Optimizing empty container repositioning in a truck-rail intermodal network

by

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Abstract

The geographic imbalance of freight moved by the transportation industry requires repositioning of empty containers. Empty container repositioning (ECR) describes the strategy for empty container relocation to reduce cost and satisfy demand. ECR costs the transportation industry billions of dollars per year worldwide, so the efficient and effective execution of ECR is necessary for maximal equipment utilization. The trucking industry is greatly impacted by ECR decisions because of the high volumes of freight moved every year, leading to thousands of empty containers in need of relocation every week. The trucking industry is incentivized to partner with other transportation modes, considered intermodal transport, for ECR movements because of other modes' lower transit costs. A breadth of research exists for ECR optimization for intermodal ocean networks, but trucking industries operate cross-country and require a low-cost transcontinental solution. Intermodal railroad networks are the ideal ECR solution for trucking companies, but a lack of research exists addressing ECR flow optimization in a strictly truck-rail network.

This thesis focuses on an optimization model for the ECR decisions of a trucking company utilizing a truck-rail intermodal network. Imbalances between inbound and outbound freight flows in metropolitan areas result in sources and demands for empty containers across the network. Empty containers are repositioned via railroad to fulfill demand between these areas. The trucking company's primary goal is to fulfill demand for empty containers while minimizing fees paid to the railroads and its own equipment relocation costs.

The research objective of this thesis is to develop an optimization model to support ECR decisions for realistic truck-rail intermodal systems. The model is demonstrated using data from

a leading trucking company in North America. Comparing the optimization model results to the plans developed by the company’s empty-planning team shows that the model produces high-quality plans, achieves cost savings, can be solved efficiently, and presents novel solutions to the business.

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Dedication

For Griffin—Thank you for your support and friendship.

Chapter 1 - Introduction

The geographic imbalance of freight moved by the transportation industry requires repositioning of empty containers. *Containers* are standardized equipment used to ship goods; they may be transported on ships, rail cars, or truck chassis. *Empty container repositioning* (ECR) describes the strategy for empty container relocation to reduce cost and satisfy demand. ECR costs the transportation industry up to $20 billion per year [1]. Efficient and effective ECR execution is necessary for maximal equipment utilization, although many trucking companies develop ECR plans manually. The trucking industry is greatly impacted by ECR decisions because of the high volumes of freight moved every year, leading to thousands of empty containers in need of relocation every week.

The trucking industry is incentivized to partner with other transportation modes, considered intermodal transport, for ECR movements because of the lower transit costs of other modes. A breadth of research exists for ECR optimization for intermodal ocean freight networks, but trucking industries operate cross-country and require a low-cost transcontinental solution. Intermodal railroad networks are the ideal ECR solution for trucking companies, but a lack of research exists addressing ECR flow optimization in a strictly truck-rail network.

The efficient, effective transportation of freight across North America is essential to economic security. The transportation sector is identified by the U.S. government as a one of the 16 critical sectors to security and economic security in the nation. Commercial trucking and freight rail are called out specifically as key contributors within this sector, and the government prioritizes protecting their ability to transport goods through the country quickly and safely [2]. The increasing economic impact of the truck-rail intermodal industry is highlighted in research for congressional research to promote more efficient intermodal operations [3]. The efficient and effective operations of the North American truck-rail network is of national importance to the U.S. government.

The research objective of this thesis is to develop an optimization model to support ECR decisions for realistic truck-rail intermodal systems. The purpose of the model is to identify a minimum cost solution, from the trucking company's perspective, to satisfy demand for empty containers using supply available via a combination of truck and rail movements. The optimization model was tested with network parameters of a North American Trucking Company (referred to as NATC throughout the thesis).

1.1. Empty Container Repositioning

In the transportation industry, the unequal movement of loaded containers between destinations requires transportation companies to reposition the empty containers. If outbound freight moves from an area do not equal inbound freight moves to that area, empty containers can begin to accumulate. To continue moving freight through the network, empty containers must be relocated to be filled with new freight for shipment. Empty container moves do not generate revenue, but they incur fuel and operator costs. In addition, the inability to route empty containers in time prevents future freight from being shipped and can incur storage and maintenance costs. ECR costs the transportation industry as a whole up to $20 billion per year [1]. An efficient and effective ECR plan is necessary for transportation companies to reduce cost, making it possible to capitalize on potential profit and available equipment. The challenges of ECR are multiplied in an interconnected intermodal network.

1.2. Empty Container Repositioning in Trucking Intermodal Networks

ECR is a major concern for the trucking industry and its partnership with other modes of transport. Partnering with another transportation mode, like the railroad, decreases the cost of moving freight or empty containers long distances while allowing flexible pick-up and delivery locations by truck. The truck-rail transportation method moved 13.7 million containers in 2019 [4], resulting in the need to reposition thousands of empty containers every week to accommodate future freight movements. Repositioning empty containers by rail is 56% cheaper to a trucking company than moving by truck [5], so an intermodal ECR strategy is advantageous to trucking companies. Many trucking companies currently manually develop ECR plans, especially in North America, relying on computational tools like Excel. Manual development is time- and expertise-intensive, relies on an experienced team, and does not ensure an optimal solution. Intra-terminal empty container management is well researched for intermodal port and depot management, but a gap exists for a rail-truck network optimization.

1.3. Case Study Overview

The research in this thesis is broadly motivated by rail-truck intermodal empty container repositioning challenges. The specific problem definition, model development, and computational analyses are informed by a partnership with NATC, one of the largest trucking companies in North America. NATC employs almost 30,000 workers and maintains more than 100,000 trailers and containers according to an anonymous employee of NATC (personal communication, April 12, 2021). The intermodal unit of NATC partners with several major railroad companies, including BNSF, Norfolk Southern, CSX and others, providing a generally lower-cost transportation solution than standard over-the-road trucking to its customers. NATC also operates the largest fleet of 53’ trailer-rail compatible containers of any company in North America [6]. The large and complex nature of NATC’s intermodal operations calls for a robust ECR plan.

The optimization model presented in this thesis was tested using system parameters from NATC's intermodal network and compared to the decisions executed by NATC. Manual ECR planning for NATC Intermodal requires nine employee hours per week, relying on expert opinion for best practices, and Excel for data tracking and computation. Using demand forecasts, data for the containers already in the network, and railroad payment contracts, the team develops the lowest cost plan considering equipment positions and variable demand.

The NATC ECR team assumes several practices to account for variable and approximated demand forecasts. The ECR team often chooses to send more than the forecasted demand to ensure that the supply of empty containers will not be depleted, regardless of the actualized demand. In high-demand areas, the team may choose to send fewer containers than demanded, because of finite supply in the network, and rely on containers already in the area to supply demand. The team prefers not to send less than 15 containers between metropolitan planning areas. This approximation method develops an initial ECR plan for the week, which is adjusted daily as demand is realized.

1.4. Thesis Outline

This thesis develops an integer programming model to support ECR decision-making in a realistic truck-rail intermodal network (Chapter 3). It improves on current literature because of the lack of research for ECR flow optimization for truck-rail intermodal networks. The results from the decision-making tool are compared to NATC's intermodal ECR plans over several planning periods (Chapter 4). The comparison shows that the decision-making tool can improve planning efficiency and reduce cost by producing quality ECR decisions. Recommendations for implementation and opportunities for future work are provided in Chapter 5.

Chapter 2 - Literature Review

This section summarizes the breadth of research around intermodal trucking optimization and empty container repositioning.

