ABSTRACT

Title of Dissertation: A STOWAGE PLANNING MODEL FOR MULTIPORT CONTAINER TRANSPORTATION

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The ship turnaround time at container terminals is an important measure of a port's efficiency and attractiveness. The speed and quality of load planning affect the length of turnaround time considerably. Container operations are extremely important from an economic standpoint, making them a prime target for productivity improvements. In addition, load planning is a very complex problem, since the planners have to account for the stability of the ship and rely on a variety of other stochastic processes.

Unfortunately, the load-planning problem is NP-hard making it difficult to obtain an optimal solution in polynomial time. Heuristics that trade quality for tractability are therefore promising tools when coping with this problem. Efficient load planning is

accomplished by formulating the stowage-planning model to minimize extra shifting as a mixed integer-programming problem.

The key contributions of this dissertation are as follows.

- A mathematical model is developed which considers real life constraints and considering loading/unloading along the entire voyage.
- A second mathematical model is formulated to obtain a lower bound on the value of the objective function of the exact solution.
- A heuristic procedure is developed that is guide by practical considerations that account for the structure of the stowage-planning problem.

All proposed mathematical models and heuristic are validated with experimental results. In all cases, these results demonstrate the stability, flexibility and efficiency of the model, and establish its potential as a versatile and practical method for large scale container loading.

A STOWAGE PLANNING MODEL FOR MULTIPORT CONTAINER TRANSPORTATION

By

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Dissertation submitted to the Faculty of the Graduate School of the
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DEDICATION

To my parents
and
To my family

ACKNOWLEDGEMENT

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Τα Υστερνια

Το Ομορφοτερο Χωριο του Αιγαιου

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Chapter 1: Introduction

1.1 General

Stowage problems arise in diverse areas, ranging from inventory management to information dispersal. Efficient solutions for this problem are critical for effective resource utilization and good system performance. However, stowage problems are hard to solve optimally; not many algorithms exist and they strain to cope with even the smallest instances, using many assumptions. From the complexity theory point of view, problems can be classified as simple or difficult, depending on whether the best known algorithms for solving them run in polynomial time or whether they are known to be NP-hard problems. It is widely believed that polynomial time algorithms to find optimal solutions do not exist for NP-hard problems. It is therefore natural to consider heuristics that can in some sense provide an approximation to the optimal solution. Such heuristics with a bounded worst-case performance, in terms of the quality of the solution, are called approximation algorithms. Approximation algorithms trade quality for tractability and therefore can deal with NP-hard stowage planning problem. Avriel et al., (2000) proved that the minimum overstowage (stowage planning) problem is NP-hard.

Stowage/loading planning is present in every circumstance involving operations. Stacking in warehouses, airplanes, parking garages, circuits and databases are very common areas where stowage problems occur. Container terminals and containerships are the most common areas where stowage problems arise with significant impact on their operation.

1.2 Containerization

Containerization is a system of intermodal cargo transport using ISO containers (also known as standard containers) that can be loaded sealed and intact onto containerships, railroad cars and trucks. Containerization is one of the most important cargo-moving techniques developed in the 20th century. Although rail and road containers were used early in the century, it was not until the 1960`s that containerization became a major element in ocean shipping. Containerization is the term that encompasses the industrial shipping process of packing goods into boxes at the point of production and transporting the container and its contents as a unit until it is unpacked at its final destination. The primary advantages in container shipping are the radical reduction in the number of cargo pieces to be handled and the high degree of protection the containers provide. The increase in container cargo since the late 1980`s is shown in Figure 1.

