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Container Handling Algorithms and Outbound Heavy Truck Movement Modeling for Seaport Container Transshipment Terminals

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CONTAINER HANDLING ALGORITHMS AND OUTBOUND HEAVY TRUCK MOVEMENT MODELING FOR SEAPORT CONTAINER TRANSSHIPMENT TERMINALS

by

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ABSTRACT
CONTAINER HANDLING ALGORITHMS AND OUTBOUND HEAVY TRUCK MOVEMENT MODELING FOR SEAPORT CONTAINER TRANSSHIPMENT TERMINALS

by

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This research is divided into four main parts. The first part considers the basic block relocation problem (BRP) in which a set of shipping containers is retrieved using the minimum number of moves by a single gantry crane that handles cargo in the storage area in a container terminal. For this purpose a new algorithm called the look ahead algorithm has been created and tested. The look ahead algorithm is applicable under limited and unlimited stacking height conditions. The look ahead algorithm is compared to the existing algorithms in the literature. The experimental results show that the look ahead algorithm is more efficient than any other algorithm in the literature.

The second part of this research considers an extension of the BRP called the block relocation problem with weights (BRP-W). The main goal is to minimize the total fuel consumption of the crane to retrieve all the containers in a bay and to minimize the movements of the heavy containers. The trolleying, hoisting, and lowering movements of the containers are explicitly considered in this part. The twelve parameters to quantify

various preferences when moving individual containers are defined. Near-optimal values of the twelve parameters for different bay configurations are found using a genetic algorithm.

The third part introduces a shipping cost model that can estimate the cost of shipping specific commodity groups using one freight transportation mode-trucking-from any origin to any destination inside the United States. The model can also be used to estimate general shipping costs for different economic sectors, with significant ramifications for public policy.

The last part mimics heavy truck movements for shipping different kinds of containerized commodities between a container terminal and different facilities. The highly detailed cost model from part three is used to evaluate the effect of public policies on truckers' route choices. In particular, the influence of time, distance, and tolls on truckers' route selection is investigated.

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To my inspiring parents and family,
who made all of this possible,
for their endless patience and encouragement.

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1- INTRODUCTION & FUNDAMENTAL CONCEPTS

Effective supply chain management requires an efficient, flexible and quick response working environment. The main objective of every supply chain is to maximize the total value generated through the supply chain stages and levels. A supply chain consists of all the parties involved in fulfilling a customer request either directly or indirectly. The supply chain includes the manufacturers, suppliers, transporters, warehouses, retailers, and customers themselves. The value a supply chain creates is the difference between the costs the supply chain incurs in filling the customer's request and what the final product is worth to the customer.

Material handling and transportation is a crucial component of any supply chain. Transportation involves moving inventory between different points in the supply chain. Transportation takes the form of a single mode or combinations of modes and routes, each with its own characteristics. Freight is transported by different modes, including ship, truck, train, aircraft and pipeline. However, 80% or more of the international trade is carried by sea. Indeed, among all the transportation modes, maritime transport remains the dominant mode for international trade both for bulk transport of commodities and containerized cargo. There are five main types of maritime cargo:

- Automobile: Shipped usually by roll-on/roll-off ships.

- Break bulk: Material stacked on wooden pallets and lifted into and out of the vessel by cranes. The volume of break bulk cargo has decreased as containerization has grown.
- Dry Bulk Cargoes: Includes the products and commodities that are neither break bulk cargoes nor containers and are not handled as individual pieces, such as salt, tallow, and scrap metal. Heavy cargoes are bulk cargoes as well like grain, gypsum, logs, wood chips, and cement.
- Containers: Containerized cargo includes everything from auto parts and machinery components to shoes, toys, and frozen meat and seafood.
- Liquid bulk: Includes petroleum, crude oil, LNG.

Among the five types of maritime cargo, containers are the largest and fastest growing cargo category at most ports worldwide. This is due to the fact that containerization has promoted the efficiency of intermodal transportation and reduced handling costs between modes of transport.

Intermodal freight transport involves the shipping of a commodity or product in a container or vehicle, using multiple modes of transportation (rail, ship, and truck), changing modes occurs without handling of the cargo itself. Intermodal freight transport reduces freight handling and allows freight to be transported faster, and also improves security, and reduces damages and losses.

Most international trade of finished goods is done via 20, 40, or 45 foot long steel containers aboard deep-sea container vessels. These vessels are loaded and unloaded at places called seaport container terminals. Container terminals are essential to global supply chains and global freight transportation. Container terminals lie at the heart of the global supply chain and they are complicated facilities supported by systems that are also often complicated. In the very largest of such facilities, there are hundreds of trucks and cranes travelling, operating, and handling 24 hours per day throughout the year. Reducing container retrieval time in container stacking areas using smart techniques, intelligent crane scheduling, and modern technologies saves time and frees up machines and labor for other tasks. It also saves energy and reduces carbon emissions. This dissertation focuses on problems related to the handling and transportation of containers in and around seaport container terminals.

1.1. Introduction to seaport container terminals

A seaport container terminal is a place where container vessels are loaded and unloaded, and where containerized cargo is temporarily stored while awaiting a future journey. The following sections describe the major components of a container terminal in more detail.

1.1.1. Containers

A freight container (intermodal container) is a reusable storage and transport unit for moving commodities and goods between locations. ISO containers are the containers that manufactured to ISO specifications. The container that is taller than the normal is called high-cube (HC) container.

Containers replaced the break bulk method of handling dry goods and revolutionized the transport of goods worldwide. Containers are invented and developed by Malcolm McLean, who launched the first container vessel voyage in 1956. McLean, often called "the father of containerization", was named "Man of the Century" by the International Maritime Hall of Fame. Figure 1.1 illustrates a 20' container and stacking shipping containers. Nowadays, more than seventeen million containers are travelling around the round, shipping different kind of commodities between ports and locations.

(i) (ii)

Figure 1.1. (i) 20' container, (ii) Stacking shipping containers.

A typical container is constructed of corrugated weathering steel and has doors fitted at one end. The common dimensions of the containers are 8 feet wide by 8.5 feet high, and either 20 feet or 40 feet long. They are often stacked up to seven units high in ports. The common dry shipping containers are 20, 40, or 45 feet long. The most common container types are as follows:

- General Purpose: It is suitable for the carriage of most types of dry goods. The size of this type of containers is 20' GP, 40' GP, 40' HC, and 45' HC. HC stands for high cube container, which is one foot higher than general purpose container (GP).
- Refrigerated: Capable of transporting cargo from -13 °F (-25 °C) to 77 °F (25 °C).

- Open Top: For carrying heavy and bulky finished products.
- Ventilated: Prevent condensation inside the container.
- Tank: For carry hazardous and non-hazardous liquids.
- Bin-liner: For carrying garbage from cities to recycling and dump sites.

The specifications of general purpose containers are shown in Table 1.1. A standardized rotating connector, which is formed from a twistlock and corner casting, is used for securing and locking a container in a designated place on trucks, intermodal train carriages or containerships; and for lifting of the containers by cranes and lifters. Each of the eight corners of the container has a twistlock.

Container capacity is often expressed in twenty-foot equivalent units (TEU). TEU cannot be converted into other units because it is not an exact unit. The most common dimensions for a 20-foot (6.1 m) container are 20 feet (6.1 m) long, 8 feet (2.4 m) wide, and 8.5 feet (2.6 m) high, for a volume of 1,360 cubic feet (39 m^3). However, both 9.5 feet (2.9 m) tall high cube and 4.25 feet (1.30 m) half height containers are also reckoned as 1 TEU. This gives a volume range of 680 cubic feet (19 m^3) to 1,520 cubic feet (43 m^3) for one TEU. While the TEU is not itself a measure of mass, some conclusions can be drawn about the maximum mass that a TEU can represent. The maximum gross mass for a 20-foot (6.1 m) dry cargo container is 30,400 kilograms (66,139 lb.). Subtracting the tare mass of the container itself, the maximum amount of cargo per TEU is reduced to approximately 28,200 kilograms (61,289 lb.). Every container has a unique container number placed on the outside for identification and tracking. Costs for transport are usually calculated in twenty-foot equivalent units (TEU).

Table 1.1. General specifications of the containers [114].

		20′ container		40′ container		40′ high-cube container		45′ high-cube container	
		imperial	metric	imperial	metric	imperial	metric	imperial	metric
external dimensions	L	20′ 0″	6.096 m	40′ 0″	12.192 m	40′ 0″	12.190 m	45′ 0″	13.716 m
	W	8′ 0″	2.438 m	8′ 0″	2.438 m	8′ 0″	2.438 m	8′ 0″	2.438 m
	H	8′ 6″	2.591 m	8′ 6″	2.591 m	9′ 6″	2.896 m	9′ 6″	2.896 m
interior dimensions	L	18′ 10 5⁄16″	5.758 m	39′ 5 45⁄64″	12.032 m	39′ 4″	12.000 m	44′ 4″	13.556 m
	W	7′ 8 19⁄32″	2.352 m	7′ 8 19⁄32″	2.352 m	7′ 7″	2.311 m	7′ 8 19⁄32″	2.352 m
	H	7′ 9 57⁄64″	2.385 m	7′ 9 57⁄64″	2.385 m	8′ 9″	2.650 m	8′ 9 15⁄16″	2.698 m
door aperture	L	7′ 8 ⅛″	2.343 m	7′ 8 ⅛″	2.343 m	7′ 6"	2.280 m	7′ 8 ⅛″	2.343 m
	W	7′ 5 ¾″	2.280 m	7′ 5 ¾″	2.280 m	8′ 5″	2.560 m	8′ 5 49⁄64″	2.585 m
volume		1,169 ft^3	33.1 m^3	2,385 ft^3	67.5 m^3	2,660 ft^3	75.3 m^3	3,040 ft^3	86.1 m^3
Max. gross mass		66,139 lb.	30,400 kg	66,139 lb.	30,400 kg	68,008 lb.	30,848 kg	66,139 lb.	30,400 kg
empty weight		4,850 lb.	2,200 kg	8,380 lb.	3,800 kg	8,598 lb.	3,900 kg	10,580 lb.	4,800 kg
net load		61,289 lb.	28,200 kg	57,759 lb.	26,600 kg	58,598 lb.	26,580 kg	55,559 lb.	25,600 kg

1.1.2. Vessels

Container vessel (ship) capacity is normally expressed in Twenty-foot Equivalent Units (TEU), which is the number of 20' x 8' x 8'6" containers it can carry; or, similarly, in Forty-foot Equivalent Units. Containerships vary considerably in size. Some of those serving major ports have capacities exceeding 10,000 TEU. New containerships for feeder service (i.e., serving small out ports from a major port) have capacities as low as 400 TEU. The containership dimensions depend on the number of containers placed abreast on deck and in the holds. Thus, one extra container box abreast in a given ship design involves an increased ship breadth of about 2.8 meters. The average loaded container weighs about 10-12 tons, so the modern container vessels are designed and dimensioned for 12-14 deadweight (dwt) per TEU.

Many generations of containerships have been developed since the beginning of containerization in the mid-1950s. Figure 1.2 shows evolution of container ships since that time. The delivery in 1980 of the 4,100 TEU Neptune Garnet was the largest container ship to date. Because of the limitation on breadth and length imposed by the Panama Canal, the maximum containership size for the next 12 years was 4,500-5,000 TEU. The dimensions of the largest containerships (Panamax-size vessels) were limited by the lock chambers length and breadth of the Panama Canal. The chambers of the locks of the Panama Canal are 305 m long and 33.5 m wide, and the largest depth of the canal is 12.5-13.7 m. The canal is about 86 km long, and passage takes eight hours. At present the canal has two lanes, but a possible third lane with an increased lock chamber size is under consideration in order to capture the next generation of container ships of more than 14,000 TEU, so a containership with maximum breadth (beam) of 32.3 m, a maximum overall length of 294.1 m (965 ft.), and a maximum draught of 12.0 m (39.5 ft.) can use the canal these days.

The sixth generation containerships came online in 2006 when Maersk, main maritime shipper, introduced a new class having a capacity in the range of 11,000 to 14,500 TEUs. The speed of the sixth generation of the containerships is 25.5 knots (47.2 km/h; 29.3 mph) with 80 MW (109,000 hp) propulsion. The required crew for this generation is between 13-30 persons. U.S. oceangoing vessels have smaller crew size of 30 years ago, the new technology and automation reduced the crew from 40 to 20 persons. In 2011, Maersk announced plans to build a new "Triple E" family of containerships with a capacity of 18,000 TEU, with an emphasis on lower fuel consumption.

Single or double stacking cones or twist locks are used to connect the containers together on vessels. The entire container block is lashed using lashing wires or rods and turnbuckles. The cross lashings are used to hold containers together over the entire width of the ship. The twist lock is used to secure containers in a vertical direction; twist locks are placed between the containers and fastened in the rounded holes on the container corners. Hatch covers are used to cover the containers in the cargo spaces and protect them. Hatch covers close off the hatch openings and make them water tight. The cell guides on containerships are “in hold” and “on deck” cell guides. The cell guides in hold include fixed cell guide and removable cell guide. The fixed cell guides are widely applied onto the container ships carrying 40 feet containers on hold.

The top container shipping companies are listed in Table 1.2. Running, maintaining and operating a fleet of container-ships requires a large capital investment, collaboration and networking with other terminals and agencies all over the world, and a lean and flexible management with global insight.

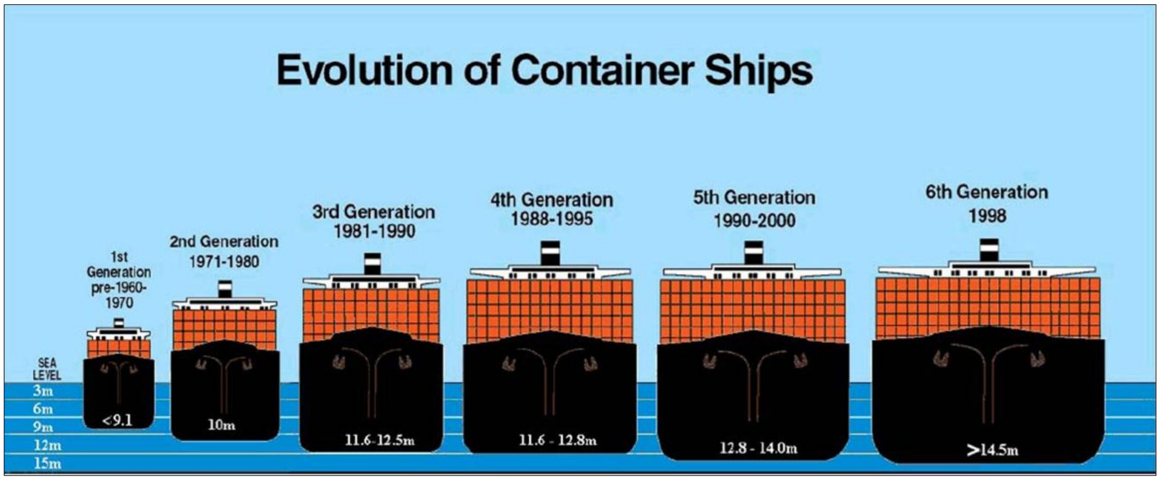


Figure 1.2. Container ship evolution

Table 1.2. 2009 Top container shipping companies (TEU & Number of Ships)

Rank	**Company**	**TEU capacity**	**Number of ships**
1	A.P. Moller-Maersk Group	2,022,956	539
2	Mediterranean Shipping Company S.A.	1,517,200	409
3	CMA CGM	1,023,208	365
4	Evergreen Marine Corporation	594,154	162
5	American President Lines	531,865	135
6	Hapag-Lloyd	475,282	120
7	COSCO	469,848	146
8	China Shipping Container Lines	449,469	139
9	NYK Line	412,711	109
10	Hanjin Shipping	406,462	90

1.1.3. Container terminal operations

As mentioned by Henesey (2004), a container terminal has several subsystems: quay, yard, and some terminals have also gate and rail subsystems. Figure 1.3 shows an illustration of a typical container terminal.

Figure 1.3. Illustration of land-scarce container terminal-*Port of Singapore*.

There are five kinds of container transshipment movements: unloading, loading, receipt, delivery, marshaling. Unloading is container movement from ship to shore (i.e. quay to yard). Loading is container movement from shore to ship (i.e. yard to quay). Receipt is container movement from the hinterland “main land” to the yard. This happens either by truck through a gate or by a rail. Delivery is container movement from the yard to the hinterland. Again, it happens either by truck through a gate or by a rail. Remarshalling is container movement within the yard. (i.e. from yard to yard).

Note that the yard is included in all of the above movements. Thus, the container yard is the heart of any container terminal. The first two investigations in this dissertation consider problems of how to optimally handle containers in the yard.

The busiest container terminals in world as in 2008 are listed in Table 1.3. Most container terminals are operated by an international company or conglomerate.

Table 1.3. 2008 Busiest Container terminals (TEU)

Rank	Port	Country	TEU "Thousands" 2008
1	Singapore	Singapore	29,918
2	Shanghai	People's Republic of China	27,980
3	Hong Kong	Hong Kong	24,248
4	Shenzhen	People's Republic of China	21,414
5	Busan	South Korea	13,425
6	Dubai	United Arab Emirates	11,827
7	Ningbo	People's Republic of China	11,226
8	Guangzhou	People's Republic of China	11,001
9	Rotterdam	Netherlands	10,784
10	Qingdao	People's Republic of China	10,320
11	Hamburg	Germany	9,737
12	Kaohsiung	Taiwan	9,677
13	Antwerp	Belgium	8,663
14	Tianjin	People's Republic of China	8,500
15	Port Klang	Malaysia	7,970
16	Los Angeles	United States of America	7,850
17	Long Beach	United States of America	6,350
18	Tanjung Pelepas	Malaysia	5,600
19	Bremen/Bremerhaven	Germany	5,529
20	New York/New Jersey	United States of America	5,265

Container terminals are divided to main five types: land-scarce terminals, straddle carrier-based terminals, reach-stacker/top-handler terminals, wheeled terminals, and automated terminals.

Land-scarce container terminals are common in small and limited land ports as in Singapore (Figure 1.3) where the scarcity of land available for container stacking requires stacking the containers vertically to higher elevation with few traffic lanes. Three main equipment types used; quay cranes that used to load and load vessels, yard trucks (YT) move containers between yard and quay crane, rubber-tired gantry cranes (RTGC) and rail-mounted gantry cranes (RMGC) that are used to stack containers in the yards. Quay crane, RTGC and RMGC load the containers to truck trailers and not allowed to place the containers on the ground. The tractor trucks are used to move the trailers from the quay crane to the ship crane. The ship cranes are used to remove the containers from the chassis and place them inside the ship. The handling time of the containers by the quay crane consists of the traveling time of the quay crane between bays, and the setup time. The setup time is the time it takes for the quay crane to position itself at the exact stop position inside the bay and stop swaying of the hoist.

Straddle carrier-based container terminals are common in US East Coast and Europe. Cargo is stacked 2-3 tiers high in lanes that are one container wide and the space between lanes very narrow. Two main equipment types are required; quay crane and manual / automated straddle carriers. Straddle carriers are responsible for moving the containers in the two directions between the vessel and the yard, and stacking the containers in the yard. Quay crane is able to place the container on the ground even if there are no free straddle carriers at the moment, which allows unloading the vessels faster than land-scarce container terminals.

Reach-stacker/Top-handler container terminals are common in US West Coast. Three main equipment types are required; quay cranes, yard trucks, and forklifts which are either “top-handlers” or “reach-stackers” that is able to reach the containers in the inner stacks. Reach-stackers, top-handlers, side-picks, and tractor-trailers are manually operated. Containers are stacked up to four tiers. Wider lanes between bays are used to give enough space for forklifts to move and handle.

Wheeled container terminals are the cheapest way to load/unload and store containers in container terminals and require a wide land space. Loaded containers sit on trailers (chassis) and parked in. Storage height is one tier. Three main equipment types are used; quay crane, yard trucks, and top-handlers/side-picks. Empty containers are stacked up to four tiers by side-picks.

Automated container terminals rely on automated equipment to move containers. Cargo is stacked up to five tiers high in large blocks and space between blocks is very narrow. Automated guided vehicles (AGV) are used to move containers between vessel and yard. Automated stacking cranes (ASC) are used to stack containers in the yard. The Ports of Rotterdam and Hamburg each have one or more automated container terminals.

1.2. Introduction to operations research techniques used for studying container terminal problems.

Many articles in the literature discuss container terminal operations from different perspectives. Comprehensive surveys of the container terminal literature have been done by Stahlbock and Voss (2008), Steenken et al. (2004), and Vis and de Koster (2003). An overview of container terminal operations is provided by Günther and Kim (2006). Summaries of the various operational decisions made in container terminals are given in Murty et al. (2005a) and Murty et al. (2005b).

This section briefly summarizes the main operation research (OR) techniques used to find optimal solutions to container terminal problems related to the topic of this research. Operations Research (OR) is a wide field which, loosely, seeks to investigate how mathematical techniques can be used to aid in solving “real-life” problems. Operation research is used to solve strategic and tactical problems where integrated systems of men, machines and materials are involved. This research focuses on two main types of operation research techniques; deterministic techniques and stochastic techniques.

1.2.1. Deterministic techniques

This section provides an introduction to some of the fundamental techniques used in OR under the assumption of "certainty" where there are no probability distributions. The general class of methods used in to solve problems of this type is termed "mathematical programming". Decision makers use mathematical programming to choose the best element from some set of available alternatives. The objective function in mathematical programming is the function to be optimized and the selected decision variables are used to maximize or minimize the objective function. More complicated problems may include more than one objective function. Mathematical programming includes many known mathematical methods as; linear programming, integer programming, geometric programming, nonlinear programming, dynamic programming, heuristics, and metaheuristics.

Linear programming attempts to maximize/minimize a linear function of the decision variables. The decision variables must satisfy a set of linear equality and inequality constraints and sign restrictions associated with each variable. Integer linear programming (ILP) essentially deals with linear programming in which some or all of the variables assume integer or discrete values. Integer linear programming is either pure or mixed "Mixed Integer Programming- MIP" depending on whether some or all the variables are restricted to integer values. The binary integer programming (BIP) is an ILP with all variables are restricted to 0-1 values. Combinatorial optimization problems

(COP) can be formulated as ILPs or BIPs, where a set of feasible solutions is discrete or can be reduced to a discrete one, and the goal is to find the best possible solution. Many algorithms have been developed for integer linear programming, but none of these methods are totally reliable from the computational standpoint, particularly as the number of integer variables increases.

Researchers have developed many procedures for solving ILP problems based on the procedure of solving LP problem. This procedure depends on relaxing the space of integer problem by ignoring the integer restriction of the decision variables. There are two methods for generating the special constraints that will force the optimum solution of the relaxed LP problem toward the desired integer solution: 1- Branch and bound and 2- Cutting planes. Branch and bound is a method that finds the optimal solution to an integer linear programming problems by efficiently enumerating the points in a subproblem's feasible region. Cutting planes/Branch & cut iteratively refines a feasible set or objective function by means of linear inequalities, termed cuts. Branch and cut is a hybrid method of branch and bound and cutting plane.

Dynamic programming is a technique is which computation is carried out in stages by breaking down the problem into subproblem. Each problem is then considered separately with the objective of reducing the volume and complexity of computations. The subproblems are interdependent, therefore the feasibility should be guaranteed after each stage for each subproblem and the entire problem. Dynamic programming usually obtains solutions by working backward from the end of a problem toward the beginning. Heuristics and metaheuristics are often used to find good feasible solutions to ILPs quickly. Different reasons may lead one to choose a heuristic: - A solution is required rapidly. - The instance is so large or complicated to be formulated by ILP or MIP. Even a problem has been formulated by MIP or ILP it difficult for branch and bound to find a good feasible solution. Heuristic designer should determine from the beginning if his heuristic just accepts any feasible solution or a local optimal feasible solution. A metaheuristic is a heuristic method for solving a very general class of computational problems by combining user-given black-box procedures, usually heuristics themselves, in the hope of obtaining a more efficient or more robust procedure. Metaheuristics are generally applied to problems for which there is no satisfactory problem-specific algorithm or heuristic; or when it is not practical to implement such a method. Most commonly used metaheuristics are targeted to combinatorial optimization problems.

A computational problem is called non-deterministic polynomial -NP- problem if it can be solved in polynomial time using a deterministic computer, where the code is executed one by one. A problem is NP-hard if it is as hard as the hardest NP problem. Using heuristics or metaheuristics is beneficial when the problem is described as NP-hard problem. First and second investigations in this dissertation are NP-hard problems.

1.2.2. Stochastic techniques: Discrete event simulation

Stochastic operations research techniques fall into two main categories: applied probability and simulation. Applied probability is usually used to model generic and/or small systems that exhibit a high degree of variability like simple single or multi-server queuing systems. Simulation used for modeling systems that exhibit a lot of variability, can achieve a large number of possible states ”systems with many components”, and have probability distribution without “nice” properties.

Albrecht (2010) mentions that the classical thinking divides simulation to three types; discrete event, continuous, and Monte Carlo. Most transportation-related research concerns the discrete event simulation. A discrete event simulation is one in which changes in the state of the simulation model occur at discrete points in time as triggered by events. State variables in a discrete event simulation are referred to as discrete change state variables.

Discrete event simulation is an appropriate methodology if the logical or quantitative operational decision is being made, the process is well defined and repetitive, and the activities and events are variable and interdependent. Discrete event simulation utilizes a mathematical/logical model of a physical system that portrays state changes at precise points in simulated time. The nature of the state change and the time at which the change occur require precise description. Customers in service system, the management of parts inventory or military combat are good examples of discrete event simulation.

Several randomized runs or replications must be made in stochastic simulation to get an accurate performance estimate because each run varies statistically. Monte Carlo simulation – also known as static simulation – is not based on time. It often involves drawing random samples to generate statistical outcomes.

1.3 Dissertation overview

This dissertation focuses on improving handling operations in the container yard and studies the influence of the public polices in shipping containers and goods by heavy trucks. The proposed algorithms and techniques in this dissertation reduce the handling operation's time and fuel consumption in the container yard. The proposed shipping cost model and the path-finding algorithm are efficient tools for a public policy maker.

This dissertation includes four main investigations. The purpose of the first investigation is twofold. First, a new mixed integer programming formulation of the BRP is introduced and shown to have considerably fewer decision variables than the formulation given in Caserta et al. (2012). Then, a new look-ahead algorithm (LA-*N*) for the BRP is introduced. We show that LA-*N* algorithm generally outperforms all of the non-LA algorithms (including the KH, DH, CM, and LL algorithms) in terms of objective value and CPU runtime on a small-, medium-, and large-scale problems.

The second investigation extends the BRP and considers the weight of the containers. The new problem is called the block relocation problem with weights (BRP-W) and it tracks the trolleying, hoisting, and lowering movements of the containers. Twelve parameters are used to quantify the preferences when moving individual containers in different bay configurations. The main goal is to reduce the total fuel consumption of the crane in the container yard.

A highly detailed cost model for shipping commodities by truck is introduced in the third investigation. A methodology for estimating shipping costs for specific commodity groups using heavy trucks has been developed and tested. The total shipping cost is comprised of the individual costs for fuel, labor, depreciation, maintenance, loading and unloading, insurance, overhead, and extra expenses. The proposed model is a policy oriented cost model and enables the public sector to estimate freight transportation costs. The model is available in the form of a spreadsheet.

The last investigation mimics heavy truck movements to transport containers of specific commodity groups between different industrial areas and a container terminal. The effects of public polices, time, and distance are considered. The highly-detailed cost model for the purposes of policy analysis introduced in investigation three has been modified and embedded in this path-finding model.

2- A NEW MIXED INTEGER PROGRAM AND LOOK-AHEAD ALGORITHM FOR THE BLOCK RELOCATION PROBLEM

The block relocation problem (BRP) is considered in this section, in which a set of identically-sized items is to be retrieved from a set of last-in-first-out (LIFO) stacks in a specific order using the fewest number of moves. The problem is encountered in the maritime container shipping industry and other industries where inventory is stored in stacks. After surveying the algorithms that have been developed for the BRP, a new mathematical formulation for the BRP is introduced and shown that it has considerably fewer decision variables than the other formulation in the literature. Then a new look-ahead algorithm (LA-*N*) is introduced that is an extension of the algorithms from the literature and show that the new algorithm generally outperforms the other algorithms in terms of objective value and CPU runtime.

2.1. Introduction and problem description

In this part of research, a problem related to the handling of steel shipping containers called the block relocation problem (BRP) is considered. The block relocation problem (BRP) is an important problem at logistics facilities such as seaport container terminals where overhead gantry cranes, straddle carriers, and/or reach stackers sort and stack containerized cargo that awaits a future journey (Figure 2.1).

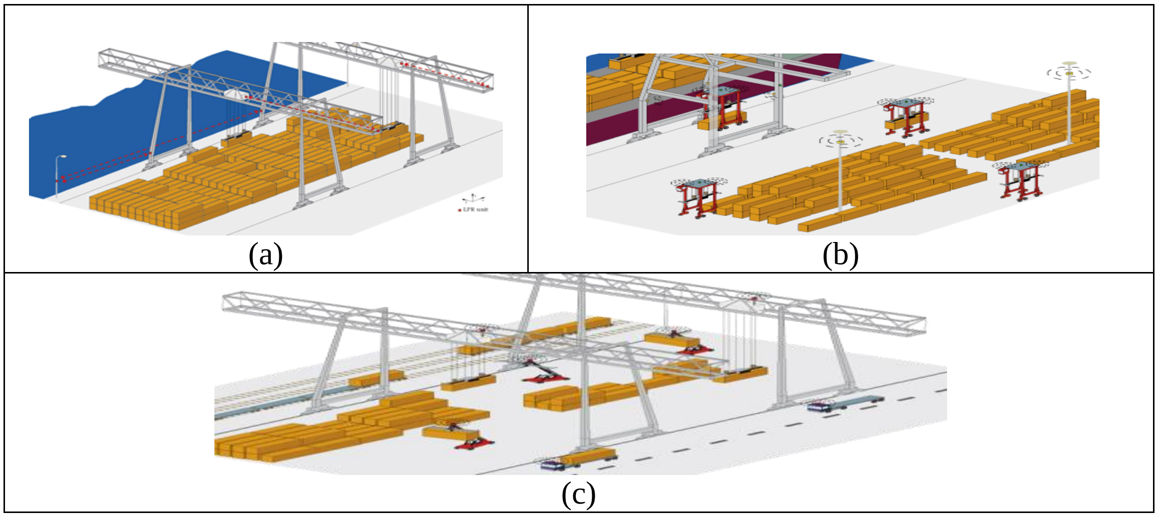


Figure 2.1. The block relocation problem (BRP) is an important problem at logistics facilities such as seaport container terminals where (a) overhead gantry cranes, (b) straddle carriers, and/or (c) reach stackers sort and stack containerized cargo that awaits a future journey. *(Source: symeo.com)*

The BRP can be defined as follows. Consider C *containers* (blocks, items) numbered 1 to C that are temporarily stored as inventory. Due to space limitations, these containers are stacked directly on top of each other in a storage *bay* consisting of S last-in-first-out (LIFO) *stacks*. As the time to move this inventory approaches, management learns that the containers must be retrieved from the bay according to the sequence 1, 2, 3, …, C. In other words, container 1 must be retrieved first; container 2 must be retrieved second, and so on. Containers that have not been retrieved must remain in one of the bay's S stacks until their retrieval time arrives. The goal is to retrieve all C containers from the bay using the minimum number of *moves*, where a move is either a direct *retrieval*, in which a container is permanently taken out of the bay, or a *relocation* (*reshuffle*), in which a container is moved from one stack to another stack. A container may only be moved when no other container is above it. Also associated with the problem is a maximum stack height, *mxHeight*, which gives the maximum number of containers that can be in any stack at any time. This limitation is important when height is limited by a ceiling or other predetermined limit such as the height of a material handling crane. Note that there is no maximum stacking height when $mxHeight \geq C$.

The most challenging aspect of the BRP is deciding when and how to relocate containers (blocks) so as to minimize the total number of moves. Hence the name "block relocation problem." Figure 2.2 shows an instance of the BRP where $C = 9$ and $S = 3$. Here, the goal is to retrieve all nine containers from the bay shown on the left using the minimum number of moves. The resulting bay will be empty as shown in the bottom right. Figure 2.6 shows three possible solutions to another instance of the BRP where $C = 9$ and $S = 3$. In solutions (i) and (ii), there is no height limit (i.e. $mxHeight = 9$). In solution (iii), there is a height limit $mxHeight = 5$.

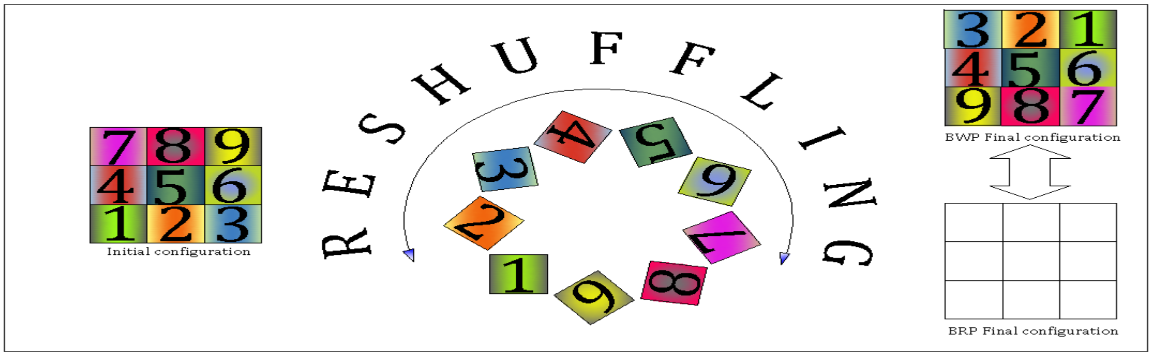


Figure 2.2. Illustration of the BRP and BWP problems.

2.2. Literature review

There are several studies in the literature concerning the optimal storage, handling, and retrieval of items stored in stacks that predate the onset of research on the BRP .The literature also covers different prospective related to the containers' port terminal handling operations rather than BRP. Sculli and Hui (1988) consider how the dimensions of a three-dimensional storage area—for example, the number of stacks and the maximum allowed stacking height—affect the number of moves needed to retrieve containers from the storage area. They presented the results of a simulation study into the stacking and handling of containers with the same dimensions. The decision variables include the maximum dimensions of the store, stacking policies, and the different number of types of containers and their relative frequencies. The results indicate that the number of different types of containers has the largest impact on the measures of performance. The effects of the stacking policy and maximum store dimensions are also significant. The measures of performance include volumetric utilization, wasteful handling ratios, storage ratio, and rejection ratio.

Gupta and Nau (1992) prove the NP-hardness of a more general problem than the BRP, called the blocks-world planning (BWP) problem, in which the final container configuration is any feasible stack configuration. Figure 2.2 in Section 2.1 illustrates the relationship between the BWP problem and the BRP. de Castilho and Daganzo (1993) develop general expressions for the expected number of moves required to retrieve a container from storage stacks under two different general storage strategies but do not evaluate options for decision making regarding individual containers. Kim (1997) computes the expected total number of moves required to empty a yard bay under probabilistic conditions where there is no advanced knowledge of container retrievals and each container is equally likely to be the next one retrieved from the bay. Avriel et al. (1998) consider how best to stow containers (assign containers to slots) in container vessels so as to minimize the number of container relocations required when unloading and loading vessels at port.

The BRP began receiving attention by academicians only recently. Thus far, only a handful of contributions have been made by researchers whose application area is the maritime container shipping industry. For the most recent and comprehensive surveys of the container shipping literature, please see Stahlbock and Voβ (2008) and Steenken et al. (2004). Li et al. (2009) is an example of recent research on container shipping.

Eight previous published and unpublished studies of the BRP were reviewed. Petering (2004) developed a mathematical formulation for the BRP that is not as economical as the one presented in Section 2.3. Petering et al. (2005) developed a heuristic algorithm for the BRP which used as a base for LA algorithm.

Kim and Hong (2006) published the first paper on the BRP. They suggest two methods for determining where to relocate blocks. The first method is a branch and bound algorithm, and the second method is a heuristic (which is called the KH algorithm in this study) that uses an estimator for the expected number of additional relocations in each stack. Numerical results show that the number of relocations calculated by the KH algorithm exceed the number found by branch and bound. However, the computational time used by the KH algorithm is far less than that consumed by branch and bound.

Aydin (2006) and Aydin and Ünlüyurt (2008) consider the basic BRP and several extensions. They develop a difference heuristic (which is called the DH algorithm in this study) for solving difficult instances of the BRP. They also introduce the concept of a *cleaning move*. Let us use the term *target block* (*target container*) to refer to the next block that is to be retrieved from (i.e. be permanently taken out of) the storage bay. A cleaning move is the relocation of a block that is not in the target block's stack. Although they are not part of the DH algorithm, the authors show that cleaning moves may reduce the total number of moves needed to empty a storage bay in some cases.

Caserta et al. (2008) develop a mathematical formulation of the BRP and prove that it is NP-hard. They independently devise the same LA algorithm that was devised by Petering at al. (2005), and show that this algorithm outperforms the KH algorithm over a range of small- and medium-scale problem instances. Caserta et al. (2009b) present a corridor method inspired algorithm (which is called the CM algorithm in this study) for the BRP and show that it outperforms the KH algorithm over a range of small-, medium-, and large-scale problem instances. Caserta et al. (2009a) develop a binary description of the BRP; attach the name "look-ahead" to the LA algorithm devised in Caserta et al. (2008); and show that the LA algorithm outperforms both the KH and CM algorithms for large-scale problem instances. Note that the name "look-ahead" have been adopted for both the LA algorithm from the literature and the new LA-*N* algorithm that is introduced in Section 2.4.

Lee and Lee (2010) present a three-phase heuristic (which is called the LL algorithm in this study) for optimizing the working plan for a crane to retrieve all the containers from a given storage area, which may have one or more adjacent bays, in a specific order. For the single bay case, the problem is identical to the BRP and it is shown that the LL algorithm outperforms the KH algorithm on several large problem instances.

2.3. Mathematical formulation

This section presents a new mixed integer programming formulation of the block relocation problem (BRP) and presents limited computational results showing the performance of CPLEX 11.2 to compare its performance to the other formulation in the literature devised by Caserta et al. (2012).

2.3.1. Mixed integer program

A new mixed integer programming formulation of the BRP is presented in Tables 2.1-2.4 below. These tables present the (1) indices, (2) parameters, (3) decision variables, and (4) mathematical program respectively. In the formulation, indices *t* and *w* represent time intervals. A maximum of one container may be moved during a time interval (constraint 11). The objective is to take the last container, container *C*, out of the bay as soon as possible, i.e. during the earliest possible time interval. Note that the three-index decision variables take real values, not binary or integer values (Tables 2.3, 2.4). Thus, the number of integer variables has been kept to a minimum.

Table 2.1. Indices in the mathematical program.

c	container	(*c* = 1 to *C*)
s	stack	(*s* = 1 to *S*)
t, w	time intervals	(*t*, *w* = 1 to *W*)

Table 2.2. Parameters in the mathematical program.

C	Number of containers (integer, > 0).
S	Number of stacks (integer, > 0).
mxHeight	Maximum height (in number of containers) allowed for any stack at any time (integer, > 1).
W	Maximum number of time intervals that could possibly be needed to retrieve all containers from the bay (integer, > 0).
$initialSetup_{c,s}$	= 1 if container *c* is in stack *s* <u>at the beginning of</u> the first time interval (binary).
$initialBury_{c}$	Number of containers burying container *c* (including itself) <u>at the beginning of</u> the first time interval (integer, > 0).

Table 2.3. Decision variables in the mathematical program.

$X_{c,s,t}$	= 1 if container *c* is in stack *s* <u>at the beginning of</u> time interval *t* (real decision variable that takes binary values).
$B_{c,t}$	Number of containers burying container *c* (including itself) <u>at the beginning of</u> time interval *t* (real decision variable that takes nonnegative integer values). This equals 0 if container *c* has already been taken out of the bay by the start of time interval *t*.
$M_{c,t}$	= 1 if container *c* is moved <u>during</u> time interval *t* (binary).
$C_{c,t}$	= 1 if container *c* moves (one step) closer to the top of its stack <u>during</u> time interval *t* (binary).
$F_{c,t}$	= 1 if container *c* moves (one step) farther from the top of its stack <u>during</u> interval *t* (binary).
$T_{c,t}$	= 1 if container *c* is permanently taken out of the bay <u>during</u> time interval *t* (binary).
$R_{s,t}$	= 1 if a container is removed from (the top of) stack *s* <u>during</u> time interval *t* (binary).
$P_{s,t}$	= 1 if a container is placed onto (the top of) stack *s* <u>during</u> time interval *t* (binary).
$R_{c,s,t}$	= 1 if container *c* is removed from (the top of) stack *s* <u>during</u> time interval *t* (real decision variable that takes binary values).
$P_{c,s,t}$	= 1 if container *c* is placed onto (the top of) stack *s* <u>during</u> time interval *t* (real decision variable that takes binary values).

Table 2.4. Mathematical formulation of the BRP.

Objective:	
Minimize: $\sum_{t=1}^{W} t * T_{C,t}$	
Subject to:	
$R_{c,s,t} \le R_{s,t} \quad \forall c, \forall s, \forall t$	(1a)
$R_{c,s,t} \le M_{c,t} \quad \forall c, \forall s, \forall t$	(1b)
$R_{c,s,t} \ge R_{s,t} + M_{c,t} - 1 \quad \forall c, \forall s, \forall t$	(1c)
$0 \le R_{c,s,t} \le 1 \quad \forall c, \forall s, \forall t$	(1d)
$\sum_{c=1}^{C} R_{c,s,t} = R_{s,t} \quad \forall s, \forall t$	(1e)
$\sum_{s=1}^{S} R_{c,s,t} = M_{c,t} \quad \forall c, \forall t$	(1f)
$P_{c,s,t} \le P_{s,t} \quad \forall c, \forall s, \forall t$	(2a)
$P_{c,s,t} \le M_{c,t} \quad \forall c, \forall s, \forall t$	(2b)
$P_{c,s,t} \ge P_{s,t} + M_{c,t} - 1 \quad \forall c, \forall s, \forall t$	(2c)
$0 \le P_{c,s,t} \le 1 \quad \forall c, \forall s, \forall t$	(2d)
$\sum_{c=1}^{C} P_{c,s,t} = P_{s,t} \quad \forall s, \forall t$	(2e)
$\sum_{s=1}^{S} P_{c,s,t} \le M_{c,t} \quad \forall c, \forall t$	(2f)
$X_{c,s,1} = initialSetup_{c,s} \quad \forall c, \forall s$	(3a)
$X_{c,s,t+1} = X_{c,s,t} + P_{c,s,t} - R_{c,s,t} \quad \forall c, \forall s, \forall t$	(3b)
$0 \le X_{c,s,t} \le 1 \quad \forall c, \forall s, \forall t$ from 1 to W+1	(3c)
$B_{c,1} = initialBury_{c} \quad \forall c$	(4a)
$B_{c,t+1} = B_{c,t} + F_{c,t} - C_{c,t} \quad \forall c, \forall t$	(4b)
$B_{c,t} \ge 0 \quad \forall c, \forall t$ from 1 to W+1	(4c)
$\sum_{s=1}^{S} X_{c,s,t} \le 1 \quad \forall c, \forall t$ from 1 to W+1	(5)
$\sum_{c=1}^{C} X_{c,s,t} \le mxHeight \quad \forall s, \forall t$ from 1 to W+1	(6)
$\sum_{c=1}^{C} X_{c,s,t} \le 2 + \sum_{c=1}^{C} X_{c,s+1,t} \quad \forall s \le S-1, \forall t$ from 1 to W+1	(7*)
$\sum_{c=1}^{C} X_{c,s,t} \ge \sum_{c=1}^{C} X_{c,s+1,t} - 2 \quad \forall s \le S-1, \forall t$ from 1 to W+1	(8*)
$B_{c,t} \le mxHeight \quad \forall c, \forall t$ from 1 to W+1	(9)

$$\sum_{t=1}^{W} M_{c,t} \geq 1 \quad \forall c \tag{10}$$

$$\sum_{c=1}^{C} M_{c,t} \leq 1 \quad \forall t \tag{11}$$

$$\sum_{c=1}^{C} M_{c,t} = 1 \quad \forall t \text{ from 1 to } C \tag{12}$$

$$\sum_{c=1}^{C} C_{c,t} \leq mxHeight \quad \forall t \tag{13}$$

$$\sum_{c=1}^{C} F_{c,t} \leq mxHeight \quad \forall t \tag{14}$$

$$\sum_{t=1}^{W} (C_{c,t} - F_{c,t}) = initialBury_c \quad \forall c \tag{15}$$

$$\sum_{c=1}^{C} T_{c,t} \leq 1 \quad \forall t \tag{16}$$

$$\sum_{t=1}^{W} T_{c,t} = 1 \quad \forall c \tag{17}$$

$$\sum_{t=1}^{W} t * T_{c+1,t} \geq 1 + \sum_{t=1}^{W} t * T_{c,t} \quad \forall c \text{ from 1 to } C\text{-1} \tag{18}$$

$$\sum_{s=1}^{S} R_{s,t} \leq 1 \quad \forall t \tag{19}$$

$$\sum_{s=1}^{S} R_{s,t} = 1 \quad \forall t \text{ from 1 to } C \tag{20}$$

$$\sum_{s=1}^{S} P_{s,t} \leq \sum_{s=1}^{S} R_{s,t} \quad \forall t \tag{21}$$

$$P_{s,t} + R_{s,t} \leq 1 \quad \forall s, \forall t \tag{22}$$

$$\sum_{s=1}^{S} P_{c,s,t} \leq \sum_{s=1}^{S} R_{c,s,t} \quad \forall c, \forall t \tag{23}$$

$$R_{c,s,t} \leq X_{c,s,t} \quad \forall c, \forall s, \forall t \tag{24}$$

$$(1 - M_{c,t})(mxHeight - 1) \geq B_{c,t} - 1 \quad \forall c, \forall t \tag{25}$$

$$T_{c,t} \leq M_{c,t} \quad \forall c, \forall t \tag{26}$$

$$T_{c,t} = \sum_{s=1}^{S} R_{c,s,t} - \sum_{s=1}^{S} P_{c,s,t} \quad \forall c, \forall t \tag{27}$$

$$X_{c,s,t} \geq C_{c,t} + R_{s,t} - 1 \quad \forall c, \forall s, \forall t \tag{28a}$$

$$R_{s,t} \geq X_{c,s,t} + C_{c,t} - 1 \quad \forall c, \forall s, \forall t \tag{28b}$$

$$C_{c,t} \geq R_{s,t} + X_{c,s,t} - 1 \quad \forall c, \forall s, \forall t \tag{28c}$$

$$X_{c,s,t+1} \geq F_{c,t} + P_{s,t} - 1 \quad \forall c, \forall s, \forall t \tag{29a}$$

$$P_{s,t} \geq X_{c,s,t+1} + F_{c,t} - 1 \quad \forall c, \forall s, \forall t \tag{29b}$$

$$F_{c,t} \geq P_{s,t} + X_{c,s,t+1} - 1 \quad \forall c, \forall s, \forall t \tag{29c}$$

The constraints are divided into three groups: constraints 1-4, constraints 5-23, and constraints 24-29. The first group of constraints introduces most of the decision variables and shows why some variables can be defined as real variables instead of binary or integer variables. The second group places basic limitations on the values of the decision variables. The third group establishes important relationships between two or more kinds of decision variables.