2.1. Intermodal Trucking Transportation

Utilizing multiple transportation modes for freight movement capitalizes on the strengths of each individual mode. Intermodal transportation is defined by the movement of freight by two or more transportation modes in conjunction. Transportation modes include transit by water, air, rail, or road, each with unique advantages and disadvantages. Intermodal freight traveling long distance over the rail may rely on truck movements to receive the freight from a depot inaccessible by rail. Trucking, as a transportation mode, allows geographic flexibility and scheduling agility unique within the transportation industry. Other transportation modes require much larger equipment and specific infrastructure, reducing their reach compared to the ubiquitous highway network of North America. In tandem, the transportation modes cooperate to bring a lower-cost and agile solution to the customer.

Combining the operations of multiple industries creates a multilayered flow-balance problem, considering container and equipment flow for two different networks in parallel. Several railroads may have many terminals in a geographic area due to high freight volume or logistic convenience. The trucking company that partners with several railroads is easily able to move equipment between each of these terminals, so considers them as a group to share access to containers and equipment. Individual terminals may also maintain their own volume of trucking equipment to handle daily operations.

This thesis focuses on an intermodal truck and railroad network. The trucking industry moved the largest volume of freight in North America of any mode in 2020, followed by the railroad industry [4]. The value of freight moved by truck is forecasted to increase from $11.5 trillion in 2018 to $37 trillion in 2045 accounting for inflation [5]. Trucking and rail networks specifically are competitive in cross-country movements, necessary in North America. Both are less expensive than air travel and more accessible inland than water transport. Utilizing a truck-rail intermodal network opens transportation paths previously unavailable to the railroad at an overall cost 56% lower than a trucking haul [5]. The truck-rail intermodal network plays a key role in North American freight transportation.

The magnitude of the trucking industry has encouraged research of logistics optimization for the trucking industry and its intermodal partnerships. Studies have considered the impact of load assignment and fleet size on trucking operations [7], [8]. Some researchers have focused on terminal or local strategies to reduce inventory management costs in intermodal trucking networks [9], [10]. Others have used heuristics to find the best path for intermodal networks of trucks, railroads, and ocean liners for full and empty containers [11], [12]. Other port intermodal research aims to optimize container-driver pairing and drayage routing [13], [14], [15]. The bulk of research for truck-rail intermodal networks is for terminal placement and inventory management [16], [17], [18]. Other research considers hazardous material management in a truck-rail intermodal network [19]. The NATC intermodal network has inspired other studies as well; one research team developed a heuristic to maximize the freight moved while minimizing empty relocation moves [20]. This thesis focuses on an intermodal truck-rail network, optimizing the cost of relocating empty containers from the trucking carrier's perspective.

2.2. Empty Container Repositioning

One of the largest issues that intermodal transportation companies face is repositioning empty containers after delivering freight. When freight is unloaded from a container, it will either be refilled at the location, or transported elsewhere in the network to be filled with freight. Empty container repositioning (ECR) is the plan to route empty containers from areas that hold them in supply to areas demanding containers to fill. Empty containers are moved at a cost to the company, without opportunity for revenue, and such moves cost the transportation industry up to $20 billion per year [1]. One in three container movements worldwide is an empty move due to imbalances of inbound and outbound containers between partners, lack of agility in repositioning, and unreliable demand forecasts [21]. The volume of empty containers at a terminal can be expressed as supply or demand across the network. Empty containers must be repositioned to capitalize on all potential sales in the system and optimize equipment utilization.

ECR seeks to fulfill the demand for empty containers with available supply at minimal cost, subject to available capacity for transport, contract quotas, and equipment positioning. The available supply may be insufficient to fulfill the demand for empty containers across the network, especially following a week of unexpectedly low freight delivery. The turnover of containers from the period before may be insufficient to capture freight demand in the next period. Locations with high volume movement and a consistent demand for empty containers can handle empty container shortage with minimal disruption to operations due to higher volumes of empty containers in the area.

Both static and dynamic models have been developed to tackle the ECR problem for ocean liner freight movements [22], [23]. Some consider non-homogeneous empty containers for relocation by ocean liner [24], [25]. Others have combined static and dynamic integer programming models to optimize ECR routing for ocean liners in a truck-liner intermodal network [26], [27]. Research also addresses optimizing the network flow of empty containers in a truck-liner intermodal network shipping internationally [28]. Empty container relocation for seaport operations is slower, higher volume, and more expensive than in a truck-rail network because of ocean liner equipment and operations. Ocean liners may take several weeks to transport freight, increasing variability in scheduling and cost. Railroads, however, deliver freight cross-country in a few days. This thesis specifically analyzes ECR for a truck-rail intermodal network.

2.3. Empty Container Repositioning in Truck-Rail Networks

Utilizing an intermodal truck-rail network for ECR is advantageous to trucking companies in North America. Moving empty containers by a mode other than driving is on average 2.25 times more cost effective for trucking companies [5]. Partnering with airlines to move freight is infeasible because of incompatible equipment, and seaport and inland waterway intermodal networks are cost efficient but only service a minority of markets in North America. To fully capitalize on intermodal savings, demands must be satisfied while considering the position, availability, and costs of all modes involved.

Seaport intermodal networks are similar to truck-rail networks because trucks are utilized for short agile movements, while railroads and ocean liners carry high volumes over long distances for lower cost. Seaport intermodal networks differ from railroad intermodal networks in North America because international imports and exports tend to travel by ocean liner, where domestic trade tends to travel by the railroad. The international and domestic operations are subject to different customers, wait times, and trade agreements.

Researchers have considered a variety of intermodal partnerships and strategies for ECR planning improvement. Some researchers consider ECR decisions for a truck-rail network and consider their interaction with ocean liners as well. Others developed a revenue management model for routing empty and full containers in this three-mode network [29]. Similar research developed an ECR model for this three-mode network as well, focusing on minimizing cost like this thesis [30]. Truck-rail-liner networks share some properties with truck-rail networks, but [29] and [30] focus on a single-layer network, not considering the interface of a trucking company utilizing an intermodal network. Although analysis has been conducted to understand ECR decisions for port interactions, there is a gap in research considering routing optimization for truck-rail intermodal networks.

2.4. Contributions of This Thesis

This thesis develops an integer programming model to optimize ECR decision-making in a realistic truck-rail intermodal network. There is a gap in research for rail-truck intermodal flow optimizations for ECR, utilizing a multi-layered network flow model to represent the interfacing of different networks. This analysis is unique by finding the optimal solution for a trucking company planning ECR in a realistic truck-rail network. Further, the proposed model is applied to case study data to demonstrate its potential to support decision-making about empty container management in a large intermodal network.

Chapter 3 - Optimization Model for Empty Container Management

In this chapter, the truck-rail intermodal network operations and associated empty container repositioning decisions are described. An integer programming model is introduced to optimize ECR management. The system and model are partially motivated by the NATC intermodal network. However, the framework is generalizable to similar decision problems faced by other firms.

3.1. Truck-Rail Intermodal Empty Container Repositioning System Description

When a trucking company utilizes a truck-rail intermodal network for ECR, it must consider the infrastructure and equipment of both the railroad and itself. The partnership reduces delivery costs by transporting containers long distances by rail, then utilizing trucks to deliver shorter and more direct loads near the destination. A *chassis* is a piece of trailing equipment attached to a truck that carries a container. Freight is transitioned between railcars and chassis at physical junctions called *ramps*. When a chassis delivers a container to a ramp to depart by rail, the movement is an *ingate*. When a container incoming by rail is retrieved by a chassis from a ramp, this is a *deramp*.

Metropolitan areas may have many ramps operated by different railroads or major customers. The trucking company recognizes these geographic ramp clusters as *ramp groups* for operational convenience. The ramps' proximity in this group allows a trucking company to cost-effectively share chassis and empty containers between ramps for ingates and deramps. The movement of a container between ramps of a ramp group by chassis is termed a *crosstown movement*.