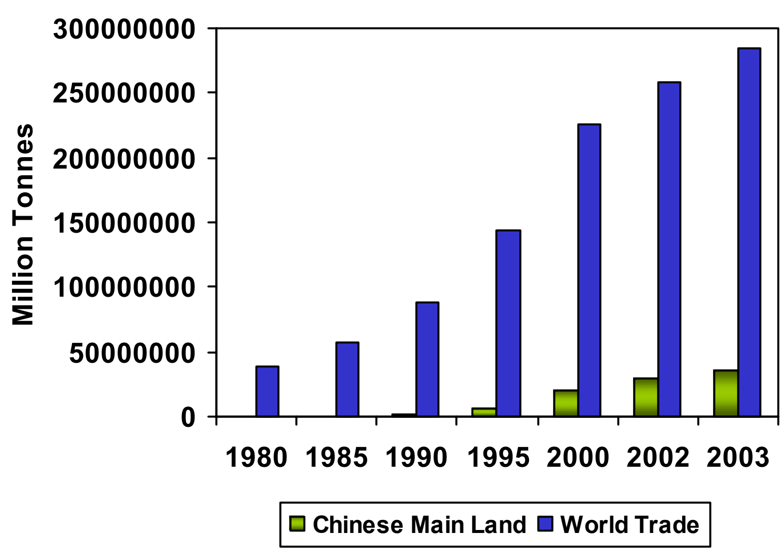

Figure 1: Container Volume (Kerr-Dineer, 2003)

In 1966 the first deep-sea container service was introduced for the transportation of general cargo (Stopford, 2002). Since then, container shipping has become the most efficient method for all types of products.

1.2.1 The First Years

Man has been experimenting with containers since the first years of commercial history. The merchants who first sought to improve cargo handling and protection by placing small parcels in the same crate or using sealed *amphorae* (Greek transportation method) took the earliest steps toward containerization.

The introduction of modern containerization in the shipping industry took place over 40 years ago and has not stopped evolving since. The containerization industry began with the plans of Malcolm McLean and the departure of the vessel Ideal X with a deck load of containers from Port Newark enrooted to Houston in 1956.

Malcolm McLean, the owner of a North Carolina trucking firm, had long believed those individual pieces of cargo needed to be handled only twice (Van Den Burg, 1975). They could be packed at the factory into a truck trailer and the entire trailer could then be moved to the seaport and across the ocean to the door of the recipient. Only then would the trailer be unloaded. McLean was aware that there were railroads already moving trailers full of cargo across the country. He purchased a small ship line, renamed it Sea-land, and initiated the movement of containers from New York to the Gulf Coast and Puerto Rico in 1956. For McLean it was simply a logical extension to load several trailers onto a refitted World War II tanker in the spring of 1966 and send them across the Atlantic. From this point on, containerization of international commerce had truly begun.

Subsequently, other ship owners began placing containers on the deck of their regular cargo freighters. Progressively, the size of containerships increased from 150 Twenty-foot Equivalent Unit (TEU) fully cellular containerships to vessels with capacities exceeding 8200 TEUs (USDA, 2002). In parallel the size of the containers themselves increased from the standard 10 to 20 foot containers to 35 and 40 foot ones (Whittaker, 1975).

Changes occurred not only in the size of the vessels and containers, but also in the transportation system itself. The concept of intermodal transportation proved to be economically and practically very efficient. Under this system, the transportation network includes both ocean and land routes. Usually, the container is loaded and sealed by the shipper and driven by truck or train to the port, where a ship is employed, moving the container to its ultimate shore side destination. From that point on truck or rail resumes the responsibility for the final delivery to the destination.

Increasing competition and ever increasing shipping costs demanded greater efficiency in every stage of the journey. With vessels carrying a large number of containers today, the time and, consequently, the cost of waiting while being loaded contribute to a continuously increasing share of the overall cost.

For any given port facility, the time required for loading and unloading is a function of the arrangement of the cargo on board the vessel (vessel stowage). Both ship operators and port managers are interested in determining the optimal vessel stowage, that is, the one that minimizes loading cost and berth time (Shields, 1984).

The main reason for delay is moving those containers not destined for a particular port so as to be able to get to the containers that are. This increases handling cost. The placing of containers might have been necessary to satisfy the minimum metacentric height requirements (e.g. stability requirements): heavier cargo must be placed lower despite destination. The result is that some lighter containers must be unloaded and re-loaded in order to unload the heavier ones. This is referred to as "Overstowage cost" (Aslidis, 1989).

Another factor that affects the loading/unloading time is the distribution of the containers along the vessel. If containers of the same destination are spread randomly along the vessel additional crane movements are necessary, resulting in longer port time. Such delays can be avoided if containers with a common destination are "Blocked" together. Blocking containers in different locations on board allow dock cranes to work simultaneously with very good results during the time that the vessels are docked at the port. In modern container terminals that service the docks with more than one crane, blocking containers with the same destination on board is an advantage for fast loading and discharge for port operations and maritime corporations as well (Imai et al., 2002).