Let's consider the first group of constraints. Constraints (1a)-(1d) allow $R_{c,s,t}$ to be real but force it to be either 0 or 1. Constraints (1e) and (1f) further define the proper relationship between $R_{c,s,t}$ and $R_{s,t}$, and between $R_{c,s,t}$ and $M_{c,t}$ respectively. Constraints (2a)-(2d) allow $P_{c,s,t}$ to be real but force it to be either 0 or 1. Constraints (2e) and (2f) further define the proper relationship between $P_{c,s,t}$ and $P_{s,t}$, and between $P_{c,s,t}$ and $M_{c,t}$ respectively. The difference between constraints (1f) and (2f) is that a container is always removed from a stack, but need not be placed onto a stack, during a turn in which it is moved. Indeed, it might be permanently taken out of the bay. Constraint (3a) initializes the $X_{c,s,t}$ variables with the proper values. Constraint (3b) ensures that the $X_{c,s,t}$ variables are updated in the appropriate manner during each time interval based upon the placements or removals of containers during that time interval. Note that $R_{c,s,t}$, $P_{c,s,t}$, and $initialSetup_{c,s}$ only take the values 0 or 1, so constraints (3a)-(3c) allow $X_{c,s,t}$ to be real but force it to be either 0 or 1. Constraint (4a) initializes the $B_{c,t}$ variables with the proper values. Constraint (4b) ensures that the $B_{c,t}$ variables are updated in the appropriate manner during each time interval based upon whether containers get further away or closer to the top of their respective stacks during that time interval. Note that $F_{c,t}$, $C_{c,t}$, and *initialBury*$_c$ are binary, so constraints (4a)-(4c) allow $B_{c,t}$ to be real but force it to take integer values.

Now let's consider the second group of constraints. Constraint (5) states that each container can only be in 0 or 1 stacks at any point in time. Constraint (6) states that stack can accommodate at most *mxHeight* containers at any point in time. Constraints (7)-(8) ensure that two adjacent stacks can never differ in height by more than two containers. These safety constraints are optional and are not enforced by the algorithms discussed in Section 2.4 or the experiments that test this formulation later in this section. Constraint (9) keeps the value of $B_{c,t}$ in the allowable range at all times. This constraint may be redundant. Constraint (10) ensures that each container is moved at least once. This constraint may be redundant. Constraint (11) ensures that no more than one container is moved during each time interval. This constraint, combined with constraints (1b) and (2b), implies that the container that is placed onto a stack (if any) must be the same container that is removed from a stack in any particular turn. Constraint (12) states that there should be exactly one container move during each of the first C time intervals. This constraint is redundant but its inclusion in the formulation may help an optimizer find an optimal solution more quickly. Constraint (13/14) ensures that the maximum "total amount of container movement (closer to/farther from) the top of stacks" during each time interval *is mxHeight*. Such movement is maximized when a container is (removed from/placed onto) a stack of the maximum height. In such a case, all containers in the stack get one step (closer to/farther from) the top of the stack. Again, constraints (13)-(14) are redundant but may be useful to include in the formulation. Constraint (15) ensures that the "total amount of movement closer to the top of a stack over container *c*'s lifetime in the bay" equals $initialBury_c$. Constraint (16) states that no more than one container can be taken out of the bay during each turn. Constraint (17) ensures that each container is taken out of the bay exactly once. Constraint (18) states that containers must be taken out of the bay in the proper sequence, i.e. in order of increasing container number. Constraint (19) ensures that no more than one container is removed from a stack during each time interval. Constraint (20) states that exactly one container should be removed from a stack during each of the first C time intervals. This constraint is redundant but its inclusion in the formulation may help an optimizer find an optimal solution more quickly. Constraint (21) states that a placement may only take place during a turn if a removal also takes place during the same turn. Constraint (22) forbids the placing of a container back onto the stack from which it was removed during the same turn. This constraint may help an optimizer find an optimal solution more quickly. Constraint (23) states that a placement of a particular container may only take place during a turn if a removal of the container also takes place during the same turn. This constraint is redundant but its inclusion in the formulation may help the optimizer find an optimal solution more quickly.

The third group of constraints is to be considered now. Constraint (24) ensures that a container can be removed from a particular stack only if the container is located in that stack. Constraint (25) ensures that only containers on the top of a stack (or that have already taken out of the bay) may be moved. Note that $B_{c,t} \geq 2$ implies that $M_{c,t} = 0$. On the other hand, $B_{c,t} \leq 1$ does not impose any restrictions on $M_{c,t}$. Thus, the only way for binary variable $M_{c,t}$ to be 1 is for $B_{c,t}$ to be either 0 or 1. In other words, container c can be moved during time interval t only if it is either on the top of a stack ($B_{c,t} = 1$) or outside the bay ($B_{c,t} = 0$) at the beginning of time interval t. Constraints (26)-(27) link $T_{c,t}$ to the other decision variables. Constraint (26) states that moving a container is a precondition for taking a container out of the bay. Constraint (27) states that, if a container is removed from a stack but not placed into a stack during a particular time interval, then it must be taken out of the bay during that time interval. Constraints (28a)-(28c) link $C_{c,t}$ to the other decision variables. These constraints state that if any two of $X_{c,s,t}$, $R_{s,t}$, and $C_{c,t}$ equal 1, then the third also equals 1. Constraints (29a)-(29c) link $F_{c,t}$ to the other variables. These constraints state that if any two of $X_{c,s,t+1}$, $P_{s,t}$, and $F_{c,t}$ equal 1, the third also equals 1.

It should be noted that the above formulation has considerably fewer integer decision variables than the model presented by Caserta et al. (2012). Table 2.5 shows the number of decision variables in each formulation for different problem instances.

Table 2.5. Number of decision variables in different mathematical formulations of the BRP.

Problem instance	Petering and Hussein # integer vars.	Petering and Hussein # real vars.	Caserta et al. (2012) # integer vars.	Caserta et al. (2012) # real vars.
$C = 5$ $S = 3$ $mxHeight = 5$ $W = 9$	234	470	11,520	0
$C = 9$ $S = 4$ $mxHeight = 9$ $W = 16$	704	1917	197,136	0
$C = 20$ $S = 6$ $mxHeight = 6$ $W = 50$	4600	19,140	1,369,000	0

2.3.2. Computational results using CPLEX

The mathematical formulations developed by Caserta et al. (2012) and in this investigation were coded into C++ using ILOG Concert Technology and tested on small problem instances using CPLEX 11.2. A total of 50 problem instances were considered—ten each with 5, 6, 7, 8, and 9 containers. The computational results are shown in Table 2.6. The first five columns show the values of the main input parameters for each instance and the final three columns show the experimental results when each instance is coded into C++ using ILOG Concert Technology and solved using CPLEX 11.2 with default settings. The parameter W for each instance equals the number of moves needed to empty the bay when container moves are decided by the LA algorithm (which is introduced in the next section). This number serves as an upper bound for the minimum number of moves required to empty the bay; setting W equal to this value prevents the generation of unnecessary decision variables and constraints when the mathematical formulation is built in C++ using ILOG Concert Technology prior to being solved by CPLEX.

The results strongly indicate that the model presented in this study outperforms the model developed by Caserta et al. (2012). Indeed, in all fifty instances, the runtime used by CPLEX to identify an optimal solution is strictly less when the model presented here is used versus the model presented by Caserta et al. (2012). Note that the LA algorithm finds the optimal solution in most cases and provides a very good upper bound on the optimal number of moves. Unfortunately, the results indicate that a math programming approach is not sufficient for real-world use. Indeed, CPLEX needs about

10 hours to find the optimal solutions to two of the 9-container instances. Yet, container bays in the real world typically have the capacity to store up to 30 containers or more. Clearly, another approach is needed for solving the larger problem instances encountered in the real world.

Table 2.6. Computational results for math program on small problem instances.

Instance	*C*	*S*	*mxHeight*	*W*	Optimal value	Petering/Hussein CPU runtime (sec)	Caserta et al. (2012) CPU runtime (sec)
5-1	5	3	5	9	9	2	4
5-2	5	3	5	7	7	0	2
5-3	5	3	5	7	7	0	1
5-4	5	3	5	7	7	0	1
5-5	5	3	5	7	7	0	1
5-6	5	3	5	6	6	0	1
5-7	5	3	5	8	8	0	1
5-8	5	3	5	7	7	0	1
5-9	5	3	5	7	7	0	3
5-10	5	3	5	7	7	0	4
6-1	6	3	6	11	11	6	107
6-2	6	3	6	10	10	20	28
6-3	6	3	6	10	10	0	12
6-4	6	3	6	9	9	2	8
6-5	6	3	6	9	9	0	3
6-6	6	3	6	8	8	0	1
6-7	6	3	6	9	9	0	2
6-8	6	3	6	9	9	0	2
6-9	6	3	6	9	9	0	5
6-10	6	3	6	12	11	62	114
7-1	7	3	7	11	11	14	133
7-2	7	3	7	13	13	340	544
7-3	7	3	7	12	12	15	581
7-4	7	3	7	11	11	25	100
7-5	7	3	7	10	10	1	15
7-6	7	3	7	10	10	1	29
7-7	7	3	7	9	9	0	3
7-8	7	3	7	9	9	0	4
7-9	7	3	7	9	9	0	4
7-10	7	3	7	13	12	270	735
8-1	8	3	8	15	15	1439	2573
8-2	8	3	8	16	16	4548	7494
8-3	8	3	8	10	10	1	7
8-4	8	3	8	11	11	1	12
8-5	8	3	8	16	15	1025	3210
8-6	8	3	8	13	13	66	134
8-7	8	3	8	10	10	1	8
8-8	8	3	8	11	11	4	24
8-9	8	3	8	13	12	32	489
8-10	8	3	8	10	10	1	23
9-1	9	4	9	16	16	36085	36647
9-2	9	4	9	12	12	8	393
9-3	9	4	9	11	11	2	19
9-4	9	4	9	13	12	15	1176
9-5	9	4	9	16	16	26294	28161
9-6	9	4	9	12	12	22	702
9-7	9	4	9	13	13	5	1047
9-8	9	4	9	11	11	1	33
9-9	9	4	9	12	12	1	129
9-10	9	4	9	12	12	25	9302

2.4. Look-ahead algorithm LA-*N*

The difficulties experienced with mathematical programming have led to search for heuristic techniques to address the BRP. This search resulted in the development of a new look-ahead algorithm (LA-*N*). The new LA-*N* algorithm extends the basic LA algorithm. Petering et al. (2005) started working on LA algorithm few years ago. The work on this algorithm is continued, tested, and submitted for publication. LA-*N* is compared to other Algorithms (KH, DH, CM, and LL) in Section 2.4; the KH algorithm is from Kim and Hong (2006); the DH algorithm is from Aydin (2006) and Aydin and Ünlüyurt (2008); the CM algorithm is from Caserta et al. (2012); the LL algorithm is from Lee and Lee (2010).

The LA and LA-*N* algorithms both make use of the following concepts. As mentioned before, the term *target container* is used to indicate the next container that is to be retrieved from (i.e. be permanently taken out of) the storage bay. If the algorithm allows a container to be moved from a stack, it is called an *origin stack*. If the algorithm allows a container to be moved to a stack, it is called a *destination stack*. Any stack that is neither an origin stack nor a destination stack is a *neutral stack*. The overall process of retrieving all *C* containers from the bay can be divided into *C stages*. Each stage consists of the moves undertaken after the retrieval of the most recent container up to and including the retrieval of the next container.

2.4.1. LA algorithm: Unlimited stack height - container approach

The basic LA algorithm is shown below. Figure 2.3 illustrates the decisions made by this algorithm in different cases. Note that *mxHeight* is not mentioned in the basic LA algorithm. In other words, it is implicitly assumed that *mxHeight* $\geq$ C.

1. Let s^* = the stack containing the target container. Only containers in stack s^* may be moved (i.e. no "cleaning moves" are allowed).
2. Let n = the container on the top of stack s^*. If n is the target container, retrieve it immediately and go to step 1. Otherwise, container n will be relocated and we go to step 3.
3. Let $Low(s)$ = the lowest numbered container in stack s. Clearly, the top container in stack s will have to be moved during stage $Low(s)$ or sooner.
4. Let $D = \{ s \mid s \neq s^* \text{ and } Low(s) > n \}$. If D is empty, container n will have to be relocated yet again before finally being retrieved. In order to delay the time of container n's next relocation, place container n on the stack $s \neq s^*$ with the highest $Low(s)$. Otherwise, if D is non-empty, there is a way to relocate container n so it is not relocated again until its retrieval. In this case, relocate container n to the stack in D with the lowest $Low(s)$. This conserves the good destination stacks for future relocations. Go to step 1.

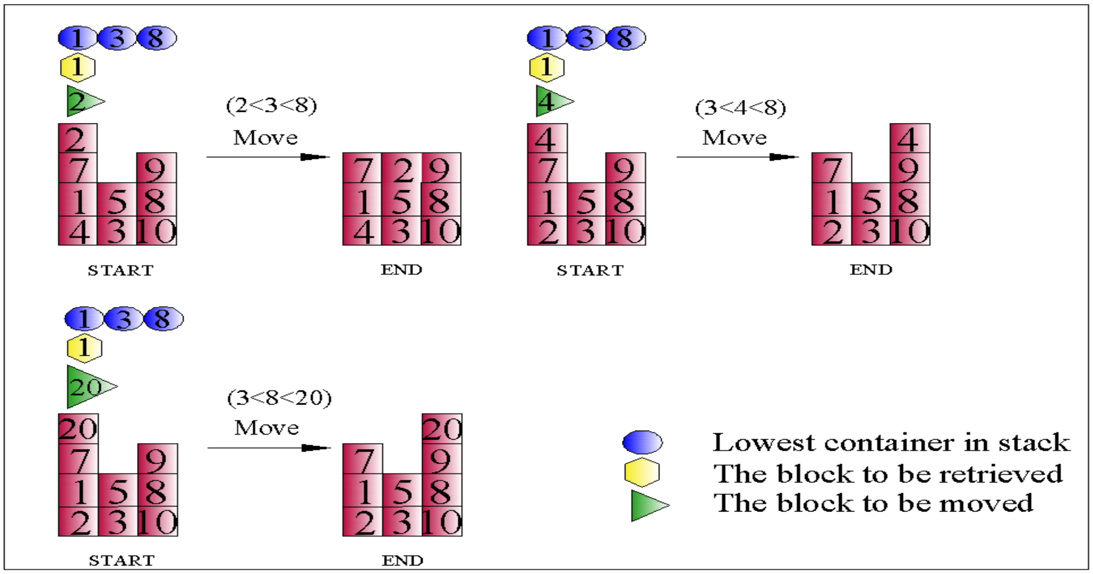


Figure 2.3. Decisions made by the LA algorithm in different cases.

2.4.2. LA-N algorithm: Container approach

The term "LA-*N*" represents a family of algorithms, each corresponding to a different value of the parameter *N*. The value of *N* specifies how many future container retrievals are considered when identifying eligible container relocations. When $N = 1$, the algorithm has a "one container look ahead" and is virtually identical to the basic LA algorithm shown above. In this case, only moves of containers that are in the same stack as the target container are allowed. In other words, no cleaning moves are allowed. For higher values of *N*, the algorithm has an "*N*-container look ahead," meaning that only moves of containers that are in the same stack as one of the next *N* containers to be retrieved are allowed. Thus, the algorithm allows cleaning moves under certain conditions.

Our description of the LA-*N* algorithm uses the following notation. Let c^* = the number of the target container. Let *Stack*(c) = the stack containing container c. Let s^* =

Stack(c^*) = the *target stack*, i.e. the stack containing the target container. Let *Top*(s) = the container on the top of stack s. Let *Stacks*[a] = the set of stacks in which the a lowest-numbered containers reside. Let Q represent a set of stacks. Let *Top*[Q] = the set of containers residing on the tops of the stacks in set Q. Let $Top_r[Q]$ = the r^{th} highest element in set *Top*[Q], i.e. the container with the r^{th} highest number among the containers on the tops of the stacks in set Q. Let *Low*(s) = the lowest numbered container in stack s. Let *Height*(s) = the height of stack s, i.e. the number of containers in stack s. These parameters take the following values in the context of the container configuration shown in Figure 2.4: c^* = 1, *Stack*(1) = 2, *Stack*(2) = 3, *Stack*(3) = 2, s^* = 2, *Top*(1) = 9, *Top*(2) = 4, *Top*(3) = 5, *Stacks*[1] = {2}, *Stacks*[2] = {2,3}, *Stacks*[3] = {2,3}, *Stacks*[4] = {2,3}, *Stacks*[5] = {2,3}, *Stacks*[6] = {1,2,3}, *Top*[{1}] = {9}, *Top*[{1,2}] = {9,4}, *Top*[{1,2,3}] = {9,4,5}, *Top*[*Stacks*[1]] = {4}, *Top*[*Stacks*[3]] = {4,5}, *Top*[*Stacks*[5]] = {4,5}, *Top*[*Stacks*[6]] = {9,4,5}, Top_1[{1,2}] = 9, Top_2[{1,2}] = 4, Top_2[*Stacks*[6]] = 5, Top_3[*Stacks*[6]] = 4, *Low*(1) = 6, *Low*(2) = 1, *Low*(3) = 2, *Height*(1) = 3, *Height*(2) = 3, *Height*(3) = 3. We now describe the LA-*N* algorithm in detail.

0. Select a value for N (the look ahead).
1. If $c^* = Top(s^*)$, retrieve container c^* immediately because it is on the top of a stack and repeat step 1. Otherwise, some container will be relocated and we go to step 2.
2. Let $N' = N$ and $r = 1$.
3. If *Stacks* [N'] includes all S stacks or if all stacks s such that $s \notin Stacks[N']$ are full (i.e. they have *mxHeight* containers in them), let $N' = N' - 1$ and repeat step 3. Otherwise, proceed to step 4.

4. We consider whether or not to relocate container *n* where $n = Top_r[Stacks[N']]$. If $n = Top(s^*)$, go to step 6. Otherwise, go to step 5.
5. Determine if there is a good cleaning move involving container *n*. Let $E = \{\, s \mid Low(s) > n$ and $Height(s) < mxHeight \,\}$. If *E* is empty or if $n = Low(Stack(n))$, there is no good cleaning move involving container n because either (i) it cannot be relocated so as never to be relocated again or (ii) it is already the lowest numbered container in its stack. In this case, let $r = r + 1$ and go to step 4. Otherwise, go to step 6.
6. Container *n* will be relocated. Let $D = \{\, s \mid Low(s) > n$ and $Height(s) < mxHeight \,\}$. If *D* is empty, container *n* will have to be relocated yet again before finally being retrieved. In order to delay the time of container *n*'s next relocation, place container *n* on the stack *s* with the highest value of $Low(s)$ such that $Height(s) < mxHeight$. Otherwise, if *D* is non-empty, there is a way to relocate container *n* so it is not relocated again until its retrieval. In this case, relocate container *n* to the stack in *D* with the lowest $Low(s)$. This conserves the good destination stacks for future relocations. Go to step 1.

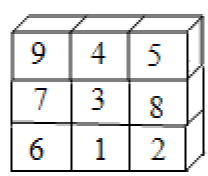


Figure 2.4. Initial configuration of nine containers.

Note the LA-*N* algorithm's similarity to the LA algorithm. Indeed, step 1 (6) of the LA-*N* algorithm is very similar to steps 1-2 (4) of the LA algorithm. The main difference between the two algorithms is that the LA-*N* algorithm initiates cleaning moves (i.e. in-between moves) under certain conditions. In particular, if there exists a container that is (1) on the top of a stack in which one of the *N* lowest-numbered containers resides and (2) this container can be relocated so it will never have to be relocated again prior to its retrieval, the container is relocated to the stack that is "best" among those stacks meeting criterion (2). The order of consideration for cleaning moves begins with the highest-numbered container satisfying criterion (1) and moves to the lower and lower container numbers satisfying criterion (1). Whenever the container under consideration is on top of the target stack, this container is moved no matter what. Note that step 3 of the LA-*N* algorithm ensures that at least one container slot is available to accommodate a potential container relocation without violating the maximum height limit. The second difference between the two algorithms is that the LA-*N* algorithm explicitly accounts for *mxHeight* in the event there is a limited stack height (*mxHeight* < *C*) whereas the LA algorithm does not. Note that the LA-1 algorithm is identical to the LA algorithm except that it also considers the maximum stacking height *mxHeight*.

Figure 2.5 shows the decisions made by the LA-5 algorithm. Figure 2.6 illustrates the (i) LA-1, (ii) LA-2 algorithms with an unlimited height assumption (*mxHeight* = 9) on a nine-container instance of the BRP, and (iii) LA-2 algorithm with *mxHeight* = 5 on the same instance.

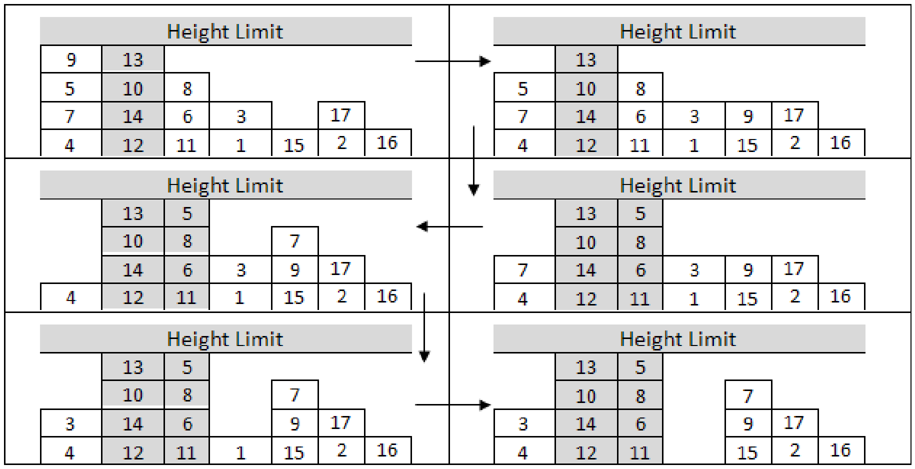


Figure 2.5. Illustration of decisions made by the LA-5 algorithm.

2.4.3. LA-N algorithm: Stack approach

The *LA-N* algorithm can be modified so that the look-ahead *N* refers to stacks, not containers. Here, we redefine stacks [a] to be the *a* stacks with the lowest numbered containers in them, i.e. the set of *a* stacks such that the lowest container number in any stack not in stacks [a] is more than the lowest container number in any stack in stacks [a]. All other parts of the algorithm are the same as in the previous section.

This approach considers more stacks for the cleaning moves. The only difference between this approach and the container approach is in defining the look-ahead. Otherwise it follows the same steps as in the container approach for limited and unlimited height. Figure 2.7 illustrates the basic difference between container approach and stack approach of *LA-N* algorithm applied to a nine-container problem instance.

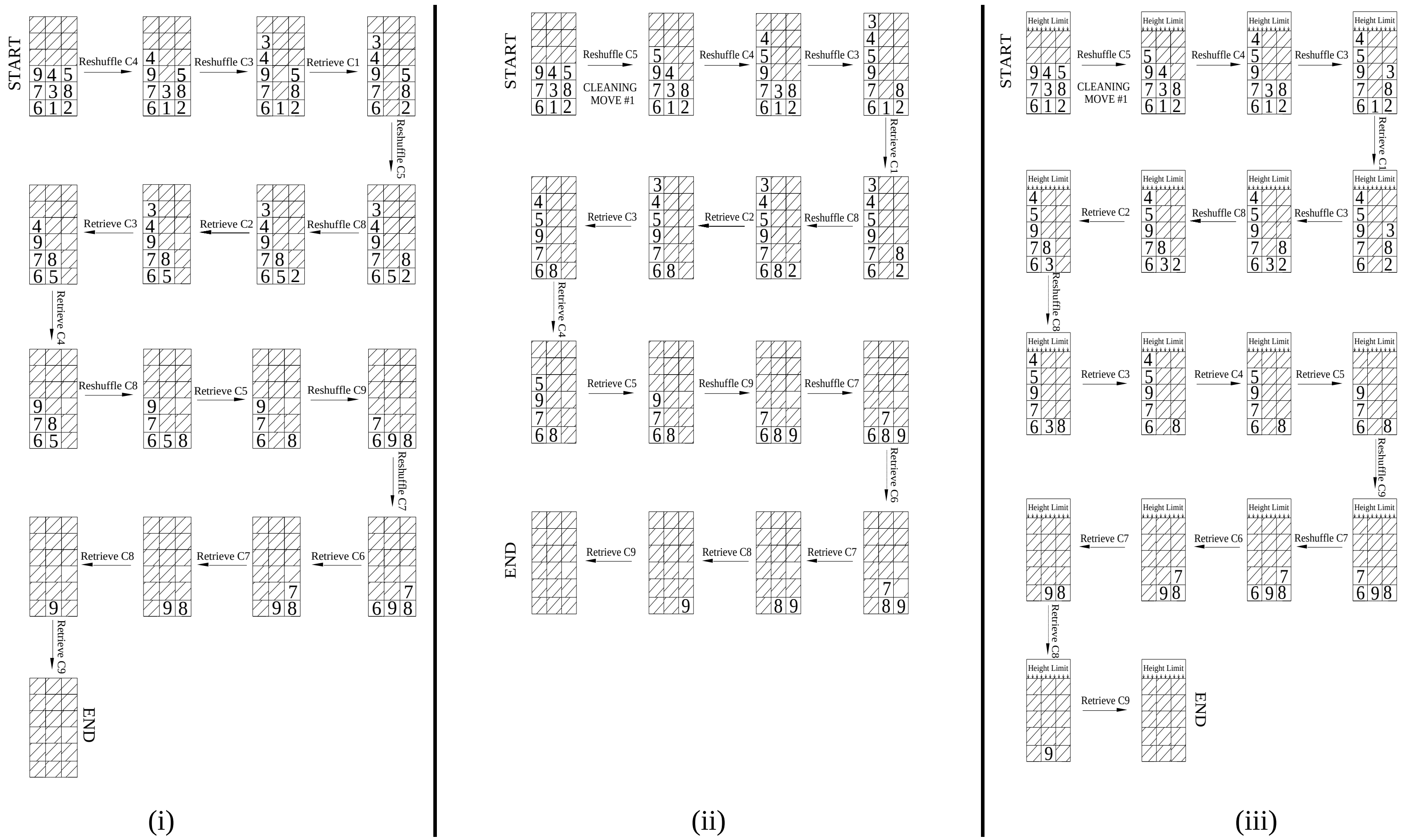


Figure 2.6. Illustration of the (i) LA-1 algorithm with unlimited height, (ii) LA-2 algorithm with unlimited height, and (iii) LA-2 algorithm with *mxHeight* = 5 on the same problem instance.

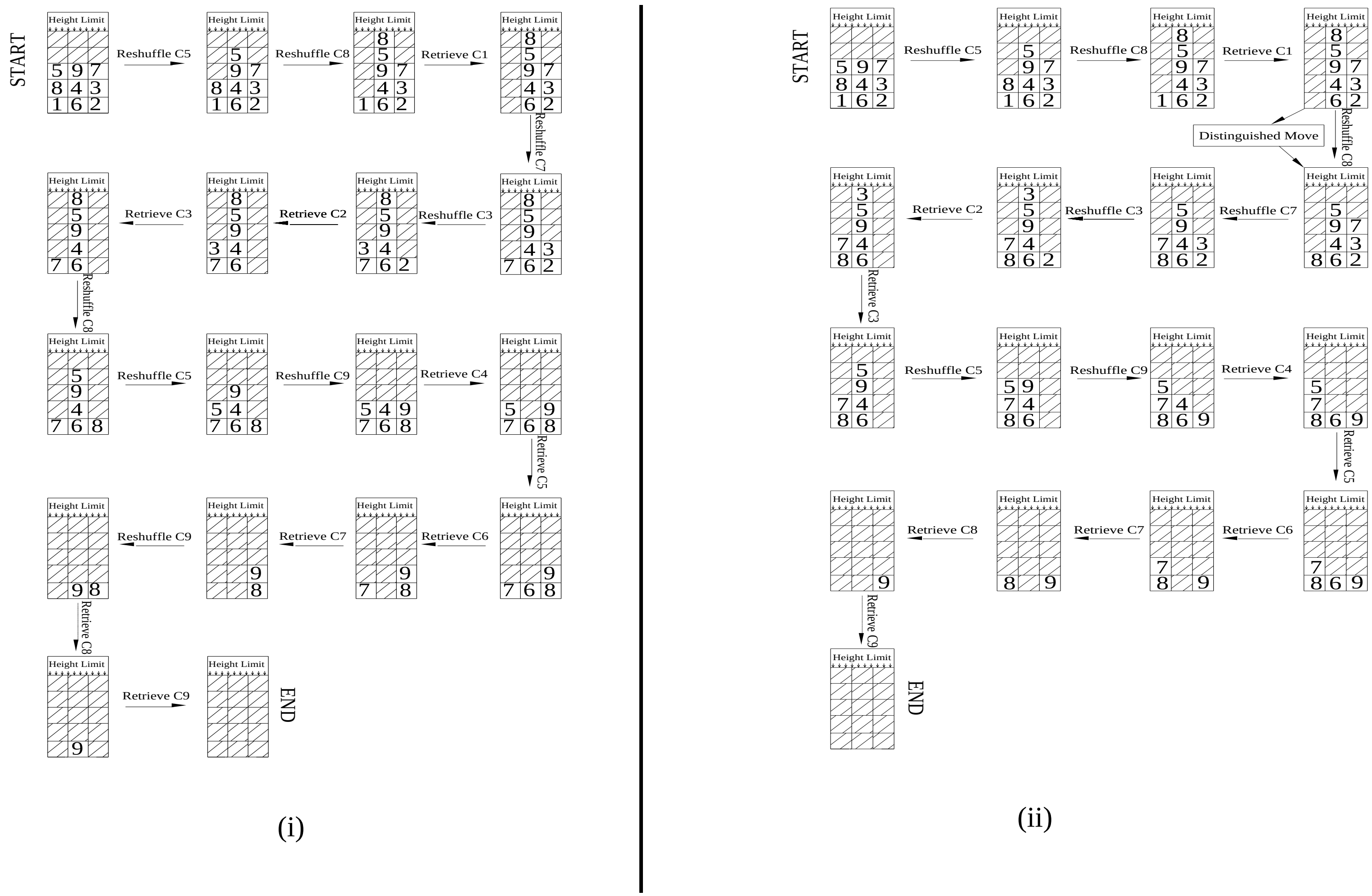


Figure 2.7. Illustration of the (i) LA-2 algorithm with limited height- container approach, (ii) LA-2 algorithm with limited height stack approach.

2.5. Cycling

Before we continue discussing *LA-N* and show the related results, the fact that *LA-N* does not cycle needs to be clarified. The procedures of different *LA-N* scenarios, schemes, and approaches, assure that the cycling will not occur while the containers are relocated. *LA-N* procedures include retrieving the target container if it is on the top of its stack. And if one or more *N* containers are on the top of their stacks, these containers should be disregarded from the cleaning moves, and the stack(s) considers neutral stack(s) as in Figure 2.8. These two protocols of *LA-N* are essential to avoid cycling. The example shown in Figure 2.8 is for *LA-N* and *N* equal 4. As container number 4 on the top of its stack, it is disregarded and stack 2 is considered a neutral stack, otherwise container 4 will be moved back and forth between stack 2 and 4. Then it is obvious there is no cycling for this configuration or other configurations according to *LA-N* procedures.

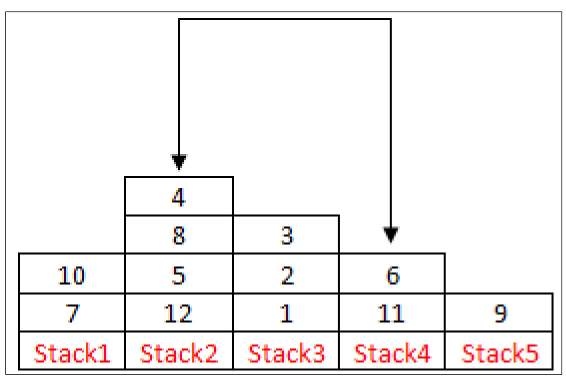


Figure 2.8. Example of LA performance to avoid cycling.

2.6. Computational results and algorithm comparisons

The performance of the five different algorithms for the BRP—LA-*N*, KH, DH, CM, and LL is compared in this section and the performance of the LA-*N* algorithm for different values of *N* is also considered. Tables 2.7 – 2.10 show the computational results. Table 2.7 shows the results when the KH, DH, CM, and LA-*N* algorithms are tested on a range of small, medium, and large-scale problems. Each row in the table corresponds to a different problem size (i.e. scenario) as defined by the initial height of each stack (H) and the number of stacks (S). The initial number of containers in the bay is H*S. A maximum height limitation (*mxHeight* = 2H-1) is enforced by all algorithms. Forty different instances (i.e. initial bay configurations) are considered for each problem size (except 100x100). These are the same forty instances considered by Caserta et al. (2009b). Thus, a total of 21*40 problem instances are considered (not including the 100x100 scenario), and each number in the table represents an average value obtained over all instances of a particular problem size. For the 100x100 scenario, each algorithm was tested on a different set of 1000 randomly generated instances. Regarding objective value, the numbers in the table show the number of relocations, not moves. The values in the KH and CM columns are copied from Caserta et al. (2012), and the values in the DH and LA columns are derived from experiments performed in the current study. These experiments were performed on a 2.8 GHz personal computer with 2 GB of RAM. Four variants of the LA-*N* algorithm are tested: LA-1, LA-2, LA-3, and LA-(S-1). Table 2.8 shows the results of the same instances with no height limitation, the height used in each stack equals the total number of containers defined in the initial number of containers.

In Table 2.7, the overall performance of the four algorithms, when ranked by objective value from highest to lowest, is KH, DH, CM, and LA-*N*. (The LA-*N* algorithms are aggregated into a single category.) The KH algorithm has the highest number of container relocations in all scenarios except one. The DH algorithm has the second-highest (third-lowest) number of relocations in the majority of scenarios. The CM algorithm has the second-lowest number of relocations in eleven, or half, of the scenarios. Regarding the other half of the scenarios, the CM algorithm has the lowest (third-lowest) number of relocations in 7 (4) scenarios. Finally, the LA-*N* algorithm has the lowest number of relocations in 15 of the 22 scenarios and the second-lowest number of relocations in the remaining 7 scenarios. Columns six and eight show the average computational time of the CM and "Best LA" algorithms. The CM runtimes are copied from Caserta et al. (2012). Although the same computer was not used to test the CM and LA-*N* algorithms, the final row indicates that the LA-*N* algorithm may have a faster runtime than the CM algorithm. Figures 2.9, 2.10, and 2.11 graphically show the performance of the algorithms on the small, medium, and large instances respectively. Overall, the LA-*N* algorithm is outperforming the KH, DH, and CM algorithms across a range of scenarios.

Table 2.7 shows that the performance of the LA-*N* algorithm varies depending on the "look-ahead" value *N*. In most scenarios, performance improves monotonically as *N* increases. In fact, in the majority of scenarios, the "Best LA" algorithm is LA-(S-1), i.e. the LA-*N* algorithm with the highest value of *N*. This is particularly true for the 15 scenarios in which the "Best LA" algorithm is the best algorithm overall. These findings indicate that cleaning moves are improving the algorithm's performance in the majority of instances. One glaring exception to this trend is the final scenario: 100x100. In this scenario, performance *deteriorates* as N increases. Although somewhat counter-intuitive, this result can be explained as follows. First, Table A1 in Appendix A shows a problem instance in which the LA-1 algorithm outperforms the LA-N algorithm when $N \geq 2$ (with an unlimited height assumption). Thus, increasing N may be harmful or helpful depending on the individual problem instance. Second, containers become more heavily concentrated in fewer stacks as N increases. In other words, we are more likely to see very high piles of containers when N increases, especially for extremely large configurations such as 100x100. This increases the risk of having to dig out a container that is deeply buried in one of the highly elevated stacks. It also increases the risk of having "full" stacks that cannot accommodate additional containers. Additional experimental results, shown in Table 2.11, indicate that the 40x40 problem size (roughly) is a threshold. Below this threshold, performance tends to improve as N increases; above this threshold, performance tends to deteriorate as N increases. Further results, Table 2.12 and Figure 2.12, show the number of times a stack of height SH is encountered, where $SH \geq Y$ and Y is the feasible limited height for large instances (SxT = 100x100). $SH \geq Y$ increases as N increases for large instances. Table 2.8 shows that LA-N algorithm with unlimited stack height has the lowest number of relocations in 15 of the 22 scenarios and the second-lowest number of relocations in the remaining 7 scenarios. However, LA-N algorithm with unlimited height shows in general less number of relocations than with limited height. The same instances and scenarios used to test LA-N algorithm– container approach are used to test LA-N algorithm – stack approach with limited height, the results are shown in Table 2.9. LA in this case outperforms other algorithm in 16 of the 22 scenarios.

Table 2.10 shows the results when the KH, LL, and LA-*N* algorithms are tested on 14 problem instances created by Lee and Lee (2010). Each row in the table corresponds to a different problem instance. The maximum stacking height (*mxHeight*), initial number of containers in the bay (*C*), and number of stacks (*S*) are shown for each problem instance in the second and third columns in the table. Note that only two problem sizes are considered: a 16-stack, 70-container problem with *mxHeight* = 6; and a 16-stack, 90-container problem with *mxHeight* = 8. Note that *mxHeight* is more restrictive in these instances than the instances considered in Table 2.7. Regarding objective value, the numbers in the table show the number of moves, not relocations. The values in the KH and LL columns are copied from Lee and Lee (2010), and the values in the LA columns are derived from experiments performed in the current study. Four variants of the LA-*N* algorithm are tested: LA-1, LA-2, LA-3, and LA-15 (i.e. LA-(S-1)).

In Table 2.10, the overall performance of the algorithms, when ranked by objective value from highest to lowest, is KH, LL, and LA-*N*. (The LA-*N* algorithms are aggregated into a single category.) The KH algorithm has the highest number of moves in all instances. The LL algorithm has the second-highest number of moves in 13 of 14 instances and ties for the lowest number of moves in one instance. Finally, the LA-*N* algorithm has the lowest number of moves in all instances. Columns six and eight show the average computational time of the LL and “Best LA” algorithms. The LL runtimes are copied from Lee and Lee (2010). Although the same computer was not used to test the LL and LA-*N* algorithms, it is clear that the LA-*N* algorithm has a faster runtime than the LL algorithm. The performance of the LA-*N* algorithm varies depending on the "look-ahead" value *N*. However, in contrast to Table 2.7, there is no notable trend linking performance of the LA-*N* algorithm to the value of *N*. Indeed, not enough problem instances are considered to discern any trend or pattern. Overall, the LA-*N* algorithm, regardless of the value of *N*, is outperforming the KH and LL algorithms on all instances.

From all of above we can say that this new algorithm generally outperforms the KH, DH, CM, and LL algorithms from the literature in terms of objective value and CPU runtime. The performance of the LA-*N* algorithm varies depending on the "look-ahead" value *N*. For small- and medium-sized instances where the maximum stacking height is not very restrictive, the algorithm performs better when *N* is large. For extremely large instances, the algorithm performs better when *N* is 1. Future work on the BRP might consider additional safety constraints that ensure that two adjacent stacks can never differ in height by more than *Z* containers (constraints 7-8 in Table 2.4).

Table 2.7. Results on instances from Caserta et al. (2012) using KH, DH, CM, and LA-*N* algorithms-container approach (*mxHeight* = 2H-1).

	Bay Size		KH	DH	CM	CM	Best LA	Best LA	LA-1	LA-2	LA-3†	LA-(S-1)††	Best Alg.
	height H	# stacks S	# Relocs.	# Relocs.	# Relocs.	Time (sec)	# Relocs.	Time (sec)	# Relocs.	# Relocs.	# Relocs.	# Relocs.	
Small Instances	3	3	7.1	5.6	5.4	< 1	5.1	< 1	5.1	5.1	-	-	LA-(S-1)*
	3	4	10.7	7.3	6.5	< 1	6.3	< 1	6.3	6.3	6.3	-	LA-(S-1)*
	3	5	14.5	8.0	7.3	< 1	7.0	< 1	7.1	7.0	7.0	7.0	LA-(S-1)
	3	6	18.1	10.2	7.9	< 1	8.4	< 1	8.5	8.4	8.5	8.5	CM
	3	7	20.1	11.3	8.6	< 1	9.2	< 1	9.3	9.3	9.2	9.3	CM
	3	8	26	12.8	10.5	< 1	10.6	< 1	10.7	10.6	10.7	10.8	CM
	4	4	16	12.2	9.9	< 1	10.4	< 1	10.9	10.4	10.4	-	CM
	4	5	23.4	15.7	16.5	< 1	13.1	< 1	13.6	13.3	13.2	13.1	LA-(S-1)
	4	6	26.2	17.3	19.8	< 1	14.0	< 1	14.5	14.3	14.1	14.0	LA-(S-1)
	4	7	32.2	20.2	21.5	< 1	16.4	< 1	16.6	16.4	16.4	16.4	LA-(S-1)
Medium Instances	5	4	23.7	18.6	16.6	< 1	15.8	< 1	16.5	15.9	15.8	-	LA-(S-1)
	5	5	37.5	23.9	18.8	< 1	19.8	< 1	20.3	20.0	19.8	20.0	CM
	5	6	45.5	27.9	22.1	< 1	22.7	< 1	23.5	23.1	23.0	22.7	CM
	5	7	52.3	31.9	25.8	1.43	24.8	< 1	25.7	25.3	25.2	24.8	LA-(S-1)
	5	8	61.8	36.4	30.1	1.46	27.8	< 1	28.7	28.6	28.3	27.8	LA-(S-1)
	5	9	72.4	40.3	33.1	1.41	30.7	< 1	31.9	31.4	31.2	30.7	LA-(S-1)
	5	10	80.9	45.2	36.4	1.87	33.5	< 1	34.5	34.1	33.6	33.5	LA-(S-1)
Large Instances	6	6	37.3	41.3	32.4	1.74	32.6	< 1	34.2	33.6	32.9	32.6	CM
	6	10	75.1	61.5	49.5	1.95	46.8	< 1	48.7	48.5	47.6	46.8	LA-(S-1)
	10	6	141.6	107.4	102.0	4.73	85.0	< 1	89.8	86.9	86.7	85.0	LA-(S-1)
	10	10	178.6	152.4	128.3	6.34	119.5	< 1	126.8	125.6	123.8	119.5	LA-(S-1)
	100†††	100	109,782.4	49,918	87,431.2	257.21	45,770.1	81.94	45,770.1	45,938.2	46,139.2	51,961	LA-1

† Only tested when $S \geq 4$. ††† Average for 1000 randomly generated instances.
†† Only tested when $S \geq 5$. * LA-(S-1) in these cases are LA-2 and LA-3 respectively.

Table 2.8. Results on instances from Caserta et al. (2012) using KH, DH, CM, and LA-*N* algorithms-container approach (*Unlimited Height*).

