot repositioning move is initiated.

<table>
<thead>
<tr>
<th>Container Fleet Size</th>
<th>Repositioning Strategy</th>
<th>Minimum repositioning quantity</th>
<th>Repositioning costs</th>
<th>Land-based transportation costs</th>
<th>Ocean-based transportation costs</th>
<th>Total costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>UDR</td>
<td>1</td>
<td>113,286</td>
<td>298,908</td>
<td>503,800</td>
<td>915,994</td>
</tr>
<tr>
<td>1000</td>
<td>WR</td>
<td>1</td>
<td>129,372</td>
<td>298,716</td>
<td>504,374</td>
<td>932,462</td>
</tr>
<tr>
<td>1000</td>
<td>BDR</td>
<td>4</td>
<td>113,668</td>
<td>298,668</td>
<td>503,920</td>
<td>916,256</td>
</tr>
<tr>
<td>600</td>
<td>UDR</td>
<td>1</td>
<td>165,546</td>
<td>294,372</td>
<td>524,589</td>
<td>984,507</td>
</tr>
<tr>
<td>600</td>
<td>WR</td>
<td>1</td>
<td>173,611</td>
<td>294,564</td>
<td>524,268</td>
<td>992,443</td>
</tr>
<tr>
<td>600</td>
<td>BDR</td>
<td>4</td>
<td>169,727</td>
<td>294,624</td>
<td>526,709</td>
<td>991,060</td>
</tr>
</tbody>
</table>

Table 4: Cost comparison for different integrated repositioning strategies.

The results indicate that it is worthwhile to make repositioning decisions daily as opposed to weekly, especially in environments with overcapacity (a difference of about 12% in repositioning costs, and of about 2% in total cost). It also appears that in the overcapacity environment, deciding the proper timing of repositioning is more important than deciding on the number of containers to reposition because imposing a lower bound on the repositioning quantity has relatively little impact on cost. When capacity is tight, however, imposing such
a lower bound does lead to a slight cost increase.

The container utilization statistics associated with the schedules produced for these strategies are presented in Table 5. The final four columns in the table present the percentage of time containers were in inventory at a depot, the percentage of time containers were being moved empty, the percentage of time containers were being moved loaded, and the percentage of time containers were being moved.

<table>
<thead>
<tr>
<th>Container Fleet Size</th>
<th>Repositioning Strategy</th>
<th>Minimum repositioning quantity</th>
<th>Inventory time</th>
<th>Empty transport time</th>
<th>Loaded transport time</th>
<th>Total transport time</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>UDR</td>
<td>1</td>
<td>45.28%</td>
<td>18.28%</td>
<td>36.43%</td>
<td>54.72%</td>
</tr>
<tr>
<td>1000</td>
<td>WR</td>
<td>1</td>
<td>49.24%</td>
<td>14.43%</td>
<td>36.33%</td>
<td>50.76%</td>
</tr>
<tr>
<td>1000</td>
<td>BDR</td>
<td>4</td>
<td>44.95%</td>
<td>18.37%</td>
<td>36.68%</td>
<td>55.05%</td>
</tr>
<tr>
<td>600</td>
<td>UDR</td>
<td>1</td>
<td>18.66%</td>
<td>26.37%</td>
<td>54.97%</td>
<td>81.34%</td>
</tr>
<tr>
<td>600</td>
<td>WR</td>
<td>1</td>
<td>21.17%</td>
<td>23.60%</td>
<td>55.24%</td>
<td>78.83%</td>
</tr>
<tr>
<td>600</td>
<td>BDR</td>
<td>4</td>
<td>18.91%</td>
<td>26.15%</td>
<td>54.94%</td>
<td>81.09%</td>
</tr>
</tbody>
</table>

Table 5: Utilization comparison for different integrated repositioning strategies.

The results in Table 5 demonstrate the potential value of integrated container management, since high levels of utilization can be realized, i.e., containers being transported over 80% of the time (when capacity is tight). The utilization statistics presented in the table are somewhat biased by start and end effects. In the four months in the middle of the planning horizon, i.e., months two through five, total transport time reaches 95% when capacity is tight. High asset utilization is of key importance to container operators due to relatively high asset capital costs. By using integrated container management models, operators may be able to increase their revenue (satisfying more demands) without having to increase the number of containers under management and thus without requiring additional capital investments.

5 Extensions and Future Research

In the model presented in this paper, we have focused on integrating container routing and repositioning decisions in a single operational model that represents the global transportation
infrastructure at a sufficient level of detail. Primarily for expositional purposes we have concentrated on the core ingredients of the model. In this section, we briefly discuss some natural extensions.

*Supporting a telescoping planning horizon.* In a telescoping planning horizon, the “time buckets” vary over time (typically increasing). For example, the first few weeks may be planned with daily time periods, whereas the remaining portion of the planning horizon is planned with weekly time periods.

*Supporting multiple container types.* One of the key characteristics of the tank container industry (as opposed to the dry container industry) is the large variety of tank container types. Multiple container types can be incorporated in integrated planning models, but may result in substantially larger instances. For example, since different tank container types may have different cleaning requirements and thus times, models have to separately account for the inventory of each tank container type at the depots. Furthermore, the fact that certain chemicals may only be transported in specific tank container types must be modeled properly.

*Supporting transportation capacity.* In many cases, transportation capacity is limited. This is especially true for port-to-port ocean transportation using common carriers.

Two important additional research topics related to the proposed integrated container management model will be investigated. First, we will consider how to handle uncertainty in the input data. There are various sources of input uncertainty. There is uncertainty related to the forecasted demand, but there may also be uncertainty related to the available transportation options, or the costs associated with the transportation options. In recent years, a body of literature has been developing under the name of robust optimization, in which we optimize against the worst-instance that might arise by using a min-max objective. We plan to investigate whether robust optimization ideas may be used effectively in the context of tank container management.
Second, we will investigate how to switch from cost minimization to profit maximization. In many industries revenue management and dynamic pricing have become accepted practice. Revenue management relies on market segmentation, price differentiation, knowledge of historical demand and forecasting capabilities. The goal is to capture high revenues from “service sensitive” customers, while attracting low revenues from “price sensitive” customers. The tank container industry may not be ready for profit maximization yet, but there is enough interest to start evaluating its potential. Operators realize that certain trade lanes are more profitable than others and they would like to be able to book more freight on such trade lanes. However, currently there are no decision tools that help them accomplish this objective, or even allow them to study the system wide effects of trying to do so, e.g., increased reposition costs or lost service levels in other areas.

We hope that in the near future we will be able to deliver such tools.

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**References**