1.2.2 ContainerShip

The first generation of containerships was made up of existing ships that were converted for the transport of containers. They were usually "self-sustaining" or "geared" in that they had their own lifting gear and thus could use any marine terminal berth that was available. For the past three decades, however, ships have been built specifically for the transportation of containers. Many are gearless in that they do not have container-lifting gear aboard. The cargo carrying section of the ship is divided into several holds with the containers racked in special frameworks and stacked one upon the other within the hold space. At times a special quayside crane handles cargo movement in a vertical motion. Containers may also be stacked on hatch covers and secured by special latching arrangements. Cargo holds are separated by a deep web-framed structure that provides the ship with transverse strength. The outboard structure of the containership hold is a box-like arrangement of wing tanks ballast and can be used to counter the heeling of the ship when discharging containers. A double bottom is fitted which adds to the longitudinal strength which is employed not only for environmental reasons but also for providing additional ballast space (Kostalas, 1980).

Accommodation and machinery spaces are usually located in the stern leaving the maximum length of a full-bodied ship for container stowage. Cargo-handling equipment is rarely fitted, since these ships travel between specially equipped terminals to ensure rapid loading and discharge. Containerships have carrying capacities that range up to 8000 TEUs (Figure 2). The twenty-foot equivalent unit (TEU) represents a 20-ft (6055-mm) 'standard' container. Containerships are faster than most general cargo ships, with speeds of up to 30 Knots.

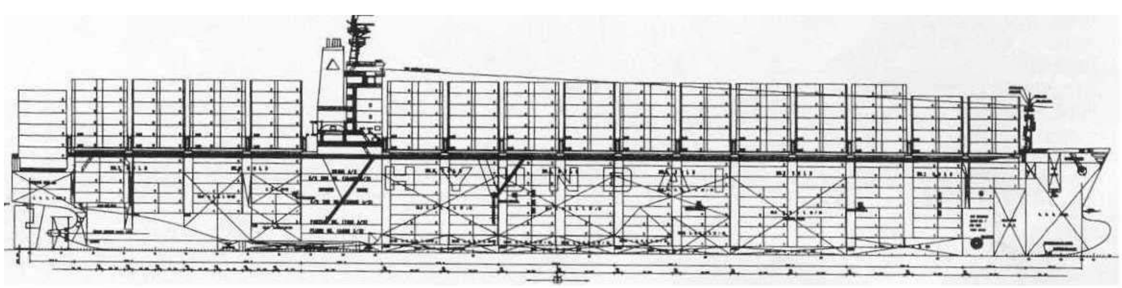

Figure 2: Containership design [(Εφοπλιστης (Greek Maritime Magazine), 1999]

One of the major components during berthing operations is the vessel's weight. The vessel's weight is composed of two parts: lightship and displacement. The lightship is the vessel's weight itself plus the weight of the miscellaneous items such as: oil, lubricants, storage, etc. The displacement is the cargo weight on board or the weight capacity of the vessel. The vessel's lightship, and miscellaneous weights are based on a series of basic formulas. These along with the fuel weight and the centers of gravity of the weight components are brought together in the total weight and center of gravity module. The weight-displacement balance is maintained through the stability constraints (Ganesan, 1999).

Vessel design has traditionally been an iterative process in which various aspects of the design pertaining to stability, strength, weight, power and space balance have been performed in sequence to arrive at a variety of feasible designs. Although the vessel design it is not the major issue in this research, we have to consider a few technical vessel characteristics such as the vessels cross section. Our research is focusing on stowage planning; therefore the containership design is beyond the scope of this research.

1.2.3 Roll on – Roll off Ships

Roll on-Roll off (RO-RO) vessels are designed to permit containers (as well as other cargo) to be driven on and off the ship. The cargo can be rapidly loaded and unloaded through the stern or bow doors and sometimes side-ports for smaller vehicles. These ships also have been adapted to carry containers. The cargo-carrying section of the ship is a large open deck with a loading ramp. In the last few years there have been shipping companies who placed their ships in the regular lines allowing this open space to be loaded by pallets. One or more hatches may be provided for containers or general cargo, served by deck cranes. Since this inevitably involves sacrificing some space for internal ramps and decks, the RO-RO vessel is less efficient than the cellular containership in handling large volumes of containers. The sizes range considerable with about 16,000 dwt (Deadweight Tones), with an equivalent to 28,000-displacement tons, being quite common. Speeds in the range of 18 to 22 knots are usual (Walter, 1996).