When a full container is deramped from the railroad, a chassis transports the container to its destination in the community, considered a *drayage movement*. After the freight is unloaded, the empty container is practically equidistant from all ramps of that group. The company considers the volume of empty containers to belong to the group as whole because of the ease of transporting the container to any available ramp. A chassis can effectively transport a container to any other ramp within the ramp group. A positive empty container volume in a ramp group results from more freight deliveries the week before than outbound freight moves. A negative volume results from more outbound than inbound freight moves. If there is only one ramp in a ramp group, all supply or demand (respectively) must pass through that ramp.

To travel long distances between ramp groups, the empty containers only travel by rail, departing and arriving on ramps connected in the network of the respective railroad company. The ramps connected by railroad companies for empty container transport are considered *rail lane movements*. Chassis are necessary for draying the containers away from the rail or transporting them by crosstown movements. Crosstown movements are only feasible among ramps of a group, and chassis do not move between different ramp groups. Each ramp has an accessible balance of chassis (either a supply or deficit), depending on the volumes of ingates and deramps in the week before. Ingates increase the chassis volume at the ramp once the freight is transitioned to the railroad. Deramps decrease the chassis volume at a ramp since the movements transport freight away from the ramp into the community. If the ramp maintains a chassis deficit , or the available chassis have already been utilized, then chassis must be relocated from another ramp to dray the containers moving through that ramp. These relocation movements are avoided because the chassis are moved without fulfilling customer orders and at a cost.

3.2. Intermodal Empty Container Repositioning Model

The integer program presented in this section represents a realistic truck-rail intermodal network mathematically, optimizing costs considering railroad fees and equipment relocation. The section begins with a description of system components and operations, after which the mathematical model is described.

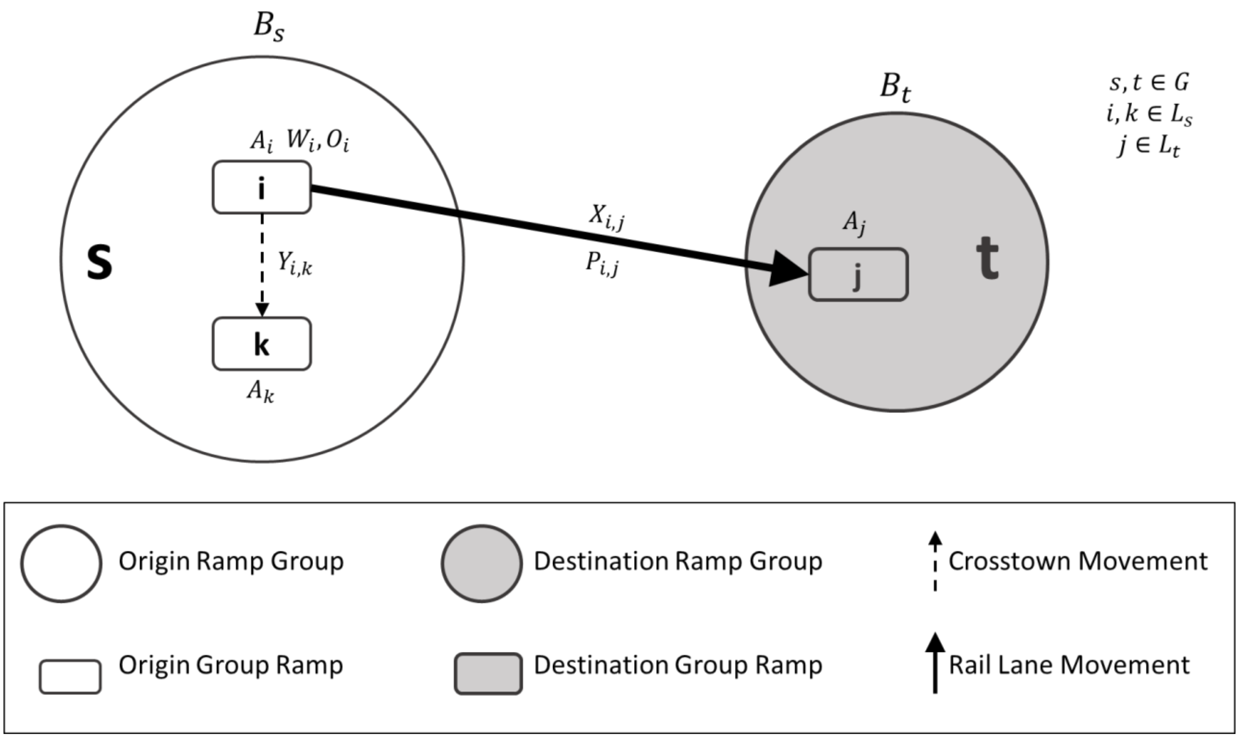

Figure 1: Container Movement in a Truck-Rail Network

3.2.1 System Components and Operations

Figure 1 depicts empty container movement in a truck-rail network in context of the parameter notation used in this thesis. The network consists of a set of ramp groups ($s \in G$), each of which comprises a set of ramps ($i \in L_s$ for all $s \in G$). The volume of empty containers available to or needed by group s is represented by B_s. When B_s is positive, the group maintains a net supply of empty containers from a surplus of freight received in the previous period. If B_s is negative, the group needs empty containers to move new freight in that period. An empty container repositioning plan consists of decisions to move empty containers between groups, via a combination of rail and chassis movements, to satisfy demands at groups with negative B_s values using supplies at groups with positive B_s values.

Supply is sent to groups in demand, departing from ramps to travel along the railroad to arrive at a ramp of another group. Although empty container supplies and demands are measured at the group level, movements occur between ramp pairs. $X_{i,j}$ is a decision variable that represents the number of empty containers moved by rail from ramp i to ramp j, where i and j belong to different ramp groups (in Figure 1, i is of group s and j is of group t). It may be advantageous to route an empty container into ramp i by rail but out of ramp k by rail to arrive at its destination group. The transfer between ramps in the same group is accomplished by a crosstown move with a chassis. These crosstown movements are tracked by decision variable $Y_{i,k}$, representing the number of empty containers moved via chassis from ramp i to ramp k in the same group (in the example in Figure 1, group s). The net number of containers moved into and out of ramp i is decided by variable O_i. Some railroad lanes have a restriction of how many empty containers can be moved per period, represented as $P_{i,j}$.

The desirability of moving an empty container by chassis between two ramps depends on chassis availability at these ramps. If the origin ramp has chassis available and the destination ramp needs chassis, the crosstown move benefits overall network operations. However, in the opposite case where the origin needs chassis and the destination has chassis available, moving the empty container by chassis exacerbates the imbalance. Chassis availability is connected to full container movements in the network. Since chassis may make multiple moves each week, the availability of chassis at each ramp i is modeled based on a three-week average balance (A_i).

If A_i is positive, then the ramp averages a greater volume of full ingates than full deramps. If A_i is negative, then ramp i averages more full deramps than full ingates. A container leaving ramp i by rail requires a chassis to dray it to the ramp, increasing the number of chassis at ramp i. The number of chassis at ramp i is also increased when an empty container is moved to ramp i by chassis. A container moved to ramp i by rail requires a chassis to dray it out, decreasing the number of chassis at ramp i. Moving a container by chassis from ramp i also decreases the chassis volume at ramp i. A chassis deficit at a ramp requires chassis to be relocated from another ramp within its group to meet the chassis demand for deramps in that period. Decision variable W_i represents the number of chassis sent out from ramp i in excess of the available chassis. When the chassis supply is depleted at the ramp, chassis must be transported from another ramp in the group to ramp i to refill its supply; these moves are penalized by value N.

3.2.2 Mathematical Model

The formal mathematical model is now presented. The objective is to minimize overall costs in the network while fulfilling supply and demand of empty containers per group. Costs include rail transportation and chassis repositioning. To satisfy the net flow for every ramp group, a dummy location is defined to siphon excess supply or demand and ensure feasible balance. A dummy ramp group maintains the needed balance, and it has a single dummy ramp. Feasible rail movement lanes exist between all ramps of all other groups and the dummy ramp. These lanes are associated with high penalty costs to discourage their usage unless necessary. The chassis balance at the dummy ramp is zero.