	Bay Size		**KH**	**DH**	**CM**	**CM**	**Best LA**	**Best LA**	**LA-1**	**LA-2**	**LA-3**†	**LA-(S-1)**††	**Best Alg.**
	height H	**# stacks S**	**# Relocs.**	**# Relocs.**	**# Relocs.**	**Time (sec)**	**# Relocs.**	**Time (sec)**	**# Relocs.**	**# Relocs.**	**# Relocs.**	**# Relocs.**	
Small Instances	3	3	7.1	5.6	5.4	< 1	5.1	< 1	5.1	5.0	-	-	LA-(S-1)*
	3	4	10.7	7.3	6.5	< 1	6.3	< 1	6.3	6.3	6.2	-	LA-(S-1)*
	3	5	14.5	8.0	7.3	< 1	7.0	< 1	7.1	7.0	7.0	7.0	LA-(S-1)
	3	6	18.1	10.2	7.9	< 1	8.4	< 1	8.5	8.4	8.5	8.5	CM
	3	7	20.1	11.3	8.6	< 1	9.2	< 1	9.3	9.3	9.2	9.2	CM
	3	8	26	12.8	10.5	< 1	10.6	< 1	10.7	10.6	10.6	10.7	CM
	4	4	16	12.2	9.9	< 1	10.4	< 1	10.9	10.4	10.4	X	CM
	4	5	23.4	15.7	16.5	< 1	13.1	< 1	13.5	13.2	13.1	12.9	LA-(S-1)
	4	6	26.2	17.3	19.8	< 1	14.0	< 1	14.4	14.3	14.1	14.0	LA-(S-1)
	4	7	32.2	20.2	21.5	< 1	16.4	< 1	16.5	16.4	16.4	16.2	LA-(S-1)
Medium Instances	5	4	23.7	18.6	16.6	< 1	15.8	< 1	16.4	15.9	15.9	-	LA-(S-1)
	5	5	37.5	23.9	18.8	< 1	19.8	< 1	20.3	20.0	19.7	19.6	CM
	5	6	45.5	27.9	22.1	< 1	22.7	< 1	23.4	23.0	22.9	22.6	CM
	5	7	52.3	31.9	25.8	1.43	24.8	< 1	25.7	25.2	25.2	24.8	LA-(S-1)
	5	8	61.8	36.4	30.1	1.46	27.8	< 1	28.6	28.6	28.2	27.7	LA-(S-1)
	5	9	72.4	40.3	33.1	1.41	30.7	< 1	31.7	31.3	31.1	30.4	LA-(S-1)
	5	10	80.9	45.2	36.4	1.87	33.5	< 1	34.2	34.0	33.6	33.2	LA-(S-1)
Large Instances	6	6	37.3	41.3	32.4	1.74	32.6	< 1	34.2	33.4	32.9	32.5	CM
	6	10	75.1	61.5	49.5	1.95	46.8	< 1	48.3	48.3	47.4	46.5	LA-(S-1)
	10	6	141.6	107.4	102.0	4.73	85.0	< 1	88.9	86.2	85.5	84.5	LA-(S-1)
	10	10	178.6	152.4	128.3	6.34	119.5	< 1	125.7	124.6	123.3	119.0	LA-(S-1)
	100†††	100	109,782.4	49,918	87,431.2	257.21	45,770.1	4	36,702	36,829	36,901	40,051	LA-1

† Only tested when S ≥ 4. †† Only tested when S ≥ 5. ††† Average for 1000 randomly generated instances.
* LA-(S-1) in these cases are LA-2 and LA-3 respectively.

Table 2.9. Results on instances from Caserta et al. (2009b) using KH, DH, CM, and LA-*N* algorithms-stack approach (*mxHeight* = 2H-1).

	Bay Size		KH	DH	CM	CM	Best LA	Best LA	LA-1	LA-2	LA-3†	LA-(S-1)††	Best Alg.
	height H	# stacks S	# Relocs.	# Relocs.	# Relocs.	Time (sec)	# Relocs.	Time (sec)	# Relocs.	# Relocs.	# Relocs.	# Relocs.	
Small Instances	3	3	7.1	5.6	5.4	< 1	5.1	< 1	5.1	5.1	-	-	LA-(S-1)*
	3	4	10.7	7.3	6.5	< 1	6.3	< 1	6.3	6.3	6.3	-	LA-(S-1)*
	3	5	14.5	8.0	7.3	< 1	7.0	< 1	7.1	7.0	7.0	7.0	LA-(S-1)
	3	6	18.1	10.2	7.9	< 1	8.4	< 1	8.5	8.5	8.4	8.5	CM
	3	7	20.1	11.3	8.6	< 1	9.2	< 1	9.3	9.3	9.2	9.3	CM
	3	8	26	12.8	10.5	< 1	10.6	< 1	10.7	10.6	10.7	10.9	CM
	4	4	16	12.2	9.9	< 1	10.4	< 1	10.9	10.6	10.3	-	CM
	4	5	23.4	15.7	16.5	< 1	13.1	< 1	13.6	13.3	13.0	13.1	LA-3
	4	6	26.2	17.3	19.8	< 1	14.0	< 1	14.5	14.3	14.1	14.1	LA-(S-1)
	4	7	32.2	20.2	21.5	< 1	16.4	< 1	20.6	20.4	20.4	20.4	LA-(S-1)
Medium Instances	5	4	23.7	18.6	16.6	< 1	15.8	< 1	16.3	16.0	16.1	-	LA-2
	5	5	37.5	23.9	18.8	< 1	19.8	< 1	20.3	20.0	19.7	19.4	CM
	5	6	45.5	27.9	22.1	< 1	22.7	< 1	23.5	23.2	23.0	22.5	CM
	5	7	52.3	31.9	25.8	1.43	24.8	< 1	25.7	25.4	25.2	24.5	LA-(S-1)
	5	8	61.8	36.4	30.1	1.46	27.8	< 1	28.7	28.5	28.3	27.7	LA-(S-1)
	5	9	72.4	40.3	33.1	1.41	30.7	< 1	31.9	31.3	31.2	31.0	LA-(S-1)
	5	10	80.9	45.2	36.4	1.87	33.5	< 1	34.5	34.1	33.8	33.6	LA-(S-1)
Large Instances	6	6	37.3	41.3	32.4	1.74	32.6	< 1	34.2	33.4	32.8	32.3	LA-(S-1)
	6	10	75.1	61.5	49.5	1.95	46.8	< 1	48.7	48.4	47.6	46.1	LA-(S-1)
	10	6	141.6	107.4	102.0	4.73	85.0	< 1	89.8	87.1	86.1	82.0	LA-(S-1)
	10	10	178.6	152.4	128.3	6.34	119.5	< 1	126.8	125.5	124.1	114.3	LA-(S-1)
	100†††	100	109,782.4	49,918	87,431.2	257.21	45,770.1	12	45,713.3	46,004.4	46,218.2	52,382.3	LA-1

† Only tested when S ≥ 4. ††† Average for 1000 randomly generated instances.
†† Only tested when S ≥ 5. * LA-(S-1) in these cases are LA-2 and LA-3 respectively.

Table 2.10**.** Results on instances from Lee and Lee (2010) using KH, LL, and LA-*N* algorithms (limited height = *mxHeight*).

Instance	**Num. Ctrs. & Bay Size**		**KH**	**LL**	**LL**	**Best LA**	**Best LA**	**LA-1**	**LA-2**	**LA-3**	**LA-15**	**Best Alg.**
	mxHeight / C	**# stacks S**	**# Moves**	**# Moves**	**Time (sec)**	**# Moves**	**Time (sec)**	**# Moves**	**# Moves**	**# Moves**	**# Moves**	
R011606_0070_001	6/70	16	173	118	6304	107	< 1	107	108	107	108	LA-1,3
R011606_0070_002	6/70	16	174	117	11081	108	< 1	108	108	108	110	LA-1,2,3
R011606_0070_003	6/70	16	176	110	5502	108	< 1	109	108	108	109	LA-2,3
R011606_0070_004	6/70	16	182	158	9026	112	< 1	117	116	116	112	LA-15
R011606_0070_005	6/70	16	184	124	9108	110	< 1	110	110	112	112	LA-1,2
R011608_0090_001	8/90	16	303	190	13269	153	< 1	154	155	154	153	LA-15
R011608_0090_002	8/90	16	253	191	11135	151	< 1	151	151	152	151	LA-1,2,15
R011608_0090_003	8/90	16	315	216	21583	154	< 1	158	157	155	154	LA-15
R011608_0090_004	8/90	16	283	178	7042	151	< 1	151	153	151	151	LA-1,3,15
R011608_0090_005	8/90	16	283	182	13738	148	< 1	153	153	152	148	LA-15
U011606_0070_001	6/70	16	---	125	17326	125	< 1	125	125	125	127	LA-1,2,3 LL
U011606_0070_002	6/70	16	---	130	11243	128	< 1	128	128	128	129	LA-1,2,3
U011608_0090_001	8/90	16	---	175	21587	166	< 1	166	167	169	177	LA-1
U011608_0090_002	8/90	16	---	180	8021	169	< 1	169	170	173	178	LA-1

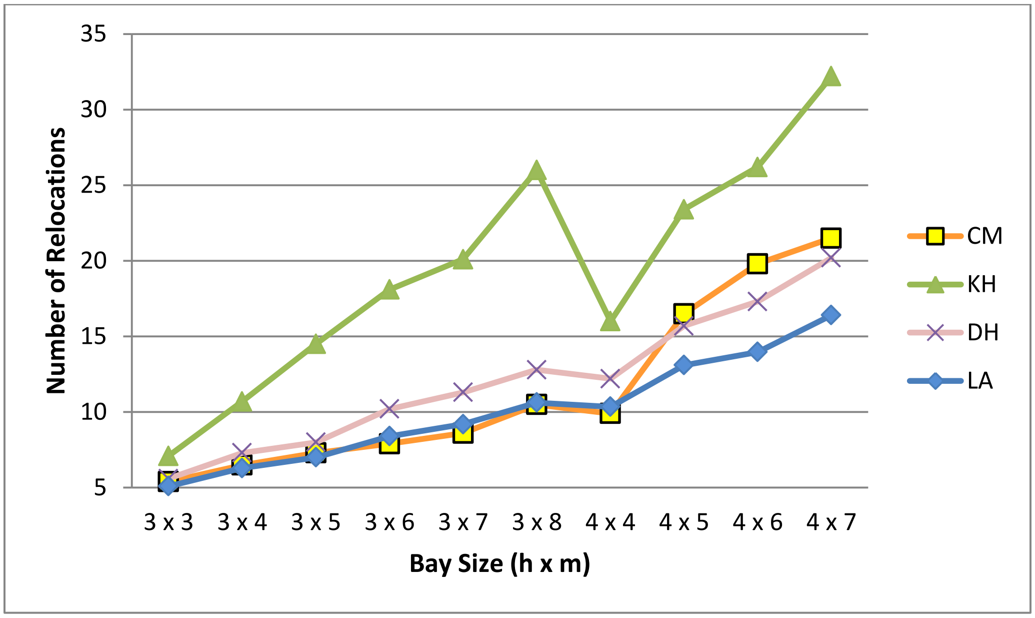


Figure 2.9. Comparison of KH, DH, CM, and “Best LA” algorithms for small instances.

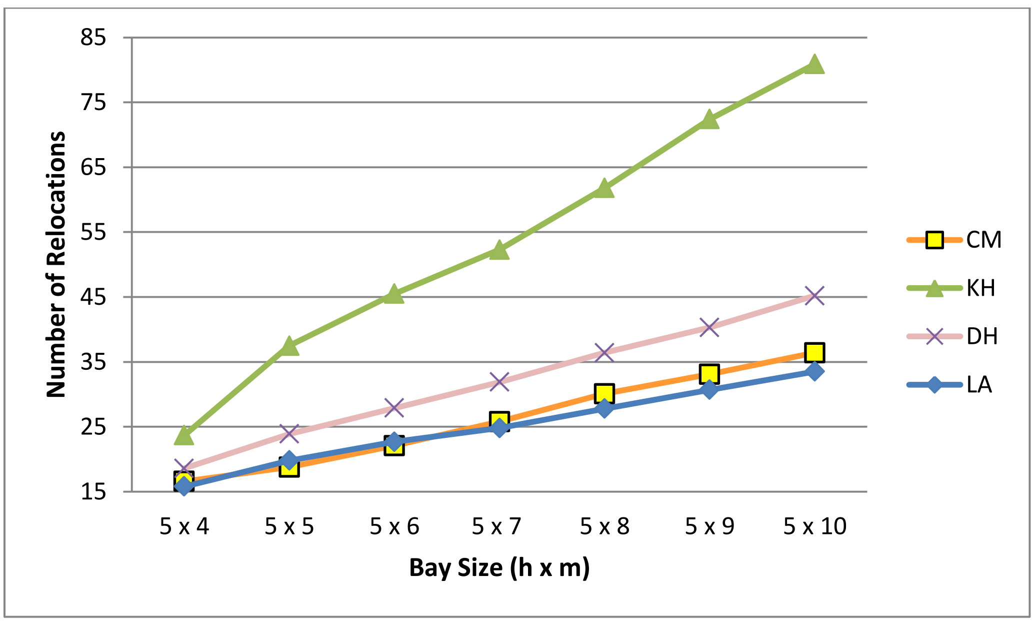


Figure 2.10. Comparison of KH, DH, CM, and “Best LA” algorithms for medium instances.

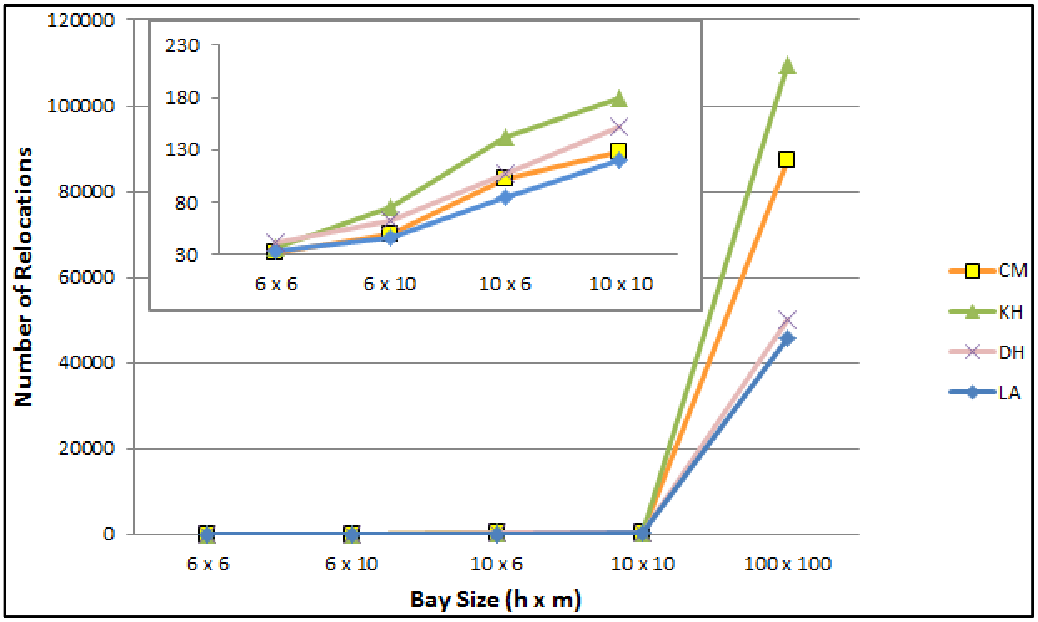


Figure 2.11. Comparison of KH, DH, CM, and “Best LA” algorithms for large instances.

Table 2.11. Number of relocations required by four different LA-*N* algorithms on eight different problem sizes with an unlimited height assumption. The values shown are averages (rounded to the nearest integer) for 10,000 randomly generated problem instances unless indicated otherwise.

Problem Size	**Num. Relocations**			
H * S	**LA-1**	**LA-2**	**LA-3**	**LA-(S-1)**
10*10	123	122	121	117
15*15	347	345	343	330
20*20	718	716	714	689
25*25	1257	1256	1255	1221
30*30	1979	1984	1985	1945
35*35	2906	2909	2912	2882
50*50†	6992	6995	7013	7138
100*100†	36702	36830	36901	40052

†Only 1000 random instances are considered.

Table 2.12. The number of times a stack of height "SH" ≥ Y is encountered during the running of the LA-*N* algorithm. The examples' size is 100x100 and Y for these examples is 199 "The feasible height limit". The number of relocations is the average of 100 random initial configurations.

LA-*N*	Avg. num of relocations	Avg. No. of occurrences of SH > Y
1	36876	366362
99	39951	383118

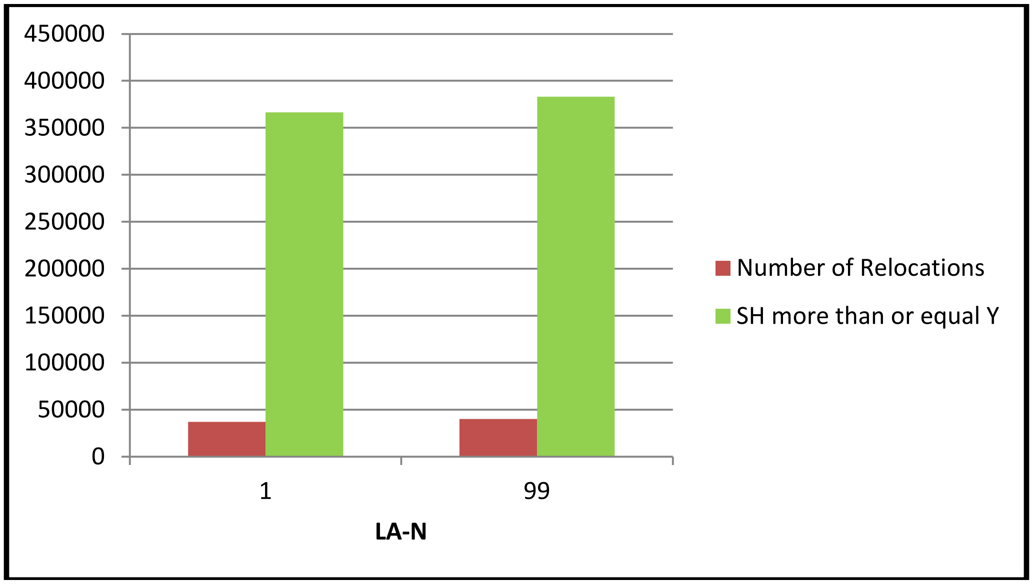


Figure 2.12. The number of times a stack of height "*SH*" ≥ *Y* and number of relocation for the LA-*N* discussed in Table 2.12.

3- ALGORITHMS FOR REDUCING YARD CRANE ENERGY CONSUMPTION AT SEAPORT CONTAINER TERMINALS

This part considers a variation of the block relocation problem (BRP), in which a set of identically-sized items is to be retrieved from a set of last-in-first-out (LIFO) stacks in a specific order using the minimum fuel consumption. In our previous part, a new mixed integer program and lookahead algorithm to retrieve containers or identical-sized blocks from a storage area in a specific order using the fewest number of moves have been presented. This part presents a global retrieval heuristic to retrieve containers in a specific order using the minimum estimated fuel consumption. New aspects of this work include explicitly considering container weight in fuel consumption calculations and explicitly tracking trolleying, hoisting, and lowering. A new “global retrieval heuristic” that uses twelve parameters to quantify various preferences when moving individual containers has been developed. This heuristic is embedded in a genetic algorithm to find optimal values for parameters. Results show that the methodology is effective in identifying near-optimal parameter settings.

3.1. Block Relocation Problem with Weights (BRP-W): Introduction and problem description

This part of the dissertation considers a new extension of the traditional BRP—the “block relocation problem with weights” (BRP-W). The BRP-W is similar to the BRP except that (1) each container is assigned a weight (in tons) in addition to a number indicating its order in the retrieval sequence and (2) the decision maker’s objective is to minimize the total energy used to remove all containers from the bay, where energy usage is a function of the weighted container travel distance. Figure 3.1 part (i) is an example of a block relocation problem with weights (BRP-W) where C = 20 and S = 6. Each container is labeled with a container number (left) and weight (right). The objective is to deliver the 20 containers to the truck lane in order of increasing container number such that the total fuel consumed is minimized.

Figure 3.1 also illustrates the trade-offs involved in container relocation decisions in the BRP-W. Here, container 18 must move to clear the way for the retrieval of container 1 beneath it. The option on the left involves more initial fuel consumption but no additional relocations of container 18 prior to its removal from the bay. The option on the right involves less initial fuel consumption but at least one additional relocation of container 18 prior to its removal from the bay. Note that the problem is so complicated that it is impossible for a human decision maker to know which option is better. However, a computer might be able to handle the decision if it uses a sophisticated algorithm that has been extensively tested under simulated operating conditions. With these thoughts in mind, the purpose of this investigation is to develop and test algorithms that automatically decide the locations and sequence of container reshuffling moves in the BRP-W.

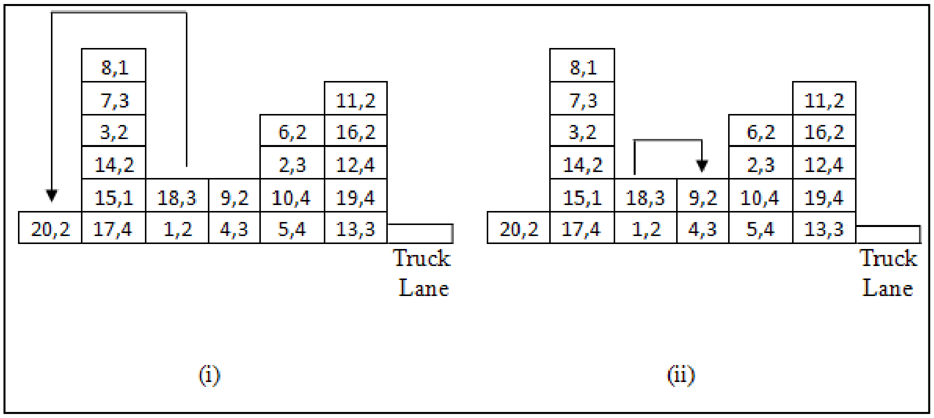


Figure 3.1. Example of a block relocation problem with weights (BRP-W) where C = 20 and S = 6 (left).

The background and literature review are presented in section 3.2. Section 3.3 formalizes the BRP-W using mathematical notation and formulae and describes the algorithm that have been developed to address this problem and section 3.4 describes a genetic algorithm (GA) that developed in order to identify the optimal parameter settings for the global retrieval heuristic. Section 3.5 describes the simulation optimization experiments that test the GA and GRH in order to identify versions of the GRH that works well in specific problem settings, this section presents the experimental results and discuss their significance. Sensitivity analysis is discussed in section 3.6.

3.2. Background and literature review

A number of published papers and work have considered the optimization in container terminals handling, storage, and energy. Casey and Kozan (2011) have developed a model for the storage system of the multimodal container terminal, which is an extension of the Block Relocation Problem. A number of consecutive heuristics are presented in order to produce good initial solutions for this problem, Meta-heuristic are also used to improve on these solutions. An optimization model is built by Zhang et al

(2007), with an objective to minimize the total number of reshuffles for the operations, and with constraints to ensure the number of reshuffles for each retrieve container operation within the average range furthest. Considering the influence of reshuffled container's relocation on the retrieving container and the containers to be retrieved later, the abstract constraints are transformed into several rules for confirming the feasible storage positions of a reshuffled container.

Jiang and Tang (2011) propose a heuristic tree search procedure for container pre-marshalling problem (CPMP) that is based on a natural classification of possible moves, makes use of a sophisticated lower bound and applies a branching schema with move sequences instead of single moves. Loading a ship can only be handled efficiently if only few rehandlings have to be carried out in the yard during loading. Otherwise, considerable delays occur. Hence, a general stacking condition (GSC) should already be fulfilled at the start of loading. To ensure a container layout consistent with the GSC when loading the ship starts, the necessary rehandlings are often performed in the time remaining before loading. This process is referred to as pre-marshalling the containers.

An additional factor of crane cost is taken into consideration for containers relocation problem (CRP) in Zhu et al (2010) work. The crane operation consists of both trolley and spreader moves within the same bay. The number of relocation is not enough to be the best overall measurement for reducing the unproductive time. Three heuristic rules including minimum basic relocation number, minimum crane costs and minimum relocation operation times are proposed for determining the storage location of relocated blocks. A filtered-beam-search heuristic algorithm is proposed and presented for CRP with crane costs.

Wan et al. (2009) introduce an integer program that optimizes the reshuffle sequence. The integer program captures the evolution of stack configurations as a function of decisions. Heuristics based on the integer program are then derived. Variants of the IP-based heuristics are applied to the dynamic problem with continual retrievals and arrivals of containers. In 2011, Caserta et al. propose two different binary integer formulations. The first one maps the complete feasible region of the BRP, but, on the other hand, generates a large search space. To obtain a more usable model, the authors have decreased the feasible region by adding assumptions in the second model. A simple heuristic based upon a set of relocation rules has been proposed.

Jiang et al (2011) present a discrete-event simulation model to dynamically simulate every detail of container stacking, reshuffling and retrieving operations. The simulation model can evaluate and compare different reshuffling rules or algorithms in real-time by animation.

3.3. Formalization of the BRP-W and Global Retrieval Heuristic (GRH)

Table 3.1 lists the parameters that define the BRP-W. These parameters include parameters that define the initial configuration of containers—their retrieval order and weight— and the energy consumed by various container movements. Note that the weight of the device that grips the containers— the spreader—is also listed. This investigation assumes its weight is 0.5 tons in this study. Also note that this investigation assumes the fuel consumption values for hoisting, lowering, and trolleying are 0.90, 0.02, and 0.08 per unit of movement respectively [119].

Table 3.2 provides the notation and formula that show how fuel consumption is computed in this study. The total fuel required to empty a bay of all its containers equals the sum of the fuel consumed in all individual moves of the spreader. Each move may occur with or without a container. The fuel consumed during a given move equals the weight of the load multiplied by a sum of the fuel consumed per ton in the hoisting, trolleying (side-to-side), and lowering movements of the spreader.

Figure 3.2 illustrates the calculation of total fuel consumption for a 4-container problem instance ($C = 4$) with three stacks ($S = 3$) and a maximum stack height of three ($mxHeight = 3$). The total fuel consumption of 13.86 can be divided into a total of 14 movements (five with a container—one relocation and four retrievals—and nine without a container). Note that the crane's spreader (i.e. grappler) returns to a reference position in the upper right corner of the bay after every delivery of a container to a truck. This closely resembles real-world crane operations at seaport container terminals in which cranes often leave a bay after a container retrieval in order to perform operations in other bays. The fuel consumption (*FC*) in each move is computed according to Tables 3.1 and 3.2. To save space, some cells in Figure 3.2 show the combined fuel consumption of two consecutive spreader moves.

Table 3.1. Initial configuration and fuel consumption parameters.

S	Number of stacks (integer, > 0).
T	Number of tiers of containers (integer, > 0).
C	Number of containers (=$S*T$, integer, > 0).
$mxHeight$	Maximum height (in number of containers) allowed for any stack at any time (integer, > 1).
$initialSetup_{c,s}$	= 1 if container c is in stack s in the initial configuration (binary).
$initialBury_c$	Number of containers burying container c (including itself) in the initial configuration (integer, > 0).
W_c	Weight of container c in tons (integer from 1 to 30).
W_s	Weight of spreader in tons (= 0.5 in this study).
W_{max}	Maximum weight of containers on hand (= max{W_c: c = 1 to C}).
h	Energy consumed per ton hoisted one tier (= 0.90 in this study).
l	Energy consumed per ton lowered one tier (= 0.02 in this study).
x	Energy consumed per ton trolleying one container to the side (= 0.08 in this study).

Table 3.2. Notation for Computing Total Energy Consumption.

h_m	Tiers hoisted during move m.
l_m	Tiers lowered during move m.
x_m	Distance trolleyed (moved side-to-side) during move m.
W_m	Moving weight during move m in tons (either $W_s + W_c$ for some c or W_s).
M	Total number of moves with containers or with spreader alone.
TFC	Total fuel consumption to remove all containers from the bay (given by the expression below) $= \sum_{m=1}^{M} W_m(h * h_m + l * l_m + x * x_m)$ (30)

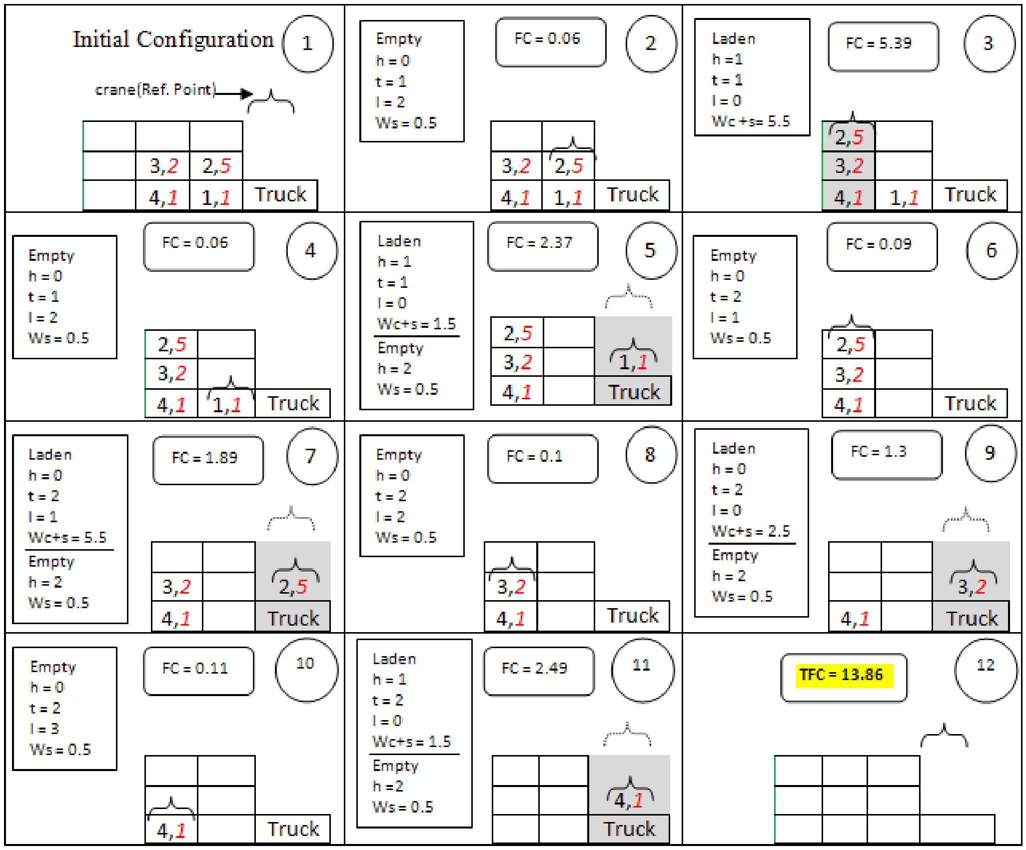


Figure 3.2. Total fuel consumption calculation for a 4-container problem instance (C = 4) with three stacks (S = 3) and a maximum stack height of three (mxHeight = 3). Notation: Ws = spreader weight, Wc+s = container + spreader weight, h = hoist distance, t = trolley distance, l = lowering distance, FC = move fuel consumption, TFC = total fuel consumption.

The global retrieval heuristic (GRH) is a generic algorithm for deciding where to relocate containers that is formalized in Tables 3.3 and 3.4. The algorithm's twelve parameters are listed in Table 3.3. These parameters are real numbers ranging from 0 to 1 that quantify the algorithm's preferences when it decides where to relocate individual containers. Although it is quite generic, the GRH is restricted in one important way—it only makes relocation moves for containers that are directly above the lowest numbered container (which is next to leave) in the bay. Relocations of other containers (i.e. cleaning moves [6, 129, and investigation one of this dissertation]) are not allowed. Forbidding cleaning moves is in accordance with most research on the BRP [18, 19, 20, and 78]. The settings of the GRH are decision variables whose best (or "optimal") values are likely to be different for different sets of input parameters defining the BRP-W (Table 3.1). The main goal in this investigation is to identify the best GRH settings for different problem classes, where all instances in a problem class share the same values of S, T, C, $mxHeight$, W_s, h, l, and x—but different values of $initialSetu_{c,s}$, $initialBury_c$, and W_c.

The GRH decides container moves as follows. If the lowest numbered container in the bay is already on the top of a stack, that container is immediately retrieved (i.e. removed from the bay). Otherwise, the container on the top of the stack where the lowest numbered container resides is relocated to another stack. Without loss of generality, we assume the container to be relocated is number c (in the retrieval sequence). Among all feasible destination stacks (whose height is not more than $mxHeight$-1), the GRH relocates the container to the stack that has the smallest penalty score. Table 3.4 shows how the penalty score for each potential destination stack s is computed.

The GRH first makes preliminary computations of the following eleven quantities: h_s, l_s, x_s, r_s, t_s, g_s, k_s, n_s, A_1, A_3, and A_4. The penalty if container c is relocated to stack s is then computed by plugging these eleven quantities into the formula at the bottom of Table 3.4. Note that each term in the formula can contribute a minimum of 0 and a maximum of 1 to the penalty score in all cases. Thus, each term in the formula is normalized so no term dominates the others. Thus, the variables in Table 3.3 truly represent the relative importance different preferences in the GRH.

Note that the quantity g_s in Table 3.4 represents “tightness.” Tightness is a measure of how close a relocated container’s number is to the smallest numbered container in a potential destination stack (assuming the relocated container will not require a further relocation after it is placed in that destination stack). For example, assume that container 9 needs to be relocated to another stack in Figure 3.1. The two possible destination stacks for container 9’s relocation that do not involve a future relocation of container 9 are the leftmost and rightmost stacks. The smallest numbered container in the leftmost (rightmost) stack is 20 (11). The tightness is (20-9-1)/20 and (11-9-1)/20 for the leftmost and rightmost stacks respectively (Table 3.4). That is, there is a larger tightness related penalty associated with relocating the container to the leftmost stack (10/20) than the rightmost stack (1/20) because the former relocation is foreclosing many opportunities for other containers (numbered 10-19) to be relocated to a “no-more- relocations” stack while the latter relocation is foreclosing only one opportunity for another container (numbered 10) to be relocated to a “no-more-relocations” stack.

Table 3.3. Decision variables (i.e. container relocation algorithm settings—all take real numbers from 0 to 1).

Variable	Description
P_1	Importance of minimizing hoisting, lowering, and trolleying of heavy (versus light) containers.
P_2	Importance of minimizing rehandling of heavy (versus light) containers.
P_3	Importance of delaying rehandling of heavy (versus light) containers.
P_4	Importance of moving heavy (versus light) containers closer to truck lane.
α	Importance of minimizing hoisting.
β	Importance of minimizing lowering.
γ	Importance of minimizing trolleying.
δ	Importance of minimizing rehandling.
ε	Importance of delaying rehandling.
η	Importance of tightness.
Θ	Importance of moving containers closer to the truck lane.
μ	Importance of keeping stack heights low.

Table 3.4. Container Relocation Algorithm Inputs (For Selecting Destination Stack *S* for Reshuffled Container *C*).

h_s	Number of tiers hoisted when moving reshuffled container to stack *s*.
l_s	Number of tiers lowered when moving reshuffled container to stack *s*.
x_s	Number of rows trolleyed when moving reshuffled container to stack *s*.
r_s	= 1 if container *c* must be reshuffled again if it is placed on stack *s* (binary).
t_s	Lowest numbered container in stack *s*.
g_s	Tightness = $\frac{t_s - c - 1}{C}$ (lower case *c* in numerator and upper case *C* in denominator). (31)
k_s	Amount of trolley movement away from truck lane if container *c* reshuffled to stack *s* (= 0 if trolley moves toward truck lane when container reshuffled to stack *s*).
n_s	Number of containers in stack *s*.
	Penalty if container *c* reshuffled to stack *s* (given by the expression below)

$$= \alpha\left(\frac{h_s}{mxHeight}\right) + \beta\left(\frac{l_s}{mxHeight}\right) + \gamma\left(\frac{x_s}{S}\right) + \delta r_s + \varepsilon r_s\left(\frac{c - t_s}{C}\right) + \eta(1 - r_s)g_s + \theta\left(\frac{k_s}{S}\right) + \mu\left(\frac{n_s}{mxHeight}\right) + P_1\left(\frac{W_c}{W_{max}}\right)\left[\frac{h_s}{mxHeight} + \frac{l_s}{mxHeight} + \frac{x_s}{S}\right] + P_2 r_s\left(\frac{W_c}{W_{max}}\right) + P_3 r_s\left(\frac{c - t_s}{C}\right)\left(\frac{W_c}{W_{max}}\right) + P_4\left(\frac{k_s}{S}\right)\left(\frac{W_c}{W_{max}}\right) \quad (32)$$

3.4. Genetic algorithm for optimizing the settings of the GRH

The nonlinear programming has been conducted to identify near-optimal parameter settings for the GRH. Cyclic coordinate method and global retrieval algorithm had been embedded and tested to find out the importance of different parameters such as hoisting, lowering, or closeness to the truck lane as in Table 3.3 for different bay configurations. Cyclic coordinate method uses the coordinate axes as the search direction. This method uses the coordinate axes as the search direction. The method searches along the directions d_1, d_2,.....d_N, where dj is a vector of zeroes except for 1 at the j^{th} position. Thus, along the search direction d_j, the variable x_j changes, while all the other variables remain fixed [8].

The cyclic coordinate method did not succeed in finding the optimal parameters values, because moving along one parameter in one direction does not guarantee increase/decrease the objective function as in Figure 3.3 and the existence of too many ties between the parameters, which leads to the same objective function for many parameter combinations.

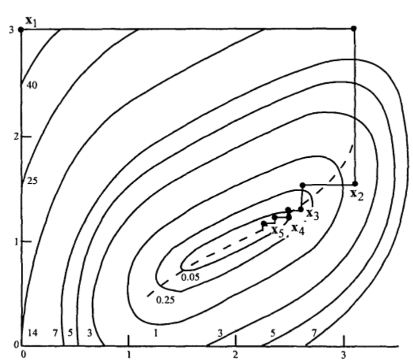
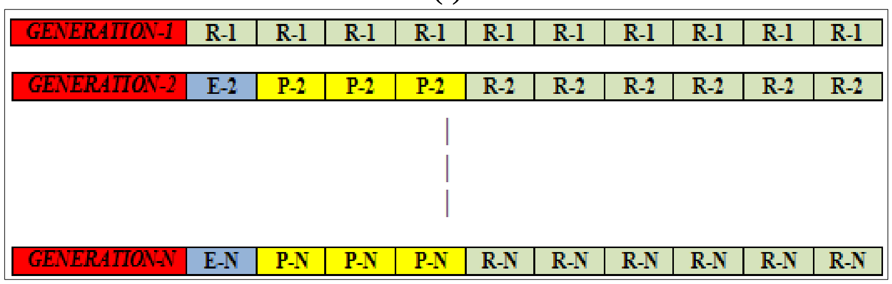


Figure 3.3. Cyclic Coordinate Method [8].

A genetic algorithm has been used to identify near-optimal parameter settings for the GRH. Genetic algorithms belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, simple crossover, and double crossover. Evolutionary computing, like other virtual intelligence tools, has its roots in nature. It is an attempt to mimic the evolutionary process using computer algorithms and instructions. The process of genetic optimization can be divided into the following steps: 1. Generation of the initial population. 2. Evaluation of the fitness of each individual in the population. 3. Ranking of individuals based on their fitness. 4. Selecting those individuals to produce the next generation based on their fitness. 5. Using genetic operations, such as crossover, inversion and mutation, to generate a new population. 6. Continue the process by going back to step 2 until the problem's objectives are satisfied. The initial population is usually generated using a random process covering the entire problem space. This will ensure a wide variety in the gene pool. Important control rate of a simple genetic algorithm "GA" include the population size, cross over rate and mutation rate. The fitness evaluation unit acts as an interface between the GA and the optimization problem. The GA assesses solutions for their quality according to the information produced by this unit but not by using direct information about their structure. Figure 3.4 shows a solution produced by mating from the previous generation and generations for an algorithm as in this section

(i)



(ii)

Figure 3.4. (i) solution (offspring) that is produced by mating from the previous generation (ii) GA-8 algorithm as in Table3.6, E: Elite solution in each generation that is copied from the previous generation, P: solution that is produced by mating from previous generation R: random solution.

A simple genetic algorithm (GA) was developed to optimize the GRH's parameter values for a given initial configuration size (*S*x*T*). The GA works as follows. The first step is to identify a configuration size of interest (e.g. *6*x*5*). Step 2 is to generate *Reps* instances. Each instance is a random initial container configuration of size *S*x*T*. Container numbers from 1 to *S*T* are assigned to the *S*T* container positions randomly and each container's weight follows a discrete uniform distribution from 1 to 30. The goal of the GA is to identify the settings for the twelve parameters in the GRH that minimize the energy required to empty an average container bay (i.e. initial configuration) among the *Reps* bays that have been generated.

The GA's main parameters are listed in Table 3.5. *G* is the number of generations and *N* is the number of solutions (12-tuples) considered in each generation. The first generation consists of N random solutions (i.e. N solutions in which each variable equals a U(0,1) random variable). The performance of each solutions is then evaluated by (1) setting the GRH's parameter values equal to the solution's values, (2) running the GRH on all *Reps* instances independently, and (3) summing the total energy consumed in all *Reps* combined. This sum is the objective value (i.e. score) assigned to the solution. Once the objective values of all N solutions have been determined, the best solution that has ever been observed is updated. Then, the next generation of solutions is formed as follows. First, the best N_e solutions are copied into the next generation. Second, N_r totally random solutions are generated and added to the next generation. Third, the best N_m solutions in the current generation are identified and placed in a mating pool. Fourth, N_p pairs of items in the mating pool are drawn with replacement and mated to form one solution which is added to the next generation ($N_p = N - N_e - N_r$). During mating, each of the child's twelve variable values takes a value that is uniformly distributed between the corresponding value of one parent and the corresponding value of the other parent. In other words, assume parent 1's v^{th} variable takes the value $P1_v$ and parent 2's v^{th} variable takes the value $P2_v$. Then the child's v^{th} variable takes a value equal to

U($\min\{P1_v , P2_v \}$, $\max\{ P1_v , P2_v \}$) (i.e. a random variable that is uniformly distributed between $\min\{P1_v , P2_v \}$ and $\max\{ P1_v , P2_v \}$). The next generation is now complete and the process continues as described above until a total of G generations have been created. The process of using the GA to identify the best solution, where each solution is evaluated by running a simulation experiment (in which the GRH is tested out on *Reps* problem instances) falls within the domain of simulation optimization.

Table 3.5. Parameters controlling the genetic algorithm-based search for the best decision variable values.

Parameter	Description
Reps	Number of replications to be considered (i.e. number of different initial container configurations of a given size to consider).
G	Number of generations.
N	Number of unique solutions (i.e. 12-tuples) per generation (population per generation).
N_e	Number of elite solutions in each generation that are copied into the next generation (= 1).
N_r	Number of randomly generated solutions in each generation.
N_p	Number of solutions in each generation that are produced by mating from the previous generation ($N_p = N - N_e - N_r$).
N_m	Number of solutions in each generation in mating pool for producing solutions in next generation.

3.5. Experiments, results, and discussion

The experiments considered ten different algorithms (Table 3.6) applied to each of twelve different configuration sizes (Table 3.7) in which *Reps* = 100. The ten algorithms consist of nine GA-based algorithms, one of which—GA-Rand—is essentially a totally random algorithm with one randomly generated solution per generation. The last algorithm---"low-high"—has no randomness and considers all 2^{12} = 4096 unique solutions when each decision variable = 0.25 or 0.75. This algorithm explores all major portions of the feasible region and provides a benchmark against which the other algorithms are judged. The twelve configuration sizes that are investigated correspond to all possible combinations of bay widths of 3, 6, 10, and 14 stacks and initial stack heights of 3, 5, and 7 containers. For each configuration size, *mxHeight* is set to the minimum value that guarantees a feasible solution to the BRP-W.

The experimental results are displayed in Tables 3.8-3.10 and Figures 3.5-3.8. Table 3.8 was generated after running each GA for a total of 10,000 *solutions* (i.e. where G = 10,000/(N-N_e) rounded to the nearest integer) and the low-high algorithm for a total of 4096 solutions. Table 3.8 displays the best solution found by any algorithm for each configuration size. The total fuel consumption (TFC) for each solution and average value of each decision variable across all solutions is also displayed. Table 3.9 (20) shows the best solution found by each algorithm after examining 4096 solutions for each configuration size with S = 3 and 6 (10 and 14). It also shows the total fuel consumption (TFC) for each algorithm's best solution and the mean and variance for each decision variable value across all algorithms for each configuration size. Figures 3.5-3.8 illustrate the progress of four selected algorithms on all problem sizes. The four algorithms include the low-high algorithm "LH," the random algorithm, and the best and worst overall performers (in terms of final solution objective value) among the other eight GAs for the configuration size at hand.

Table 3.6. Algorithms considered in the experiments.