There is considerable variation in the design of RO-RO vessels. In addition to roll-on/roll-off capability, many Ro-Ros also have lift capability, which is called lifton-liftoff (LO-LO). These ships can, either use their own cranes or those of the terminal. These vessels are sometimes referred to as LO-RO. The proportion of cargo space available to LO-LO handling can vary. In some cases, the ship is equipped with cellular holds. In others, LO-LO cargo can only be accommodated on deck (Kostalas, 1980).

Today with a diverse cargo that may or may not fit in containers, there exist alternatives to cargo space as general cargo, Ro-Ro and finally containerships. In the maritime industry the use of containers has decreased the cost of loading/unloading, the time that is spent in port, and the extent of damage to the cargo.

1.2.4 Fleet Capacity

Although containerized cargo will continue to grow, the capacity of the ocean container carriers is likely to grow even faster on a percentage basis. Throughout the 1980s, the global container carrying capacity was 20-30 percent ahead of demand. In the nineties the world containership fleet have reached forty million dead weight tones (>38.2 DWT). ** Drewry is forecasting an average growth of over 9% p.a. in container handling up to 2010 (Figure 3). In the recent times maritime corporations have placed orders for a fleet of bigger and faster ships an example could be the COSCO HELLAS with a capacity 9,500 TEU, including 700 refrigerated containers, and a total capacity 109,140 gt (Lloyds` List, 2006)

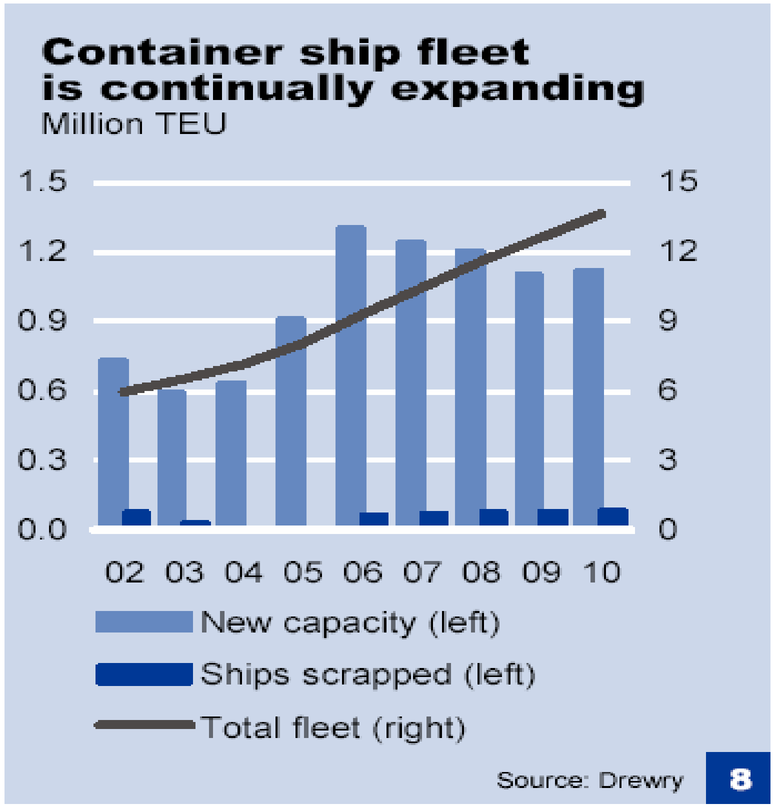

Figure 3: Containership fleet expanding (Drewry, 2006)

Often it is more economical to build a ship larger than to make it faster. This is due to several fixed relationships between hull shapes, construction material costs, propulsive power requirements, and vessel speed. However, a few maritime companies own containerships usually 3700 to 5300 TEU that are used in the pacific area for the express service between USA and overseas (i.e. China, Malaysia, etc). Express traffic is approximately less than 8% of the whole traffic. Also we have a class of smaller vessels for coastal, between secondary ports, lower volume trades that service special areas such as the Mediterranean ports. In addition, barges and ships with low depth are very commonly used for inland transportation. For instance, in inland transportation in US, and particularly in inland European transportation, special ships are used to navigate the rivers as well as the open seas (MARAD, 2000).