Notation and Parameters

The model considers the cost $C_{i,j}$ of moving a container from ramp i to ramp j on the railroad lane. A cost N is associated with chassis relocation because of an excess sent from any ramp.

Sets

G set of groups, indexed by s, t

L_s set of ramps in group s, indexed by i, j, k

Parameters

$C_{i,j}$ cost of moving a container from ramp i to ramp j by rail

$P_{i,j}$ maximum number of containers moved from ramp i to ramp j by rail

N penalty for chassis relocation

A_i 3-week average chassis availability at ramp i:

$A_i < 0$ indicates chassis deficit,

$A_i > 0$ indicates chassis surplus

B_s empty container balance at ramp group s:

$B_s < 0$ indicates net demand,

$B_s > 0$ indicates net supply

Decision Variables

The decisions considered in this model include empty container movements by rail and by chassis, as well as the number of chassis to relocate to ramp i if chassis usage exceeds the chassis availability.

$X_{i,j}$ number of containers moved from ramp i to ramp j by rail

$Y_{i,k}$ number of containers moved from ramp i to ramp k by chassis crosstown

O_i net number of containers moved into and out of ramp i

W_i number of chassis to relocate to ramp i if usage exceeds chassis availability

Mathematical Formulation

Minimize

$$\sum_{s\in G}\sum_{i\in L_s}\left(N\,W_i+\sum_{t\in G}\sum_{j\in L_t}C_{i,j}X_{i,j}\right)$$

Subject to

$$B_s-\sum_{i\in L_s}\sum_{t\in G}\sum_{j\in L_t}\left(X_{i,j}-X_{j,i}\right)=0\quad\forall\, s\in G$$

(1)

$$\left(\sum_{k\,\in\,L_s}Y_{i,k}+\sum_{t\,\in\,G}\sum_{j\,\in\,L_t}X_{i,j}\right)-\left(\sum_{k\,\in\,L_s}Y_{k,i}+\sum_{t\,\in\,G}\sum_{j\,\in\,L_j}X_{j,i}\right)=\ O_i$$

$$\forall\, i\in L_s,\, s\in G$$

(2)

$$\left(\sum_{k\,\in\,L_s}Y_{k,i}+\sum_{t\,\in\,G}\sum_{j\,\in\,L_t}X_{i,j}\right)-\left(\sum_{k\,\in\,L_s}Y_{i,k}+\sum_{t\,\in\,G}\sum_{j\,\in\,L_j}X_{j,i}\right)+A_i\le W_i$$

$$\forall\, i\in L_s\colon A_i<0, s\in G$$

(3)

$$\left(\sum_{k\,\in\,L_s}Y_{i,k}+\sum_{t\,\in\,G}\sum_{j\,\in\,L_j}X_{j,i}\right)-\left(\sum_{k\,\in\,L_s}Y_{k,i}+\sum_{t\,\in\,G}\sum_{j\,\in\,L_t}X_{i,j}\right)-A_i\le W_i$$

$$\forall\, i\in L_s\colon A_i>0, s\in G$$

(4)

$$\left(\sum_{k\,\in\,L_s}Y_{i,k}+\sum_{t\,\in\,G}\sum_{j\,\in\,L_t}X_{j,i}\right)-\left(\sum_{k\,\in\,L_s}Y_{k,i}+\sum_{t\,\in\,G}\sum_{j\,\in\,L_t}X_{i,j}\right)\le W_i$$

$$\forall\, i\in L_s\colon A_i\le 0, s\in G$$

(5)

$$\left(\sum_{k\,\in\,L_s}Y_{k,i}+\sum_{t\,\in\,G}\sum_{j\,\in\,L_t}X_{i,j}\right)-\left(\sum_{k\,\in\,L_s}Y_{i,k}+\sum_{t\,\in\,G}\sum_{j\,\in\,L_t}X_{j,i}\right)\le W_i$$

$$\forall\, i\in L_s\colon A_i\ge 0, s\in G$$

(6)

$$X_{i,j} \leq P_{i,j} \quad \forall\, i \in L_s; j \in L_t; s, t \in G$$
(7)

$$X_{i,j} \in Z^+ \quad \forall\, i \in L_s; j \in L_t; s, t \in G$$
(8)

$$Y_{i,k} \in Z^+ \quad \forall\, i, k \in L_s; s \in G$$
(9)

$$O_i \in Z \quad \forall\, i \in L_s, s \in G$$
(10)

$$W_i \in Z^+ \quad \forall\, i \in L_s, s \in G$$
(11)

The model's objective function minimizes the cost of meeting demand for empty containers using existing supply, where costs include a penalty for chassis over-utilization (first term) and those for rail movements (second term).

Constraint (1) and (2) are flow balance constraints. Constraint (1) is a flow balance constraint for empty containers at the ramp group level. For each ramp group s, the net number of containers leaving (respectively, entering) must reflect the ramp group empty container supply (respectively, demand). Constraint (2) is a flow balance constraint at the ramp level. For each ramp i, the difference between the volume of outbound and inbound empty containers at a ramp must equal the ramp's empty container balance. Outbound and inbound moves include those made both by chassis crosstown and by rail. The ramp's empty container balance, O_i, is variable, and if all the ramp balances of a group are summed, they add to the group's empty container balance.$O_i > 0$ indicates net supply from this ramp; $O_i < 0$ indicates net demand at this ramp.

Constraints (3) – (6) relate empty container movements by truck to chassis available to support those movements. Constraint (3) and (5) function together when $A_i < 0$. Constraint (3) states that when $A_i < 0$, $W_i = 0$ until the negative net flow is greater than the magnitude of the chassis balance deficit. Constraint (5) states that if the chassis balance at the ramp is a deficit, a net decrease in the number of chassis would incur a penalty. Constraint (4) and (6) function together when $A_i > 0$. Constraint (4) states that when $A_i > 0$, $W_i = 0$ until the positive net flow of chassis is greater than the supply at ramp i. Constraint (6) states that if the chassis balance at the ramp is a supply, a net increase in the number of chassis would incur a penalty. Additionally, Constraints (5) and (6) ensure that, when $A_i = 0$, both a positive and negative net flow will incur a penalty for the net volume of chassis moved.

Constraint (7) describes the maximum number of empty containers that can be moved from ramp i to ramp j according to contract agreements. Constraints (8) – (11) define the decision variables. Constraint (8) states that the number of containers moved by rail from ramp i to ramp j must be a non-negative integer. Constraint (9) expresses that the number of containers moved from ramp i to ramp k by a crosstown chassis move must be a non-negative integer. Constraint (10) states that the net number of containers moved into and out of ramp i must be an integer. Constraint (11) states that the number of chassis that must be relocated to ramp i must be a non-negative integer.

This model formulation contributes uniquely to the existing literature because of its multi-layered network balance approach. Grouping subsets of ramps into ramp groups allows a trucking company to optimize its equipment utilization while capitalizing on the cost savings of a truck-rail network for ECR.

Chapter 4 - Case Study Analysis

This chapter describes the application of the model introduced in Chapter 3 to NATC data. The data processing steps and computational environment are described. The model solutions are then compared to plans generated by the NATC ECR team over three planning periods to account for network variability.

4.1. Computational Settings and Data Requirements

The computational settings applied to large optimization problems impact run time. Each instance was solved on a personal computer with an Intel Core i7-10610U processor, clock rate of 1.80GHz, and 32 GB RAM. A web application with a .netcore framework was built in C#, utilizing version 2.8 of the COIN-OR CBC mixed integer linear programming solver (COIN) to solve the instances [31], [32]. Each instance solved in 0.05-0.06 CPU seconds.