Algorithm	N	N_e	N_r	N_p	N_m
GA-Rand	1	0	1	0	0
GA-01	20	1	6	13	6
GA-02	20	1	12	7	6
GA-03	20	1	6	13	10
GA-04	20	1	12	7	10
GA-05	15	1	5	9	8
GA-06	15	1	9	5	8
GA-07	10	1	3	6	5
GA-08	10	1	6	3	5
low-high	This algorithm considers all 2^{12} = 4096 unique solutions when each decision variable = 0.25 or 0.75.				

Table 3.7. Twelve initial configuration sizes are tested in the experiments.

Stacks (S)	Tiers (T)	Containers (C)	*mxHeight*
3	3	9	4
3	5	15	7
3	7	21	10
6	3	18	4
6	5	30	6
6	7	42	9
10	3	30	4
10	5	50	6
10	7	70	8
14	3	42	4
14	5	70	6
14	7	98	8

Table 3.8. Best solution found for each configuration size (SxT) after examining 10,000 solutions.

Var	3x3	3x5	3x7	6x3	6x5	6x7	10x3	10x5	10x7	14x3	14x5	14x7
P1	0.59	0.61	0.04	0.85	0.53	0.32	0.68	0.46	0.39	0.45	0.47	0.63
P2	0.71	0.43	0.05	0.85	0.34	0.29	0.65	0.54	0.16	0.72	0.5	0.03
P3	0.42	0.47	0.6	0.68	0.9	0.29	0.29	0.42	0.59	0.15	0.03	0.6
P4	0.04	0.03	0.01	0.08	0.02	0.08	0.03	0.04	0.07	0.19	0.11	0.02
α	0.58	0.54	0.69	0.56	0.98	0.1	0.48	0.74	0.57	0.85	0.7	0.61
β	0.25	0.49	0.47	0.14	0.31	0.69	0.03	0.37	0.46	0.41	0.41	0.09
γ	0.1	0.15	0.05	0.23	0.15	0.14	0.42	0.14	0.17	0.61	0.09	0.03
δ	0.64	0.31	0.54	0.56	0.36	0.13	0.52	0.22	0.23	0.62	0.26	0.35
ε	0.33	0.87	0.54	0.36	0.88	0.66	0.09	0.62	0.42	0.21	0.09	0.57
η	0.74	0.56	0.52	0.93	0.77	0.9	0.53	0.91	0.83	0.8	0.62	0.68
θ	0.02	0.04	0.03	0.07	0.03	0.06	0.01	0.03	0.05	0.12	0.02	0.04
μ	0.9	0.74	0.51	0.91	0.54	0.91	0.59	0.81	0.66	0.84	0.8	0.52
TFC	**292.1**	**892.83**	**1950.7**	**666.95**	**1814.04**	**3820.51**	**1241.98**	**3270.6**	**6521.02**	**1951.5**	**4862.6**	**9571.37**

Table 3.9. Best solution found by each algorithm after examining 4096 solutions for configuration sizes with S = 3 and 6.

3x3	Ran	GA1	GA2	GA3	GA4	GA5	GA6	GA7	GA8	LH	Avg	Var
P1	0.19	0.59	0.05	0.39	0.49	0.68	0.03	0.35	0.07	0.25	0.31	0.053
P2	0.12	0.71	0.88	0.43	0.17	0.30	0.31	0.34	0.76	0.25	0.43	0.069
P3	0.61	0.42	0.61	0.55	0.63	0.22	0.51	0.72	0.40	0.75	0.54	0.026
P4	0.08	0.04	0.04	0.08	0.15	0.16	0.05	0.07	0.24	0.25	0.12	0.006
α	0.53	0.58	0.56	0.28	0.29	0.26	0.6	0.73	0.71	0.75	0.53	0.036
β	0.79	0.25	0.27	0.45	0.38	0.27	0.47	0.52	0.8	0.25	0.45	0.044
γ	0.08	0.10	0.16	0.34	0.08	0.61	0.35	0.03	0.12	0.25	0.21	0.032
δ	0.74	0.64	0.53	0.43	0.39	0.56	0.44	0.61	0.52	0.75	0.56	0.016
ε	0.98	0.33	0.94	0.80	0.59	0.63	0.66	0.81	0.85	0.75	0.73	0.036
η	0.27	0.74	0.83	0.40	0.83	0.71	0.55	0.29	0.49	0.75	0.59	0.046
ϑ	0.10	0.02	0.19	0.06	0.04	0.08	0.04	0.23	0.09	0.25	0.11	0.007
μ	0.78	0.90	0.41	0.51	0.58	0.56	0.80	0.58	0.54	0.75	0.64	0.024
TFC	292	292	301	296	297	301	304	307	306	298		

6x3	Ran	GA1	GA2	GA3	GA4	GA5	GA6	GA7	GA8	LH	Avg	Var
P1	0.50	0.11	0.69	0.48	0.56	0.71	0.85	0.54	0.50	0.25	0.52	0.047
P2	0.40	0.92	0.54	0.74	0.57	0.55	0.85	0.61	0.86	0.75	0.68	0.029
P3	0.23	0.44	0.51	0.34	0.26	0.59	0.68	0.01	0.75	0.25	0.41	0.053
P4	0.01	0.03	0.22	0.14	0.09	0.09	0.08	0.32	0.08	0.25	0.13	0.010
α	0.16	0.90	0.64	0.22	0.40	0.41	0.56	0.65	0.69	0.75	0.54	0.056
β	0.16	0.96	0.37	0.48	0.38	0.62	0.14	0.53	0.18	0.75	0.46	0.072
γ	0.24	0.87	0.28	0.63	0.35	0.57	0.23	0.58	0.41	0.75	0.49	0.050
δ	0.23	0.65	0.94	0.58	0.50	0.72	0.56	0.82	0.23	0.75	0.60	0.054
ε	0.05	0.33	0.17	0.45	0.2	0.05	0.36	0.23	0.11	0.25	0.22	0.018
η	0.72	0.8	0.81	0.49	0.61	0.77	0.93	0.65	0.81	0.75	0.73	0.015
ϑ	0.03	0.01	0.04	0.08	0.02	0.06	0.07	0.12	0.05	0.25	0.07	0.005
μ	0.72	0.41	0.91	0.40	0.81	0.89	0.91	0.89	0.43	0.75	0.71	0.047
TFC	666	675	678	677	674	670	667	680	674	679		

3x5	Ran	GA1	GA2	GA3	GA4	GA5	GA6	GA7	GA8	LH	Avg	Var
P1	0.15	0.24	0.23	0.79	0.37	0.61	0.05	0.27	0.10	0.25	0.31	0.053
P2	0.40	0.56	0.19	0.52	0.55	0.43	0.43	0.29	0.80	0.25	0.44	0.032
P3	0.76	0.79	0.40	0.45	0.83	0.47	0.27	0.68	0.91	0.75	0.63	0.046
P4	0.02	0.02	0.14	0.11	0.04	0.03	0.00	0.17	0.22	0.25	0.10	0.008
α	0.97	0.60	0.72	0.49	0.46	0.54	0.10	0.46	0.71	0.75	0.58	0.054
β	0.10	0.60	0.05	0.41	0.34	0.49	0.30	0.35	0.18	0.25	0.31	0.029
γ	0.08	0.11	0.09	0.07	0.30	0.15	0.56	0.35	0.16	0.25	0.21	0.024
δ	0.16	0.48	0.82	0.83	0.05	0.31	0.74	0.95	0.47	0.75	0.56	0.095
ε	0.31	0.47	0.85	0.47	0.61	0.87	0.35	0.56	0.63	0.75	0.59	0.038
η	0.54	0.22	0.26	0.81	0.23	0.56	0.96	0.84	0.73	0.75	0.58	0.076
ϑ	0.13	0.03	0.02	0.04	0.05	0.04	0.01	0.16	0.08	0.25	0.08	0.006
μ	0.53	0.77	0.88	0.74	0.82	0.74	0.31	0.86	0.63	0.75	0.70	0.030
TFC	909	902	908	909	920	893	914	927	901	933		

6x5	Ran	GA1	GA2	GA3	GA4	GA5	GA6	GA7	GA8	LH	Avg	Var
P1	0.39	0.53	0.24	0.72	0.47	0.50	0.55	0.61	0.21	0.25	0.45	0.029
P2	0.29	0.34	0.39	0.84	0.35	0.38	0.20	0.89	0.62	0.25	0.46	0.059
P3	0.94	0.9	0.64	0.53	0.43	0.90	0.62	0.67	0.02	0.75	0.64	0.075
P4	0.06	0.02	0.09	0.03	0.01	0.12	0.06	0.06	0.03	0.25	0.07	0.005
α	0.80	0.98	0.38	0.72	0.77	0.21	0.47	0.44	0.38	0.75	0.59	0.060
β	0.03	0.31	0.57	0.19	0.19	0.70	0.47	0.14	0.21	0.75	0.36	0.063
γ	0.07	0.15	0.55	0.18	0.27	0.32	0.19	0.06	0.11	0.25	0.22	0.021
δ	0.23	0.36	0.36	0.19	0.54	0.65	0.40	0.91	0.19	0.25	0.41	0.054
ε	0.87	0.88	0.37	0.65	0.14	0.92	0.47	0.76	0.97	0.75	0.68	0.074
η	0.80	0.77	0.8	0.83	0.99	0.97	0.65	0.66	0.91	0.75	0.81	0.014
ϑ	0.04	0.03	0.02	0.04	0.01	0.01	0.04	0.07	0.08	0.25	0.06	0.005
μ	0.17	0.54	0.62	0.94	0.68	0.75	0.75	0.57	0.45	0.75	0.62	0.044
TFC	1817	1814	1843	1854	1821	1846	1842	1867	1844	1873		

3x7	Ran	GA1	GA2	GA3	GA4	GA5	GA6	GA7	GA8	LH	Avg	Var
P1	0.05	0.04	0.02	0.34	0.14	0.20	0.35	0.20	0.10	0.25	0.17	0.014
P2	0.19	0.05	0.66	0.89	0.42	0.26	0.70	0.28	0.06	0.25	0.38	0.081
P3	0.82	0.60	0.84	0.83	0.41	0.53	0.71	0.97	0.21	0.75	0.67	0.053
P4	0.01	0.01	0.28	0.08	0.19	0.06	0.02	0.08	0.10	0.25	0.11	0.010
α	0.12	0.69	0.42	0.16	0.52	0.25	0.43	0.97	0.28	0.75	0.46	0.076
β	0.06	0.47	0.54	0.58	0.26	0.75	0.23	0.35	0.11	0.25	0.36	0.049
γ	0.01	0.05	0.08	0.03	0.05	0.61	0.05	0.06	0.18	0.25	0.14	0.033
δ	0.69	0.54	0.73	0.15	0.78	0.02	0.38	0.87	0.96	0.25	0.54	0.104
ε	0.99	0.54	0.84	0.64	0.37	0.93	0.93	0.84	0.97	0.75	0.78	0.042
η	0.77	0.52	0.99	0.36	0.70	0.69	0.80	0.66	0.94	0.75	0.68	0.068
ϑ	0.02	0.03	0.07	0.04	0.06	0.08	0.05	0.10	0.03	0.25	0.07	0.004
μ	0.00	0.51	0.92	0.76	0.80	0.75	0.72	0.76	0.59	0.75	0.66	0.066
TFC	1986	1951	2030	2016	2020	2055	1989	1984	1998	2095		

6x7	Ran	GA1	GA2	GA3	GA4	GA5	GA6	GA7	GA8	LH	Avg	Var
P1	0.39	0.53	0.32	0.03	0.26	0.28	0.44	0.23	0.27	0.25	0.30	0.018
P2	0.29	0.43	0.29	0.70	0.55	0.44	0.43	0.81	0.66	0.25	0.49	0.036
P3	0.94	0.65	0.29	0.46	0.66	0.70	0.30	0.04	0.82	0.75	0.56	0.079
P4	0.06	0.04	0.08	0.14	0.12	0.13	0.05	0.02	0.10	0.25	0.10	0.004
α	0.80	0.90	0.10	0.57	0.07	0.75	0.87	0.39	0.84	0.75	0.60	0.098
β	0.03	0.22	0.69	0.64	0.72	0.44	0.26	0.03	0.14	0.75	0.39	0.085
γ	0.07	0.35	0.14	0.25	0.10	0.17	0.11	0.14	0.02	0.25	0.16	0.010
δ	0.23	0.29	0.13	0.25	0.15	0.24	0.20	0.08	0.15	0.25	0.20	0.004
ε	0.87	0.69	0.66	0.92	0.78	0.56	0.81	0.36	0.00	0.75	0.64	0.077
η	0.80	0.74	0.90	0.88	0.59	0.81	0.74	0.82	0.94	0.75	0.80	0.010
ϑ	0.04	0.06	0.06	0.01	0.03	0.09	0.05	0.04	0.03	0.25	0.07	0.005
μ	0.17	0.79	0.91	0.63	0.80	0.71	0.69	0.47	0.28	0.75	0.62	0.057
TFC	3850	3924	3821	3900	3911	3862	3853	3862	3839	4072		

Table 3.10. Best solution found by each algorithm after examining 4096 solutions for configuration sizes with S = 10 and 14.

	Ran	GA1	GA2	GA3	GA4	GA5	GA6	GA7	GA8	LH	Avg	Var
P1	0.89	0.78	0.66	0.68	0.64	0.85	0.26	0.42	0.89	0.25	0.63	0.059
P2	0.51	0.85	0.49	0.65	0.69	0.70	0.02	0.25	0.38	0.75	0.53	0.065
P3	0.08	0.09	0.57	0.29	0.06	0.37	0.60	0.10	0.79	0.25	0.32	0.066
P4	0.02	0.15	0.10	0.03	0.13	0.28	0.20	0.16	0.04	0.25	0.14	0.008
α	0.29	0.30	0.60	0.48	0.01	0.12	0.91	0.67	0.67	0.75	0.48	0.085
β	0.30	0.28	0.19	0.03	0.08	0.07	0.23	0.13	0.21	0.75	0.23	0.042
γ	0.84	0.34	0.32	0.42	0.27	0.61	0.44	0.60	0.44	0.75	0.50	0.036
δ	0.81	0.54	0.66	0.52	0.59	0.80	0.90	0.82	0.80	0.75	0.72	0.017
ε	0.08	0.16	0.26	0.09	0.03	0.07	0.04	0.08	0.22	0.25	0.13	0.008
η	0.95	0.84	0.78	0.53	0.81	0.92	0.77	0.67	0.57	0.75	0.76	0.019
ϑ	0.00	0.27	0.13	0.01	0.04	0.15	0.12	0.13	0.07	0.25	0.12	0.008
μ	0.84	0.52	0.88	0.59	0.53	0.85	0.91	0.43	0.87	0.75	0.72	0.033
TFC	1263	1277	1276	1242	1258	1262	1281	1263	1272	1284		

14x3	Ran	GA1	GA2	GA3	GA4	GA5	GA6	GA7	GA8	LH	Avg	Var
P1	0.50	0.52	0.64	0.20	0.71	0.45	0.68	0.74	0.42	0.25	0.51	0.035
P2	0.16	0.64	0.89	0.36	0.78	0.72	0.36	0.36	0.40	0.25	0.49	0.061
P3	0.01	0.48	0.74	0.17	0.37	0.15	0.65	0.19	0.19	0.25	0.32	0.056
P4	0.07	0.14	0.11	0.20	0.04	0.19	0.27	0.33	0.12	0.25	0.17	0.009
α	0.84	0.44	0.56	0.66	0.67	0.85	0.78	0.29	0.56	0.75	0.64	0.032
β	0.13	0.19	0.28	0.25	0.25	0.41	0.26	0.27	0.13	0.25	0.24	0.007
γ	0.06	0.41	0.12	0.43	0.05	0.61	0.73	0.45	0.57	0.75	0.42	0.069
δ	0.35	0.35	0.28	0.71	0.45	0.62	0.86	0.70	0.41	0.75	0.55	0.041
ε	0.05	0.24	0.36	0.05	0.24	0.21	0.16	0.51	0.10	0.25	0.22	0.020
η	0.31	0.84	0.86	0.75	0.68	0.80	0.94	0.87	0.79	0.75	0.76	0.030
ϑ	0.11	0.03	0.04	0.10	0.03	0.12	0.01	0.04	0.07	0.25	0.08	0.005
μ	0.65	0.78	0.91	0.73	0.88	0.84	0.99	0.76	0.74	0.75	0.80	0.010
TFC	1964	1961	1958	1963	1954	1952	1953	1969	1964	1982		

10x5	Ran	GA1	GA2	GA3	GA4	GA5	GA6	GA7	GA8	LH	Avg	Var
P1	0.47	0.59	0.28	0.80	0.42	0.40	0.30	0.46	0.73	0.25	0.47	0.035
P2	0.63	0.03	0.15	0.44	0.57	0.11	0.66	0.54	0.57	0.75	0.45	0.065
P3	0.33	0.62	0.15	0.38	0.49	0.41	0.24	0.42	0.77	0.75	0.46	0.042
P4	0.16	0.04	0.21	0.07	0.06	0.23	0.05	0.04	0.20	0.25	0.13	0.008
α	0.20	0.76	0.49	0.57	0.36	0.55	0.79	0.74	0.32	0.75	0.55	0.044
β	0.12	0.19	0.20	0.27	0.51	0.58	0.51	0.37	0.33	0.75	0.38	0.040
γ	0.03	0.11	0.00	0.47	0.18	0.32	0.80	0.14	0.37	0.25	0.27	0.057
δ	0.23	0.50	0.55	0.66	0.37	0.68	0.66	0.22	0.20	0.25	0.43	0.040
ε	0.08	0.29	0.02	0.52	0.14	0.64	0.30	0.62	0.40	0.75	0.38	0.064
η	0.57	0.85	0.68	0.78	0.84	0.77	0.84	0.91	0.84	0.75	0.78	0.010
ϑ	0.00	0.12	0.02	0.06	0.08	0.02	0.02	0.03	0.03	0.25	0.06	0.006
μ	0.46	0.58	0.68	0.58	0.84	0.52	0.79	0.81	0.76	0.75	0.68	0.018
TFC	3301	3287	3282	3315	3313	3310	3283	3271	3292	3380		

14x5	Ran	GA1	GA2	GA3	GA4	GA5	GA6	GA7	GA8	LH	Avg	Var
P1	0.27	0.47	0.61	0.84	0.93	0.66	0.67	0.33	0.69	0.25	0.57	0.055
P2	0.12	0.50	0.32	0.22	0.21	0.59	0.38	0.63	0.07	0.25	0.33	0.037
P3	0.22	0.03	0.02	0.77	0.14	0.47	0.66	0.31	0.72	0.75	0.41	0.091
P4	0.07	0.11	0.08	0.10	0.07	0.05	0.03	0.22	0.15	0.25	0.11	0.005
α	0.60	0.7	0.78	0.49	0.88	0.44	0.00	0.82	0.30	0.75	0.58	0.075
β	0.33	0.41	0.08	0.26	0.15	0.24	0.33	0.33	0.34	0.75	0.32	0.032
γ	0.19	0.09	0.05	0.40	0.01	0.59	0.19	0.04	0.23	0.25	0.20	0.032
δ	0.47	0.26	0.52	0.47	0.45	0.26	0.12	0.40	0.54	0.75	0.42	0.031
ε	0.40	0.09	0.49	0.50	0.45	0.47	0.45	0.04	0.27	0.25	0.34	0.029
η	0.93	0.62	0.72	0.70	0.98	0.77	0.82	0.93	0.92	0.75	0.81	0.015
ϑ	0.02	0.02	0.03	0.02	0.12	0.04	0.06	0.01	0.07	0.25	0.06	0.005
μ	0.65	0.8	0.28	0.67	0.85	0.58	0.61	0.68	0.89	0.75	0.68	0.030
TFC	4891	4863	4909	4920	4917	4921	4911	4908	4926	5025		

10x7	Ran	GA1	GA2	GA3	GA4	GA5	GA6	GA7	GA8	LH	Avg	Var
P1	0.39	0.50	0.39	0.68	0.83	0.66	0.07	0.23	0.47	0.25	0.45	0.054
P2	0.57	0.47	0.16	0.43	0.16	0.30	0.09	0.43	0.83	0.25	0.37	0.051
P3	0.81	0.81	0.59	0.61	0.86	0.81	0.83	0.43	0.52	0.75	0.70	0.023
P4	0.22	0.19	0.07	0.05	0.00	0.03	0.03	0.07	0.02	0.25	0.09	0.008
α	0.68	0.39	0.57	0.48	0.50	0.20	0.26	0.54	0.88	0.75	0.53	0.044
β	0.08	0.59	0.46	0.36	0.24	0.55	0.76	0.73	0.42	0.75	0.49	0.052
γ	0.18	0.11	0.17	0.08	0.03	0.93	0.57	0.13	0.29	0.25	0.27	0.076
δ	0.03	0.21	0.23	0.23	0.64	0.47	0.41	0.25	0.16	0.25	0.29	0.030
ε	0.88	0.83	0.42	0.44	0.82	0.96	0.18	0.72	0.12	0.75	0.61	0.090
η	0.67	0.72	0.83	0.81	0.94	0.86	0.99	0.61	0.91	0.75	0.81	0.015
ϑ	0.00	0.15	0.05	0.07	0.03	0.01	0.05	0.06	0.02	0.25	0.07	0.006
μ	0.21	0.42	0.66	0.72	0.26	0.78	0.89	0.79	0.88	0.75	0.64	0.062
TFC	6587	6689	6521	6538	6628	6683	6655	6644	6622	6806		

14x7	Ran	GA1	GA2	GA3	GA4	GA5	GA6	GA7	GA8	LH	Avg	Var
P1	0.54	0.34	0.43	0.74	0.63	0.73	0.54	0.63	0.35	0.25	0.51	0.029
P2	0.45	0.41	0.16	0.24	0.74	0.49	0.45	0.03	0.41	0.25	0.36	0.040
P3	0.60	0.08	0.64	0.65	0.59	0.62	0.43	0.60	0.73	0.75	0.56	0.037
P4	0.04	0.22	0.10	0.23	0.05	0.19	0.14	0.02	0.03	0.25	0.12	0.008
α	0.81	0.87	0.38	0.65	0.79	0.59	0.19	0.61	0.64	0.75	0.62	0.043
β	0.04	0.06	0.24	0.53	0.30	0.35	0.35	0.09	0.65	0.75	0.33	0.060
γ	0.02	0.13	0.32	0.15	0.12	0.39	0.21	0.03	0.64	0.25	0.22	0.035
δ	0.11	0.13	0.31	0.41	0.23	0.25	0.30	0.35	0.54	0.25	0.28	0.016
ε	0.78	0.83	0.69	0.71	0.72	0.82	0.40	0.57	0.93	0.75	0.72	0.022
η	0.85	0.80	0.89	0.90	0.81	0.80	0.68	0.68	0.96	0.75	0.81	0.008
ϑ	0.04	0.07	0.09	0.12	0.02	0.08	0.06	0.04	0.04	0.25	0.08	0.004
μ	0.30	0.06	0.44	0.78	0.42	0.66	0.64	0.52	0.70	0.75	0.50	0.056
TFC	9544	9633	9643	9710	9642	9733	9769	9571	9714	9911		

We now discuss the experimental results. Table 3.8 shows the algorithm preferences that are performing the best for each configuration size. According to this table, variables θ and P_4 are not important for any of the configuration sizes. In other words, when selecting a destination stack for a container relocation, it is not important to move the container closer to the truck lane, and moving heavy containers closer to the truck lane is hardly more important (if at all) than moving light containers closer to the truck lane. On the other hand, variable η and μ are important for all configuration sizes. That is, tightness and keeping the stack height low are important consideration regardless of the configuration size. Note that the value of P_2 decreases as the configuration height increases. That is, the importance of minimizing rehandling of heavy (versus light) containers decreases as the container stacks get higher. The importance of minimizing hoisting, lowering, and trolleying of heavy containers, P_1, for high stack configuration ($T=7$) increases when the number of stacks increases. Note that for the low configuration stack (T=3), the value of γ increases as the configuration stacks "width" increases. That is for low stacks, the importance of minimizing trolleying increases when number of stacks increases. The Importance of minimizing rehandling, δ, is more important for low configuration stacks ($T=3$).

Tables 3.9-3.10 provide an enormous amount of information that can be summarized in a few sentences. As expected, the total fuel consumption (TFC) is increasing in the number of stacks when the number of tiers is constant and is increasing in the number of tiers when the number of stacks is constant. Upon first sight, it appears there is no relationship among the solutions found by the various algorithms for a particular configuration size. Indeed, the values across any given column vary quite a bit and appear at first sight to be random. If they were random, then the average value in the "Var" column would be (1/12) = .0833 = the variance of a U(0,1) random variable. However, upon further inspection of the table, we see that the vast majority of values in the "Var" column are below (1/12), proving that the numbers in each row are not random and are gathered (albeit loosely) about a center. Thus, it appears that all ten algorithms are succeeding somewhat in finding a "global optimal solution." We hypothesize that the variances would be substantially reduced if more configurations (e.g. 1000) were examined for each problem size.

Tables 3.9-3.10 yield only few insights about the relative performance of the algorithms. The main insights here are that the low-high algorithm is worse than the random algorithm in all cases and that the random algorithm is doing quite well. This calls into question the strategy of using an elaborate GA to identify the best settings for the GRH. However, additional experiments with a larger number of configurations examined for each problem size (e.g. 1000) need to be performed before any concrete conclusions are drawn on this subject. Note that no single algorithm is dominating the others over a majority of configuration sizes. In addition, the best objective value (i.e. least fuel consumption) found by each algorithm is usually no more than 5% greater than the best objective value found by the best algorithm for each configuration size.

Figures 3.5-3.8 reveal that most gains in objective value for most algorithms are achieved within the first 1000 solutions viewed. On another note, the low-high algorithm is the "slowest starter," in that it begins its first 100 solutions with an objective value that is notably inferior to the other algorithms. Finally, we can see that the performance difference between the best GA-based algorithm and worst GA-based algorithm is about 5% in both cases.

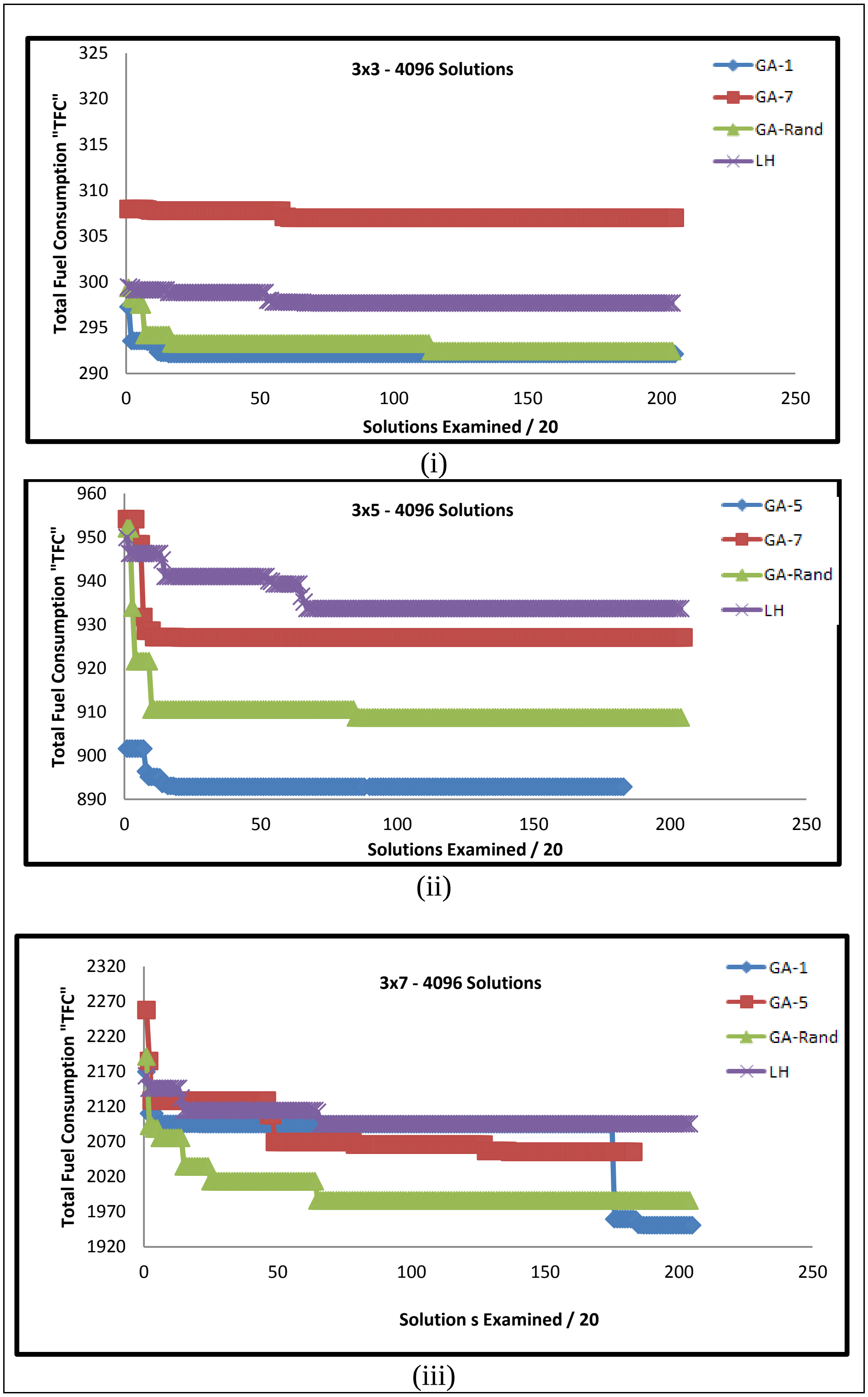


Figure 3.5. Illustration of the progress of four selected algorithms on (i) 3x3, (ii) 3x5, and (iii) 3x7 problem sizes.

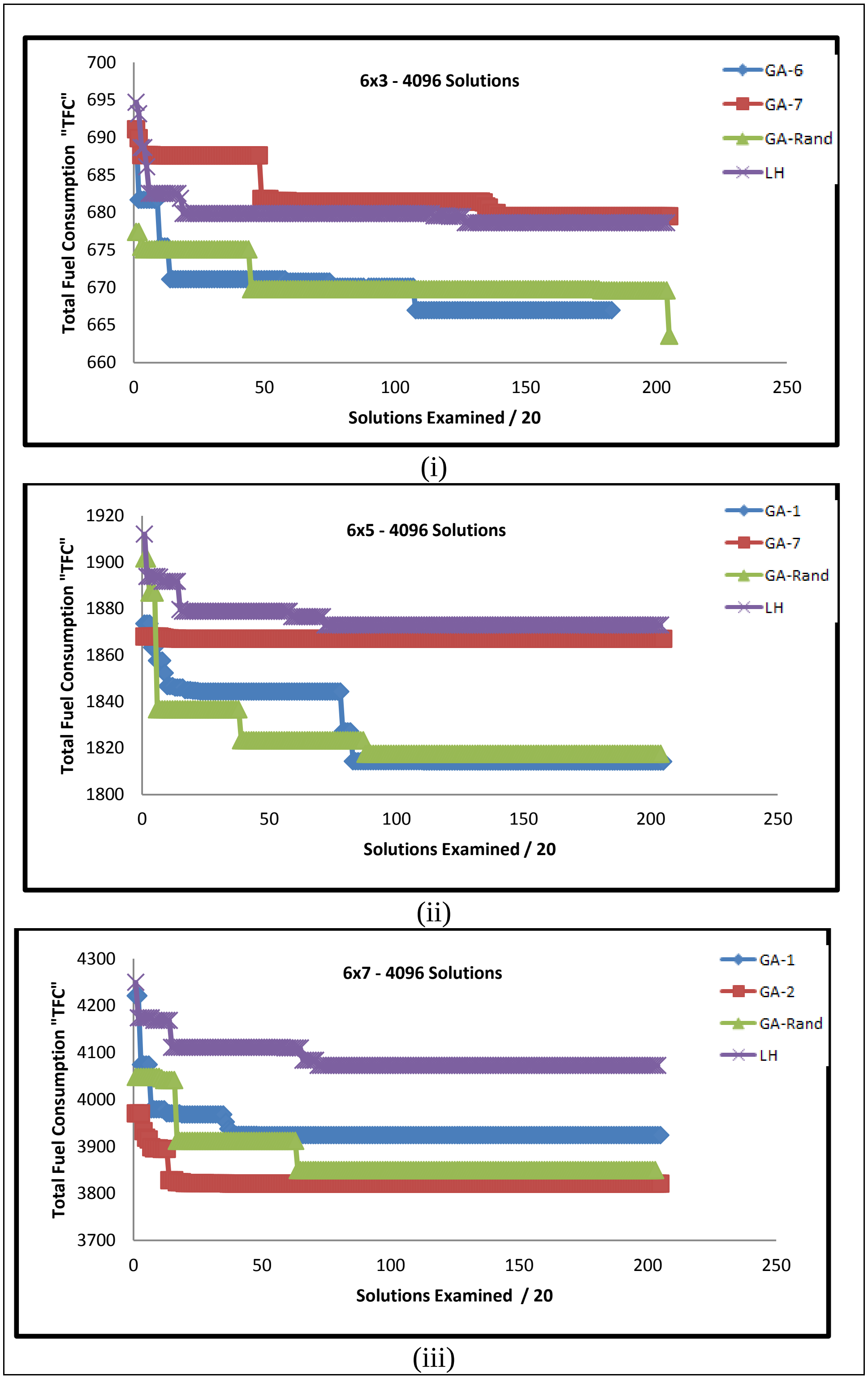


Figure 3.6. Illustration of the progress of four selected algorithms on (i) 6x3, (ii) 6x5, and (iii) 6x7 problem sizes.

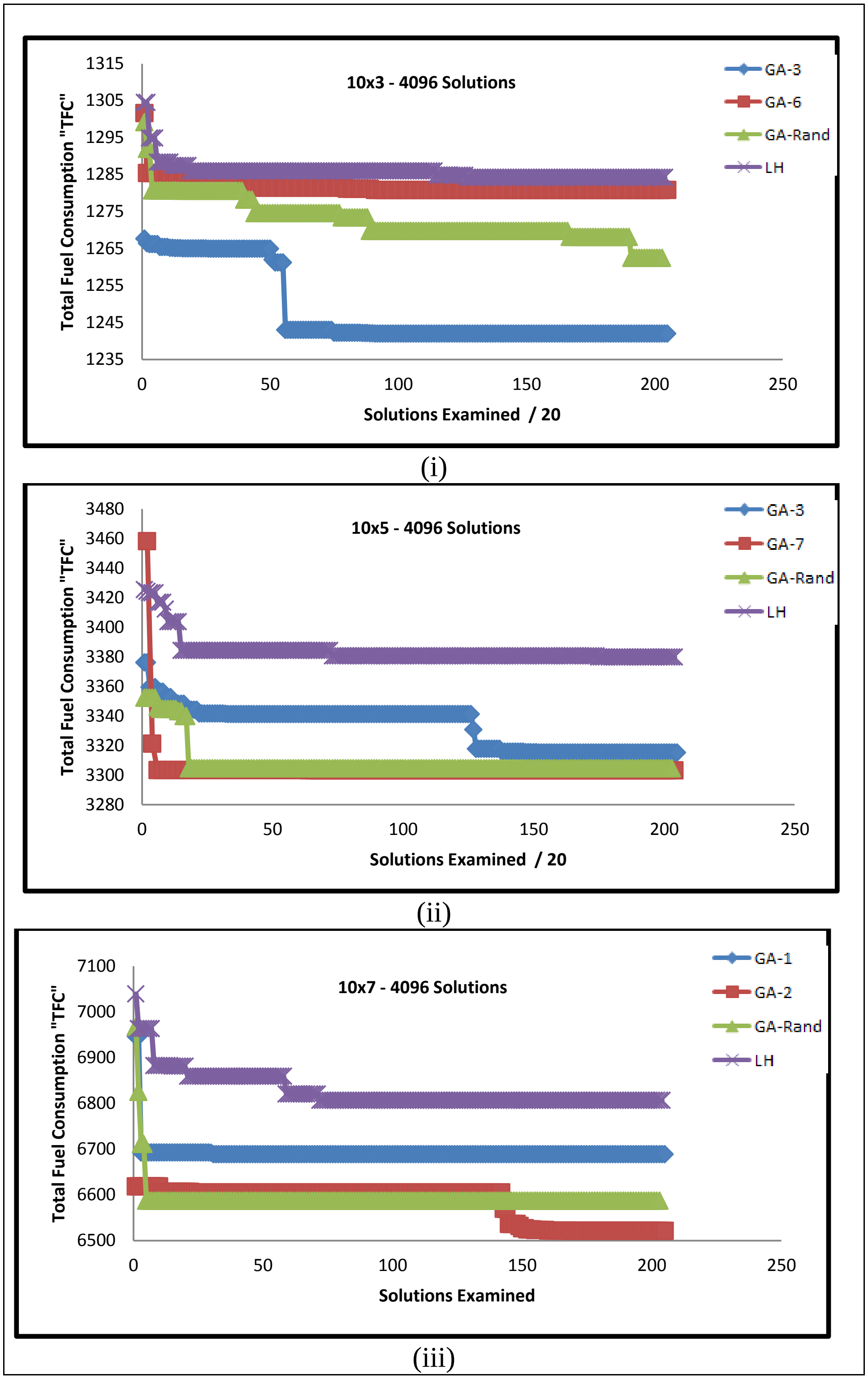
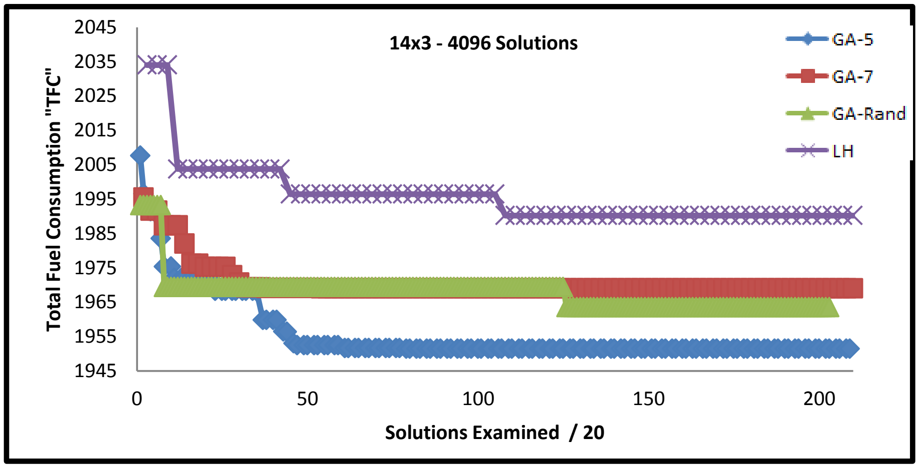
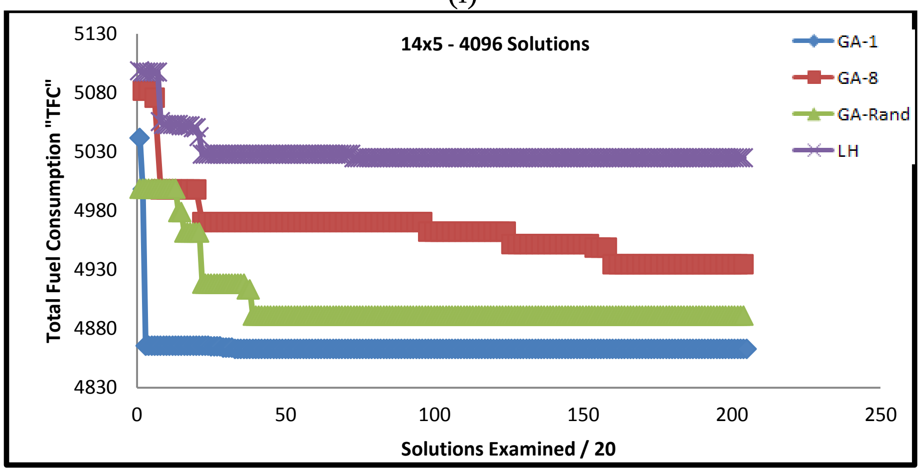


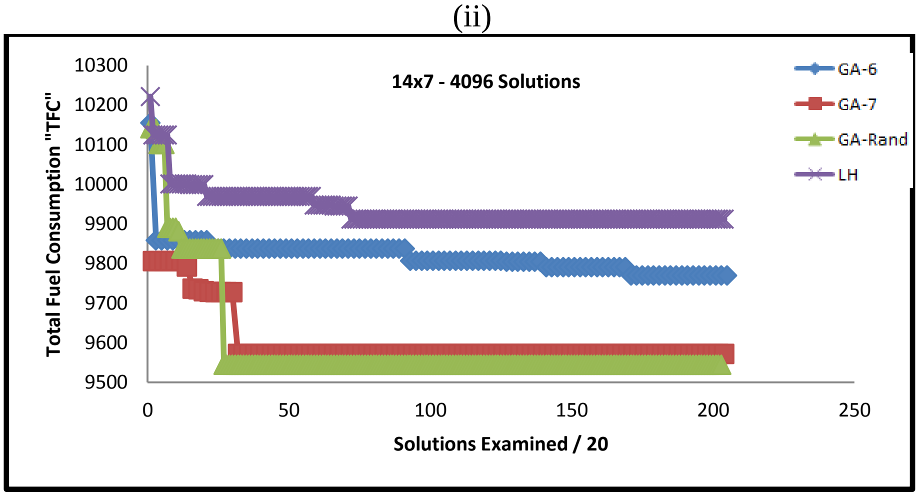
Figure 3.7. Illustration of the progress of four selected algorithms on (i) 10x3, (ii) 10x5, and (iii) 10x7 problem sizes.



(i)



(ii)



(iii)

Figure 3.8. Illustration of the progress of four selected algorithms on (i) 14x3, (ii) 14x5, and (iii) 14x7 problem sizes.

3.6. Sensitivity analysis

Two experiments were conducted to measure the algorithms' sensitivity. In experiment A, the variability in performance of the same algorithm is considered, at the same 1000 problem instances. In particular, we examine how the randomness in the GA itself- regarding selecting pairs for mating, the mating process itself, and the generation of random solutions- affects best solution found and it's total fuel consumption. In experiment B, we investigate the performance of the same algorithm on different sets of 1000 problem instances. In this experiment, the randomness exists with the GA itself and the set of instances considered.

Six runs for configuration size 6x7 were considered for the two experiments. The results of experiment A are shown in Table 3.11. We see that the values in the "Var" column are below (1/12), proving that the values of the parameters are not random and are gathered about a center. Table 3.12 summarizes the results of experiment B. The majority of "Var" are below (1/12), which is again proving that the parameters are not random even with different sets of instances. The low-high algorithm is the least sensitive algorithm for changing the sets of instances.

Table 3.11. Sensitivity-A for GA-01 and random algorithms, 1000 instances are used.

	Variable	*1*	*2*	*3*	*4*	*5*	*6*	*Avg*	*Var*
GA 1	***P1***	0.43	0.75	0.27	0.14	0.41	0.52	0.42	0.04
	P2	0.17	0.28	0.85	0.27	0.58	0.2	0.39	0.07
	P3	0.53	0.76	0.54	0.56	0.66	0.21	0.54	0.03
	P4	0.07	0.08	0.07	0.19	0.2	0.06	0.11	0.00
	α	0.48	0.64	0.53	0.56	0.67	0.65	0.59	0.01
	β	0.63	0.3	0.59	0.78	0.49	0.05	0.47	0.07
	γ	0.06	0.14	0.19	0.48	0.12	0.3	0.22	0.02
	δ	0.36	0.67	0.21	0.24	0.4	0.48	0.39	0.03
	ε	0.56	0.4	0.6	0.85	0.6	0.25	0.54	0.04
	η	0.85	0.61	0.68	0.75	0.83	0.64	0.73	0.01
	ϑ	0.12	0.02	0.02	0.02	0.04	0.02	0.04	0.00
	μ	0.85	0.69	0.58	0.66	0.8	0.68	0.71	0.01
	TFC	3933.3	3957.19	3946.64	3945.42	3958.83	3952.92	3949.05	88.79

Table 3.12. Sensitivity-B for GA-01, random, and low-high algorithms, 1000 instances are used.