1.3 Containers

The container is the key element in the marine network. The freight containers include many different types (Figure 4). In general, they all have the same shape (rectangular) and a relatively weatherproof outer shell over a strong inner structure that protects the load (Whittaker, 1975). Containers are built using strong materials to resist the weight of a big stack above them, the wear and tear of continuous loading and unloading, and the turbulence of heavy seas that ships usually face in the oceans. They must also be durable to meet their long life expectancy and survive both marine and land transportation.

International organizations not only have established the technical guidelines for container construction, but also have established the security plates the containers must bear for approval. These plates have to be placed in an easily visible location and must contain the following information:

- Manufacturing data.
- The name of the country that approved the container.
- Container number.
- Its weight and its test data.

Containers that do not bear these identifying plates are not accepted at ports even if their origin is from a country that has not signed the international treaty regarding containers. This treaty, among other things, specifies that containers can only vary in length, not the other two dimensions. However, changes in this treaty in the last few years allow changes in the height as well.

The construction material depends on the utilization purpose. Possible choices include steel, aluminum with steel reinforcement, plastic and wood with fiberglass reinforcement (Fiberglass – Reinforced Plywood, FRP).

Depending on the load and the container's use, different kinds of containers (types, length, etc.) that facilitate operations on board or in port terminals are used (Figure 4). Materials carried in containers, when properly fitted, are less likely to suffer damage due to loading or unloading and handling.

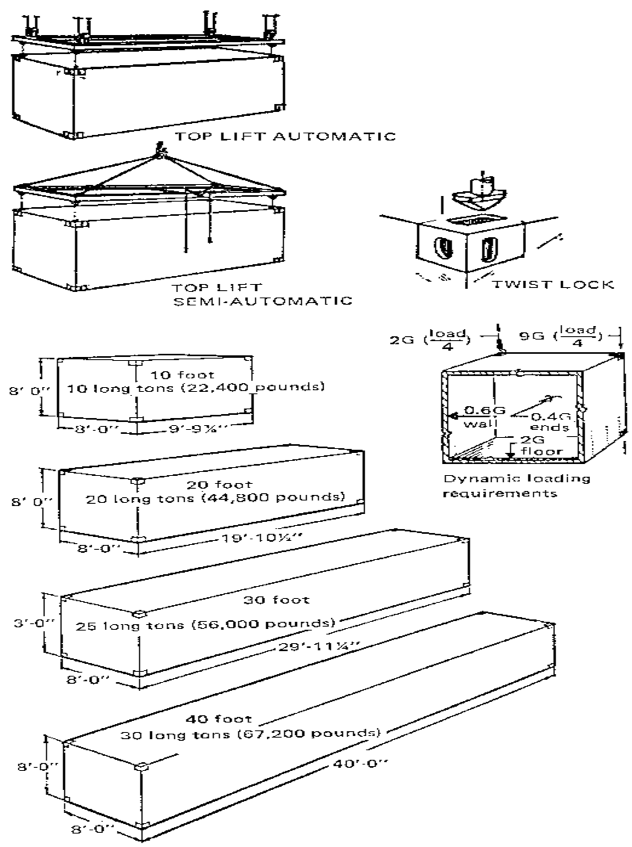

Figure 4: Container Characteristics and Dimensions (Van Den Burg, 1975)

Different types of containers exist in the market today. The most common type is the general-purpose container. General-purpose containers are very popular in trade transportation. Table 1 lists possible container dimensions for two types (steel construction) that are very common in container industry.

Table 1: ZIM Corporation Containers Suitable for Commodities in Bundles, Cartons, Boxes, and any Other Cargo (www.zim.com, 2003).