Implementing the model required querying NATC's databases and cleaning the data before analysis. Since data come from different sources, three distinct queries are required. If a ramp or group appears in one query but not all three, that node is not considered in the optimization. The model was solved for a network consisting of 55-60 ramp groups and 80-100 ramps, considering 220-240 rail movement lanes for each instance.

The cost for every feasible railroad lane was queried, filtering for only lanes utilized within the last three years. These ramps and groups were compared with a separate query that reported the network ramp groups and their forecasted supply or demand for empty containers in the current and upcoming week. If the group was forecast to have a supply of containers this week, then that supply would be recorded as the group's container balance (B_s). If the forecasts for this week and next week were negative, the group had a demand for its container balance. If the forecast for this week was negative and next week was positive, the demand is considered fulfilled, and the group's balance is 0.

The final consideration was the chassis balance at the ramp level. The data gathering method used to inform the model required information for each ramp and group from several tables, and if a ramp or group had not been utilized for ECR within three months, it would not appear in the data set.

4.2. Decision Comparisons

The model was implemented using data from three planning periods, namely March 18, March 25, and April 1, 2021, and the results were compared to the NATC ECR team's plan. The model produced good quality results and lower cost solutions for ECR planning. For each instance, the non-zero empty container movement decisions between ramp groups are compared on the ramp level and differences are discussed. The entire ramp-ramp solution comparisons are listed for every instance in Appendix A; focused tables are provided in this section to more effectively express the discussion points noted.

4.2.1 Metric Definitions

This thesis uses a variety of metrics to ensure an accurate analysis of the difference between solutions. The total cost of the NATC ECR plan is calculated by multiplying the volume of movement on a lane by the cost of moving a container along that lane. The total cost of the model solution is calculated by subtracting the cost of dummy node movements and chassis relocation penalties. The resulting number accounts only for the cost of moving containers by rail, comparable to the NATC total cost. The difference between the total cost of the two plans is the difference of the two strategy's cost of rail movements.

The two solutions produced by the ECR team and the model may differ in total volume moved in that period. To provide an equitable comparison, the cost per move is shown to describe the relative cost per decision. The cost per move for each solution is calculated by dividing the total cost by the volume moved, disregarding transient volumes in the model's solution. Transient volumes are defined as the number of moves to ramp groups of supply or from ramp groups of demand. In either case, the total volume moved in or out of that group is destined to supply another group, since both of those movements exacerbate the group volume imbalance rather than resolving it. Transient moves need to be disregarded from the overall calculus of cost per move because the model and the ECR team account for these decisions differently. The model considers transient moves as two separate decisions, whereas the ECR team considers a similar group-group move as a single decision. Thus, the transient volumes artificially increase the overall volume of moves decided by the model, deflating its respective cost per move.

4.2.2 Instance Comparisons

The analysis of the first instance provided a comparison of the empty container repositioning decisions of the model presented in Chapter 3 and the NATC ECR at the ramp level for the period of March 18. COIN solved this instance in 0.05 CPU seconds. The model's solution moved two more empty containers than did the ECR team's solution. This is because the model must move all supply and demand in the network, whereas the ECR team may ignore a group with an operationally insignificant balance. The optimal solution produced by the model incurred $761,434.51 in rail movement costs, a decrease of $174,632.99 (18.7%) compared to the ECR team's plan, which resulted in $936,067.50 in rail movement costs. The model solution incurred costs of $165.28 per empty container move compared to $203.27 per move of the ECR team. The ECR team's approach allows for variability in demand and does not reflect the exact forecasted supply or demand of the groups. The ECR team's plan generally differs in volume from the optimization model for that reason, but the same lanes or comparable lanes are often chosen. To see the full solution comparison, see Table 7 in Appendix A.

The analysis of the second instance provided the difference between ramp-ramp ECR decisions for the model and the NATC ECR for the period of March 25. COIN solved this instance in 0.05 CPU seconds. The model's solution moved 1183 fewer empty containers than did the ECR team's solution because the team considered factors not available to the model. During the week of March 25, the system was recovering after several derailments and storms across the network, with many containers in the system but few from the previous week's supply. Thus, the team significantly padded empty container movements out of some groups, namely Dallas, Harrisburg, and Jacksonville. The model solution incurs costs of $178.39 per empty container move compared to $209.18 per move of the ECR team, a savings of 14.7%. The model produced a plan with a total cost of $701,599.04, whereas NATC ECR team found a solution totaling $1,070,179.00, a savings of $368,579.96. To see the full solution comparison, see Table 8 in Appendix A.

The analysis of the third instance provided the difference between ECR decisions for the model and the NATC ECR for the period of April 1. COIN solved this instance in 0.06 CPU seconds. The model's solution moved 310 fewer empty containers than the ECR team's solution because the team considered factors not available to the model. There was a large disparity between supply and demand for the week of April 1, so the dummy group moved a larger than normal volume. Movement from the dummy group is actualized as shortage in the system. The model solution incurs costs of $178.12 per empty container move compared to $206.05 per move of the ECR team, a savings of 13.6%. The model produced a plan with a total cost of $803,842.48, whereas NATC ECR team found a solution totaling $993,775.00, a savings of $189,932.52. To see the full solution comparison, see Table 9 in Appendix A.

4.2.3 Decision Similarities

Table 1 shown below describes comparable moves between the two solutions. Comparable moves are decisions where the ECR team and model chose the same ramp to ramp move. The differences in volume between the solutions for comparable moves express the variability of larger groups, volume in the system, and estimation strategy of the ECR team. Comparable decisions make up between 31-33% of the overall solution comparison across the instances.

Table 1: Instance 1 Comparable Decisions

No.	Lane				Empty Containers Moved	
	Origin Ramp Group	**Origin Ramp**	**Dest. Ramp Group**	**Dest. Ramp**	**ECR Team**	**Model**
1	ALBANY	A$	BUFFALO	B!	225	180
2	ALLENTOWN	N!	ST LOUIS	R!	75	54
3	CHAMBERSBURG	+P	CHICAGO	C+	175	196
4	CINCINNATI	T$	CHICAGO	C!	25	40
5	DALLAS	D?	SALINAS VICTORIA	M?	150	546
6	DALLAS	DR	KANSAS CITY	E-	100	300
7	EDMONTON	E%	VANCOUVER	V%	35	25
8	HARRISBURG	H!	COLUMBUS	O!	50	135
9	HARRISBURG	H!	TOLEDO	U!	50	30
10	HOUSTON	H-	LOS ANGELES	CR	100	133
11	JACKSONVILLE	J!	MEMPHIS	R&	50	66
12	LAREDO	XL	SALINAS VICTORIA	M?	25	14
13	MONTREAL	M%	CHICAGO	C%	20	33
14	ORLANDO	O+	CHICAGO	C+	275	196
15	ORLANDO	O+	NORTH BALTIMORE	+R	300	415
16	PHOENIX	PR	LOS ANGELES	CR	300	250
17	PHOENIX	PR	SAN BERNARDINO	SR	100	50

No.	Lane				Empty Containers Moved	
	Origin Ramp Group	Origin Ramp	Dest. Ramp Group	Dest. Ramp	ECR Team	Model
18	PORTLAND	P=	SEATTLE	S=	250	150
19	SPRINGFIELD	+W	CHICAGO	C+	35	152
20	TITUSVILLE	#T	MEMPHIS	R&	35	32

Table 2: Fungible Move Comparison

No.	Lane				Empty Containers Moved	
	Origin Ramp Group	Origin Ramp	Dest. Ramp Group	Dest. Ramp	ECR Team	Model
1	SAINT PAUL	M=	CHICAGO	IR	0	45
2	SAINT PAUL	M=	CHICAGO	C=	75	0
3	SYRACUSE	Y+	CHICAGO	C+	50	0
4	SYRACUSE	Y+	CHICAGO	G+	0	73
5	TAMPA	F+	CHICAGO	G+	0	24
6	TAMPA	F+	CHICAGO	C+	20	0
7	JACKSONVILLE	J#	CHARLOTTE	T!	0	50
8	JACKSONVILLE	J!	CHARLOTTE	T!	50	0

For some ramp groups, the ECR team and the model produced comparable decisions but chose different ramps within a group. Table 2 shows the decisions in Instance 1 for St. Paul (Decisions 1-2), Syracuse (Decisions 3-4), and Tampa (Decisions 5-6), which all sent their supply to Chicago in both solutions, but the optimization model chose another ramp within the group to reduce the chassis relocation penalty. Jacksonville (Decisions 7-8) sent to Charlotte, but from different ramps. Similar decisions were observed across all instances.