	Variable	1	2	3	4	5	6	Avg	Var
GA 1	P1	0.06	0.43	0.06	0.69	0.07	0.67	0.33	0.09
	P2	0.06	0.21	0.14	0.16	0.22	0.11	0.15	0.00
	P3	0.39	0.59	0.53	0.24	0.05	0.69	0.42	0.06
	P4	0.64	0.43	0.43	0.7	0.01	0.87	0.51	0.09
	α	0.35	0.87	0.45	0.72	0.92	0.37	0.61	0.07
	β	0.67	0.09	0.3	0.06	0.52	0.44	0.35	0.06
	γ	0.02	0.33	0.37	0.2	0	0.27	0.20	0.02
	δ	0.3	0.84	0.62	0.48	0.62	0.76	0.60	0.04
	ε	0.79	0.51	0.35	0.15	0.95	0.27	0.50	0.10
	η	0.81	0.72	0.83	0.61	0.84	0.93	0.79	0.01
	ϑ	0.19	0.17	0.11	0.1	0.08	0.12	0.13	0.00
	μ	0.69	0.14	0.55	0.14	0.2	0.47	0.37	0.06
	TFC	3803.99	3863.9	3913.3	3796.7	3876.01	3848.41	3850.39	1967.21
	Variable	1	2	3	4	5	6	Avg	Var
Random	P1	0.84	0.65	0.03	0.55	0.78	0.08	0.68	0.01
	P2	0.24	0.1	0.12	0.04	0.27	0.17	0.12	0.00
	P3	0.72	0.02	0.12	0.79	0.66	0.11	0.14	0.08
	P4	0.67	0.29	0.44	0.84	0.59	0.91	0.35	0.02
	α	0.78	0.33	0.66	0.92	0.93	0.58	0.41	0.03
	β	0.62	0.03	0.56	0.22	0.18	0.13	0.13	0.06
	γ	0.23	0.17	0.14	0.17	0.22	0.33	0.18	0.00
	δ	0.7	0.38	0.46	0.7	0.93	0.52	0.43	0.02
	ε	0.36	0.17	0.05	0.91	0.76	0.17	0.20	0.01
	η	0.71	0.92	0.34	0.7	0.53	0.92	0.89	0.01
	ϑ	0.09	0.1	0.07	0.1	0.06	0.28	0.10	0.00
	μ	0.4	0.33	0.78	0.14	0.13	0.46	0.34	0.00
	TFC	3862.31	3864.59	3904.09	3901.73	3883.49	3882.97	3849.40	883.20
	Variable	1	2	3	4	5	6	Avg	Var
low-high	P1	0.25	0.25	0.25	0.75	0.25	0.25	0.33	0.04
	P2	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.00
	P3	0.75	0.75	0.75	0.75	0.25	0.25	0.58	0.07
	P4	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.00
	α	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.00
	β	0.25	0.25	0.75	0.75	0.25	0.75	0.50	0.08
	γ	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.00
	δ	0.25	0.75	0.25	0.25	0.25	0.25	0.33	0.04
	ε	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.00
	η	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.00
	ϑ	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.00
	μ	0.25	0.75	0.75	0.75	0.75	0.75	0.67	0.04
	TFC	4066.91	4061.81	4068.75	4052.5	4062.09	4045.59	4059.61	78.99

4- A POLICY COST MODEL FOR SHIPPING COMMODITIES BY TRUCK

Surprisingly, transportation planners and policy makers do not have the ability to estimate the cost of shipping a quantity of a commodity between two locations for broad categories of goods. Costs of shipping are important components in mode, route, and location choice processes. Good knowledge of costs can aid public sector decision makers in determining the economic benefits of infrastructure improvements or determining the impacts on the private sector of various policies and operational strategies. Shipping costs relate to logistics practices of businesses, and these practices have been changing rapidly in recent years. This investigation inventories cost models that have been used in the past and evaluate the availability of data sets containing shipment cost information. Then a cost model for shipping various commodities and commodity groups by truck has been built and several examples to show how the model can address issues of interest to carriers, shippers, and governments have been presented.

This investigation has been submitted to the National Center for Freight & Infrastructure Research & Education as a warking paper (Paper No. 09-4) entiteled "A Policy-Oriented Cost Model for Shipping Commodities by Truck".

4.1. Introduction

Freight can be broadly defined as the movement of goods from one place to another. The United States freight transportation network consists of hundreds of thousands of miles of transportation infrastructure and hundreds of thousands of transportation facilities devoted to five different modes of transport: road, rail, air, water, and pipeline. Increases in population, economic activity, and global trade have put tremendous pressure on this network in recent years. Indeed, it appears that the U.S. is now reaching a crossroads with respect to transportation planning that calls for drastic action. With the majority of transportation infrastructure in the public domain, the best chance for change lies with federal, state, and local policy makers. During the next few years, it is crucial for elected and non-elected public officials to adopt wise policies that will chart a favorable course for the U.S. transportation system in the 21st century.

Transportation policies are usually judged in terms of their environmental, social, and economic impacts. Economic impact usually dominates policy analysis, with environmental and social impacts playing a secondary role. Yet, even economic analysis of transportation policy is often incomplete. In particular, the impact of a proposed project or policy on private sector shipping costs is rarely studied. Instead, most analyses focus on the jobs created by an infrastructure project; the public sector infrastructure and maintenance costs of the project or policy; and the impact on traffic congestion. Meanwhile, the discussion of costs borne by private sector shipping companies is muted. The purpose of the current study is to develop a methodology that will allow private sector shipping costs to become a larger part of the equation in transportation policy analysis.

Freight transportation costs are of interest to at least three kinds of institutions—carriers, shippers, and governments. Carriers need to know freight transportation costs because they are the providers of transportation services. Shippers need to have a handle on freight transportation costs in order to better understand decisions regarding facility location and supply chain management. Finally, governments need to be able to estimate freight transportation costs if they are to formulate sound transportation policies. Surprisingly, these costs have played only a minor role in transportation planning and policy analysis. Shipping costs are an important component of mode, route, and location choice decision making processes in the freight industry. Good knowledge of shipping costs is therefore vital to the formulation of effective public policy. For example, it is important for policy makers to know how potential changes in truck flows, sizes, and weights could affect shipping costs. It is also important for transportation officials to know how proposed infrastructure improvements or construction projects affect shipping costs for different economic sectors.

In order to raise the profile of private sector shipping costs in freight transportation policy analysis, there needs to be a method for estimating the cost of shipping commodities between any two locations. At the moment, there are a few tools developed by academic researchers that can estimate the cost of shipping individual commodities between any two locations. However, to the authors' knowledge, no tools are designed to estimate the costs of shipping broad categories of cargo that correspond to various sectors of the U.S. economy. Thus, a policy-oriented methodology for estimating shipping costs is still missing.

In this study, the first few section inventory freight cost models that have been used in the past and evaluate the availability of data sets containing shipment cost information. Then a methodology has been developed for estimating shipping costs for one freight transportation mode—trucking. U.S. Census Figures indicate that shipments by truck were valued at about USD $6235 billion in 2002. This represents 75% of the total value of all shipments made within the U.S. The main objective is to build a model that can estimate the cost of shipping a certain quantity of a specific commodity or commodity group by truck from any origin to any destination inside the United States. The model can also be used to estimate general shipping costs for different economic sectors, with significant ramifications for public policy. The field-testing of the model and expansion of the model to include at least one additional mode of transportation — rail, air, or water — is left to a future study.

This section is organized as follows. Section 4.2 reviews the literature relevant to the current study. Section 4.3 evaluates the availability of data sets containing shipment cost information. Section 4.4 introduces the concept of commodity aggregation as a way to model shipping costs from a public policy perspective. A mathematical model of shipping costs in the trucking industry is presented in Section 4.5. Section 4.6 illustrates the use of the cost model in various hypothetical scenarios.

4.2. Literature review

A literature review was conducted to determine what research has already been done on freight planning and other topics related to freight cost modeling.

Berwick and Dooley (1997) built a truck cost model for motor vehicle owners and/or operators. A spreadsheet simulation model was developed to estimate truck costs for different truck configurations, trailer types, and trip movements. A shipper may need to know product unit costs to determine the transportation cost per item. Alternatively, a lessor (shipper) may want total trip costs while the owner/operator may want per hour or per mile costs. The trucking industry has a perfect competition environment due to its non-homogeneity, limited entry barriers, large number of firms, and virtually perfect information. Furthermore, its small independent truckers are mainly price takers. Therefore, cost tracking and control are essential for survival of the owner/operator. However, the authors point out that owner/operators may have less knowledge of the full cost of their operation than shippers, larger trucking companies, and logistics firms. Cost information is important because it allows shippers to reconcile freight rates with trucking costs. This may assure revenue adequacy for the truckers, without sacrificing efficiency in the shippers' industry. Current cost estimates may be beneficial to both parties (lessor and trucker) in negotiating a lease agreement. Sustainability for the independent trucker may reduce search costs, improve quality for the lessor, and reduce turnover.

Recent changes in manufacturing practice and supply chain management have lowered inventories and created a move toward just-in-time inventory management. These new changes have increased the need for quality transportation. With owner/operators moving 30 to 40 percent of all intercity freight (Griffin and Rodriguez, 1992), assessing the costs borne by owner/operators is important. The model proposed by Berwick and Dooley (1997) was the first effort to understand such costs.

Berwick and Dooley point out that change in trailers and combinations of trailers continue to affect the cost structure of the trucking industry. New safety requirements have affected the costs for truckers. Safety costs such as anti-lock braking systems and air ride suspension have added to the price of a new tractor and trailer. However, safety features may reduce risk (insurance) costs because of fewer crashes and less damage to products hauled. The use of cell phones and other technological changes also may create more changes in the trucking industry. The authors develop a spreadsheet model that contains several sheets. One of them contains decisions and exogenous variables, another one has performance measures, and the remaining sheets contain data and sensitivity analysis calculations, and linkages for the costing and revenue associated with particular truck movement. Fixed costs in this model include equipment costs, depreciation, return on investment, license fees insurance and sales tax, and management and overhead costs, while the variable costs include labor, fuel, tires, and maintenance and repair costs.

Berwick and Farooq (2003) continue the work of Berwick and Dooley. They argue that, while the spreadsheet costing model developed in 1996 was useful, it lacked the functionality of a stand-alone model or software product. Thus, a new visual basic model was developed to be a stand-alone product to be utilized by transportation professionals and researchers.

William and Allen (1996) find that the cost per mile of operating a motor vehicle is a key parameter in many transportation studies. They defined the auto operating cost as a result of dividing the sum of annual cost of maintenance, oil, and tires by average miles driven vehicle per year.

Forkenbrock (1999) defines private costs as the direct expenses incurred by providers of fright transportation. Such costs consist of operating costs, as well as investments in capital facilities while the external costs include: accident; emissions; noise; and unrecovered costs associated with the provision, operation, and maintenance of public facilities. Freight trucking creates certain adverse impacts. These impacts are referred to as external costs because they are not borne by those who generate these costs. Internalizing external costs makes it possible to return to society an amount equal to the costs one imposes. Forkenbrock's analysis reveals that external costs are equal to 13.2% of private costs and user fees would need to be increased about three fold to internalize these external costs. These results depend on the data of intercity truck freight transportation which accounts for a very large share of the total ton-miles of transportation.

Forkenbrock (2001) extends the above work related to external costs of intercity truck freight transportation to include rail transportation and makes a comparison between the trucking and rail transportation modes. He finds that rail external costs are USD $0.24 to $0.25 per ton-mile, well less than the $1.11 for freight trucking, but that external costs for rail generally constitute a larger amount relative to private costs—9.3% to 22.6%--than is the case for trucking (13.2%).

Ergun et al. (2007) propose an optimization model for reducing truckload transportation costs. A highly effective and extremely efficient heuristic had been designed and implemented that incorporates fast routines for checking time feasibility for a tour in the presence of dispatch time windows and for minimizing the duration of a tour by appropriately selecting a starting location and departure time.

Woensel and Curz (2009) studied the costs of transportation congestion. They show that contemporary traffic pricing typically does not reflect the external congestion costs. In order to induce road users to make the correct decision, marginal external costs should be internalized. Optimal use of a transportation facility cannot be achieved unless each additional user pays for the additional costs that he/she imposes on all other users on the facility. The main advantage of the authors' methodology is the possibility to derive the marginal congestion costs in an analytical way while taking into account the inherent stochasticity of the real world. This approach relies less on the availability of data than most other techniques.

One of the most comprehensive freight studies that has been done is described in Report 260 of the National Cooperative Highway Research Program (NCHRP 260). NCHRP is administered by the Transportation Research Board (TRB) and sponsored by various state DOTs in cooperation with the Federal Highway Administration (FHWA). NCHRP was created in 1962 as a means to conduct research in acute problem areas that affect highway planning, design, construction, operation, and maintenance nationwide. NCHRP Report 260 proposes and describes a set of freight demand forecasting techniques that together form a user's manual. This user's manual is a guide for conducting studies that involve or require freight demand forecasts. Its development is motivated by the observation that freight oriented studies are often adversely affected by inadequate freight flow data. Indeed, in most states the collection of truck traffic flow data, and the preparation of demand forecasts is treated as an appendage to similar data collection and forecasting that is done for passenger vehicles. Thus, passenger flows have received the majority of attention, while freight flows have been largely ignored.

The limited capability for undertaking truck-oriented freight demand forecasts in both highway and non-highway modes stems more from the lack of a database rather than from any inability to devise suitable truck traffic forecasting techniques. The lack of freight flow data usually means that future truck volumes are forecasted as a percentage of aggregated traffic volumes for both existing and proposed facilities. Thus, forecasts are usually prepared using trend extension forecasting techniques rather than by relating observed volumes with present economic activities. NCHRP proposes a method that can still accomplish freight demand forecasting despite the limited freight flow data. The NCHRP user's manual presents an overall process or methodology to be followed in conducting such studies along with appropriate sub-techniques. Before attempting to apply the technique the user should first take time to fully determine the parameters and constraints both affecting and shaping the application at hand. Secondly, the user should reduce the scope of application to the maximum extent possible.

The overall freight demand forecasting technique consists of four phases: (1) traffic generation; (2) traffic distribution; (3) mode division; and (4) traffic assignment. The product of freight traffic generation and distribution is one or more commodity flow matrices. These matrices show how much of a given commodity is being shipped between any two locations. A multidimensional commodity flow matrix may differentiate cargo according to commodity class, mode, shipment origin, and shipment destination and can be reported in annual tons, annual dollar value, and annual ton-miles. One matrix represents the base case. The others, developed from the base case matrix, represent predictions for future years. If vehicular origin-destination or commodity flow data are available to the user, that data should be used as the basis of the base year commodity flow matrix. The need for additional matrices depends on the alternatives being evaluated, the extent to which the application involves alternative (1) futures (cases of increasing or decreasing commodity or vehicle flow); (2) scenarios (changes in infrastructure, rates, or services); and/or (3) conditions (when constraints or limitations are placed upon system use or revenue and cost structure).Phase 3—mode division—consists of three main components: (1) summarizing base commodity (or vehicle) flows, carrier costs, and carrier revenue/shipper costs; (2) for each alternative being considered, dividing commodity flow among competing modes using a split model, and then summarizing resulting flows, costs, and revenues; and (3) performing selected constancy tests to insure the reasonableness of the results obtained from the mode split model, and then preparing final outputs. Phase 4—traffic assignment—consists of four main components: (1) converting commodity flows into vehicle flows, if not already done in estimating carrier costs; (2) assigning the resulting traffic to modal networks; (3) estimating changes in vehicle/vessel volumes and loadings expected to occur on a segment basis; and (4) for highway segments, estimating expected changes in pavement service life on a segment basis.

The NCHRP 260 user's manual contains three sub-techniques related to the freight cost. These are (1) a truck unit costing model, (2) a shipper costing model, and (3) a freight rate estimating model. The truck unit cost sub-technique estimates the per-mile cost contributions for 16 components including insurance, fuel, and driver wages. These components are then combined to produce estimates for the truck load cost, cost per mile, and cost per ton-mile. The model has a total of 35 variables. Users must provide eight specific inputs including fuel price ($/gallon) and can interactively change any of the remaining 27 variables or use supplied default values. As unit cost varies with the carrier, mode, and time, the resulting cost estimate is very rough and is not intended to be a true cost. Indeed, today most large carriers have developed extensive costing systems for strategic planning and internal management purposes. The second cost model is a shipper costing model. In recent years, shippers have increasingly recognized that the mode offering the lowest rate may not in fact be the least cost mode, after considering other logistics costs. Thus, costs accruing to shippers typically include transport logistics (rates, loss and damage, pickup and delivery) and non-transport logistics costs (order, storage, inventory, and stock-out costs). These costs are taken into account in the shipper cost model. The third model is a rate estimating model. Completely separate from unit costs are the rates charged for specific transport services. Rates may be supplemented by charges for special or accessorial services and penalties assessed. Rates, charges, and penalties, taken together, represent carrier income. None of the above costing models directly consider issues related to public policy.

Huang and Smith (1999) mention that many state departments of transportation are becoming interested in developing statewide truck travel-demand (TTD) forecasting models. Estimates of future truck traffic are useful for making better decisions on highway improvements. Four similar TTD models are developed for Wisconsin using 1993 Commodity Flow Survey (CFS) origin-destination (O-D) data and a limited amount of truck classification count data. First, statewide zonal-level trip tables are developed from the CFS database. Then, gravity models for four trip types are calibrated to match the trip-length frequency distributions of the CFS O-D trip tables. Finally, zonal trip productions and attractions are adjusted using an iterative procedure. The four alternative TTD models differ only in the method used to assign external trips to the external stations. All of the models provide reasonable levels of goodness-of-fit to the 40 selected calibration links, as well as 104 additional count locations across the state.

Gordon and Pan (2001) propose a three step modeling structure for the non-survey freight transportation model which includes freight trip generation, freight trip distribution and freight traffic assignment. A freight origin-destination (OD) matrix of freight flows can be developed using secondary data sources. The estimated freight flows can be loaded together conventional passenger flows on the regional highway network of a large metropolitan area. GIS can potentially improve the non-survey approach in data validation, model operations, and evaluation.

Tadi and Balbach (1994) mention that trip generation rates for trucks are lower than rates for autos in the case of all land use categories except for truck terminals. This appears logical as the main activity at truck terminals relates to trucks.

García-Ródenas and Marín (2009) established a new methodology to model and to simultaneously solve the problems of calibration and O-D (origin-destination) matrix estimation for the multi-modal assignment problem with combined modes (MAPCM). A new approach called the calibration and demand adjusting model (CDAM), has been formulated based on nonlinear bi-level programming. The existence of an infinite number of solutions for any reasonable means of calibration of the MAPCM is proved. This is due to the use of a nested logit model for the modeling of the demand and the cost structure of the model. A heuristic column generation algorithm (HCGA) has been proposed to solve the bi-level model.

De Jong, Gunn, and Walker (2004) found that national model systems that can be used for forecasting future freight transport volumes and/or vehicle flows have been developed in a number of European countries. For the trip generation step, several European and national models now use input-output and related methods. Distribution in those models is also based on input-output analysis, or in gravity formulations. For modal split, many different model forms can be found in practice. But most of the large model systems use multi-modal network assignment, in which mode choice and assignment are handled simultaneously.

Internationally, the Great Britain Freight Model (GBFM) is perhaps the most comprehensive freight demand forecasting model to be developed outside the United States (GBFM, 2003). The GBFM project objective was to combine a group of existing software components and data sources into a single entity, and to develop a comprehensive model of international and domestic freight flows within Great Britain. GBFM used a path enumeration technique which is the process of defining sequences of links connecting the source (origin) to the sink (destination). By attaching the trip matrix to a route choice model, traffic can be assigned back to the underlying network, so that the assigned traffic volumes for a given link can be recorded. A basic concept of a network path freight network used in this model can be simplified to that of a “service”. A service can be regarded as a wrapper for a path, where only the customer-oriented information (cost, time taken, reliability, access terminal, egress terminal) are known. Within GBFM, it is possible to define services that can be added directly to the paths within the choice set, or as hyper-links within the multimodal network. In principle, this choice model, expressed as a mapping from generalized cost i to probability i, is a straightforward process to simulate within a computer model. The approach taken has been to follow the F-Logit method established by Fowkes and Toner (1996) within the STEMM5 project, itself influenced by Cascetta's C-Logit16 Model (1995). The C-Logit/ F-Logit approach is intuitive and logical, suggesting that a route can win traffic if it is attractive (in terms of generalized cost) but not dominated by a similar, better alternative. GBFM has been designed to read data created by GIS Software18, and to generate results that can be re-interpreted as maps. Representing data in a geo-coded form (with latitude and longitude co-ordinates) is a simple way of imposing a degree of referential integrity between the components of a transport model. Simple algorithms can be built to test the distance between objects, and whether one object contains or intersects with another.

Winston (1982) and Gray (1982) discuss different kinds of freight models. Freight demand is essentially required to analyze most of the issues related to the freight transportation system. Freight demand models can be classified in different ways. Many models are built according to an aggregation flow approach that considers an aggregate and disaggregate model. In the aggregate model, the basic unit of observation is an aggregate share of a particular fright mode at the regional or non-regional level. The basic unit of observation in the disaggregate model is an individual decision maker's distinct choice of a particular freight mode for a given shipment.

Janic (2007) analyzes the full cost of a given intermodal and equivalent road transport network based on the network size, intensity of operations, technology in use, and internal and external costs of individual components of the system. Both networks are assumed of equivalent size in terms of spatial coverage, number of nodes, and the demand volume they serve. A model is developed for calculating the full costs of a given intermodal or road freight transport network. The model is applied to simplified configurations of intermodal rail-truck and equivalent road transport networks in Europe.

Zhang et al. (2003) develop a methodology for statewide intermodal transportation planning using public domain databases. The State of Mississippi is used as an example to describe the method. The commodity flow data analysis, transportation planning model, and intermodal transportation simulation model are the main components in this study. The 1997 Commodity Flow Survey (CFS), Vehicle Inventory and Use Survey (VIUS), and Cargo Density Database (CDD) were used in the study to describe freight flows coming into, going out, within and through the State of Mississippi. Geographic information systems (GIS) are used along with the transportation planning software TransCAD to model the transportation system performance. The method does not include or consider the cost of shipping commodities by truck or by any other transportation mode.

Decorla-Souza, et al. (1997) propose total cost analysis (TCA) as an alternative to benefit-cost analysis (BCA) in evaluating transportation alternatives. One advantage of TCA over traditional BCA is that the concept of “total cost” is more easily understood by the public and political decision makers than BCA concepts such as “net present worth.” A second advantage is that there is no suggestion that all benefits have been considered; decision makers are free to use their own value judgments. The TCA approach is based on assessing the relative economic efficiency of alternatives by estimating the total costs of travel for various travel market segments under each alternative. The full costs of each alternative—including travel time costs and quantifiable environmental and social costs—are considered. Many amounts which are considered as benefits in benefit-cost analysis become costs in a total cost framework. In the TCA approach, the total cost differences among alternatives are traded off against their estimated non-monetized benefits or impacts to determine the relative merit of each alternative.

In conclusion, there is still no study looking at impact of public transportation policy on private sector shipping costs. However, Berwick and Dooley (1997) developed a truck costing model that can be used by shippers and owners/operators. The main objective of that model was to provide owner/operator cost information to more readily reflect the differences in equipment, product, and trip characteristics of the individual firm. In this investigation, a policy oriented cost model for shipping various commodities at different aggregation levels by truck will be presented.

4.3. Evaluation of data sets

Transportation, commodity flow, and transshipment analyses require different kinds of data sets. Some of the required data can be obtained through comprehensive and scientific surveys or available data sets from related departments, affiliations, associations and companies. Data sets for transportation modeling are available either publicly or privately. Most of them are available on the internet or in electronic form. A list of databases relevant to U.S. commodity flows and the trucking industry is displayed in Table 4.1. We now discuss these data sets in more detail.

4.3.1. U.S. Census Bureau Data Sets

The U.S. Census Bureau issues data, statistics, and censuses classified in different categories like geography, business, and industry. It has many transportation-related publications such as the Commodity Flow Survey, Vehicle Inventory and Use Survey, and Transportation and Warehousing. All of these data sets are compiled within the transport sector of the Bureau's economic census. The economic census is the major source of facts about the structure and functioning of the nation's economy. It provides the framework for such composite measures as the gross domestic product, input/output measures, production and price indexes, and other statistical indices that measure short-term changes in economic conditions.

Commodity Flow Survey (CFS)

The Commodity Flow Survey (CFS) for the entire U.S., individual states, regions, divisions, metropolitan areas (MAs), and reminder of state areas (ROS) is conducted every five years as part of the economic census by the U.S. Census Bureau in partnership with the Bureau of Transportation Statistics (BTS). BTS provides information and assistance for survey respondents and data users. The data from the CFS are used for public policy analysis and for transportation planning and decision-making to assess the demand for transportation facilities and services, energy use, safety risks, and environmental concerns.

Table 4.1. List of Important Truck Databases and Their Publishers.

Data Base	Publisher	Description	Publisher Website
Commodity Flow Survey (CFS)	U.S. Census Bureau	Tabular results on shipment characteristics by mode of transportation, commodity, distance shipped, and shipment weight	www.census.gov (all websites should be preceded by "http://")
Vehicle Inventory and Use Survey (VIUS)	U.S. Census Bureau	Data on the physical and operational characteristics of the nation's private and commercial truck population	www.census.gov
Transportation and Warehousing	U.S. Census Bureau	Summary statistics includes number of establishments, revenues and annual payroll for different trucking and warehousing companies	www.census.gov
The North American Transborder Freight Database	Bureau of Transportati on Statistics (BTS)	Contains freight flow data by commodity type and by mode of transportation for U.S. exports to and imports from Canada and Mexico	www.bts.gov
Freight Analysis Framework (FAF^2 & FAF^3)	The Federal Highway Administrati on (FHWA)	Commodity origin-destination database providing tonnage and value of goods shipped by type of commodity and mode of transportation among and within 114 areas; to and from 7 international trading regions; and through the 114 areas plus 17 additional international gateways	ops.fhwa.dot.gov /freight/index.cfm
Truck Size and Weight	The Federal Highway Administrati on (FHWA)	Provides a ready source of information about the compliance of the commercial motor vehicle with the Federal standard "size and weight standards" and guidelines, state enforcement activities, reporting requirements, and contacts.	ops.fhwa.dot.gov /freight/index.cfm

The CFS presents detailed tabular results on shipment characteristics by mode of transportation, commodity, distance shipped, and shipment weight reported in annual tons, annual dollar value, annual ton-miles, and miles. The 2007 CFS includes data from business establishments in the mining, manufacturing, wholesale trade, and selected retail industries. The survey also covers selected auxiliary establishments (e.g. warehouses) of retail companies. The survey coverage excludes establishments classified as farms, fisheries, governments, foreign establishments, and most establishments in the construction, transportation, service, forestry, and retail industries. The items available on the CFS website include the commodity flow survey itself, a CFS instruction guide, the CFS survey questionnaire, a shipment sampling tool which assists in identifying those data of particular interest to the user, and commodity descriptions corresponding to the five-digit SCTG (Standard Classification of Transportation Goods) commodity codes.

Vehicle Inventory and Use Survey (VIUS)

The Vehicle Inventory and Use Survey (VIUS) is another publication product of U.S. Census Bureau. This publication includes census data from the years 1997 and 2002. Prior to 1997 the survey was known as the Truck Inventory and Use Survey (TIUS).

VIUS provides data on the physical and operational characteristics of the nation's private and commercial truck population. Its primary goal is to produce national and state-level estimates of the total number of trucks. This survey was conducted every 5 years, until 2002, as part of the economic census. Recent cuts in federal government spending led to the elimination of the survey. The survey includes private and commercial trucks registered (or licensed) in the United States as of July 1 of the survey year. The survey excludes vehicles owned by federal, state, or local governments. VIUS data are of considerable value to government, business, academia, and the general public. Businesses and others make use of these data in conducting market studies and evaluating market strategies; assessing the utility and cost of certain types of equipment; calculating the longevity of products; determining fuel demands; and linking to, and better utilizing, other data sets representing limited segments of the truck population.

The VIUS product consists of 52 data releases available for the entire United States, each of the fifty states, and the District of Columbia. All files are released as pdf files which provide general survey information, information on how to use the survey data, and program changes that impact comparability. Survey micro-data files contain un-aggregated records for individual trucks by state. Individual data records are masked to avoid disclosure. A “data dictionary” .pdf file provides a listing of each variable, a description of the variable, the survey question that was asked to obtain the data, and a list of valid responses to the question. VIUS has issued separate reports about the trucking industry in the USA, each individual state, and the District of Columbia. These reports estimate the number of trucks in a given year that fall into one or more of the following types of categories: vehicle size, truck type, number of miles traveled; and vehicle operational characteristics. The reports also include a comparative summary of truck operational characteristics—such as type of business, body type, vehicle size, and annual mileage—in different years. They also give a summary of the total truck mileage and average annual mileage by equipment type, fuel type and engine size, refueling location, maintenance, vehicle size and weight, total length, and fuel economy.

Transportation and Warehousing

The Transportation and Warehousing portion of the U.S. Census includes data sets and reports for all transportation modes—water, rail, air, pipeline, and truck. These data sets distinguish seven main types of activities: five corresponding to transportation in each of the five transportation modes and two corresponding to (A) warehousing and storage and (B) transportation support activities. A separate subsector for transportation support activities is established for many reasons. First, most transportation support activities—such as freight transportation arrangement—are inherently multimodal or have multimodal aspects. Second, there are production process similarities among the support activity industries. In addition, the data set tracks activities associated with establishments providing passenger transportation for scenic and sightseeing purposes, postal services, and courier services.

The 2002 Truck Transportation Report has summary statistics including the number of establishments, revenue, and annual payroll for different truck transportation companies. These companies are categorized according to the 2002 NAICS (North American Industry Classification System) code. It compares the 2002 data to the data from the previous (1997) study.

4.3.2. Bureau of Transportation Statistics (BTS)

The Bureau of Transportation Statistics (BTS) was established as a statistical agency of the United States federal government in 1992. The Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 created BTS to administer data collection, analysis, and reporting and to ensure the most cost-effective use of transportation-monitoring resources. BTS brings a greater degree of coordination, comparability, and quality standards to transportation data, and facilitates the closing of important data gaps. It provides reports and censuses related to freight and truck transportation from different departments and publications like VIUS, the 1990 and 200 versions of the Census Transportation Planning Package (CTPP), motor carrier financial and operating information, and the Commodity Flow Survey. BTS has issued many data and statistical reports such as Freight in America (2006), Freight Shipments in America (2004), America's Freight Transportation Gateways (2004), National Transportation Statistics, and North American Transborder Freight Data. All of these reports are available at the BTS website. At the BTS website, users can access reports related to commodity shipments, hazardous materials shipments, transportation by air and truck, most important commodities by weight or ton-miles, economic impact of shipment choices, and domestic freight movements by commodity, mode, value and distance.

The North American Transborder Freight Database

The North American Transborder Freight Database has been available since April 1993. It contains freight flow data by commodity type and by mode of transportation (rail, truck, pipeline, air, water, and other) for U.S. exports to and imports from Canada and Mexico. The database includes two sets of tables; one is commodity-based while the other provides geographic detail. The purpose of the database is to provide transportation information on North American trade flows. This type of information is being used to monitor freight flow changes since the signing of the North American Free Trade Agreement (NAFTA) by the United States, Canada, and Mexico in December 1992 and its entry into force on January 1, 1994. The database is also being used for trade corridor studies, transportation infrastructure planning, marketing and logistics plans and other purposes. It allows users to analyze movement of merchandise by all land modes, waterborne vessels, and air carriers. The data are available for any month since 1994 to the current year. These data can be aggregated and disaggregated geographically, by mode, and by commodity type. Flows are measured by dollar value, pounds, short tons, and metric tons.

Beginning in 1997, the North American Transborder Freight Database represents official U.S. trade with Canada and Mexico for shipments that entered or exited the United States by surface modes of transport (other than air or maritime vessel). The data from April 1993 to December 1996 included official U.S. trade with Canada and Mexico by surface modes and transshipments that moved from a third country through Canada or Mexico to the United States or from the United States to a third country through Canada or Mexico. During this time period, it was not possible to separate transshipment activity from the official trade activity at a detailed level. Due to customer requests, BTS discontinued the inclusion of transshipment activity in the North American Transborder Freight Database beginning in January 1997. This allowed customers to perform comparable trade analyses by mode of transportation.

The North American Transborder Freight Database is extracted from the Census Foreign Trade Statistics Program. Import and export data are captured from administrative records required by the Departments of Commerce and Treasury. Historically, these data were obtained from import and export paper documents that the U.S. Customs Service (Customs) collected at a port of entry or exit. However, an increasing amount of import and export statistical information is now being captured electronically.

4.3.3. Federal Highway Administration (FHWA)

The Federal Highway Administration (FHWA) considers freight issues in studies of highway condition and performance, cost allocation, truck size and weight limits, and the economic consequences of highway investments. FHWA consists of several offices. The Office of Transportation Policy studies issues of truck size and weight and freight bottlenecks on highways. The Office of Legislative and Governmental Affairs considers highway condition and performance. Of particular importance to this working paper is the Office of Freight Management and Operations.

Office of Freight Management and Operations

The Office of Freight Management and Operations was established in 1999 as a part of the Federal Highway Administration's Office of Operations in the US Department of Transportation (USDOT). This office promotes efficient, seamless, and secure freight flows on the U.S. transportation system and across US borders. The Office has five major program areas: freight analysis, freight professional development, freight infrastructure, freight operations and technology, and vehicle size and weight.The Freight Analysis Program (FAP) conducts research on commodity flows and related freight transportation activities, develops analytical tools, measures system performance, and examines the relationship between freight transportation improvements and the economy. The FAP produces several regular publications including the Freight Analysis Framework, Freight Congestion, Data Source, Freight Facts and Figures 2008, Freight Model Improvement Program, Freight Planning, and Freight Studies by the FHWA Policy Offices. FAP provides both original data and links to other sources of national freight transportation data such as the commodity flow survey (CFS) and the North American Transborder Freight Database.

Freight Analysis Framework (FAF3)

The Freight Analysis Framework (FAF3) is a network database and flow assignment. FAF3 estimates the weight of trucks, movement of commodity by truck, and the long distance moves over specific highways.

Freight Analysis Framework (FAF2)

The Freight Analysis Framework (FAF2) is a commodity origin-destination database that estimates the tonnage and value of goods shipped by type of commodity and mode of transportation among and within 114 areas, as well as to and from 7 international trading regions though the 114 areas and 17 additional international gateways.

FAF2 integrates data from a variety of sources to estimate commodity flows and related freight transportation activity among states, regions, and major international gateways. FAF2 provides estimates for 2002 and the most recent year plus forecasts through 2035. FAF2 also provides information on commodity flows and related transportation activity among major metropolitan areas, states, regions, and international gateways. These products include a national summary for the year 2002 (listing tonnage and value shipped by mode or commodity); similar summaries for each state for the year 2002; a 2002 origin-destination matrix with accompanying technical documentation; annual provisional estimates (again listing tonnage and value shipped by mode or commodity); annual provisional origin-destination matrix/technical documentation; a summary of the national freight forecast for the years 2002 through 2035; similar summaries for each state for the years 2002 through 2035; origin-destination forecast matrices with accompanying technical documentation for the years 2002 through 2035; and national summary maps for the years 2002 to 2035.

FAF2 Data and Documentation-2002-2035

The FAF commodity origin-destination database estimates tonnage and value of goods shipped by type of commodity and mode of transportation among and within 114 areas, as well as to and from 7 international trading regions though the 114 areas and 17 additional international gateways. The 2002 estimate is based primarily on the commodity flow survey and other components of the economic census. Forecasts are included for 2010 to 2035 in 5 year increments.

FAF2 Provisional Commodity Origin-Destination Data and Documentation – 2007

The FAF is based primarily on data collected every five years as part of the economic census. Recognizing that goods movement shifts significantly during the years between each economic census, the federal highway administration produces a provisional estimate of goods movement by origin, destination, and mode for the most recent calendar year. These provisional data are extracted and processed from yearly, quarterly, and monthly publicly available publications for the current year or past years and are less complete and detailed than data used for the 2002 base estimate.

FAF2 Highway Link and Truck Data and Documentation - 2002 and 2035

The FAF estimates commodity movements by truck and the volume of long distance trucks over specific highways. Models are used to disaggregate interregional flows from the commodity origin-destination database into flows among individual counties and assign the detailed flows to individual highways. These models are based on geographic distributions of economic activity rather than a detailed understanding of local conditions. While the FAF provides reasonable estimates for national and multi-state corridor analyses, FAF estimates are not a substitute for local data to support local planning and project development.

FAF2 Historical Commodity Origin-Destination Data and Documentation-1997

To provide national freight movement trend analysis, the FHWA has re-processed the 1997 commodity flow survey data and additional data by using the 2002 FAF data algorithm and methodologies. The 1997 data has the same coverage as the FAF2 2002 and 2010-2035 data. The 1997 data also maintain the same data dimension and terminologies to ensure all databases and GIS components are compatible with other FAF2 products.

4.4. Commodity aggregation

Public policy usually considers commodity groups, not individual commodities. Our freight cost model is therefore designed to consider not only the costs of shipping individual commodities, but also the costs of shipping certain groups (categories) of commodities. Each commodity group typically corresponds to an economic sector. For example, public policymakers are probably not too concerned about the impact of a new regulation on the cost of shipping grapes in particular, but they may be concerned, on a more general level, about the cost of shipping refrigerated fruits and vegetables or refrigerated goods in general. The process of collecting similar commodities together into groups for analysis is called commodity aggregation.

The concept of commodity grouping is not new. In fact, all of the major commodity coding systems—including SCTG and HS (the Harmonized System)—assign similar numerical values to commodities that share one or more characteristics. We use the SCTG (Standard Classification of Transported Goods) coding system in this study. This system uses five digits to identify individual commodities when they are transported. The first two digits indicate a broad cargo category. Each additional digit beyond the first two provides an extra degree of resolution that describes the nature of the cargo. For example, the first two digits "07" signify "other prepared foodstuffs, and fats and oils." Within this category, dairy products are given the code "071"; milk products are given the code "0711"; and items that fit the description "milk and cream, in powder, granules, or other solid forms" are assigned the numerical code "07112." This hierarchical system gives organizations the flexibility to decide the level of granularity of a particular study or survey. More expensive studies may consider 5-digit commodities; less expensive surveys may consider 2-digit commodities. Other studies may use one level of granularity to analyze certain commodities and another level to analyze other commodities. In such cases, the data collected at different granularity levels can still be merged into the same report. In this study, we consider how 5-digit cargo information in various databases (e.g. the Commodity Flow Survey) can be aggregated at a higher level for public policy purposes.

Geographical Information Systems (GIS) handle granularity by using three different methods. The first method is predominant type coding, the second one is precedence coding, and the third method is center point coding. Suppose a square is divided to many areas, and has many grid cells. In the predominant method each grid cell is assigned the value corresponding to the predominant characteristic of the area it covers, in other words, if grid cell "X" is divided between areas A and B, and the largest portion of X lies in A, the cell is assigned the value A. Each cell in the precedence coding method is assigned the value of the highest ranked category present in the corresponding area. The cell in center point coding method is assigned the category value corresponding to its center point.

This working paper recommends using the predominate method to determine commodity characteristics in the most precise level of a group of commodities, which is the 5 - digit commodities level. Even the SCTG's 5-digit commodities may include more than one commodity. If most commodities or shipped goods in a 5-digit commodity group are hazardous, the entire group would be considered hazardous. The same idea applies to the other characteristics such as fragility, perishability, etc. Everything is assumed to be constant and deterministic in 5-digit level commodities and that includes the type of carrier (contract, hired, company), trucks used for shipping, and the packaging method.

When commodities are aggregated, the characteristics of the individual, 5-digit, commodities should be averaged to determine the overall characteristics of the commodity group. These characteristics impact shipping costs. For example, shipping costs may increase substantially if the transported commodity is (A) hazardous, (B) fragile, and/or (C) perishable (i.e. requires refrigeration). The characteristics of individual commodities with respect to the above criteria are usually known when all five digits are provided. However, measures of such characteristics for aggregated commodity groups are often not known. For example, we can be confident that cotton seeds (SCTG code 03505) are not hazardous, fragile, or perishable and that fresh-cut flowers (SCTG code 03910) are fragile and perishable. On the other hand, it is more difficult to determine the characteristics of commodity group 03 as a whole, of which cotton seeds and fresh-cut flowers are both a part.

This study proposes the following solution to the aggregation problem. We assign a numerical value to each commodity characteristic that can impact shipping costs. This numerical assignment is done at the 5-digit commodity level. Let a_{ij} be the numerical value assigned to commodity i's j^{th} characteristic (e.g. hazard level, fragility level, perishability level, typical cargo temperature, density). Let t_i be the quantity of commodity i shipped annually (in ton-miles or tons). Also, let G be the set of all commodities in group g. Then A_{gj}, the numerical value assigned to commodity group g's j^{th} characteristic, is a weighted average of the values assigned to the individual commodities in the group:

$$A_{gj} = \frac{\sum_{i \epsilon G}(t_i a_{ij})}{\sum_{i \epsilon G}(t_i)}$$

The above expression is a simple weighted average that gives the best available estimate for a characteristic of a commodity group. We use this formula to help compute shipping costs in the freight cost model described in the following section.

4.5. Cost model for shipping by truck

We now present a cost model for shipping commodities by truck. Shipping by trucks includes medium and heavy trucks as well as light trucks, pickups, and minivans. In this model, however, we assume that all transportation is performed by large trucks in class 8 (see Appendix B).

The following units are used throughout this model with respect to the following quantities:

- Traveling distance: English system (miles)
- Fuel volume: English system (gallons)
- Weight: English system (lbs., tons (1 ton = 2000 lbs.))
- Cargo volume: English system (ft3)
- Temperature: English system (degrees Fahrenheit)

The model has two kinds of inputs—parameters and constants as shown in Tables 4.2 and 4.3. Parameters are model inputs that define the service to be provided—the commodity (group) that is shipped, how much is shipped, where it is to be shipped, and any additional requests. The constants define the industry environment for providing transportation services. They include the price of fuel, equipment costs, insurance costs, the current state of technology, and various regulations such as the maximum allowed driving time in a 24-hour period. The values of the constants are likely to change over time and should therefore be reviewed periodically.

The model is relatively broad in scope but still has some limitations. First, in the final form of this model we assume there is only one driver per truck. In other words, we do not account for the possibility that two or more drivers (e.g. a husband and wife) may share the same truck and thereby increase the total distance driven per day. However, we show later how to determine if another driver is necessary or not. Secondly, we do not consider multi-trailer units; we assume only one trailer per tractor. We do, however, allow a shipment to be carried by multiple trucks. Featured relations in this model are shown in Table 4.4.

Table 4.2. Parameters in Transportation Cost Model.

	Description
X_o	Shipment origin (5-digit zip code)
X_d	Shipment destination (5-digit zip code)
X_c	Commodity (5-digit SCTG code) or commodity group (2- to 4-digit SCTG)
X_w	Shipment weight (lbs.)
X_{tw}	Truck weight (lbs.)
X_{temp}	Requested cargo temperature (degrees Fahrenheit)
X_{time}	Requested maximum journey time (hrs)[1]
$X_{trailer}$	Trailer and dock type
X_{plu}	Packaging, loading, and unloading method (0 = no unloading service

[1]Includes time spent idling and/or resting.

The total transportation cost is a function of the parameters. This total cost is comprised of the individual costs for fuel, labor, depreciation, maintenance, loading and unloading, insurance, overhead, and extra expenses.

Total Cost = $Cost(X_o, X_d, X_c, X_w, X_{temp}, X_{time}, X_{trailer}, X_{plu}) =$
$Fuel(X_o, X_d, X_c, X_w, X_{tw}, X_{temp}, X_{time}, X_{trailer}, X_{plu}) +$
$Labor(X_o, X_d, X_c, X_w, X_{tw}, X_{temp}, X_{time}, X_{trailer}, X_{plu}) +$
$Deprec(X_o, X_d, X_c, X_w, X_{tw}, X_{temp}, X_{time}, X_{trailer}, X_{plu}) +$
$Maint(X_o, X_d, X_c, X_w, X_{tw}, X_{temp}, X_{time}, X_{trailer}, X_{plu}) +$
$Load(X_o, X_d, X_c, X_w, X_{tw}, X_{temp}, X_{time}, X_{trailer}, X_{plu}) +$
$Insur(X_o, X_d, X_c, X_w, X_{tw}, X_{temp}, X_{time}, X_{trailer}, X_{plu}) +$
$Over(X_o, X_d, X_c, X_w, X_{tw}, X_{temp}, X_{time}, X_{trailer}, X_{plu}) +$
$Extra(X_o, X_d, X_c, X_w, X_{tw}, X_{temp}, X_{time}, X_{trailer}, X_{plu})$

4.5.1. Model setup

Let *Speed* be the average speed while traveling. The time spent idling, sleeping, on breaks, and at rest stops is not considered here. Depending on driver preference, *Speed* might take the value C_{optspd}, C_{spdlim}, C_{spdlim} + 10, or any other value.

Let $dist(X_o, X_d)$ be the trip distance.

4.5.2. Fuel

Let $density(X_c)$ be the cargo density in lbs/ft^3. This density can be derived from the commodity type X_c. Let *NumVeh* be the number of trucks needed to haul the shipment. This quantity depends on whether shipment weight or shipment volume is the determining factor. In other words, we must determine whether the cargo will "weigh out" a trailer before it "cubes out" a trailer or vice versa. Note that $\frac{X_w}{C_{maxWt}}$ gives the number of trailers required based on a consideration of shipment weight alone.

Table 4.3. Constants in Transportation Cost Model.

Constant	**Description**	**Estimated values as of April, 2009**
C_{maxWt}	Truck capacity (lbs.)	Appendix B
C_{maxVol}	Trailer inside volume (ft^3)	Appendix B
$C_{fuel\$}$	Cost of fuel ($/gal)	2. 1
C_{optSpd}	Truck speed that yields optimum fuel efficiency	55
C_{maxEff}	Truck fuel efficiency while traveling with empty trailer at optimum speed for fuel efficiency (miles/gal)	7-7.5
C_{minEff}	Truck fuel efficiency while traveling with full load (by weight) at optimum speed for fuel efficiency	5-6
C_{spdLim}	Official truck speed limit on highway (miles/hr)	45-65
C_{hours}	Maximum allowed driving time for a single driver in any 24-hour period (hrs)	11
C_{ref}	Refrigeration unit fuel consumption per Fahrenheit degree difference between outside temperature and requested cargo temperature per hr (gal/(degree*hr))	0.4
C_{perish}	Commodity's perishablity value (0-1)	X[†]
C_{idle}	Average fuel consumption during idling (gal/hr)	1
C_{wage}	Driver wage ($/mile)	0.40
C_{hthIns}	Annual cost of driver health insurance ($)	6000
$C_{pension}$	Annual cost of driver pension plan ($)	6,500
$C_{SocialMed}$	Annual cost of driver social security tax and Medicare tax ($)	7,650
C_{annual}	Distance an average truck is driven annually (miles)	120,000
C_{new}	Cost of new tractor + trailer ($)	125,000
C_{life}	Truck expected lifetime (years)	5
C_{salv}	Truck salvage value at end of expected lifetime ($)	25,000
$C_{maintGM}$	Truck general maintenance cost per mile for engine and non-engine maintenance purposes ($/mile)	X[††]
C_{maintT}	Truck tires maintenance cost per mile ($/mile)	X[†††]
C_{unload}	Average truck unloading cost ($/trailer)	40
C_{trkIns}	Annual cost of full liability, collision, and theft insurance for a truck ($/truck)	5,000
C_{crgIns}	Cost of cargo damage insurance for a commodity with maximum fragility level (= 1) per mile per $10,000 in value of the commodity (pro-rated for commodities with fragility levels less than 1) ($/truck-mile)	X[†]
C_{othIns}	Annual cost of other insurance for a truck ($/truck)	5,000
C_{OH}	Overhead and indirect cost ($/truck-mile)	0.17

Table 4.3. Constants in Transportation Cost Model (continuation).

Constant	**Description**	**Estimated values as of April, 2009**
C_{regLic}	Annual cost of vehicle registration and driver licensing ($/truck)	Appendix B (State of Indiana is used as an example)
C_{haz}	Cost of shipping a commodity with maximum hazard level (= 1) (pro-rated for commodities with hazard levels less than 1) ($/truck-mile)	X†

† Value is determined according to commodity and shipper considerations.
†† Varies according to total truck shipment load.
††† Varies according to total truck shipment load, and total trailer and tractor tires .

Table 4.4. Featured Relations in Cost Model.

Milwaukee approximation for heavy truck fuel consumption "Total trip distance"

$$TFC = \begin{cases} \sum_{i=5}^{15} Wsli55 * \mathrm{Dist}\,(\mathrm{X_{is}} - \mathrm{X_{if}}) \,/\, \left[\left(\frac{33{,}000}{\mathrm{M}}\right)\left[\frac{1.536}{0.17 + \left(\frac{2.43}{\mathrm{V}}\right)}\right]\right] & (\text{speed} < 55\text{mph}) \\ + & \\ \sum_{i=0}^{4} Wsmi55 * \mathrm{Dist}(\mathrm{X_{is}} - \mathrm{X_{if}}) \Big/ \left[\frac{1}{[(1.53 * 10^{-6} * \mathrm{M}) + (2.94 * 10^{-5} + 1.94 * 10^{-13} * \mathrm{M}) * \mathrm{V}^2]}\right] & (\text{speed} \geq 55\text{ mph}) \end{cases}$$

Total shipping cost per truck †

Cost(X_o, X_d, X_c, X_w, X_{temp}, X_{time}, $X_{trailer}$, X_{plu}) =

$$(C_{fuel\$})(FuelTrav + FuelRefr + FuelIdle) + LaborWage + LaborHealthIns + LaborSocialMed + LaborPension + \left(\frac{dist(X_o, X_d)}{C_{annual}}\right) AnnualDepr + \left(dist(X_o, X_d)\right)(C_{maintGM} + C_{maintT}) + (C_{unload})(X_{plu}) + TrkIns + CargIns + OthIns + (C_{OH})(dist(X_o, X_d)) + RegLic + Haz$$

† These relations built according to 2009 technologies for heavy trucks "class 8"

Also, $\frac{X_w/density(X_c)}{C_{maxVol}}$ gives the number of trailers required based on a consideration of shipment volume alone. The number of trailers required based on a consideration of both shipment weight and volume is therefore the maximum of these two values rounded up to the nearest integer.

$$NumVeh = \left\lceil \max\left(\frac{X_w}{C_{maxWt}}, \frac{X_w/density(X_c)}{C_{maxVol}}\right) \right\rceil^{\dagger}$$

In the case of palletized shipment using boxes or pallets, or a combination of both of them the pallet specification should be considered. To find out number of trucks required we need to know the number of pallets used. Let *PallCap* be the capacity of one pallet (lbs.) and *NumPall* be the number of pallets required for the shipment.

$$NumPall = \left\lceil \frac{X_w}{PallCap} \right\rceil$$

Number of each kind of pallet inside any trailer depends on the inside trailer and pallet dimensions. Let *PallTra* be number of pallets that can fit inside the trailer while *PaDim1*, *PaDim2* and *PalDim3* are the pallet dimensions and *InTraDim1*, *InTrDim2* and *InTrDim3* are inside trailer dimensions. In many cases you can orient the boxes or the pallets inside the trailer in any direction to maximize number of pallets in the stack.

† $\lceil X \rceil$: Rounding X up to the nearest integer. $\lfloor X \rfloor$: Rounding X down to the nearest integer.

$$PallTra = \max\left(\begin{array}{c}\left\lfloor\frac{InTraDim\ X}{PalDim\ X}\right\rfloor\cdot\left\lfloor\frac{InTraDim\ Y}{PalDim\ Y}\right\rfloor\cdot\left\lfloor\frac{InTraDim\ Z}{PalDim\ Z}\right\rfloor, \\ \left\lfloor\frac{InTraDim\ X}{PalDim\ Y}\right\rfloor\cdot\left\lfloor\frac{InTraDim\ Y}{PalDim\ X}\right\rfloor\cdot\left\lfloor\frac{InTraDim\ Z}{PalDim\ Z}\right\rfloor\end{array}\right)$$

Number of trailers if the shipment is palletized is given by the following expression:

$$NumVeh2 = max$$

Fuel Consumed for Traveling Purposes Only

According to the current technology used in today's trucks, for a tractor plus empty trailer weighing around 20,000 lbs., the fuel efficiency is roughly 7.5 miles/gallon. For each additional 20,000 lbs. of cargo hauled, the truck fuel efficiency decreases by about 1 mile/gallon.

This working paper developed its own heavy truck fuel approximation. The authors of this working paper call this formulation the Milwaukee Approximation for heavy truck fuel consumption. This approximation combines the most updated theoretical and empirical relations. The approximation has discontinuous equations and relates truck fuel consumption (mpg) to driving speed (mph).The energy required to run a truck is given in equation 33.

$$F = A + Bv + Cv^2 \tag{33}$$

Coefficients A, B and C are defined according to Giannelli et al. (2005). Since 55 mph is the most fuel efficient driving speed according to most of the theoretical resources and the available practical data, equation 33 is used for speeds of 55 mph and above. The equation has been converted from its original units of Newtons to miles per gallon (MPG) as in equation 34. See Appendix C for more details about our calculations and conversions.

$$MPG = 1 / [(1.53*10^{-6}*M) + (2.94*10^{-5}+1.94*10^{-13}*M)*V^2] \qquad (34)$$

In equation 34, M is the total truck mass in lbs, and V is the truck driving speed in mph.

To find MPG for a speed less than 55 mph, Papacostas's textbook (Transportation and Engineering Planning, 2000) has been used. Papacostas reports a relation from the early 1980s between MPG and speed when the speed is less than 35 mph. The data in Factors Affecting Fuel Economy paper (Good Year, 2003) was used to update Papacostas's relation and extend it to include driving speeds less than 55 mph as in equation 35.

$$MPG = [1/(0.17 +(2.43/V))] \qquad (35)$$

In equation 35, V is the speed in miles per hour.

The model created in this paper divides driving speeds into 16 classes, each class being a different 5-mph interval, starting with 0 mph and ending at 80 mph. Class 0 pertains to speeds from 75-80 mph, class 1 pertains to speeds from 70-75 mph, and so on so that class 15 pertains to speeds from 0-5 mph. The probability (i.e. relative amount of time) the driver drives at each of these speed classes is found using data published in the Transportation Energy Data Book edition 2008-2009 as a part of a vehicle duty cycle project (Oak Ridge, 2008). These data show the distance traveled in each speed class. A reverse Poisson distribution (with parameter depending on the average driving speed) is the most appropriate distribution that fits these data. For more details see Appendix C. The total fuel consumption for any trip is found using the relation below.

$$TFC = \begin{cases} \sum_{i=5}^{15} Wsli55 * \mathrm{Dist}\,(X_{is} - X_{if}) \,/\, [\left(\frac{33,000}{M}\right)\left[\frac{1.536}{0.17 + \left(\frac{2.43}{V}\right)}\right]] & (\text{speed} < 55\text{mph}) \\ + & \\ \sum_{i=0}^{4} Wsmi55 * \mathrm{Dist}(X_{is} - X_{if}) \Big/ \left[\frac{1}{[(1.53 * 10^{-6} * M) + (2.94 * 10^{-5} + 1.94 * 10^{-13} * M) * V^2]}\right] & (\text{speed} \geq 55\text{ mph}) \end{cases}$$

Where,

TFC : Truck fuel consumption (gallons).

M: Total truck and trailer mass (lb), $M = Xt_w + X_w$

V: Driving speed (mi/hr)

W_{sli55}: The probability of driving at speed class i, when i > 4 (less than 55 mph).

W_{smi55}: The probability of driving at speed class i, when i ≤ 4 (more than 55 mph).

Dist (X_{is}-X_{if}): The distance traveled at velocities in speed class i, which has a minimum speed of X_{is} and a maximum speed of X_{if} .

Average speed (AvgSpeed) in this model is calculated by any of the following expressions, according to the user's data and requirements. Let Dist (X_{is}-X_{if}) be the distance traveled by speed class i, which starts with speed more than X_{is} and ends by speed equal or less X_{if} mph, and Time (X_{is}-X_{if}) is the time consumed in traveling by speed class i.

$$\text{AvgSpeed}_1 = \sum_0^{15} \frac{\text{Dist (Xis}-\text{Xif)}}{\text{Time (Xis}-\text{Xif)}}$$

Or,

$$AvgSpeed_2 = \ dist(X_o, X_d)/TravTime$$

Or,

AvgSpeed₃ = Estimated average speed for a required shipping trip given by shipping parties.

Let *FuelTrav* be the fuel consumption for travelling purposes. Final fuel consumption for travelling purposes is as follows:

$$FuelTrav = TFC$$

More details are provided in Appendix C, regarding the Milwaukee approximation for heavy truck fuel consumption, and calculations mentioned in this section.

We now turn our attention to indirect fuel consumption. Indirect fuel consumption includes the fuel consumed for refrigeration of perishable goods and for idling, which includes the cooling or heating of the driver cabin.

Fuel Consumed for Refrigeration Purposes Only

Refrigeration and auxiliary operations use power from the engine which causes additional consumption of fuel. An average trailer refrigeration unit consumes roughly 0.5 gallons/hour for an average shipment. Many new technologies are available for reducing this consumption. The efficiency of the prevailing technology is reflected in the constant C_{ref}.

Let *TravTime* be the time (in hours) spent traveling, not including time spent on breaks, at rest stops, and for miscellaneous idling. Then *TravTime* is given by the following expression.

$$TravTime = dist(X_o, X_d)/Speed$$

Let *NumBreaks* be the number of long breaks made by the driver for the entire journey. According to industry regulations, drivers can only drive C_{hours} hours in any 24-hour time period. After that, they must put in a total of (24 - C_{hours}) hours of non-driving time before resuming their journey. Then *NumBreaks* is given by the following expression.

$$NumBreaks = \left\lfloor \frac{TravTime}{C_{hours}} \right\rfloor$$

Let *IdleTime* be the time (in hours) spent idling during breaks, at rest stops, and for miscellaneous purposes. Then *IdleTime* is given by the following expression.

$$IdleTime = (NumBreaks)(24 - C_{hours})$$

Let *JournTime* be the total time (in hours) required to complete the journey. Then *JournTime* is given by the following expression.

$$JournTime\ =\ TravTime + IdleTime$$

Let $temp(X_o, X_d)$ be the average outdoor temperature for the journey.

Let *FuelRefr* be the total volume of fuel consumed per truck for refrigeration purposes only. Then *FuelRefr* is given by the following expression.

$$FuelRefr\ = (JournTime)\left(C_{ref}\right)(C_{perish})\left|temp(X_o, X_d) - X_{temp}\right|$$

Fuel Consumed During Idling for Non-refrigeration Purposes

Idling is common practice for heavy duty trucks in operation in the US for one or more of the following reasons: to power climate control (e.g. heaters, air conditioners); to power electrical appliances in the sleeper compartment (e.g. refrigerators, microwave ovens, televisions); to prevent start-up problems in cold weather; to drown out noise; and to maintain brake system air pressure (Lutsey et. al 2004). Truckers have also cited that they idle their engines for reasons of safety and habit (U.S. EPA 2002). Overall, idling provides truckers comfort, security, and convenience on the road.

The authors of the "Heavy-Duty Truck Idling Characteristics – Results from a Nationwide Truck Survey" found according to their survey and data from VIUS and other resources that the truck annual fuel consumption (gal/yr) = 18,846 while the idled fuel consumption was between 2,370 and 3,440. Based on this data, the average proportion of fuel consumed for idling is roughly 0.154.

Many factors effect on the idling fuel consumption, including (1) the engine speed at idling (rpm); (2) the season; (3) whether any technology is deployed to reduce the idling; (4) driver attitude; and (5) the appliances and auxiliary equipment in the driver cabin. For case 3, an alternative power unit can be used which reduces the fuel consumption by 80%. In this model, we aggregate the above factors into a single term C_{idle}, which gives the average fuel consumption during idling (gallons/hr).

Let *FuelIdle* be the total volume of fuel consumed per truck during idling for non-refrigeration purposes. Then *FuelIdle* is given by the following expression.

$$FuelIdle = (IdleTime)(C_{idle})$$

Overall Fuel Cost

We are now ready to write an expression for the overall fuel cost per truck.

$$Fuel(X_o, X_d, X_c, X_w, X_{temp}, X_{time}, X_{trailer}, X_{plu}) =$$
$$(C_{fuel\$})(FuelTrav + FuelRefr + FuelIdle)$$

Taxes are a major component of fuel prices. Currently, the U.S. federal fuel tax is 24.4¢/gal and the State of Wisconsin fuel tax is 32.9¢/gal. In this model, taxes are already accounted for by the constant $C_{fuel\$}$.

4.5.3. Labor

Today's average salary for a driver is \$40,000-\$50,000 a year and the average annual driving mileage is 100,000 - 120,000 miles. Based on these Figures, the average wage for a driver, C_{wage}, is roughly \$.40 per mile. Driver health insurance costs are estimated to be \$500 monthly or \$6000 annually.

Let *LaborWage* be the wage (in dollars) earned by the driver for the given journey. Then *LaborWage* is given by the following expression.

$$LaborWage = \left(dist(X_o, X_d)\right)(C_{wage})$$

Let *LaborHealthIns* be the portion of the driver's annual health insurance costs (in dollars) that can be attributed to the current journey. Then *LaborHealthIns* is given by the following expression.

$$LaborHealthIns = \left(\frac{dist(X_o, X_d)}{C_{annual}}\right)(C_{hthIns})$$

Social security tax, Medicare tax, and Pension plan cost are included in this model as a part of labor cost. Social security tax and Medicare tax are withheld from employees and then matched by the employer. Total Social Security tax and Medicare tax are 15.3% on the first \$106,800 of each employee's earnings paid by the employer in the year 2009. Depending on these information the total social security tax and Medicare tax $C_{SocialMed}$ in 2009 is \$7,650. *LaborSocialMed* is the share of total Social Security and Medicare taxes in a specific journey

$$LaborSocialMed = \left(\frac{dist(X_o, X_d)}{C_{annual}}\right)(C_{SocialMed})$$

A pension or retirement plan is an arrangement to provide people with an income when they are no longer earning a regular income from employment. It is a tax deferred savings vehicle that allows for the tax-free accumulation of a fund for later use as a retirement income. Often retirement plans require both the employer and employee to contribute money to a fund during their employment in order to receive defined benefits upon retirement. Besides the social security tax there are different kinds of retirement plans like 401K and IRA (Individual Retirement Account). Each of these plans has different contribution limits.

The maximum contribution limit for 401K is $16,500 which applied to higher paid employee that means an employee with a total compensation package of $105,000-110,000 can contribute $16,500 in 2009, this working paper expect annual driver income as $50,000. There can be an additional contribution made by the employer. The contribution limit for employers is set at 6% of the employee's pre-tax compensation. If the employee/driver is age 50 or older, he may also be eligible to make "catch-up 401k contributions" in addition to the regular 401k limits. The maximum contribution limit for the catch up plan is $5,500 in 2009. IRA maximum contribution limit in 2009 is $5,000 and 6,000 for 50 years old or older.

A trucker driver may work for a big shipping company or work for his own, we estimated the average pension plan cost of truck driver by assuming most of truck drivers are less than 50 years old, and working for a shipping company. We assumed a truck driver contribution in his pension plan is 10% ($5,000), and employer contribution 3%

(\$1,500) according to 2009 instructions. The total annual estimated pension cost $C_{pension}$ is \$6,500. *LaborPension* is the attribute of pension plan cost in the current journey.

$$LaborPension = \left(\frac{dist(X_o, X_d)}{C_{annual}}\right)(C_{pension})$$

We are now ready to write an expression for the overall labor cost per truck.

$Labor(X_o, X_d, X_c, X_w, X_{temp}, X_{time}, X_{trailer}, X_{plu}) =$

$LaborWage + LaborHealthIns + LaborSocialMed + LaborPension$

As we mentioned before, we assume there is only one driver for each trip in the final form of this model. However, we show here how to find out if another driver is required and if the requested maximum journey time X_{time} is reasonable or not.

Let's assume that the policy maker wants to limit the shipping trip time by X_{time}, the trip is limited by specific average driving speed, and Journey time (*JournTime*), which is calculated as shown in part 5.1.2, if *JournTime* < X_{time}, then the shipping trip requires only one driver, else if *JournTime* > X_{time}, hire another driver to eliminate the idle time, the new journey time now is *JournTime2 = TravTime* , else if *JournTime2* > X_{time}, then X_{time} is not reasonable and should be modified to accommodate with other shipping process requirements and parameters.

4.5.4. Depreciation

There many methods for calculating depreciation. We use the method of straight-line depreciation. This method assumes that the asset will lose an equal amount of value each year. To calculate how much the asset depreciates annually, three pieces of information are required: 1) the purchase price of the asset; 2) the asset's estimated useful life (in years); and 3) the salvage value, or estimated value of the asset at the end of its useful life. To determine how much the asset depreciates annually, subtract the salvage value from the purchase price and divide the difference by the estimated useful life. Our discussions with trucking industry professionals indicate that a new truck costs \$100,000-\$125,000 on average; it lasts 5-10 years; and its trade-in value after five years is approximately \$25,000. These are good estimates for the values of the constants C_{new}, C_{life}, and C_{salv}.

Let *AnnualDepr* be a truck's annual depreciation in dollars. Then *AnnualDepr* is given by the following expression.

$$AnnualDepr = \left(\frac{C_{new} - C_{salv}}{C_{life}}\right)$$

Capital recovery (*CapitalRec*) is added to the depreciation in this work, capital recovery represents the income sufficient to recover the amount of the original investment plus returns and profits.

$$CapitalRec = (C_{new} - C_{salv})(A/P,i,n) + C_{salv}\,(i\,)$$

(A/P,i,n) can be found from any engineering economy text book, where *i* is annual interest rate, and n = 5.The current journey represents a small fraction of the truck's annual activities. We are now ready to write an expression for the depreciation cost per truck that is attributable to the current journey.

$$Deprec(X_o , X_d , X_c , X_w , X_{temp} , X_{time} , X_{trailer} , X_{plu}) =$$

$$\left(\frac{dist(X_o,X_d)}{C_{annual}}\right)(AnnualDepr + CapitalRec)$$

4.5.5. Maintenance

The engine and transmission systems are the main truck components that receive maintenance. Other maintenance expenses include replacement tires, replacement lights, and trailer repair. A truck's engine is overhauled every 500,000 miles on average. Thus, the engine is overhauled every 4-5 years. Some operators prefer to trade in their truck every 4-5 years instead of overhauling the engine at considerable expense. The tires in this model are divided to two kinds, tractor's tires and trailer's tires. The total tire's cost is the cost of the tire price and tire wear makeup cost.

In this model and its case studies, $C_{maintGM}$ is a truck general maintenance cost per mile for engine and non-engine maintenance purposes, C_{maintT} is a truck tires maintenance cost per mile. The total maintenance cost is the summation of $C_{maintGE}$ & $C_{maintT..}$ Faucett and Associate formulas, 1991 have been used in this model to estimate the general maintenance cost. General maintenance cost for engine and non-engine purposes are directly related to gross vehicle weight GVW. Let *PercentLoad* be a percent time the truck is loaded, and *PercentEmpty* be the percent time the truck is empty, Faucett and Associate formulas for loaded truck maintenance per mile *LoadTruckMaint* and empty truck maintenance per mile *EmpTruckMaint* are as follows:

$$LoadTruckMaint = ((\text{GVW-58,000})/1{,}000) \times WeightAdjMainCost) \times PercentLoad$$

$$EmpTruckMaint = ((\text{58,000-GVW})/1{,}000) \times WeightAdjMainCost) \times PercentEmpty$$

Where *WeightAdjMainCost* is weight adjusted maintenance cost. Total general maintenance cost is as follows:

$$C_{maintGM} = BaseCost + LoadTruckMaint + EmpTruckMaint$$

Where *BaseCost* is base cost and estimated to be 9 cents in 1991 and *WeightAdjMainCost* is 0.097 per mile in 1991. After including the inflation rates (1991 – 2009), *BaseCost* in 2009 is estimated to be 14.8 Cent ($0.148), and for *WeightAdjMainCost* 0.16 cent ($0.0016).

Service cost (*BaseCost, WeightAdjMainCost)* is a directly affected by the technology used in the truck, maintenance efficiency, preventive maintenance, and driving attitude of truck driver.

The tire cost and wear are function of weight. Faucett and Associate, 1991, found that the tire life is not affected by weight, if the weight per tire is less than 3,500 Ib. Increasing the weight by 1% per tire above the 3,500 Ib increases tire wear by 0.7%. Heggeness, 1996, estimated tractor tire cost (*TractorTireCost*) at $400 and wear

(*TractorTireMile*) was estimated to be 100,000 miles on average. When consider the inflation rates from 1996-2009, the tractor tire estimated cost is \$550. For a trailer tire the estimated cost (*TrailerTireCost*) in 1996 was \$262, and \$360 in 2009, the wear (*TrailerTireMile*) is estimated at 204,500 miles.

NumTractorTires is total number of tractor tires and *NumTrailerTires* is the total trailer tires, the total tiers is *TotTiers* = *NumTractorTires* + *NumTrailerTires*, it is required to check if the tire is overloaded or not by dividing the gross vehicle weight by total tires. (GVW/ TotTiers) > 3500. In the overload case, extra cost should be added to the tractor and trailer tire mileage cost, due to the increasing in the wear rate of the tire.

Let extra tire cost due to overload for tractor and trailer, *TractorTireExtraCost* and *TrailerTireExtraCost*, then,

$$TractorTireExtraCost = [\,((GVW/TotTire)\text{-}3500) / 3500] \times 100 \times 0.007 \times TractorTireCostMile$$

$$TrailerTireExtraCost = [\,((GVW/TotTire)\text{-}3500) / 3500] \times 100 \times 0.007 \times TrailerTireCostMile$$

Where,

$$TractorTireCostMile = TractorTireCost/TractorTireMile$$

$$TrailerTireCostMile = TrailerTireCost/TrailerTireMile$$

Loaded tractor tire cost and loaded trailer tire cost can be estimated from the following relations:

$$LoadTractorTireCost = TractorTireCostMile + TractorTireExtraCost$$

$$LoadTrailerTireCost = TrailerTireCostMile + TrailerTireExtraCost$$

Empty tractor tire is *EmpTractorTireCost* and equals *TractorTireCostMile*. Empty trailer tire cost is *EmpTrailerTireCost* and equals *TrailerTireCostMile*.

Let *PercentLoad* be percent time the truck is loaded, and *PercentEmpty* be the percent time the truck is empty, then the total tractor tire cost *TotTractorTireCost* and total trailer tire cost *TotTrailerTireCost* can be found as follows:

$$TotTractorTireCost = (LoadTractorTireCost \times PercentLoad) + (EmpTractorTierCost \times PercentEmpty)$$

$$TotTrailerTireCost = (LoadTrailerTireCost \times PercentLoad) + (EmpTrailerTierCost \times PercentEmpty)$$

The total tire cost per mile C_{maintT} is:

$$C_{maintT} = TotTractorTireCost + TotTrailerTireCost$$

The maintenance cost per truck that is attributable to the current journey can be written as follows.

$$Maint(X_o, X_d, X_c, X_w, X_{temp}, X_{time}, X_{trailer}, X_{plu}) =$$

$$\left(dist(X_o, X_d)\right)(C_{maintGM} + C_{maintT})$$

4.5.6. Loading and unloading

Loading and unloading refers to the services of transferring cargo between the inside of the trailer and any place or point of rest on a wharf or terminal. Truck loading consists of moving cargo over the wharf or terminal facility to the truck from a place of rest, elevating the cargo onto the truck and stowing the cargo in the truck, but shall not include sorting or grading or otherwise selecting the cargo for the convenience of the trucker or the consignee. Truck unloading consists of removing cargo from the body of the truck, and moving it over the wharf or terminal facility to a place of rest.

Drivers are usually not responsible for loading their vehicles. They may, however, participate in unloading at the destination. Unloading palletized cargo using a forklift costs about $ 40 per truck and it consumes about 20 minutes. Unloading non-palletized cargo by hand consumes 2-3 hrs and is far more costly. In this model, we only consider the former scenario.

We are now ready to write an expression for the loading and unloading cost per truck for the current shipment.

$$Load(X_o, X_d, X_c, X_w, X_{temp}, X_{time}, X_{trailer}, X_{plu}) =$$
$$(C_{unload})(X_{plu})$$

4.5.7. Insurance

There are two types of insurance: truck and cargo. Truck insurance covers the truck itself and the damage it can cause. It includes the following kinds of insurance: full liability, physical damage, collision, fire, and theft insurance. Cargo insurance covers the shipment in the event that goods are damaged in transit.

Let *TrkIns* be the cost of truck insurance per truck that is attributable to the current journey. Then *TrkIns* is given by the following expression.

$$TrkIns \ = \left(\frac{dist(X_o, X_d)}{C_{annual}}\right)(C_{trkIns})$$

Let *value*(X_c) be the dollar value of 100 lbs of commodity X_c.

Let *Value* be the dollar value of the cargo hauled per truck. Then *Value* is given by the following expression.

$$Value \ = \left(\frac{(value(X_c))(X_w/NumVeh)}{100}\right)$$

Let *frag*(X_c) be the cargo fragility level on a 0-1 scale, where 0 = not fragile and 1 = extremely fragile. The cargo fragility level can be derived from the commodity type X_c.

Let *CargIns* be the cargo insurance cost per truck. Then *CargIns* is given by the following expression.

$$CargIns \ = \big(dist(X_o, X_d)\big)(frag(X_c))(Value)(C_{crgIns}/10000)$$

Let *OthIns* be the cost of all other kinds of insurance not included above that is attributable to the current journey. Then *OthIns* is given by the following expression.

$$OthIns \ = \left(\frac{dist(X_o, X_d)}{C_{annual}}\right)(C_{othIns})$$

We are now ready to write an expression for the total insurance cost per truck that is attributable to the current journey.

$$Insur(X_o , X_d , X_c , X_w , X_{temp} , X_{time} , X_{trailer} , X_{plu}) =$$
$$TrkIns + CargIns + OthIns$$

4.5.8. Indirect costs

Indirect cost includes all costs which are not classified as direct labor or materials, some of the items which may be included as indirect costs are management and administration staff, property taxes, utilities, advertising, communication equipment, rental of facilities, insurance of facilities, etc. Different methods are used to allocate overhead cost, in this model overhead cost is allocated over trucks.

This cost varies according to different shippers and truckers considerations and estimations. Dooley, Bertram, and Wilson (1988) weighted average this cost per truck as \$10,721 annually. After considering inflation, this cost is estimated to be in today's dollar (2009) about \$20,327 per truck. The indirect (overhead) C_{OH} in this model is calculated per driven mile. C_{OH} in 2009 according to Dooley average is 20,327 / 120000 = \$0.17 per mile. The indirect (overhead) C_{OH} cost per truck that is attributable to the current journey is given by the following expression,

$$Over(X_o , X_d , X_c , X_w , X_{temp} , X_{time} , X_{trailer} , X_{plu}) =$$
$$(C_{OH})(dist(X_o, X_d))$$

4.5.9. Extra costs

Extra expenses include highway user and licensing fees and additional costs for transporting hazardous cargo. Individual long-haul truckers pay a truck registration fee for the right to haul freight on U.S. roads. The cost is roughly $2500 per year. An additional cost of $0.50 to $1 per mile is typically added to the shipping cost when hazardous cargo is moved.

Let *RegLic* be the truck registration and licensing cost that is attributable to the current journey. Then *RegLic* is given by the following expression.

$$RegLic \ = \left(\frac{dist(X_o, X_d)}{C_{annual}}\right)\left(C_{regLic}\right)$$

Let $haz(X_c)$ be the cargo hazard level on a 0-1 scale, where 0 = non-hazardous and 1 = extremely hazardous. The cargo hazard level can be derived from the commodity type X_c.

Let *Haz* be the additional cost per truck associated with a hazardous shipment. Then *Haz* is given by the following expression.

$$Haz \ = \ (C_{haz})(haz(X_c))(dist(X_o, X_d))$$

We are now ready to write an expression for the extra cost borne per truck for the current journey.

$$Extra(X_o , X_d , X_c , X_w , X_{temp} , X_{time} , X_{trailer} , X_{plu}) =$$

$$RegLic + Haz$$

4.5.10. Overall shipping costs

The total cost per truck for the shipment is equal to the sum of the component costs.

$$
\begin{aligned}
&Cost(X_o , X_d , X_c , X_w , X_{tw} , X_{temp} , X_{time} , X_{trailer} , X_{plu}) = \\
&Fuel(X_o , X_d , X_c , X_w , X_{tw} , X_{temp} , X_{time} , X_{trailer} , X_{plu}) + \\
&Labor(X_o , X_d , X_c , X_w , X_{tw} , X_{temp} , X_{time} , X_{trailer} , X_{plu}) + \\
&Deprec(X_o , X_d , X_c , X_w , X_{tw} , X_{temp} , X_{time} , X_{trailer} , X_{plu}) + \\
&Maint(X_o , X_d , X_c , X_w , X_{tw} , X_{temp} , X_{time} , X_{trailer} , X_{plu}) + \\
&Load(X_o , X_d , X_c , X_w , X_{tw} , X_{temp} , X_{time} , X_{trailer} , X_{plu}) + \\
&Insur(X_o , X_d , X_c , X_w , X_{tw} , X_{temp} , X_{time} , X_{trailer} , X_{plu}) + \\
&Over(X_o , X_d , X_c , X_w , X_{tw} , X_{temp} , X_{time} , X_{trailer} , X_{plu}) + \\
&Extra(X_o , X_d , X_c , X_w , X_{tw} , X_{temp} , X_{time} , X_{trailer} , X_{plu})
\end{aligned}
$$

The overall cost of transporting the entire shipment equals *NumVeh* multiplied by the above quantity.

4.6. Case studies

4.6.1. Case one: Shipping crops

The first case study is about shipping 45,000 lb. of corn from farm to elevator and from elevator to food plant. These three businesses are located in the same state. The distance from farm to elevator is 10 miles, while the distance from elevator to the food plant is 30 miles. Corn is classified under the cereal grains category in SCTG coding system. Corn's three-digit SCTG code is 022 and includes just one commodity at the five-digit level. Corn's five-digit code is 02200. The three-digit and five-digit codes are the same in this case. As we mentioned in Section 4.4, the "predominate" method would be used to determine the characteristics of the shipment of corn, but it is unnecessary in this case.

According to *Iowa farm and rural life poll, 2007 Survey Report on Grain Storage and Transportation*, semi-trailer trucks are used to ship grains with total capacity about 1,370 bushels.

Let's assume the truck used in this case is three-axle ten-tire truck, and attached to eight- tire trailer to ship corn from farm to elevator. This trailer is 48 feet long, 96 inches wide and 102 inches high. This truck gross weight is 80,000 lb. and 33,000 lb. empty. Corn is shipped loose from farm to elevator. The corn shipping unit is a bushel. A bushel is an imperial and U.S. customary unit of dry volume. Each bushel is 1.244 cubic foot or 2150.42 cubic inches. Each corn bushel at 15.5% moisture by weight is 56 lb. Farm bushel price is estimated to be $4.2 and the elevator price is $5. The farm per lb. price is $0.075. This shipment is neither fragile nor hazardous, and doesn’t require a refrigeration unit. Only one truck is required for this shipment. Average travel speed for this trip is 40 mi/hr. Total shipping cost for this case is $62.74; variables parameters and constants used in this case study are shown on Table 4.5. In case 1-b we consider shipping corn from elevator to food plant. The same constants, parameters and variables as in case 1-a are used in this case except for the total trip distance and the corn price per lb.; see above for more details. The total shipping rate in case 1-b is $108.21. More detailed computations for these case studies are shown in Table 4.6. The same weight and characteristics of other grains like soybean gives the same rate as in case 1-a and case 1-b.

Table 4.5. Constants, parameters, and variables used in the case study 1-a.

Constant/Parameter/Variables	**Estimated values**
C_{maxWt}	48000
C_{maxVol}	3,264
$C_{fuel\$}$	2.1
C_{optSpd}	55
C_{maxEff}	7.5
C_{minEff}	6
C_{spdLim}	55
C_{hours}	11
C_{ref}	0.4
C_{perish}	0
C_{idle}	1
C_{wage}	0.4
C_{hthIns}	6000
C_{annual}	120,000
C_{new}	125,000
C_{life}	5
C_{salv}	25,000
$C_{maintGM}$	0.184
C_{maintT}	0.00729
C_{unload}	40
C_{trkIns}	5,000
C_{crgIns}	0
C_{othIns}	5000
C_{haz}	0
C_{OH}	0.17
C_{regLic}	$965.75
$C_{pension}$	6,500
$C_{SocialMed}$	7,650
X_c ***(density-Ib/ft3)***	45.016
X_w	45000
X_{temp}	39.200
X_{plu}	1.000
X_{tw}	33000
Speed	64.33
$dist(X_o,X_d)$	10.000
$temp(X_o, X_d)$	33.100
Value (X_c)	7.500
Empty GVW (X_{tw})	33000

Table 4.5. Constants, parameters, and variables used in the case study 1-a (continuation)

Constant/Parameter/Variables	**Estimated values**
M	78000
Total GVW (M)	78000
Percent Load	0.50
Percent Empty	0.50
Tractor tire	10
Trailor tire	12
Total Tire	22
TractorTire Cost	550.00
TractorTire Mile	100000
Tractor TireCostMile	0.0055
TractorTire ExtraCost	0.00005
LoadTractorTireCost	0.0056
LoadTractorTireCost x Percent Load	0.00278
EmptyTractorTireCost	0.00550
EmptyTractorTireCost x Percent Empty	0.00275
TotalTractor TireCost	0.0055
TrailorTire Cost	360.00
TrailorTire Mile	204500
TrailorTireCostMile	0.00176
TrailorTire ExtraCost	0.00002
LoadTrailerTireCost	0.00178
LoadTrailerTireCost x Percent Load	0.00089
EmptyTrailorTireCost	0.00176
EmptyTrailorTireCost x Percent Empty	0.00088
TotalTrailorTireCost	0.0018
WeightAdjMainCost	0.00160
LoadTruckMain	0.01600
EmptyTruckMain	0.02000
BaseCost	0.148
Interest rate	0.100
A/P,0.1,5	0.264
Captal recovery	38880.000

Table 4.6. Case studies shipping rates in details.

Case	Description	Shipping rate ($)	Fuel ($)	Labor ($)	Depr ($)	Maint. ($)	L/UnL ($)	Insurance ($)	Indirect ($)	Extra ($)
Case 1-a	Shipping corn (farm to elevator)	62.74	7.64	5.68	4.91	1.91	40	0.82	1.7	0.08
Case 1-b	Shipping corn (elevator to food plant)	108.21	22.93	17.04	14.72	5.74	40	2.45	5.1	0.24
Case 2-a	Shipping brake discs 10 miles trip distance	62.63	7.55	5.68	4.91	1.90	40	0.82	1.7	0.08
Case 2-b	Shipping brake discs 200 miles trip distance	492.67	150.92	113.58	98.13	38.09	40	16.33	34	1.61
Case 2-c	Shipping brake discs 1000 miles trip distance	2330.66	781.91	567.92	490.67	190.44	40	81.67	170	8.05
Case 2-d	Shipping motor vehicle parts, 1000 miles trip distance	2330.66	781.91	567.92	490.67	190.44	40	81.67	170	8.05
Case 3-a	Shipping milk 200 miles trip distance, 52°F land temperature	531.91	187.06	116.33	98.13	38.44	40	16.33	34	1.61
Case 3-b	Shipping milk 200 miles trip distance, 28°F land temperature	527.72	182.88	116.33	98.13	38.44	40	16.33	34	1.61
Case 3-c	Shipping milk 200 miles trip distance, 92°F land temperature	636.36	291.52	116.33	98.13	38.44	40	16.33	34	1.61
Case 3-d	Shipping Diary 200 miles trip distance, 52°F land temperature	530.46	185.62	116.33	98.13	38.44	40	16.33	34	1.61

4.6.2. Case two: Shipping auto products

SCTG divided commodities to different groups and levels according to their types and properties. A commodity at the two- digit level is aggregated from finer levels. Three-digit level groups are child of a two-digit level group. Each three-digit level breaks down to four-digit level groups to include fewer commodities with less number of common characteristics and properties. The finest level is five digits, where each 5-digit number represents a specific commodity. As we discussed earlier in Section 4.4, the "predominate" method is used to determine the characteristics by the 5-digit level. In this investigation, the main shipping characteristics by hazard level, fragility level, perishability level, and typical cargo temperature are defined. The first three characteristics were determined by using binary codes (1,0). 1 implies the commodity possesses the characteristics and 0 it does not. For the cargo temperature, 0 is given to room temperature, 1 for (-18 ºC/-0.4 ºF), and for any temperature in between a value from 0-1 is proportionally calculated. Aggregated commodities' shipping characteristics are determined by averaging each characteristic in a finer level for each aggregated commodity group. The weighted average value is assigned as illustrated in Section 4.4.

Some aggregated commodity groups have commodities with the same shipping characteristics. Shipping rates will be the same for any commodity in five-digit level and three-digit level within these groups. In this case we discus one of these aggregated commodity groups. Shipping the same weight of brake discs or any kind of gear boxes costs the same. This is because both of them belong to motor vehicle parts category in

SCTG and have the same shipping characteristics. Both of them are neither hazardous nor fragile nor perishable. These characteristics apply on all commodities of this category as in Table 4.7. Brake's 5-digit code is 36401. Let's assume a shipment of brake discs, and the brake disc dimensions are 15″ inches diameter and 1.4″ inches thick. A brake disc average weight is 20.2 lb., and each brake price is about $200. A trailer with the following internal dimensions 630″ x 97″ x 99 ″ is used for this shipment. The shipment is containerized. The container weight empty is 107 lb., and its dimensions are 48″x40″x45.5″. Each container holds 31 brake discs with 626.2 lb. of brakes weight. We considered the shipping distances of 10,200, and 1000 miles. Shipping at an aggregated level (like 3-digit) gives the same cost as a 5-digit level. Shipping rates and its details are shown in Table 4.6.

Table 4.7. Motor vehicle parts' sctg codes and its shipping characteristics.

5Digit	Motor vehicle parts	2Digit	3Digit	4Digit	Haz	Frag	Perish	Ton-Miles 3Digit
36401	Brakes	36	364	3640	0	0	0	25,847
36402	Gear boxes (except parts, see 36409)	36	364	3640	0	0	0	25,847
36403	Road wheels	36	364	3640	0	0	0	25,847
36404	Metal stampings such as bumper, fender, door, hood, trim, and hub cap	36	364	3640	0	0	0	25,847
36409	Other parts for motor vehicles, including seat belts and seat covers (except parts for motorcycles, mopeds and armored fighting vehicles, see 36351 and 36391; and except engines and engine parts, see 341xx; pumps for liquids, see34310; filters, see 34999; tires, see 24310; glass, see 313xx; lighting and signaling equipment, see 35992; ignition and starting equipment, see 35991; windshield wiper sand defrosters, see 35992; seats, see 39029; and catalytic converters, see 34999)	36	364	3640	0	0	0	25,847

4.6.3. Case three: Shipping dairy products

Dairy products are perishable. A refrigeration unit is required to keep these products edible and nutritious, and to maintain their physical characteristics. We start in this case by shipping milk from dairy plant to vendors. Milk is packed in different sized cardboard or plastic containers. Diary shipping containers are used to ship milk product containers. The shipping container weight is 107 lb. and it dimensions are 48″ x 40″ x 45.5″. 650 lbs. of milk can fit into each shipping containers. Five-axle ten-tire truck attached to eight-tire trailer is used in this case. Trailer inside dimensions are 630" x 97" x 99". Sixty shipping containers fit inside the trailer, and the total shipment weight is 45,420 lb. Total trip distance is 200 miles. The required shipping temperature for milk is 39.2 °F. Let’s assume three different atmospheric conditions for shipping milk from trip’s origin to its final destination. 52 °F, 28 °F, and 92 °F are used as different shipping atmospheric conditions. C_{perish} is equal 1 for the dairy products at any aggregation level.

The shipping rates for these different temperatures are higher than the shipping rates we studied earlier, for the same trip distance as in Table 4.6. This increase is from fuel for the refrigeration unit. Shipping in moderate temperature reduces the fuel consumption for refrigeration. However, to avoid freezing the milk cargo while shipping in below freezing conditions, the refrigeration unit should heat the trailer. Using new auxiliary energy saving equipment types reduces the refrigeration unit fuel consumption. Table 4.8 shows the fuel consumption for travelling and refrigeration for each case.

Table 4.8. Case 3 fuel consumption.

Case Study	Travelling fuel consumption (gallons)	Refrigeration fuel consumption (gallons)
Shipping milk, 200 mile trip, 52 °F shipping temp	73.16	9.32
Shipping milk, 200 mile trip, 28 °F shipping temp	73.16	8.22
Shipping milk, 200 mile trip, 92 °F shipping temp	73.16	38.74

Now let's consider shipping diary in general from plant to vendors, diary category group number in SCTG at three digit level is 071, and that includes seven commodities. Diary commodities list and its shipping characteristics are shown in Table 4.9. The shipping characteristics for diary are the same except for the shipping temperature "requested cargo temperature- X_{temp}". Shipping temperature for ice cream should be very low, while shipping temperature for milk powder is room temperature. For shipping commodities at three-digit level we should weight the average of the shipping temperatures assigned for each individual commodity in this group, as we discussed before in Section 4.4. Weighted average for any shipping characteristics is used to get an average shipping rate at aggregated levels.

Due to confidentiality issues, the lack of data for entire nation at 5-digit level led us to use data provided from Wisconsin. These data are for commodities shipped from and to Wisconsin in tonnage, up to level 4 in STCC code. We reassembled these data to be at the 5-digit level in SCTG code as shown on Table 4.9. In this case the weighted average is used to assign a value for shipping temperature for diary group products at the three-digit level.

$$A_{gj} = \frac{\sum_{i \epsilon G}(t_i a_{ij})}{\sum_{i \epsilon G}(t_i)}$$

Where:

a_{ij} : The numerical value assigned to commodity i's j^{th} characteristic.

t_i: The quantity of commodity i shipped annually (in ton-miles or tons).

G: The set of all commodities in group g.

A_{gj}: The numerical value assigned to commodity group g's j^{th} characteristic, is a weighted average of the values assigned to the individual commodities in the group.

The assigned value for diary shipping temperature "Requested cargo temperature", X_{temp} = 39.75 °F, from the data we have. More than 90% of the shipped commodities in this group are milk. Milk plays the major role in determining the shipping characteristics for his groups at any aggregated level. Shipping rates are as shown in Table 4.6.

Table 4.9. SCTG diary commodities.