4.2.4 Capability Advantage

The model presented in Chapter 3 provides advantages over the manual process of the NATC ECR team by finding more complex solutions and avoiding error. In the case of the Denver ramp group in Instance 1, shown in Table 3 below, the ECR team chose to send the supply to a single source, San Bernardino, whereas the model found it most cost effective to distribute the supply among three groups: El Paso, Los Angeles, and Memphis. This decision represents the advantaged decision-making capabilities of an integer programming model, finding a more complex but less costly solution in a complex network.

Table 3: Instance 1 Advanced Solutions

No.	Lane				Empty Containers Moved	
	Origin Ramp Group	**Origin Ramp**	**Dest. Ramp Group**	**Dest. Ramp**	**ECR Team**	**Model**
1	DENVER	D-	EL PASO	XR	0	40
2	DENVER	D-	LOS ANGELES	CR	0	276
3	DENVER	D-	MEMPHIS	MR	0	127
4	DENVER	D-	SAN BERNARDINO	SR	450	0

The comparable moves for Instance 3, shown in Table 4, provide an example of the model's ability to avoid oversight in decision-making. The forecasted demand for the ramp group Buffalo (Decision 1) in Instance 3 was 200 empty containers. The model fulfilled the demand of Buffalo exactly, in accordance with the assumptions of the model described in Chapter 3. The ECR team, however, planned to send only 150, 25% less than the demand. The source, Albany, could have supplied Buffalo its entire demand (as shown in Decision 2). The decision to short Buffalo in this instance was a planning oversight by the ECR Team. Shortage of empty containers will cause a disruption in a small ramp group's network and reduce its ability to react to future freight demand. This oversight is eliminated by the model.

Table 4: Instance 3 Error Avoidance

No.	Lane				Empty Containers Moved	
	Origin Ramp Group	**Origin Ramp**	**Dest. Ramp Group**	**Dest. Ramp**	**ECR Team**	**Model**
1	ALBANY	A$	BUFFALO	B!	150	200
2	ALBANY	A$	CHICAGO	I!	150	18

4.2.5 Shortage Management

The ECR decisions made by the NATC ECR team and the model are largely similar but can differ in what ramp groups are selected for shortage.

Table 5: Instance 1 Dummy Moves

	Lane				Empty Containers Moved
No.	**Origin Ramp Group**	**Origin Ramp**	**Dest. Ramp Group**	**Dest. Ramp**	**Model**
1	Dummy Group	DN	VANCOUVER	V%	6
2	Dummy Group	DN	CLEVELAND	+C	45
3	Dummy Group	DN	SALINAS VICTORIA	M?	25
4	Dummy Group	DN	SAN LOIS POTOSI	P?	115
5	Dummy Group	DN	ELIZABETH	E+	75
6	Dummy Group	DN	PHILADELPHIA	P+	40
7	Dummy Group	DN	NORFOLK	N&	75
8	TOLUCA	T?	Dummy Group	DN	8

Table 5 relates the decisions of the optimization model for groups receiving from or sending to the dummy ramp group in Instance 1. Receiving supply from the dummy node is actualized as the group not receiving that supply. Sending to the dummy ramp group is actualized as container inventory held at the group. To balance the network in the first instance, the dummy ramp group had a supply of empty containers. If there are no rail movement lanes indicated in the databases for a group, the dummy ramp group will fill the role of receiver or sender to support that group's empty container balance. The optimization model does not indicate preference for which groups to short, whereas the ECR team prefers to short ramp groups of consistently high demand, namely Chicago and Los Angeles. In contrast to the groups with shortages, Toluca (Decision 8) did not have a lane available to unload its supply, so the dummy ramp group absorbed it. The ECR team did not consider Toluca in its solution because the empty container volume was too low. Similar dummy relocation decisions were observed across the instances.

4.2.6 Effects of Disruption

Over the instances studied in this thesis, the NATC network experienced a network-wide disruption resulting from a week-long storm in the northeast U.S. and several train derailments across the network. These disruptions impacted the data available to the model and the decisions it made in the following period.

Table 6: Instance 2 Disruption Effect

No.	Lane				Empty Container Moves	
	Origin Ramp Group	**Origin Ramp**	**Dest. Ramp Group**	**Dest. Ramp**	**ECR Team**	**Model**
1	DALLAS	D?	SALINAS VICTORIA	M?	150	330
2	DALLAS	D?	SAN LUIS POTOSI	P?	50	55
3	DALLAS	DR	KANSAS CITY,JA	E-	50	175
4	DALLAS	DR	CHICAGO	C=	0	7
5	DALLAS	DR	LOS ANGELES	AR	0	36
6	DALLAS	DR	LOS ANGELES	CR	300	0
7	DALLAS	DR	SALINAS VICTORIA	M?	600	0
8	DALLAS	DR	SAN LUIS POTOSI	P?	50	0

The analysis of the two ECR plans for Instance 2 was conducted after a period of disruption in the network. A major difference between the NATC ECR team and the model was the volume of supply sent; the amount sent from several ramp groups by the NATC team was well above its forecasted supply. The decisions made for Dallas in Instance 2 are a prominent example, as shown by Table 6. These decisions depend on factors to which the model does not have access. The previous period's network-wide disruptions resulted in uncharacteristically low freight movements. This low freight movement resulted in low forecasted supply and demand in Instance 2 as the network recovered. The ECR team chose to utilize containers already in the system to pad supply movements and accommodate for higher levels of expected demand in the future.

4.2.7 Summary of Results

The model produced comparable solutions in three instances compared to the ECR team at NATC, introducing an option for cost savings and reduced planning time. The COIN solver produced a solution in between 0.05-0.06 CPU seconds. Over the three instances, the COIN model averaged $244,381.82 in savings per week. Many of the differences between the solutions were due to information not available to the model. Variability in the system due to weather events and derailments resulted in differences in the solutions, as well as the team's foresight into future demand. The model would often recommend alternative moves between similar groups as the ECR team, but to or from different ramps within that group to account for chassis relocation costs. Overall, the analysis showed that the developed model can be an effective decision-making tool for ECR and accurately represents a realistic truck-rail network. Utilizing a multi-layered network flow model for intermodal ECR optimization can decrease planning time and operational costs.

Chapter 5 - Conclusions and Future Work

Empty container repositioning (ECR) is a major concern for the transportation industry because of geographic inbound and outbound freight imbalances in every network. The economic impact of the trucking industry and its partnership with the railroads escalated it to a security necessity for the U.S. government. Truck-rail intermodal networks are responsible for repositioning thousands of empty containers every week and require a time efficient and effective ECR plan. ECR is a $20 billion problem every year [1]. Many trucking companies manually develop their ECR plans, a process that is time intensive and dependent on employee experience. This thesis presents an integer programming optimization model to minimize cost from the perspective of a trucking company planning ECR in a realistic truck-rail network in North America. When compared against the ECR plan for NATC Intermodal, the model produced a comparable solution, providing a lower cost plan and a potential reduction in employee planning time. A fast and accurate ECR plan ensures availability to capture demand for the upcoming week and optimize equipment utilization.