5-Digit	Dairy products (except beverages and preparations)	3-Digit	Haz.	Frag.	Perish.	Temp. (ºC/ ºF) 5-Digit X_{temp}	Ton-Miles 3-Digit†	Fraction of Total 3-Digit Ton-Miles (%)	Temp. (ºC/ ºF) 3-Digit X_{temp}
07111	Milk and cream, unconcentrated and unsweetened	071	0	0	1	(4/39.2)	20,111	91.63	(4.3/39.75)
07112	Milk and cream, in powder, granules, or other solid forms	071	0	0	1	(21/69.8)	20,111	2.01	(4.3/39.75)
07119	Other milk and cream	071	0	0	1	(4/39.2)	20,111	3.65	(4.3/39.75)
07120	Cheese and curds	071	0	0	1	(4/39.2)	20,111	1.56	(4.3/39.75)
07130	Ice cream, ice milk, sherbets, and ices (excludes frozen yogurt, see 07199, and ice cream and ice milk mixes, see 06399)	071	0	0	1	(-18/-0.4)	20,111	0.12	(4.3/39.75)
07191	Butter and other fats and oils derived from milk	071	0	0	1	(4/39.2)	20,111	0.51	(4.3/39.75)
07199	Other dairy products, (excludes mixtures of butter and vegetable oil, see 0743x, preparations based on milk, see 06399, eggnog and flavored milk drinks, see 07899)	071	0	0	1	(4/39.2)	20,111	0.51	(4.3/39.75)

† As in Commodity Flow Survey (2002)

5- IMPACT OF TOLLWAY POLICES ON TRUCK ROUTE SELECTION FOR SHIPPING CONTAINERS OF SPECIFIC COMMODITY GROUPS NEAR A CONTAINER TERMINAL

The model from Section 4.5 is extended to consider the impact of tollway polices on truck route selection for shipping containers of specific commodity groups near a container terminal. A path-finding model is built for this purpose.

5.1. Background on the value of time for trucks on USA highways

Tolls are charges for permission to use particular roads or bridges. Toll amounts vary regarding the vehicle size and class. The value of time is the cost that a traveler is willing to pay in his journey for a change in the total travel time. In order to minimize the cost, the truck drivers select shorter routes with fewer and cheaper tolls. Usually, travel time is considered as the only path building criterion for many freight route selection models. However, other variables, such as the value of time, should be considered for better understanding of the driver's choice in the presence of toll. There are many values of time that depend on factors such as the parameters of haul, mainly the truck type and the commodity.

Mei (2010) [86] modified the cost model from Section 4.5 and embedded it in a microsimulation model. The original version of the cost model is distance-based model while the modified version is time and distance-based model. The original cost model is modified by changing some constants to be time based as in Table 5.1. The comparison between the two version shows that the time and distance cost model gives better estimations of the shipping costs by heavy trucks. Mei (2010) considered five indicator commodities — corn, soybean, diary, plastics, and motor vehicle parts — and two FHWA truck classes — two and five —. The characteristics of class five trucks are very similar to the ones of class eight used in the cost model in Section 4.5.

Table 5.1. Some constants of the time and distance--based cost model for shipping motor vehicle parts using class 5 trucks [86].

Constant	**Estimated value ($)**
Cwage(h)	18
Cannual(h)	8760
COH(h)	2.32

The modified cost model is used to estimate the cost of shipping the five indicator commodities using the two truck types first when the time is constant then when the distance is constant as in table 5.2. The linear regression analysis was conducted to establish the relationship of cost & time and cost & distance for the five inductor commodities and two truck classes. The value of time (β) and per-mile cost (γ) can be found from the slopes of the regression lines as in table 5.3.

Table 5.2. Motor vehicle parts shipping costs by class 5 truck for different distances with constant time (2 hours) using time and distance-based cost model [86].

Speed (mile/h)	**Distance (mile)**	**Class 5 Cost ($)**
20	40	94.95
30	60	136.88
40	80	173.53
50	100	208.30
60	120	243.08
64.33	128.66	259.76
70	140	285.35

In order to mimic the truck drivers' route choice to ship containers of different commodity types between an origin and different destinations, a path-finding model is used in this investigation with the capability of modeling the effects of tolls and other pricing factors.

5.2. Experimental setup

The General Network Editor (GNE) is developed by Professor Alan Horowitz, University of Wisconsin–Milwaukee. The GNE is a graphical and data base manager for computer-aided design of transportation networks. The GNE provides the environment in which the path-finding model is used to mimic the truck traffic between a container terminal and different industrial areas in this investigation.

Impedance is a model variable of each network link "road" in the path-finding model in this investigation. In general, impedance represents the level of undesirability for using a particular link in a transportation network. The impedance is a function of travel time, distance, cost or a combination of them. The drivers select the route that has the least cost. The route cost is determined by actual travel time, distance, and user costs (tolls). The equation for the costs on a given route is:

$$Cost = f\,(real\ time,\ distance,\ toll) = \beta^*(real\ time) + \gamma^*distance + toll \qquad (36)$$

Where,

β: Constant (dollar per hour), also defined as Value of Time

γ: Constant (dollar per mile), also defined as Per-mile Cost

The value of tolls on non-toll roads and bridges will, of course, always be zero.

The truck costs in units of dollars are converted to units of time "minutes" by dividing equation (36) by β. The formula above can be written as in equation 37:

$$Impedance = (real\ time) + (\gamma/\beta) * distance + (toll/\beta) \quad (37)$$

From the above expression, it can be seen that two constants (β and γ) determine the conversion from the costs to the time. In this section, we can imagine impedance to be like a penalty score measured in units of time. The values of β and γ for different commodities and two truck types were found by Mei 2010 [86] as in table 5.3 and these values will be used in this investigation.

Table 5.3. Values of β and γ for five commodities and two truck classes– time and distance cost model [86].

	Commodity	Class 2		Class 5	
		β ($/h)	**γ ($/mile)**	**β ($/h)**	**γ ($/mile)**
Hypothesis One	Corn	6.8	1.86	14.16	1.95
	Soybean	5.9	1.86	12.04	1.95
	Dairy	10.28	1.94	22.77	1.95
	Plastics	3.39	1.86	11.01	1.95
	Motor Vehicle Parts	4.79	1.86	10.56	1.96
Hypothesis Two	Corn	29.5	1.06	36.89	1.15
	Soybean	28.6	1.06	34.77	1.15
	Dairy	46.14	1.06	52.22	1.15
	Plastics	26.06	1.06	33.74	1.15
	Motor Vehicle Parts	27.48	1.06	33.29	1.15

5.3. Experiments: Setup, outcomes, & discussion

The theory introduced in Sections 4.5 and 5.2 is used to mimic the trucker's choice for shipping different containerized commodities between a container terminal and different industrial areas in the Houston metropolitan area. The impedance equation (37) in section 5.2 is used to estimate the shipping time-cost of each link in the road network between the container terminal and the industrial areas.

5.3.1 Introduction to Port of Houston area.

The container terminal in the Port of Houston and six main industries and industrial areas in Houston area are considered for the path-finding model in this section. The shipping is to be carried out by class 5 trucks (FHWA classification). The industrial areas are defined by the main industry/ business in each area as in Table 5.4.

Table 5.4. The main industries in the selected industrial areas in Houston used in the truck movement path-finding.

Industrial Area	Main Industry
A	Electrical products
B	Food beverages
C	Aircraft parts
D	Auto parts
E	Plastic products
F	Construction area

The Port of Houston is the fourth-largest port in the United States. It is the busiest port in the United States in terms of foreign tonnage, second-busiest in the United States in terms of overall tonnage, and thirteenth-busiest in the world. In 1977 the Port of Houston opened the Barbours Cut Terminal, Texas' first cargo container terminal, at Morgan's Point. Approximately 215 million tons of cargo moved through the Port in 2005, about half of which was containerized cargo (1.6 million TEU). Figure 5.1 shows the locations of the container terminal and the six industrial areas.

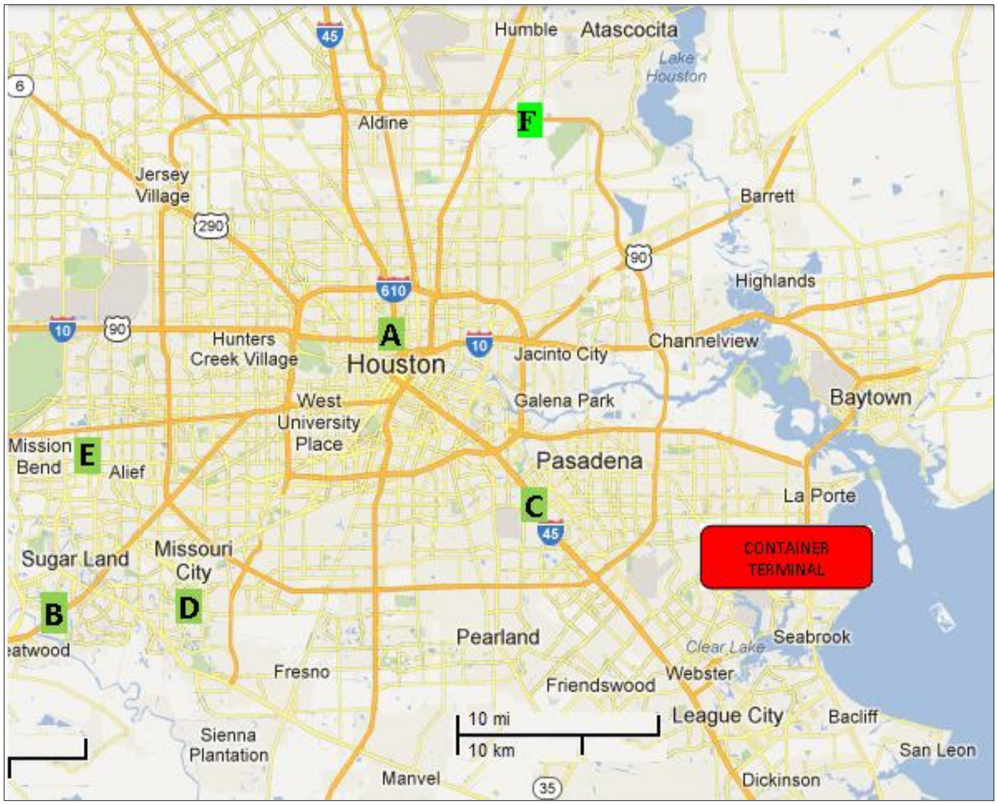


Figure 5.1. Barbours Cut Terminal and the six industrial areas.

5.3.2 Collection of travel distance and truck speed data

The tollways in Houston area can be specified by six major roads and connections: Sam Houston Tollway, Sam Houston Tollway Northeast, Hardy Toll Road, Westpark Tollway, Katy Managed Lanes, and Fort Bend Parkway. Houston's toll way total length is around 148 miles. Most of the tollway length is managed by The Harris County Toll Road Authority. Figure 5.2 shows the tollways in Houston. The length, toll, and toll per mile for each road are as in Table 5.5, pass through tolls are considered in this study.

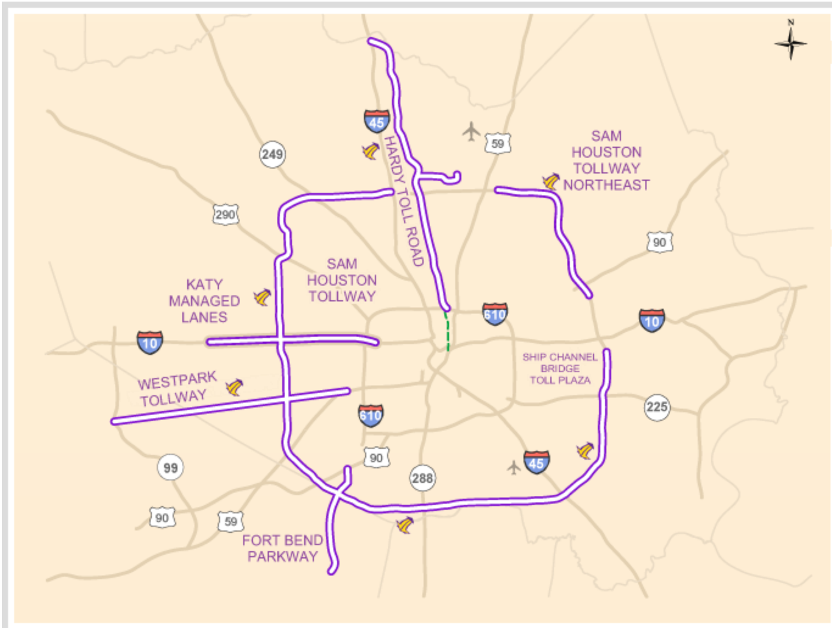


Figure 5.2. Tollways in Houston area.

Table 5.5. Tollway length in Houston area, tolls, and toll cost per mile for class 5 trucks.

Tollway	Length (mile)	Toll ($)	Toll / mile ($/mile)
Sam Houston Tollway	70	52.5	0.75
Sam Houston Tollway Northeast	13	7.5	0.58
Hardy Toll Road	25.6 *	20	0.78
Westpark Tollway	20	21.7	1.09
Katy Managed Lanes	12	3.36	0.28
Fort Bend Parkway	7.5	14	1.87

* Including 4 miles spur to George Bush intercontinental Airport.

The speed on each tollway and highway in the area of study has been estimated by monitoring the traffic speed on each tollway/highway using the Live Traffic Map of Houston TranStar and it is a partnership of four government agencies that are responsible for providing Transportation Management to the Greater Houston. The traffic flow was monitored for five consecutive working days from 12:00 pm to 6:00 pm as in Figure 5.3.

The traffic speeds on Houston's tollways and highways were averaged and each of the tollways and highways were divided into connected segments and links regarding the average speed as in Figure 5.4.

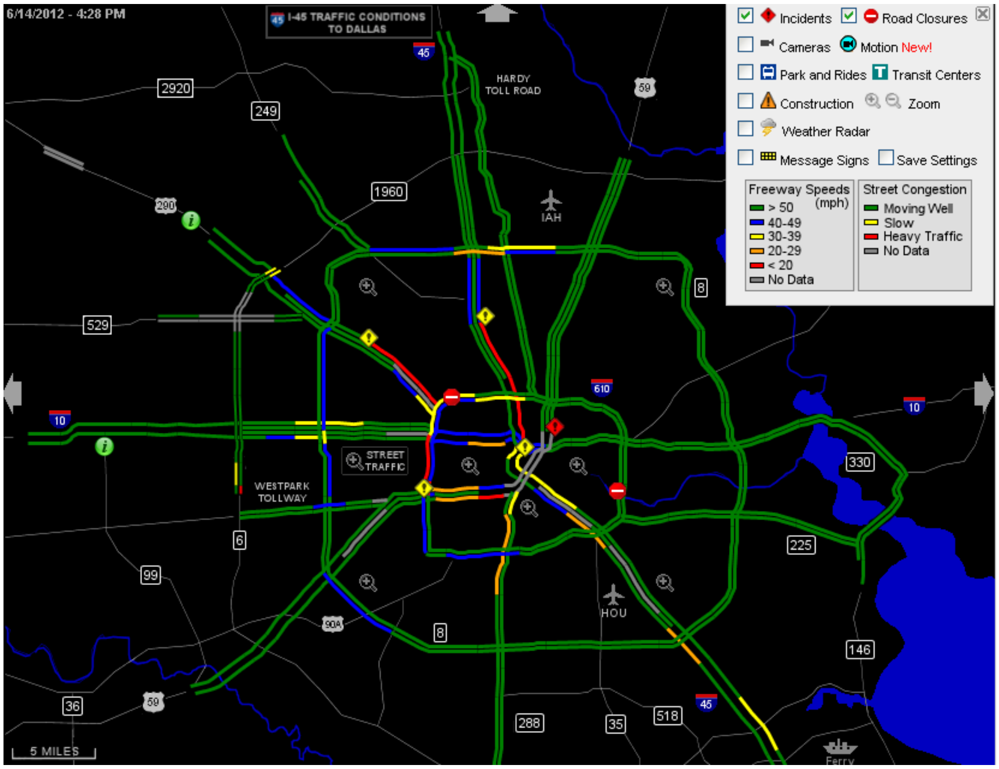


Figure 5.3. Traffic flow on Houston's tollways and highways as on Thursday 6/14/2012 at 4:28 pm.

5.3.3 Model run and summary of the outcomes

The GNE was used to perform the path-finding model. The map with Houston's tollways and highways was used and the road network was built on the map. The length, speed, and toll were defined for each link of the tollways and highways. The impedance equation (37) was used in the model runs. Figure 5.4 shows the average speed for each segment of Houston's road network, the speed of each segment is marked between the two red lines. The traffic speed is 60 mph for all the unmarked segments. The truck's route choices to ship specific containerized commodities from a container terminal to different industrial areas are simulated by using hypothesis two's value of time "β" for truck class-5 as in Table 5.3. The value of time of corn is used for the food beverage. The value of time of auto parts is used for electrical parts, aircraft parts, and the construction materials in this model.

The outcomes of the model run using the current tollways cost per mile show that the trucker selects the route without tollways between the container terminal and the electrical product parts industrial area (A). Reducing the toll cost per mile during the rush hours may make the truckers use the tollways between the container terminal and the industrial area A. The trucker does not use the tollways for shipping goods between the container terminal and the industrial areas of food beverages (B) & aircraft parts (C) and changing the tollways cost does not change the trucker's choice. The trucker does not use the tollway between the container terminal and the auto parts industrial area (D) (except for a short distance). However, reducing the cost of using the toll will convince the trucker to use the tollway between the container terminal and the industrial area D. A small portion of the Sam Houston Tollway is used by the trucker between the plastic products industrial area (E) and the container terminal and changing the tolls cost up or down does not change the trucker's choice. The trucker chooses to use Sam Houston Tollway and Sam Houston Tollway Northeast between the construction area (F) and the container terminal. Increasing the toll cost to a certain limit will not divert the trucker from using these tollways.

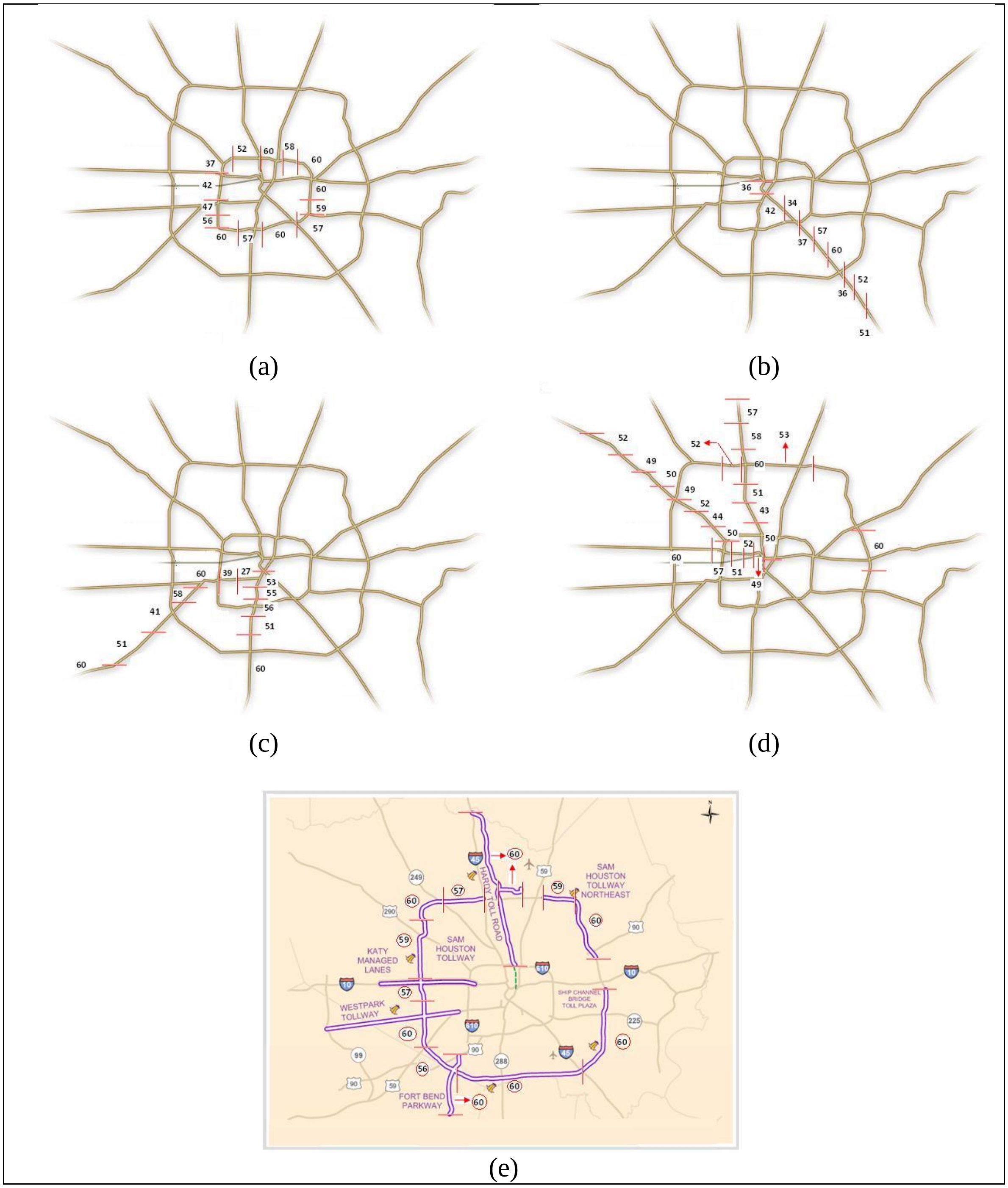


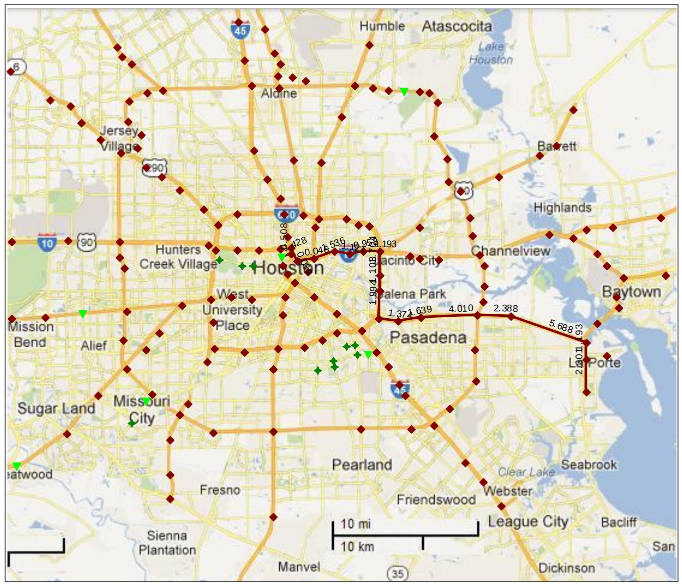
Figure 5.4. a,b,c,d-Traffic speed on each segment of Houston's highways, e- Traffic speed on each segment of Houston's tollways.

The model runs' outcomes are shown in Figures 5.5-5.10 and Table 5.6. The concepts of consumer surplus and dynamic pricing can be used to analyze the outcomes of the model run. It may be desirable for heavy trucks to use tollways instead of local roads during the rush hours for safety and reducing the traffic jam purposes. Using a dynamic toll that changes regarding the day and time may reduce the congestion in Houston's highways by diverting the trucks to alternative routes. The dynamic toll may affect the trucker's route selection for industrial areas A & D. Reducing the toll at the Sam Houston Tollway or segments of it during the rush hours to \$0.04/mile and \$0.05/mile will convince the trucker to use the tollways to/from the electrical product parts industrial area (A) and the auto parts industrial area (D) respectively as in the outcomes of the model run in Figure 5.5 and Figure 5.6. The value of time for shipping electrical products are not more than \$0.04/mile and the truckers are not willing to pay more than that to use the tollway. The value of time for shipping auto products is not much more than the one for electrical products, which is \$ 0.05/mile. Both values of time for shipping products from/to industrial areas A & D are much less than the current toll at Sam Houston Tollway.

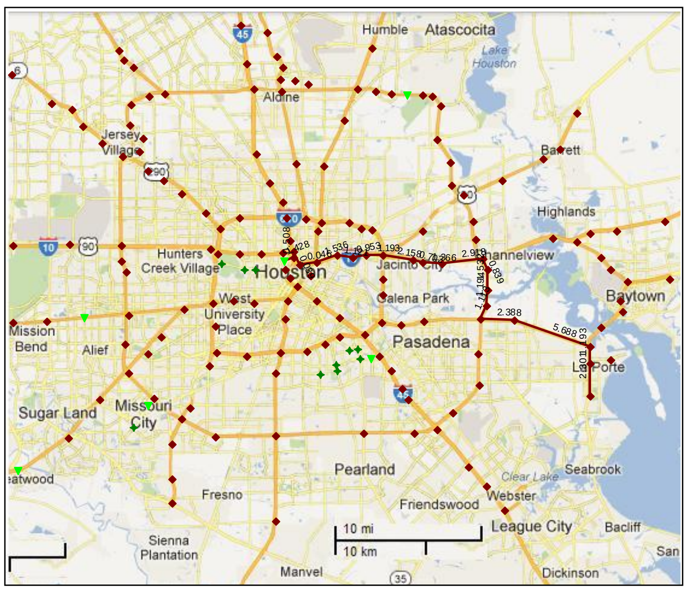
The consumer surplus is a measure of the welfare that people gain from the consumption of goods and services, or a measure of the benefits they derive from the exchange of goods. Consumer surplus is the difference between the total amount that consumers are willing and able to pay for a good or service and the total amount that they actually do pay (i.e. the market price for the product). There are two demand functions for the consumer surplus, Hicksian and Marshallian. The Hicksian demand function includes four measures, compensating variation, equivalent variation, compensating surplus and equivalent surplus. The equivalent variation is the minimum payment the customer would require were the price not to fall (how much money we need to take away from the consumer before the price change to make him just as well off as he was after the price change). The compensating variation is the amount the customer would be willing to pay for the privilege of purchasing at the new price rather than the old (how much money we need to give the consumer after the price change to make him just as well off as he was before the price change). The Hicksian's compensating variation will be used in this section.

The run's outcomes show that the route for shipping construction and building materials and machines between the construction area (F) and the container terminal in Houston will be by using Sam Houston Tollway and Sam Houston Tollway Northeast as in Figure 5.7. Raising the toll at Sam Houston Tollway Northeast only to 0.92 $/mile will divert the trucker from using both toll ways as in Figure 5.8-a. In this case, the consumer surplus of using the Sam Houston Tollway Northeast is (0.92 – 0.58 = 0.34 $/mile). The toll range (0.58 - 0.91) $/mile at Sam Houston Tollway Northeast will keep the trucks on the tollway and makes it part of the best route between the construction area and the container terminal. The same result will be obtained if the two tolls (Sam Houston Tollway and Sam Houston Tollway Northeast) are raised simultaneously up to 0.85 $/mile at Sam Houston Tollway Northeast and 0.86 $/mile at Sam Houston Tollway, the consumer surplus for this case is [(0.85 – 0.58) + (0.86 – 0.75) = 0.38 $/mile]. Raising the toll only at the Sam Houston Tollway to be 0.87 $/mile makes the truckers avoid this tollway and use an alternative highway, however, the truckers will keep using the Sam Houston Tollway Northeast to reach the construction area as in Figure 5.8-b. The consumer surplus for this case is (0.87 – 0. 75 = 0.12 $/mile).

Changing the toll costs does not change the trucker's route selection for the industrial areas B, C, and E. Reducing the tolls did not change the trucker choice of avoiding the tollways for shipping goods between the container terminal and the industrial areas of food beverages (B) & aircraft parts (C). Other factors rather than time and tolls should be considered to convince the truckers to use the tollway instead of local roads and highways during the rush hours. The model run's outcomes show that the trucker will use small portion of Sam Houston tollway from/to the plastic products industrial area (E). Changing the tolls up or down does change the route selection. Trucker's route choice from/to B, C, and E and the container terminal are as in Figure 5.9.

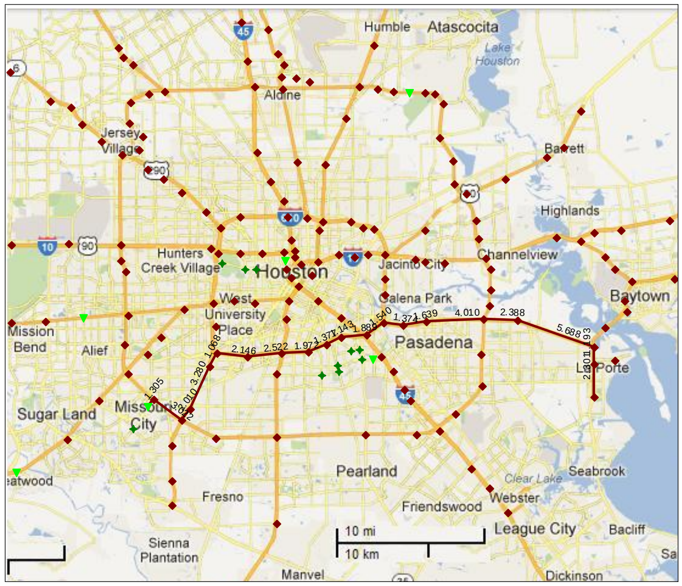


(a)

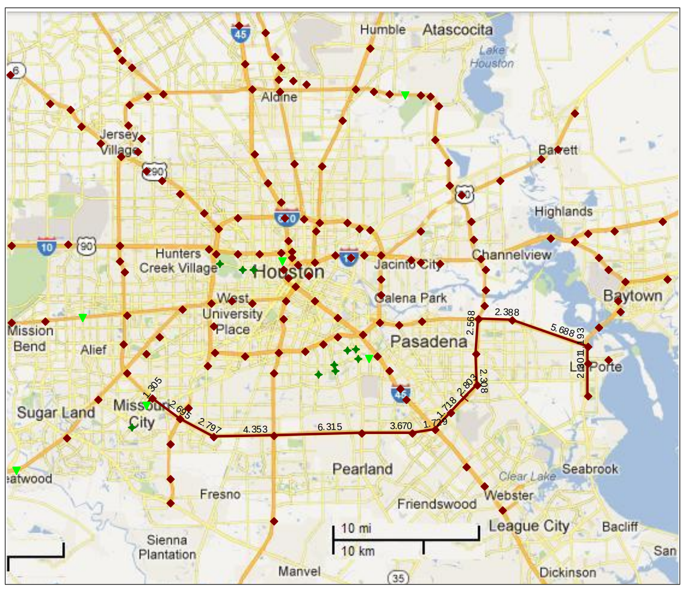


(b)

Figure 5.5. Route between the container terminal and the electrical parts industrial area A (a) Trucker's choice using the current toll at Sam Houston Tollway. (b) Trucker's choice by reducing the toll during the rush hours from \$0.75 /mile to \$0.04 /mile.



(a)



(b)

Figure 5.6. Route between the container terminal and the auto parts industrial area D (a) Trucker’s choice using the current toll at Sam Houston Tollway. (b) Trucker’s choice by reducing the toll during the rush hours to 0.05 $/mile.

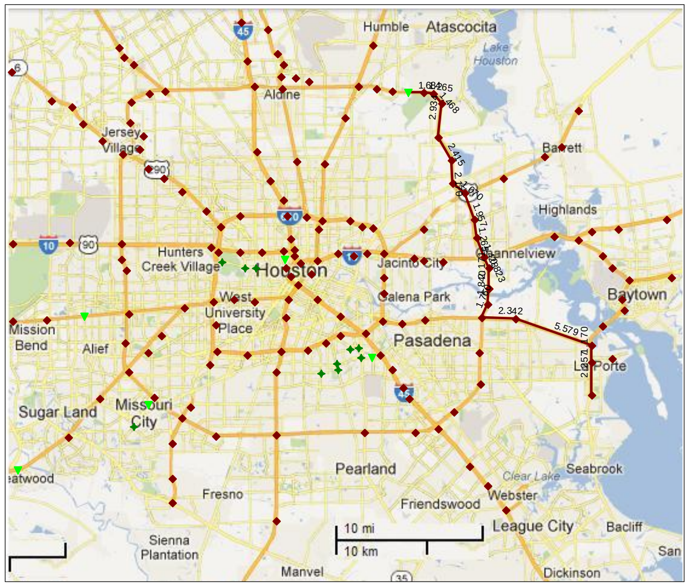
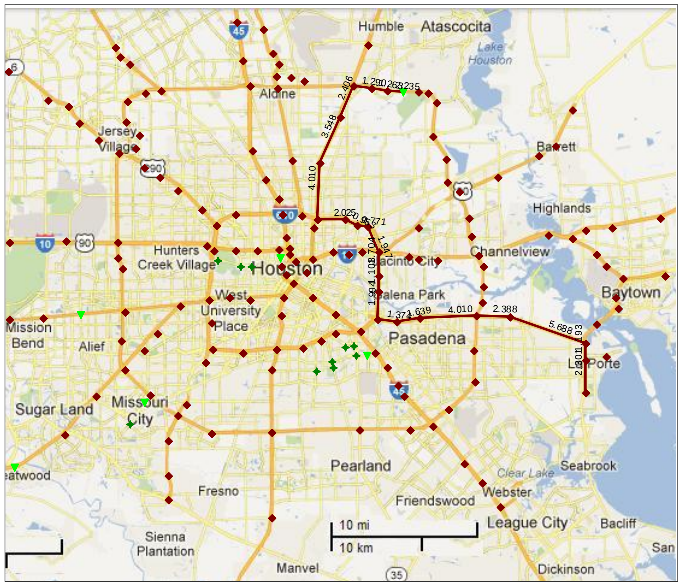
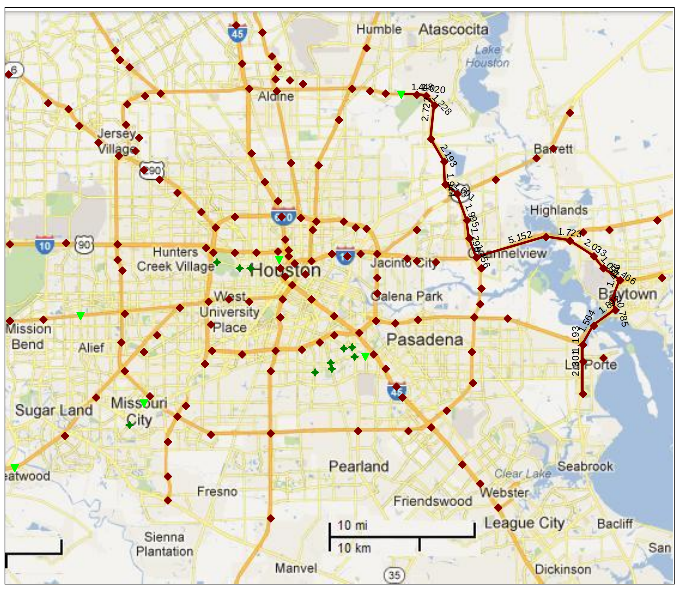


Figure 5.7. Trucker's route between the container terminal and the construction area (F).

Increasing the toll in one destination and decreasing the toll on the other will be a good compensation for the toll authorities and also that will reduce the traffic congestions and improve the safety during the rush hours. Figure 5.10 shows the route choice for the tucker between the container terminal and any of the industrial areas according to current tolls. From Figure 5.10, the trucker avoids the toll ways between the container terminal and the electrical products (A), food beverages (B), aircraft parts (C), plastic products (E), and the auto parts (D) industrial areas. Note that the numbers on each segment in the figure represent the segment length.



(a)



(b)

Figure 5.8. Trucker's choice between the container terminal and the construction area (a) when the toll at the Sam Houston Tollway Northeast = 0.92 $/mile or when the tolls are 0.85 and 0.86 $/mile at Sam Houston Tollway Northeast & Sam Houston Tollway respectively (b) when the toll is 0.87 $/mile at Sam Houston Tollway.

Figure 5.9. Truckers route between the container terminal and (a) the industrial area-B (b) the industrial area-C (C) the industrial area-E.

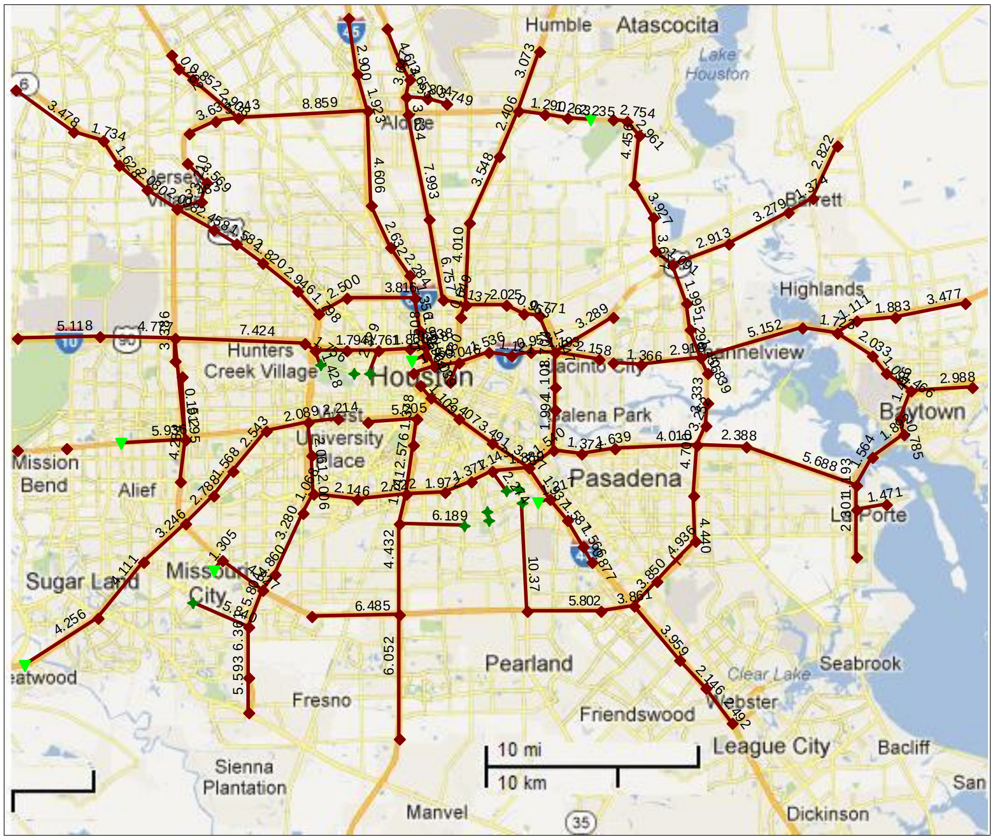


Figure 5.10. The trucker's choices route between the container terminal and the six industrial areas in Houston by using the current toll, *GNE -Skim Tree*.

5.3.4 Discussion

The values of time were used to mimic the truck's choices to ship containers of different commodities between container terminal and different facilities. The influence of tollways polices in the trucker's choices was studied. It was found that having a dynamic toll can improve the traffic and road conditions and divert the heavy truck from certain highways at specific times and days. The consumer surplus is used in the outcomes analysis of this investigation. Table 5.6 shows the current use of the tollways and some recommendations to use the tollways more efficiently by heavy trucks.

Table 5.6. Current tolls and recommended tolls (during the rush hour) as in the model run's outcomes for the six industrial areas

Industrial Area	Current use of toll	Current toll $/mile	Recommended toll to be used	Recommended toll $/mile
A	-	-	Sam Houston Tollway	0.04
B	-	-	-	-
C	-	-	-	-
D	Sam Houston Tollway	0.75	Sam Houston Tollway	0.05
E	Sam Houston Tollway	0.75	Sam Houston Tollway	0.75
F	Sam Houston Tollway & Sam Houston Tollway Northeast	0.75 & 0.58	Sam Houston Tollway & Sam Houston Tollway Northeast	0.75-0.85 & 0.58-0.86

6- CONCLUSION AND FUTURE WORK

This dissertation is divided into four parts that relate to container transportation. In the first part, a new mathematical formulation of the block relocation problem (BRP) is introduced in first investigation and shown to have considerably fewer decision variables than the other existing formulation in the literature. A new look-ahead algorithm (LA-*N*) for the BRP is also introduced. This new algorithm generally outperforms the KH, DH, CM, and LL algorithms from the literature in terms of objective value and CPU runtime. The performance of the LA-*N* algorithm varies depending on the "look-ahead" value *N*. For small- and medium-sized instances where the maximum stacking height is not very restrictive, the algorithm performs better when *N* is large. For extremely large instances, the algorithm performs better when *N* is 1.

The second investigation of this research considers a new problem called the block relocation problem with weights (BRP-W) in which a set of identically-sized items of different, known weights are to be retrieved from a set of last-in-first-out (LIFO) stacks in a specific order using the minimum amount of energy. The efforts to address this real-world problem resulted in the creation of a sophisticated algorithm—the global retrieval heuristic (GRH)—that decides where to relocate the containers that must be moved to allow access to containers in lower tiers. The GRH was embedded inside a genetic algorithm-based optimization method in a simulation-optimization structure that identifies the best settings of the GRH for a particular container configuration size. Results from the preliminary experiments described here indicate that the GRH and GA have the potential to be effective tools to solve this very difficult problem.

The third investigation considers the problem of estimating the cost of shipping commodities by truck between a given origin and destination inside the United States. The study takes an inventory of cost models that have been used in the past and evaluates the availability of data sets containing shipment cost information. A cost model is built for shipping various commodities and commodity groups by truck and several examples are presented to show how the model can address several issues of interest to carriers, shippers, and governments.

In the fourth investigation, the truck cost model is used to obtain values of time and to test those values of time within a full-scale path-finding model. It is found that the highly-detailed cost model of trucking previously developed for the purposes of policy analysis is suitable for ascertaining truck values of time for individual commodities carried by specific truck types. It is found that the flow of heavy trucks can be diverted to specific routes during the rush hours by using an appropriate pricing policies at the tollways.

Future work on the problems investigated in this dissertation can be extended in several directions. Regarding the block relocation problem, testing more algorithms to solve the BRP and include more practical aspects to the problem is part of the intended future work. Another possible investigation is to explore additional aspects of container terminal operations, while focusing on crane utilization problems and using optimization techniques to solve them. The main intention is to schedule cranes in the seaport container yard in order to reduce job lateness to the minimum possible level, while reducing the energy used to power and run the cranes. Another container yard problem to be considered is as follows. *R* yard cranes are working in a single storage block consisting of 20' *B* bays, where each bay has *S* stacks and the maximum stacking height in each stack is *T* tiers (i.e. *T* containers). In other words, the block has dimensions *B*x*S*x*T*. At time 0, the block is empty. The planning horizon is divided into discrete time intervals. During this planning horizon a total of *n* 20' containers will be stored in, and subsequently retrieved from, the storage block. The earliest possible storage and retrieval time for each container is given. The goal is to schedule the time and location of the storage and retrieval of each container so as to minimize the total lateness of all storage and retrieval operations combined.

Developing more algorithms to solve the *BRP-W* is part of the future work. The results of the new algorithms will be compared to the GRH results. *BRP-W* can be extended to include more than one block, bay, and crane. Different genetic algorithm and/or optimization techniques will be used to solve *BRP-W*. Investigating problems related to time and workforce *BRP-T & BRP-WF* will be new practical additions to the original problem *BRP*.

Regarding the truck cost model, future work might consider more commodities, truck types, and shipping modes. The path-finding model can be improved to deal with the dynamic pricing problem. Future work should incorporate more public policies into the current path-finding model.

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APPENDICES

Appendix A

Table A1. Problem instance in which the LA-1 algorithm outperforms the LA-*N* algorithm for all $N \geq 2$ with an unlimited height assumption.

LA1					LA2					LA3					LA4				
Initial bay configuration:					Initial bay configuration:					Initial bay configuration:					Initial bay configuration:				
8	6	4	12	13	8	6	4	12	13	8	6	4	12	13	8	6	4	12	13
15	10	9	7	14	15	10	9	7	14	15	10	9	7	14	15	10	9	7	14
2	3	1	5	11	2	3	1	5	11	2	3	1	5	11	2	3	1	5	11
		Turn					Turn					Turn					Turn		
0	0	0	4	0	0	0	0	0	8	0	0	0	0	8	0	0	0	0	8
8	6	0	12	13	0	6	4	12	13	0	6	4	12	13	0	6	4	12	13
15	10	9	7	14	15	10	9	7	14	15	10	9	7	14	15	10	9	7	14
2	3	1	5	11	2	3	1	5	11	2	3	1	5	11	2	3	1	5	11
		Turn					Turn					Turn					Turn		
0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	6
0	0	0	4	9	0	0	0	4	8	0	0	0	0	8	0	0	0	0	8
8	6	0	12	13	0	6	0	12	13	0	0	4	12	13	0	0	4	12	13
15	10	0	7	14	15	10	9	7	14	15	10	9	7	14	15	10	9	7	14
2	3	1	5	11	2	3	1	5	11	2	3	1	5	11	2	3	1	5	11
		Turn					Turn					Turn					Turn		
0	0	0	0	0	0	0	0	0	9	0	0	0	0	6	0	0	0	0	6
0	0	0	4	9	0	0	0	4	8	0	0	0	4	8	0	0	0	4	8
8	6	0	12	13	0	6	0	12	13	0	0	0	12	13	0	0	0	12	13
15	10	0	7	14	15	10	0	7	14	15	10	9	7	14	15	10	9	7	14
2	3	0	5	11	2	3	1	5	11	2	3	1	5	11	2	3	1	5	11
		Turn					Turn					Turn					Turn		
0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	9
0	0	0	0	8	0	0	0	0	9	0	0	0	0	6	0	0	0	0	6
0	0	0	4	9	0	0	0	4	8	0	0	0	4	8	0	0	0	4	8
0	6	0	12	13	0	6	0	12	13	0	0	0	12	13	0	0	0	12	13
15	10	0	7	14	15	10	0	7	14	15	10	0	7	14	15	10	0	7	14
2	3	0	5	11	2	3	0	5	11	2	3	1	5	11	2	3	1	5	11
		Turn					Turn					Turn					Turn		
0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	9
0	0	0	0	8	0	0	0	0	9	0	0	0	0	6	0	0	0	0	6
0	0	0	4	9	0	0	0	4	8	0	0	0	4	8	0	0	0	4	8
0	6	0	12	13	0	6	0	12	13	0	0	0	12	13	0	0	0	12	13
0	10	0	7	14	0	10	0	7	14	15	10	0	7	14	15	10	0	7	14
2	3	15	5	11	2	3	15	5	11	2	3	0	5	11	2	3	0	5	11
		Turn					Turn					Turn					Turn		
0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	9
0	0	0	0	8	0	0	0	0	9	0	0	0	0	6	0	0	0	0	6
0	0	0	4	9	0	0	0	4	8	0	0	0	4	8	0	0	0	4	8
0	6	0	12	13	0	6	0	12	13	0	0	0	12	13	0	0	0	12	13
0	10	0	7	14	0	10	0	7	14	0	10	0	7	14	0	10	0	7	14
0	3	15	5	11	0	3	15	5	11	2	3	15	5	11	2	3	15	5	11
		Turn					Turn					Turn					Turn		
0	0	0	0	6	0	0	0	0	6	0	0	0	0	9	0	0	0	0	9

0	0	0	0	8	0	0	0	0	9	0	0	0	0	6	0	0	0	0	6
0	0	0	4	9	0	0	0	4	8	0	0	0	4	8	0	0	0	4	8
0	0	0	12	13	0	0	0	12	13	0	0	0	12	13	0	0	0	12	13
0	10	0	7	14	0	10	0	7	14	0	10	0	7	14	0	10	0	7	14
0	3	15	5	11	0	3	15	5	11	0	3	15	5	11	0	3	15	5	11
		Turn					Turn					Turn					Turn		
0	0	0	0	6	0	0	0	0	6	0	0	0	0	9	0	0	0	0	9
0	0	0	0	8	0	0	0	0	9	0	0	0	0	6	0	0	0	0	6
0	0	0	4	9	0	0	0	4	8	0	0	0	4	8	0	0	0	4	8
0	0	0	12	13	0	0	0	12	13	0	0	0	12	13	0	0	0	12	13
0	0	10	7	14	0	0	10	7	14	0	0	10	7	14	0	0	10	7	14
0	3	15	5	11	0	3	15	5	11	0	3	15	5	11	0	3	15	5	11
		Turn					Turn					Turn					Turn		
0	0	0	0	6	0	0	0	0	6	0	0	0	0	9	0	0	0	0	9
0	0	0	0	8	0	0	0	0	9	0	0	0	0	6	0	0	0	0	6
0	0	0	4	9	0	0	0	4	8	0	0	0	4	8	0	0	0	4	8
0	0	0	12	13	0	0	0	12	13	0	0	0	12	13	0	0	0	12	13
0	0	10	7	14	0	0	10	7	14	0	0	10	7	14	0	0	10	7	14
0	0	15	5	11	0	0	15	5	11	0	0	15	5	11	0	0	15	5	11
		Turn					Turn					Turn					Turn		
0	0	0	0	6	0	0	0	0	6	0	0	0	0	9	0	0	0	0	9
0	0	0	0	8	0	0	0	0	9	0	0	0	0	6	0	0	0	0	6
0	0	0	0	9	0	0	0	0	8	0	0	0	0	8	0	0	0	0	8
0	0	0	12	13	0	0	0	12	13	0	0	0	12	13	0	0	0	12	13
0	0	10	7	14	0	0	10	7	14	0	0	10	7	14	0	0	10	7	14
0	0	15	5	11	0	0	15	5	11	0	0	15	5	11	0	0	15	5	11
		Turn					Turn					Turn					Turn		
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0	0	0	0	9	0	0	0	0	8	0	0	0	0	8	0	0	0	0	8
0	0	0	0	13	0	0	0	0	13	0	0	0	0	13	0	0	0	0	13
0	0	10	7	14	0	0	10	7	14	0	0	10	7	14	0	0	10	7	14
12	0	15	5	11	12	0	15	5	11	12	0	15	5	11	12	0	15	5	11
		Turn					Turn					Turn					Turn		
0	0	0	0	6	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0
0	0	0	0	8	0	0	0	0	9	0	0	0	0	6	0	0	0	0	6
0	0	0	0	9	0	0	0	0	8	0	0	0	0	8	0	0	0	0	8
0	0	7	0	13	0	0	7	0	13	0	0	9	0	13	0	0	9	0	13
0	0	10	0	14	0	0	10	0	14	0	0	10	7	14	0	0	10	7	14
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		Turn					Turn					Turn					Turn		
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0	0	0	0	8	0	0	0	0	9	0	0	0	0	6	0	0	0	0	6
0	0	0	0	9	0	0	0	0	8	0	0	7	0	8	0	0	7	0	8
0	0	7	0	13	0	0	7	0	13	0	0	9	0	13	0	0	9	0	13
0	0	10	0	14	0	0	10	0	14	0	0	10	0	14	0	0	10	0	14
12	0	15	0	11	12	0	15	0	11	12	0	15	5	11	12	0	15	5	11
		Turn					Turn					Turn					Turn		
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0	0	7	0	13	0	0	7	0	13	0	0	9	0	13	0	0	9	0	13
0	0	10	0	14	0	0	10	0	14	0	0	10	0	14	0	0	10	0	14
12	0	15	0	11	12	0	15	0	11	12	0	15	0	11	12	0	15	0	11

		Turn					Turn					Turn					Turn		
0	0	0	0	8	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0
0	0	0	0	9	0	0	0	0	8	0	0	7	0	8	0	0	7	0	8
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0	0	10	0	14	0	0	10	0	14	0	0	10	0	14	0	0	10	0	14
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		Turn					Turn					Turn					Turn		
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		Turn					Turn					Turn					Turn		
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		Turn					Turn					Turn					Turn		
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		Turn					Turn					Turn					Turn		
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		Turn					Turn					Turn					Turn		
0	0	15	0	0	0	14	15	0	0	0	14	15	0	0	0	14	15	0	0
		Turn					Turn					Turn					Turn		
0	0	0	0	0	0	0	15	0	0	0	0	15	0	0	0	0	15	0	0
							Turn					Turn					Turn		
					0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Appendix B

Trucks/Vehicle Classifications

The single unit and combination trucks are divided into 17 classes reflecting differences in the number of cargo carrying units and the number and types of axles. The 20 vehicle classes used for this study are:

Automobiles and motorcycles.

Pickups, vans and other light 2-axle, four tire vehicles.

2-, 3-, and 4- or more axle single unit trucks.

3-, 4-, 5-, 6-, and 7- or more axle tractor-semitrailer trucks with two categories of 5-axle vehicles, one with standard tandem axles and one with split tandem axles.

3-, 4-, 5-, and 6- or more axle truck-trailer combinations.

5-, 6-, 7-, and 8- or more axle twin trailer/semitrailer combinations.

Triple trailer combinations.

Buses.

Table B1 shows the different categories of the vehicle classes and Table B2 shows vehicle classes by weight.

Table B1. Vehicle class categories.

VC	Acronym	Description
1	AUTO	Automobiles and Motorcycles
2	LT4	Light trucks with 2-axles and 4 tires (Pickup Trucks, Vans, Minivans, etc.)
3	SU2	Single unit, 2-axle, 6 tire trucks (includes SU2 pulling a utility trailer)
4	SU3	Single unit, 3-axle trucks (includes SU3 pulling a utility trailer)
5	SU4+	Single unit trucks with 4- or more axles (includes SU4+ pulling a utility trailer)
6	CS3	Tractor-semitrailer combinations with 3-axles
7	CS4	Tractor-semitrailer combinations with 4-axles
8	CS5T	Tractor-semitrailer combinations with 5-axles, two rear tandem axles
9	CS5S	Tractor-semitrailer combinations with 5-axles, two split (>8 feet) rear axles
10	CS6	Tractor-semitrailer combinations with 6-axles
11	CS7+	Tractor-semitrailer combinations with 7- or more axles
12	CT34	Truck-trailers combinations with 3- or 4-axles
13	CT5	Truck-trailers combinations with 5-axles
14	CT6+	Truck-trailers combinations with 6- or more axles
15	DS5	Tractor-double semitrailer combinations with 5-axles
16	DS6	Tractor-double semitrailer combinations with 6-axles
17	DS7	Tractor-double semitrailer combinations with 7-axles
18	DS8+	Tractor-double semitrailer combinations with 8- or more axles
19	TRPL	Tractor-triple semitrailer or truck-double semitrailer combinations
20	BUS	Buses (all types)

Table B2. Vehicle classes by weight (in 10,000 pound increments).

VC	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150
Auto	X														
LT4	X	X													
SU2	X	X	X	X	X	X									
SU3		X	X	X	X	X	X	X							
SU4+			X	X	X	X	X	X	X	X					
CS3		X	X	X	X	X	X	X							
CS4			X	X	X	X	X	X	X						
CS5T					X	X	X	X	X	X	X				
CS5S					X	X	X	X	X	X	X				
CS6					X	X	X	X	X	X	X	X	X		
CS7+								X	X	X	X	X	X	X	
CT3,4	X	X	X	X	X	X	X	X	X						
CT5			X	X	X	X	X	X	X	X	X				
CT6+					X	X	X	X	X	X	X	X	X	X	
DS5						X	X	X	X	X	X				
DS6							X	X	X	X	X	X	X		
DS7							X	X	X	X	X	X	X	X	X
DS8+								X	X	X	X	X	X	X	X
TRPL							X	X	X		X	X	X		X
BUS		X	X	X	X										

The SCAG HDT model represents heavy-duty trucks only, that is, trucks that are over 8,500 pounds. The primary use of this model is for air quality purposes and so it uses the weight-based classification system. These are:

- Light-heavy (8,500 to 14,000 pounds).
- Medium-heavy (14,000 to 33,000 pounds).
- Heavy-heavy (greater than 33,000 pounds).

The PSRC truck model also classifies trucks based on weight but these categories also are loosely correlated to other defining characteristics of trucks for other purposes. These are:

• **Light Trucks –** Four or more tires, two axles, and less than 16,000 pounds (this also includes nonpersonal use of cars and vans);

• **Medium Trucks –** Single unit, six or more tires, two to four axles and 16,000 to 52,000 pounds; and

• **Heavy Trucks –** Double or triple unit, combinations, five or more axles, and greater than 52,000 pounds.

The San Joaquin Valley truck model in central California is designed to generate truck volumes based on truck classes that the California Air Resources Board defines as medium-heavy and heavy-heavy duty for regulatory purposes (more than 14,000 pounds gross vehicle weight "GVW" rating). These are:

• **Medium-Heavy Duty Trucks –** GVW rating between 14,001 and 33,000 pounds; and

• **Heavy-Heavy Duty Trucks –** GVW rating of 33,001 pounds and more.

The current Maricopa Association of Governments (MAG) truck model is based on GVW as well that includes three classes – light (less than 8,000 pounds), medium (8,000 to 28,000pounds), and heavy (greater than 28,000 pounds). As the vehicle classification counts are based on FHWA classes, and due to the difficulty in correlating the GVW classes to FHWA classes, the new MAG truck model will include three groups of trucks. These are based on the FHWA classification system, as shown below:

• Class 3 – 2-axle, 4-tire commercial vehicles (“Light”);

• Classes 5-7 – 3+ axle, 6+ tire, single unit commercial vehicles (“Medium”); and

• Classes 8-13 – 3+ axle, 6+ tire, combination unit commercial vehicles (“Heavy”).

Figure B1 illustrates the vehicle classes.

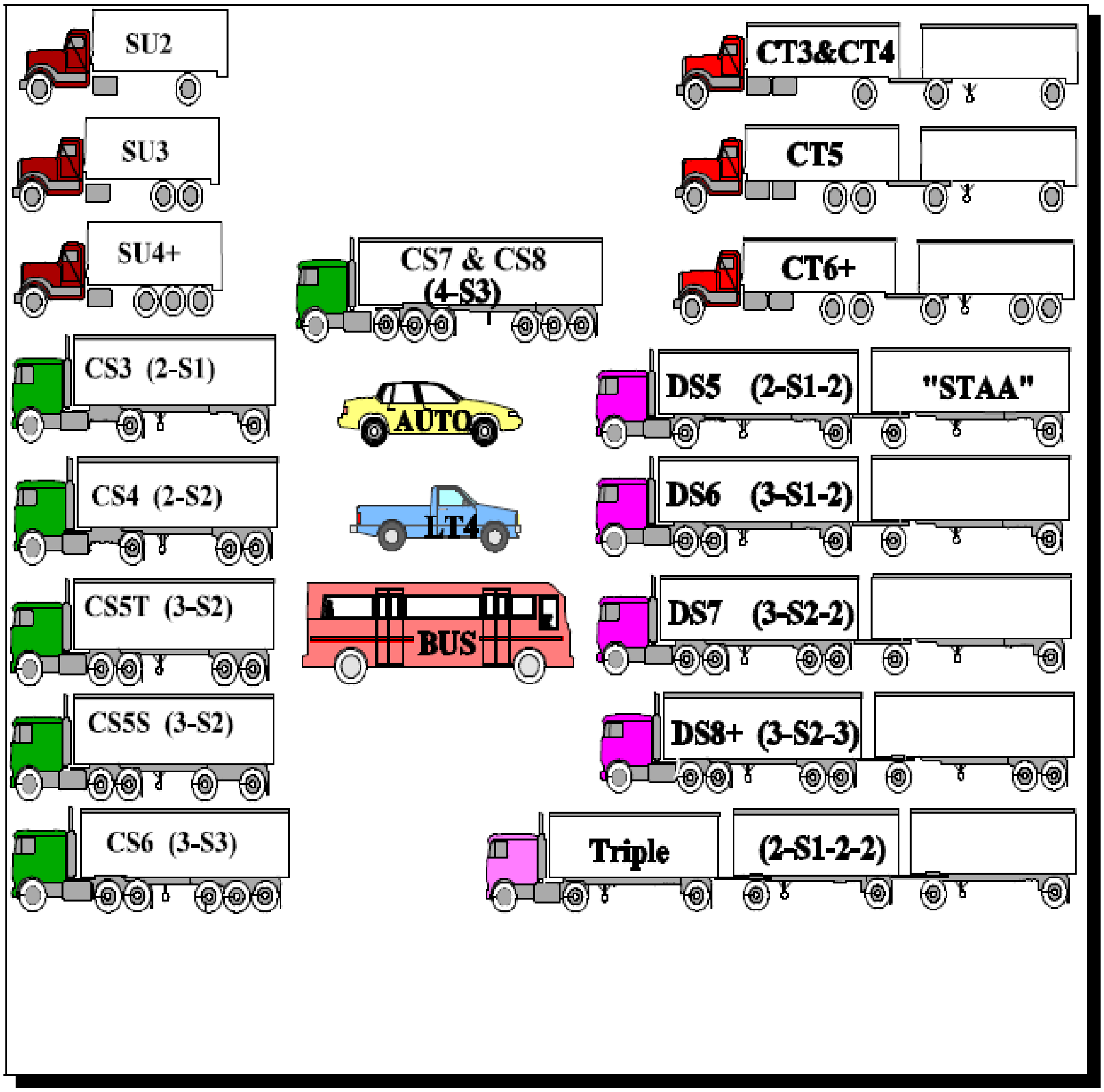

Figure B1. Vehicle classes.

Table B3. Indiana truck registration fees.

Truck Registration Transactions (By declared gross weight)	Full Fees	Half Fees
Truck: 7,000 pounds or less • **Valid for one year.** • **May bear special recognition and personalized license plates.**	$30.05	Not available
Truck: 7,001 to 9,000 pounds • **Valid for one year.** • **May bear special recognition and personalized license plates.**	$50.05	Not available
Truck: 9,001 to 10,000 pounds • **Valid for one year.** • **May bear special recognition and personalized license plates.**	$80.05	Not available
Truck: 10,001 to 11,000 pounds • **Valid for one year.** • **May bear special recognition and personalized license plates.**	$84.75	Not available
Truck: 11,001 to 16,000 pounds • **Valid for one year.**	$144.75	$75.25
Truck: 16,001 to 20,000 pounds • **Valid for one year.**	$184.75	$95.25
Truck: 20,001 to 23,000 pounds • **Valid for one year.**	$244.75	$125.25
Truck: 23,001 to 26,000 pounds • **Valid for one year.**	$244.75	$125.25
Truck: 26,001 to 30,000 pounds • **Valid for one year.**	$304.75	$155.25
Truck: 30,001 to 36,000 pounds • **Valid for one year.**	$422.75	$214.25
Truck: 36,001 to 42,000 pounds • **Valid for one year.**	$515.75	$260.75
Truck: 42,001 to 48,000 pounds • **Valid for one year.**	$636.75	$321.25
Truck: 48,001 to 54,000 pounds • **Valid for one year.**	$739.75	$372.75
Truck: 54,001 to 60,000 pounds • **Valid for one year.**	$819.75	$412.75

Table B3. Indiana truck registration fees (continuation).

Truck Registration Transactions (By declared gross weight)	**Full Fees**	**Half Fees**
Truck: 60,001 to 66,000 pounds • **Valid for one year.**	$867.75	$436.75
Truck: 66,001 pounds or more • **Valid for one year.**	$965.75	$485.75
Other Truck Registration Transactions	Full Fees	Half Fees
Replaced registration • **To replace a lost, stolen, or destroyed registration.** • **Valid until next renewal date.**	$6	Not available
Amended registration • **To change the registration holder's name, address, or personal information.** • **Valid until next renewal date.**	$6	Not available
Replaced license plate or sticker • **To replace a lost, stolen, or destroyed plate or sticker.** • **Valid until next renewal date.**	$10	Not available
License plate transfer • **To transfer a plate from one vehicle to another vehicle.** • **Valid until next renewal date.**	$10.75	Not available

Appendix C

Milwaukee Approximation for Heavy Truck Fuel Consumption

There is no clear relationship between fuel consumption and heavy trucks' driving speeds. The available theoretical relations are valid for specific technologies and some of them became obsolete due to new technologies. Some theoretical relations have congruent results with practical data for specific ranges of driving speeds. However, applying these relations beyond these specific ranges leads to an obvious contradiction with practical data. On the other hand, we should know that the practical relations depend on the truck type, model, and technology and don't rely on equations.

There are many factors affecting the relationship between truck fuel consumption and driving speed, like the proficiency of truck driver and terrain. All of the above make it hard to come up with reliable correlation between truck fuel consumption and speed. This approximation combines the most updated theoretical and practical relations. The approximation is made up of discontinuous equations relating to truck fuel consumption (mpg) to driving speeds (mph).

Running a truck requires energy to overcome the aero drag force and tire rolling resistance force. The total force can be expressed as in equation C1

$$F = A + Bv + Cv^2 \text{ ………….(C1).}$$

Giannelli in his paper "Heavy-duty diesel vehicle fuel consumption modeling based on road load and power train parameters" updated the A,B and C coefficients and redefined them as in Table C1.

Table C1. A, B, and C road load parameters developed from Petrushov.

Vehicle classification	**A (kW*s/m)**	**B ($kW*s^2/m^2$)**	**C ($kW*s^3/m^3$)**
8500 to 14000 lbs. (3.855 to 6.350 tonnes)	$\frac{0.0996M}{2204.6}$	0	$1.47+\frac{5.22\ X\ 10^{-5}M}{2205}$
14000 to 33000 lbs. (6.350 to 14.968 tonnes)	$\frac{0.0875M}{2204.6}$	0	$1.93+\frac{5.90\ X\ 10^{-5}M}{2205}$
>33000 lbs. (>14.968 tonnes)	$\frac{0.0661M}{2204.6}$	0	$2.89+\frac{4.21\ X\ 10^{-5}M}{2205}$
Buses	$\frac{0.0643M}{2204.6}$	0	$3.22+\frac{5.06X\ 10^{-5}M}{2205}$

Where,

$$A = C_{R0}Mg$$

B=0

$$C = \frac{C_D A_f \rho_{air}}{2} + C_{R2}Mg$$

Most of the data resources emphasize 55 mph as the most efficient speed that can give the higher mpg. This approximation considers equation C1 for 55 mph speed and above.

Equation C1 is divided and multiplied by many factors to convert it from Newton to MPG, this includes the truck engine losses. Equation C2 shows the relation between MPG and speed mph for speeds more than or equal 55 mph.

$$MPG = 1 / [(1.53*10^{-6}*M) + (2.94*10^{-5}+1.94*10^{-13}*M)*V^2] \ldots\ldots\ldots (C2)$$

Where M is the total truck mass in lb., and V is Truck driving speed in mph.

For speed less than 55 mph, this approximation uses truck's fuel consumption equation mentioned in Papacostas's textbook (Transportation and Engineering Planning,2000). This relation considers 1970's trucks' technologies and it is valid for speed less than 35 mph. This approximation assumes the speed range (35-54) is more related to this equation rather than equation C1 mentioned above. Papacosta's equation for tracks is shown in equation C3.

$$MPG = [1/(0.17 + (2.43/V))] \ldots\ldots\ldots (C3)$$

Where, V is the speed in mile per hour.

To update equation C3, the data (graph) given in Factors Affecting Fuel Economy paper (Good year, 2003) had been used. From this paper the most efficient fuel consumption speed is 55 mph and it will be the reference speed in this investigation. Table C2 shows % differences in MPG for different speeds.

Table C2. % Difference in mpg for different speeds (55 mph is the reference speed) using good year 2003 data-graph.

speed	**% Difference**
35	18
40	16
45	13
50	8
55	0

We know from equation C1 for an empty truck (33,000 lb) the MPG is 7.17, the estimated MPGs for different speeds as in Table C3.

Table C3. Estimated mpg for different speeds using equation C1 with 55 mph reference speed and data from Table C2.

Speed	% Difference	Estimated MPG
35	18	5.88
40	16	6.02
45	13	6.24
50	8	6.60
55	0	7.17

By using equation C3 the MPG for the speeds from 35-50 has been found as in Table C4.

Table C4. Estimated mpg for speed range (35-50) mph using equation C3.

Speed	MPG (Equation 3)
35	4.18
40	4.33
45	4.46
50	4.57

A correction factor had been calculated to update equation C3, this correction factor found by calculating the difference in MPG for different speeds as shown on Table 2 and 4. Table C5 shows the correction factor.

Table C5. Correction factor for equation C3.

Speed	MPG (Equation C.3)	MPG (Good Year)	Diff	Correction Factor
35	4.18	5.88	0.41	1.41
40	4.33	6.02	0.39	
45	4.46	6.24	0.40	
50	4.57	6.60	0.44	

To update equation C.3 for speed $\leq$ 54mph, we could multiply that equation by the correction factor which is 1.41. But to make the relation more practical and smoother we multiply the equation by 1.536. The Milwaukee approximation for heavy truck fuel consumption is as follows:

$$TFC_{mpg} = \begin{cases} \sum_{i=5}^{15} Wsli55 \left(\frac{33,000}{\mathrm{M}}\right)\left[\frac{1.536}{0.17 + \left(\frac{2.43}{\mathrm{V}}\right)}\right] & (\text{ speed} < 55\text{mph}) \\ + & \\ \sum_{i=0}^{4} Wsmi55 \left[\frac{1}{[(1.53 * 10^{-6} * \mathrm{M}) + (2.94 * 10^{-5} + 1.94 * 10^{-13} * \mathrm{M}) * \mathrm{V}^2]}\right] & (\text{speed} \geq 55 \text{ mph}) \end{cases}$$

TFC_{mpg} : Truck fuel consumption (mileage per gallon).

The total truck fuel consumption (mpg) for a shipping trip is as below:

$$TFC = \begin{cases} \sum_{i=5}^{15} Wsli55 * \mathrm{Dist}\ (\mathrm{Xis} - \mathrm{Xif}) / [\left(\frac{33,000}{\mathrm{M}}\right)\left[\frac{1.536}{0.17 + \left(\frac{2.43}{\mathrm{V}}\right)}\right]] & (\text{ speed} < 55\text{mph}) \\ + & \\ \sum_{i=0}^{4} Wsmi55 * \mathrm{Dist}(\mathrm{Xis} - \mathrm{Xif}) / \left[\frac{1}{[(1.53 * 10^{-6} * \mathrm{M}) + (2.94 * 10^{-5} + 1.94 * 10^{-13} * \mathrm{M}) * \mathrm{V}^2]}\right] & (\text{speed} \geq 55 \text{ mph}) \end{cases}$$

Where,

TFC: Truck fuel consumption (gallon).

M: Total truck and trailer Mass (lb.)

V: Driving speed (mi/hr)

W_{sli55}: The probability of driving at speed class i, while i more than 4 (less than 55 mph).

W_{smi55}: The probability of driving at speed class i, while i less than or equal 4 (more 55 mph).

Dist (X_{is}-X_{if}): The distance traveled by speed class i, which starts by speed more than X_{is} and end by speed equal or less X_{ie}

According to the available data of the relation between speed and distance traveled from heavy truck duty cycle project, W_{sl55} = 0.124, and W_{sm55} = 0.876.The relation between speed (mph) and distance traveled follows Poisson distribution with mean = 2.61.

The relation between speed (mph) and travelled distance (mile) published in Transportation Energy Data Book, edition 28-2009 as a part of vehicle Duty Cycle Project, are used to find the probability of each driving speed class more, less, and equal 55 mph. Vehicle Duty Cycle Project data are summarized in Table C6, the four main columns of this Table are organized by the type of tires that were mounted on the tractor and trailers, speed classes are divided into 5-mile intervals, going from0 + mph (i.e., speed > 0.00 mph) to 80 mph.

Table C6. Fuel economy for class 8 trucks as function of speed and tractor-trailer tire combination.

Speed (mph)	**Dual Tire Tractor -** Dual Tire Trailer			**Dual Tire Tractor -** Single (Wide) Tire Trailer			**Single (Wide) Tire Tractor -** Dual Tire Trailer			**Single (Wide) Tire Tractor -** Single (Wide) Tire Trailer			**Average Distance Traveled (miles)**
	Distance Traveled (miles)	Fuel Cons. (gal)	Fuel Econ. (MPG)	Distance Traveled (miles)	(miles) Cons. (gal)	Fuel Econ. (MPG)	Distance Traveled (miles)	Fuel Cons. (gal)	Fuel Econ. (MPG)	Distance Traveled (miles)	Fuel Cons. (gal)	Fuel Econ. (MPG)	
Idling	N/A	1,858.5	N/A	N/A	967.9	N/A	N/A	1,676.4	N/A	N/A	706.0	N/A	N/A
0+ to 5	281	101.8	2.76	148	50.4	2.93	368.0	124.2	3.0	156	52.8	2.96	238.25
5+ to 10	674	198.8	3.39	368	103.2	3.56	808.0	245.4	3.3	331	98.8	3.35	545.25
10+ to 15	723	192.0	3.77	396	98.3	4.03	848.0	216.5	3.9	343	87.0	3.95	577.5
15+ to 20	744	199.1	3.73	404	100.9	4.00	882.0	221.6	4.0	361	90.5	3.98	597.75
20+ to 25	938	228.4	4.11	489	113.6	4.31	1,111.0	244.2	4.6	462	101.1	4.57	750
25+ to 30	1,178	266.9	4.41	609	131.5	4.63	1,420.0	286.9	5.0	580	117.6	4.93	946.75
30+ to 35	1,481	336.8	4.40	753	154.2	4.88	1,774.0	341.1	5.2	708	141.1	5.02	1179
35+ to 40	1,917	403.5	4.75	1,000	193.6	5.17	2,284.0	433.6	5.3	941	184.3	5.10	1535.5
40+ to 45	2,955	584.1	5.06	1,543	285.9	5.40	3,380.0	603.6	5.6	1,350	254.4	5.31	2307
45+ to 50	4,935	907.9	5.43	2,573	447.7	5.75	5,410.0	872.8	6.2	2,177	360.4	6.04	3773.75
50+ to 55	9,397	1,629.8	5.77	4,962	811.5	6.11	10,046.0	1,622.7	6.2	3,877	625.5	6.20	7070.5
55+ to 60	20,656	3,297.2	6.26	11,707	1,721.9	6.80	22,373.0	3,257.8	6.9	8,710	1,246.9	6.99	15861.5
60+ to 65	38,964	5,879.6	6.63	21,472	2,980.8	7.20	34,517.0	4,840.0	7.1	14,944	2,049.4	7.29	27474.25
65+ to 70	58,304	8,313.2	7.01	27,931	3,652.2	7.65	65,063.0	9,256.4	7.0	27,144	3,880.1	7.00	44610.5
70+ to 75	56,378	7,483.2	7.53	21,751	2,745.5	7.92	66,882.0	8,435.6	7.9	32,887	4,056.1	8.11	44474.5
75+ to 80	7,849	808.2	9.71	3,610	403.2	8.95	11,513.0	911.1	12.6	6,817	512.2	13.31	7447.25
Total[a]	207,374	30,831.0	6.73	99,714	13,994.0	7.13	228,680.0	31,913.0	7.2	101,790	13,858.0	7.35	159389.5

The relation between speed classes and each truck distance traveled, and average distance for all truck types are shown in Figure C1 and C2. Where DD : Dual tire tractor - Dual tire trailer, DS: Dual tire tractor – Single tire trailer, SD: Single tire tractor – Dual tire trailer, and SS: Single tire tractor – Single tire trailer.

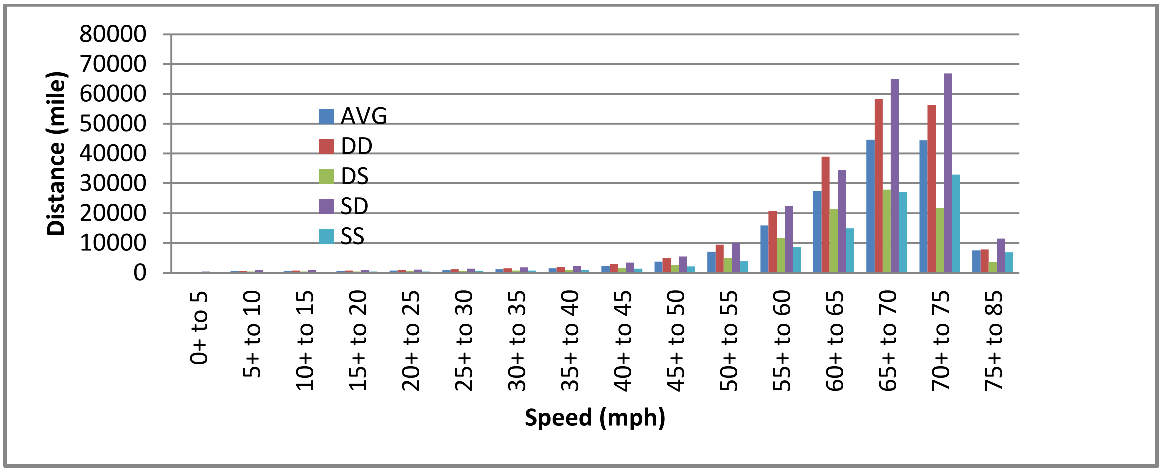

Figure C1. The relation between traveled distance (miles) and speed (mph), for all trucks types, as in Table C6.

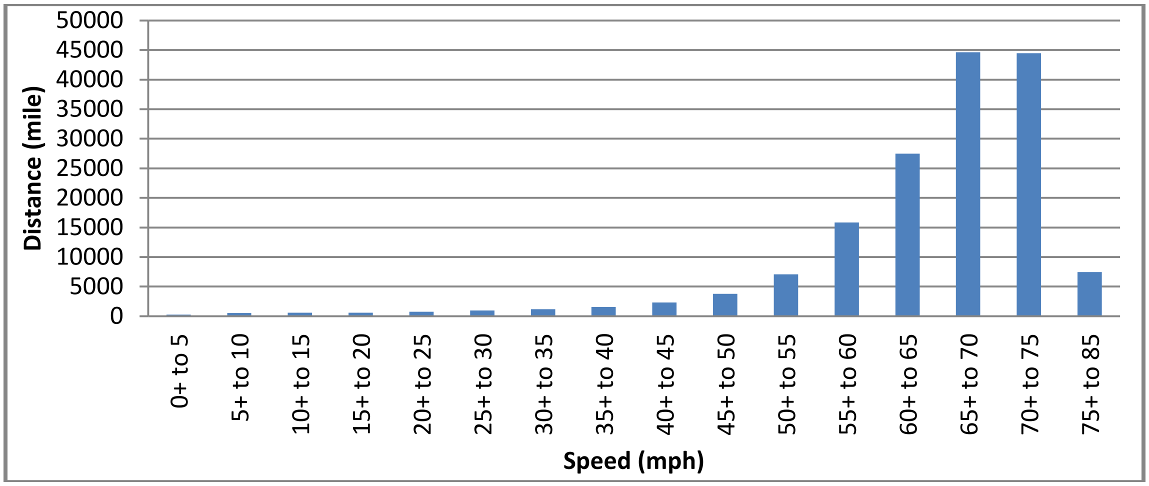

Figure C2. The relation between average-traveled distance (miles), for all trucks types, and speed (mph), as in Table C6.

The Figure C1 and C2, show that the relation between traveled distance and speed has the same behavior of reverse Poisson distribution and reverse gamma distribution.

Gamma and Poisson distributions are candidates to represent the available data of speed and traveled distance. Testing for goodness of fit is used to find out the appropriate distribution that represents the available data. Using a small number of data points leads to no candidates may be rejected, while all candidates may not be rejected for a large number of data points.

Each mile in these data represents one observation for statistic test purposes, from data in Table C6, it is obvious that these tables have a large number of data points which causes the rejection of all the distribution candidates. Comparing the histogram of the data points with the shape of the candidate distributions' density functions are valid for large sample sizes. (Reverse) gamma and Poisson distribution have the same shape as in the data we have. The Poisson distribution has been selected to represent the data of traveled distance and speed. This distribution was selected because the available data for truck driving speeds in term of travelled distances can be represented as a discrete distribution, and the gamma distribution can be defined as a cumulative Poisson distribution.

Table C7 shows Poisson calculations for the available data, the classes are arranged in descending order to avoid the difficulties in calculating reverse Poisson distribution, each speed class had given a Poisson number from 0-15, speed class 75+-80 has a (0) Poisson number value. Column 6 includes the observations, which is a truncated traveled distance to two digits. The mean speed of this data is 64.33 mph with Poisson number equal 2.61. This model fuel consumption formula is divided into two parts, less than 55 mph and more than and equal to 55 mph. 55 mph has Poisson No. equal 4.5.

Figure C3 shows the Poisson distribution for all truck types. Figure C4 shows the Poisson distribution for the average data of all trucks.

Table C7. Poisson Distribution For Table C6 Data.

Class Order	Poisson No. (Class No.)	Speed Class	mid-class	Traveled Dist (mile)	Trun. Obs.	Avg. Speed	Prob	Cum Prob	1- Cum Prob
16	0	75+ to 80	77.5	7447.3	**74**	**5735**	0.074	0.074	0.926
15	1	70+ to 75	72.5	44474.5	**445**	**32262.5**	0.192	0.265	0.735
14	2	65+ to 70	67.5	44610.5	**446**	**30105**	0.250	0.516	0.484
13	3	60+ to 65	62.5	27474.3	**275**	**17187.5**	0.218	0.734	0.266
12	4	55+ to 60	57.5	15861.5	**159**	**9142.5**	0.142	0.876	0.124
11	5	50+ to 55	52.5	7070.5	**71**	**3727.5**	0.074	0.950	0.050
10	6	5+ to 10	47.5	3773.8	**38**	**1805**	0.032	0.983	0.017
9	7	45+ to 50	42.5	2307	**23**	**977.5**	0.012	0.995	0.005
8	8	40+ to 45	37.5	1535.5	**15**	**562.5**	0.004	0.998	0.002
7	9	35+ to 40	32.5	1179	**12**	**390**	0.001	1.000	0.000
6	10	30+ to 35	27.5	946.8	**9**	**247.5**	0.000	1.000	0.000
5	11	25+ to 30	22.5	750	**8**	**180**	0.000	1.000	0.000
4	12	20+ to 25	17.5	597.8	**6**	**105**	0.000	1.000	0.000
3	13	15+ to 20	12.5	577.5	**6**	**75**	0.000	1.000	0.000
2	14	10+ to 15	7.5	545.3	**5**	**37.5**	0.000	1.000	0.000
1	15	0+ to 5	2.5	238.3	**2**	**5**	0.000	1.000	0.000
			Total	159389.6	**1594**	**102545**	1		
					Average	**64.33**			

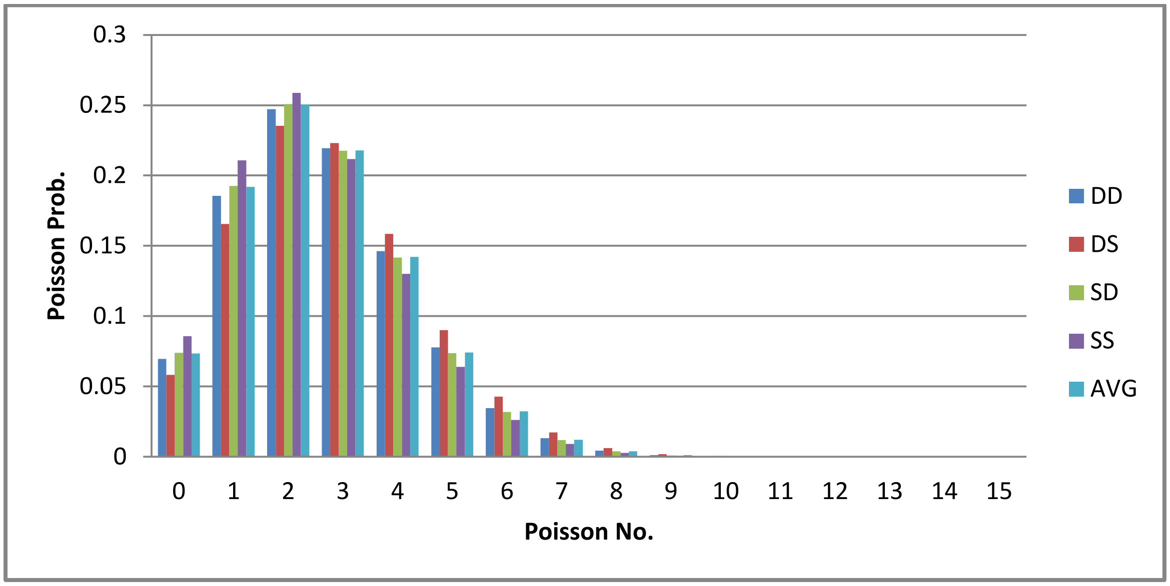

Figure C3. Poisson distribution for the data in Table C6.

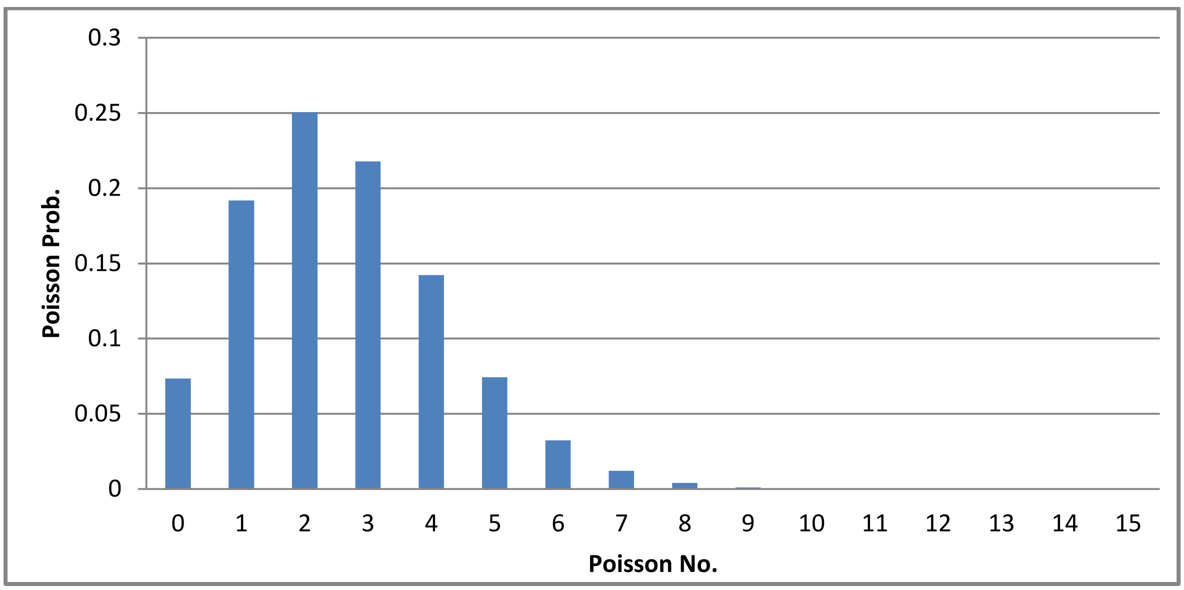

Figure C4. Poisson distribution for average traveled distance for all trucks in Table C6, while average speed is 64.33 mph and 2.61 Poisson No.

The flow chart in Figure C5 shows the required data, calculation, and procedure of total shipping trip fuel consumption.

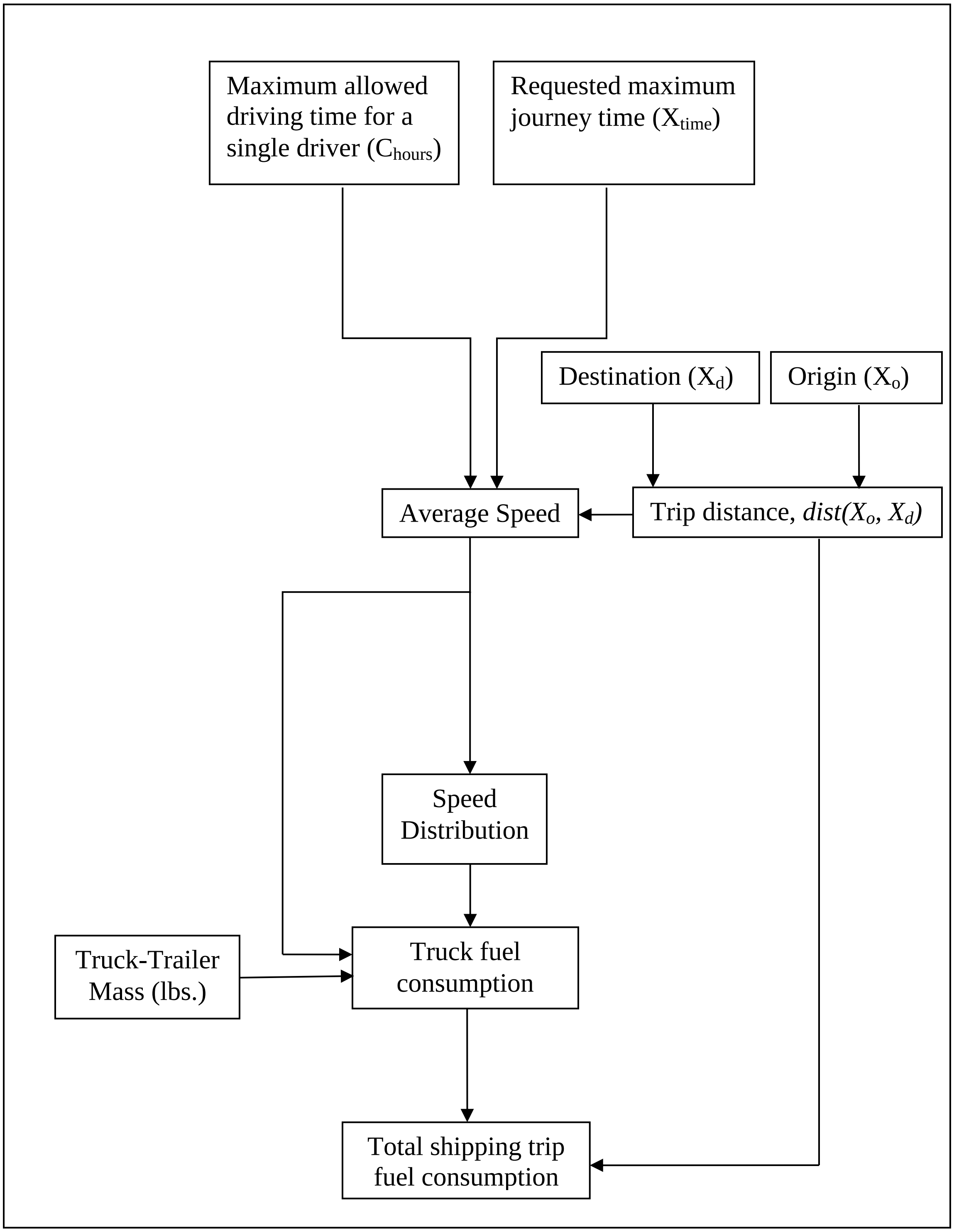

Figure C5. Flow chart of required data and procedure for calculating total trip fuel consumption (for traveling purposes only).

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