5.1. Future Work

This thesis contributes to a base of research in ECR and intermodal trucking logistics, as well as providing paths for future implementation and theoretical investigation. Next steps exist for improving the results in comparison to the NATC ECR team's decisions, as well as expanding the research and applicability broadly.

A few of the inconsistencies between the model solution and the ECR team's decisions could be rectified through additional practical changes. The model may be improved if a minimum volume of movement were implemented, removing groups unable to send or receive enough volume to operationally justify a rail movement. The model implementation could be better suited for the NATC ECR team by including dynamic constraints that allow for the team to update daily demand as it is actualized and account for disruptions in the network, such as derailments. This would save the team planning time throughout the week as they update the empty plan.

Multi-layered network models such as the one presented here may be generalized to other transportation problems. The formulation approach of grouping network nodes into regional subsets may allow a transportation firm to represent realistic, geographically driven decision processes. In the field of ECR for trucking intermodal transport, incorporating a predictive or stochastic modeling element may improve empty container utilization in the network. A reliable demand forecast is key to optimized equipment utilization. Additionally, the multi-layered flow-balance modeling approach would benefit any system where an entity is utilizing another network for its purposes or considering resource management.

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Appendix A

Appendix A contains the full solution comparisons between the ECR team and the presented model.

Table 7: Instance 1 Full Solution Comparison

No.	Lane				Empty Containers Moved	
	Origin Ramp Group	Origin Ramp	Dest. Ramp Group	Dest. Ramp	ECR Team	Model
1	ALBANY	A$	BUFFALO	B!	225	180
2	ALBANY	A$	CHICAGO	I!	0	74
3	ALLENTOWN	N!	KANSAS CITY	G!	75	0
4	ALLENTOWN	N!	ST LOUIS	R!	75	54
5	CALGARY	%E	VANCOUVER	V%	0	14
6	CHAMBERSBURG	+P	CHICAGO	C+	175	196
7	CHAMBERSBURG	+P	CLEVELAND	+C	50	0
8	CINCINNATI	T$	CHICAGO	C!	25	40
9	DALLAS	D?	SALINAS VICTORIA	M?	150	546
10	DALLAS	DR	KANSAS CITY	E-	100	300
11	DALLAS	DR	SALINAS VICTORIA	M?	550	0
12	DALLAS	DR	LOS ANGELES	CR	0	246
13	DENVER	D-	EL PASO	XR	0	40
14	DENVER	D-	LOS ANGELES	CR	0	276
15	DENVER	D-	MEMPHIS	MR	0	127
16	DENVER	D-	SAN BERNARDINO	SR	450	0
17	EDMONTON	E%	VANCOUVER	V%	35	25
18	HARRISBURG	H!	COLUMBUS	O!	50	135
19	HARRISBURG	H!	ELIZABETH	K!	50	0
20	HARRISBURG	H!	TOLEDO	U!	50	30
21	HARRISBURG	H!	ST LOUIS	R!	0	71
22	HARRISBURG	H!	PITTSBURG	D!	0	20
23	HARRISBURG	P$	CHICAGO	I$	0	213
24	HOUSTON	H-	LOS ANGELES	CR	100	133
25	INDIANAPOLIS	U+	ELIZABETH	E+	40	0
26	JACKSONVILLE	J#	CHARLOTTE	T!	0	50
27	JACKSONVILLE	J!	CHARLOTTE	T!	50	0
28	JACKSONVILLE	J!	MEMPHIS	R&	50	66
29	JACKSONVILLE	J!	SAN BERNARDINO	SR	50	0
30	LAREDO	XL	SALINAS VICTORIA	M?	25	14
31	MIAMI	M#	KANSAS CITY	G!	50	0

No.	Lane				Empty Containers Moved	
	Origin Ramp Group	Origin Ramp	Dest. Ramp Group	Dest. Ramp	ECR Team	Model
32	MIAMI	M#	JACKSONVILLE	J#	0	63
33	MIAMI	M#	MEMPHIS	R&	20	0
34	MONTREAL	M%	CHICAGO	C%	20	33
35	ORLANDO	O+	ATLANTA	Q+	0	25
36	ORLANDO	O+	CHICAGO	C+	275	196
37	ORLANDO	O+	NORTH BALTIMORE	+R	300	415
38	PHILADELPHIA	P+	CHICAGO	C+	20	0
39	PHILADELPHIA	V!	KANSAS CITY	G!	75	0
40	PHOENIX	PR	LOS ANGELES	CR	300	250
41	PHOENIX	PR	SAN BERNARDINO	SR	100	50
42	PORTLAND	P=	CHICAGO	IR	0	50
43	PORTLAND	P=	LOS ANGELES	CR	0	7
44	PORTLAND	P=	SEATTLE	S=	250	150
45	SAINT PAUL	M=	CHICAGO	IR	0	45
46	SAINT PAUL	M=	CHICAGO	C=	75	0
47	SASKATOON	%K	CHICAGO	C%	0	2
48	SPOKANE	W=	LOS ANGELES	CR	0	38
49	SPOKANE	W=	CHICAGO	C=	75	0
50	SPRINGFIELD	+W	CHICAGO	C+	35	152
51	STOCKTON	ER	LOS ANGELES	CR	400	0
52	STOCKTON	ER	SAN BERNARDINO	SR	0	150
53	SYRACUSE	Y+	CHICAGO	C+	50	0
54	SYRACUSE	Y+	CHICAGO	G+	0	73
55	SYRACUSE	Y+	ST LOUIS	T+	50	0
56	TAMPA	F+	CHICAGO	G+	0	24
57	TAMPA	F+	CHICAGO	C+	20	0
58	TITUSVILLE	#T	MEMPHIS	R&	35	32
59	WINNIPEG	%W	CHICAGO	C%	0	2
60	WORCESTER	R+	CHICAGO	C+	80	0

Table 8: Instance 2 Full Solution Comparison

No.	Lane				Empty Containers Moved	
	Origin Ramp Group	Origin Ramp	Dest. Ramp Group	Dest. Ramp	ECR Team	Model
1	ALBANY	A$	BUFFALO	B!	125	130
2	ALBANY	A$	CHICAGO	I!	125	132
3	ALLENTOWN	N!	KANSAS CITY	G!	25	0
4	ALLENTOWN	N!	ST LOUIS	R!	25	43
5	AYER	Y!	CHICAGO	I!	150	0
6	BALTIMORE	B+	CHICAGO	G+	0	17
7	CALGARY	%E	VANCOUVER	V%	0	14
8	CHAMBERSBURG	+P	CHICAGO	C+	200	224
9	CHICAGO	C!	CLEVELAND	C&	0	35
10	CHICAGO	C!	COLUMBUS	O!	0	63
11	CHICAGO	C%	CALGARY	%E	0	14
12	CHICAGO	I$	TOLEDO	U!	0	15
13	CINCINNATI	T$	CHICAGO	C!	40	25
14	DALLAS	D?	SALINAS VICTORIA	M?	150	330
15	DALLAS	D?	SAN LUIS POTOSI	P?	50	55
16	DALLAS	DR	KANSAS CITY	E-	50	175
17	DALLAS	DR	CHICAGO	C=	0	7
18	DALLAS	DR	LOS ANGELES	AR	0	36
19	DALLAS	DR	LOS ANGELES	CR	300	0
20	DALLAS	DR	SALINAS VICTORIA	M?	600	0
21	DALLAS	DR	SAN LUIS POTOSI	P?	50	0
22	DENVER	D-	CHICAGO	WQ	0	124
23	DENVER	D-	EL PASO	XR	0	45
24	DENVER	D-	MEMPHIS	MR	0	7
25	DENVER	D-	LOS ANGELES	CR	0	254
26	DENVER	D-	SAN BERNARDINO	SR	450	0
27	EDMONTON	E%	VANCOUVER	V%	30	26
28	HARRISBURG	H!	COLUMBUS	O!	100	57
29	HARRISBURG	H!	NORFOLK	N&	50	30
30	HARRISBURG	H!	TOLEDO	U!	25	0
31	HOUSTON	H-	LOS ANGELES	CR	100	75
32	INDIANAPOLIS	U+	ELIZABETH	E+	50	50
33	JACKSONVILLE	J#	CHARLOTTE	T!	0	25
34	JACKSONVILLE	J!	CHARLOTTE	T!	50	0
35	JACKSONVILLE	J!	KANSAS CITY	G!	75	0
36	JACKSONVILLE	J!	MEMPHIS	R&	50	108
37	JACKSONVILLE	J!	SAN BERNARDINO	SR	50	0

No.	Lane				Empty Containers Moved	
	Origin Ramp Group	Origin Ramp	Dest. Ramp Group	Dest. Ramp	ECR Team	Model
38	JERSEY CITY	K!	CHICAGO	I$	0	50
39	LAREDO	XL	SALINAS VICTORIA	M?	25	25
40	MIAMI	M#	KANSAS CITY	G!	25	0
41	MIAMI	M#	MEMPHIS	R&	25	0
42	MONTREAL	M%	EDMONTON	E%	0	6
43	MONCTON	%M	MONTREAL	M%	1	0
44	ORLANDO	O+	CHICAGO	C+	200	153
45	ORLANDO	O+	NORTH BALTIMORE	+R	350	390
46	PHILADELPHIA	P+	CHICAGO	C+	30	0
47	PHOENIX	PR	EL PASO	XR	30	0
48	PHOENIX	PR	LOS ANGELES	CR	100	325
49	PHOENIX	PR	SAN BERNARDINO	SR	300	40
50	PORTLAND	P=	LOS ANGELES	CR	125	0
51	PORTLAND	P=	SEATTLE	S=	125	150
52	SAINT PAUL	M=	CHICAGO	C=	75	0
53	SPOKANE	W=	LOS ANGELES	CR	0	65
54	SPOKANE	W=	CHICAGO	C=	75	0
55	SPRINGFIELD	+W	CHICAGO	C+	35	153
56	STOCKTON	ER	LOS ANGELES	AR	0	375
57	STOCKTON	ER	LOS ANGELES	CR	400	0
58	SYRACUSE	Y+	CHICAGO	C+	50	0
59	SYRACUSE	Y+	ST LOUIS	T+	50	32
60	TAMPA	F+	CHICAGO	G+	0	3
61	TAMPA	F+	CHICAGO	C+	15	0
62	TITUSVILLE	#T	MEMPHIS	R&	0	35
63	TITUSVILLE	#T	ST LOUIS	R!	40	0
64	TORONTO	T%	CHICAGO	C%	0	15
65	TORONTO	T%	MEMPHIS	P%	30	0
66	WORCESTER	R+	CHICAGO	C+	90	0

Table 9: Instance 3 Full Solution Comparison

No.	Lane				Empty Containers Moved	
	Origin Ramp Group	Origin Ramp	Dest. Ramp Group	Dest. Ramp	ECR Team	Model
1	ALBANY	A$	BUFFALO	B!	150	200
2	ALBANY	A$	CHICAGO	I!	150	18
3	ALLENTOWN	N!	ST LOUIS	R!	0	8
4	AYER	Y!	CHICAGO	I!	225	0
5	CALGARY	%E	VANCOUVER	V%	15	8
6	CHAMBERSBURG	+P	CHICAGO	C+	250	224
7	CINCINNATI	T$	CHICAGO	C!	25	8
8	CLEVELAND	+C	CHICAGO	C+	0	71
9	DALLAS	D?	SALINAS VICTORIA	M?	75	0
10	DALLAS	D?	SAN LUIS POTOSI	P?	100	0
11	DALLAS	DR	CHICAGO	IR	0	110
12	DALLAS	DR	KANSAS CITY	E-	0	200
13	DALLAS	DR	LOS ANGELES	AR	0	187
14	DALLAS	DR	LOS ANGELES	CR	200	0
15	DALLAS	DR	SAN BERNARDINO	SR	0	488
16	DALLAS	DR	SEATTLE	S=	0	15
17	DALLAS	DR	SALINAS VICTORIA	M?	500	0
18	DENVER	D-	EL PASO	XR	0	40
19	DENVER	D-	LOS ANGELES	AR	0	367
20	DENVER	D-	SAN BERNARDINO	SR	450	0
21	EDMONTON	E%	CHICAGO	C%	0	1
22	EDMONTON	E%	VANCOUVER	V%	20	32
23	ELIZABETH	K!	CHICAGO	I$	0	191
24	HARRISBURG	P$	CHICAGO	I$	0	15
25	HARRISBURG	H!	COLUMBUS	O!	150	155
26	HARRISBURG	H!	LOS ANGELES	CR	100	0
27	HARRISBURG	H!	TOLEDO	U!	25	20
28	HOUSTON	H-	LOS ANGELES	CR	125	107
29	INDIANAPOLIS	U+	ELIZABETH	E+	35	31
30	JACKSONVILLE	J!	ATLANTA	A!	0	125
31	JACKSONVILLE	J#	CHARLOTTE	T!	0	150
32	JACKSONVILLE	J!	CHARLOTTE	T!	50	0
33	JACKSONVILLE	J!	MEMPHIS	R&	100	69
34	JACKSONVILLE	J!	SAN BERNARDINO	SR	200	0
35	LAREDO	XL	SALINAS VICTORIA	M?	25	24
36	MIAMI	M#	JACKSONVILLE	J#	0	72

No.	Lane				Empty Containers Moved	
	Origin Ramp Group	Origin Ramp	Dest. Ramp Group	Dest. Ramp	ECR Team	Model
37	MIAMI	M#	CHARLOTTE	T!	80	0
38	MIAMI	M#	MEMPHIS	R&	10	0
39	MONTREAL	M%	CHICAGO	C%	0	10
40	ORLANDO	O+	CHICAGO	C+	175	503
41	ORLANDO	O+	ATLANTA	Q+	0	25
42	ORLANDO	O+	NORTH BALTIMORE	+R	300	0
43	PHOENIX	PR	EL PASO	XR	30	0
44	PHOENIX	PR	LOS ANGELES	AR	0	310
45	PHOENIX	PR	LOS ANGELES	CR	200	0
46	PHOENIX	PR	SAN BERNARDINO	SR	200	0
47	PITTSBURGH	D!	CHICAGO	I$	25	15
48	PORTLAND	P=	SEATTLE	S=	250	233
49	SAINT PAUL	M=	CHICAGO	IR	0	2
50	SAINT PAUL	M=	CHICAGO	C=	50	11
51	SASKATOON	%K	CHICAGO	C%	3	3
52	SPOKANE	W=	LOS ANGELES	CR	0	29
53	SPRINGFIELD	+W	CHICAGO	C+	35	83
54	STOCKTON	ER	LOS ANGELES	CR	200	0
55	STOCKTON	ER	SAN BERNARDINO	SR	0	212
56	SYRACUSE	Y+	CHICAGO	G+	0	71
57	SYRACUSE	Y+	CHICAGO	C+	50	0
58	SYRACUSE	Y+	ST LOUIS	T+	50	0
59	TAMPA	F+	CHICAGO	G+	0	1
60	TAMPA	F+	CHICAGO	C+	15	0
61	TITUSVILLE	#T	CHARLOTTE	T!	70	0
62	TITUSVILLE	#T	MEMPHIS	R&	10	56
63	TORONTO	T%	MEMPHIS	P%	15	0
64	WINNIPEG	%W	CHICAGO	C%	10	13
65	WORCESTER	R+	CHICAGO	C+	75	0