Size	Weight Kilograms Lbs.			Internal Dimensions Millimeters feet/inches			Vol. M^3 ft^3
Feet	Max Gross Wt.	Tare Wt.	Max Payload	Length	Width	Height	Capacity
20	24,000	2,200	21,800	5,902	2,350	2,392	33.2
	59,910	4,850	48,060	19'4^{23}/64"	7'8^{33}/64"	7'10^{11}/64"	1,172
40	30,480	3,800	26,580	12,033	2,390	2,390	67.6
	67,200	8,380	58,600	39'5^{47}/64"	7'8^{33}/64"	7'10^{7}/64"	2,387

General-purpose containers are the same as dry containers but have a higher volume capacity, like 76, 2 M^3 and 2,690 ft^3.

Another major category is the refrigerator containers. These containers are used to transport temperature sensitive cargo. They are very popular in meat and fruit transportation. Tank containers are another type that are used for the transportation of non-solid materials. Tank containers were initially used for wine and olive oil in the Mediterranean Sea. As a rule containers were used for small cargo between islands and coastal transportation. In recent years however, tank containers have become very popular for chemical cargo. Tank containers carrying hazardous materials are stored in a special location on board for safety reasons. As a rule they have open sides for adequate ventilation.

Bulk containers are very popular today. These containers are used for the transportation of material like gravel and seeds. Finally platform containers are used for the transportation of merchandise that is not affected by atmospheric conditions. These containers are preferable for the transportation of materials such as wood, yachts, etc.

1.3.1 Container Loading Methods

Two methods are used for loading containerships:

a. Vertical "lift on-lift off" in the special cargo holds. Ships have cellular type holds onto which the containers can be latched for extra security.

b. Horizontal "Ro-Ro": containers are rolled on and off the ship either on their wheels, or on trailers, or other wheeled platforms or machines onto which almost any kind of cargo can be loaded.

The cargo holds might have two levels (twindeck) that can be served by special elevators. The unloading procedure can also use escalators to assist in pulling out. Most containers are loaded / unloaded vertically. They are placed in columns in the cargo holds and on the deck of the ship by the port equipment (cranes etc.) or by the ship's own equipment (bridge crane telescopic cranes, etc.) (Kostalas, 1980).

The loading and discharge by ship equipment is not as efficient as operations performed by cranes built in port. However, vessels with cranes have the advantage of being able to service ports that do not possess the proper equipment. It is customary for containerships with less than a 1000 TEU capacity to have cranes on deck. Usually, these ships are preferable for particular areas such as the Black Sea or the Adriatic. Larger vessels are used to carry containers to major hubs leaving smaller ships to service these particular areas. For instance, Piraeus represents a hub for several corporations. One of these, COSCO, uses Piraeus as a hub for large vessels (Shipping and Trade, 2006). Cargo arriving here is shipped to the Adriatic and Baltic Seas using smaller ships.

COSCO either owns these smaller ships or they can be leased from other corporations that service this particular area.

1.3.2 Loading Restrictions

Containers are loaded from the bottom up on the vessel, tier by tier. This compiles with the requirement that containers going to the later ports of call should be stowed under those going to earlier ones. Violation of this condition is referred as “overstowage” (Aslidis, 1989, Avriel et al., 1998, Wilson et al, 2000).

Under-deck bays are usually dedicated to a specific container size such as 20 feet and 40 feet in most cases generally. The loading of two 20 foot containers is allowed above a 40 foot container but not vise versa. In most cases on deck bays loading of a mix of containers are allowed. For instance, 45-foot containers are stowed on deck in a specific bay. Reefer containers can only be stowed in areas with electric outlets, either on-deck or under deck. Hazardous material containers can only be stowed in the bays that have been assigned and which are not close to areas of accommodation.

The containers that are on deck must be secured to the deck before the vessel departs. This should be done so that container movement is minimized as the vessel moves. Usually lashing systems are used for securing a container on deck.

Total container weight in a stack must not exceed a certain strength limit. This restriction often forces some light-weight containers to be selected for on deck stowage. Guidelines for loading containers on the vessel were developed by the Maritime Administration with the help of the Technical and Research Panel 0-31 of the society of naval architects and marine engineers.

1.4 Thesis Organization

The rest of this thesis is organized as follows: Chapter 2 presents the problem statement and discuses the important issues of vessels stability and cargo safety. Chapter 3 presents a survey of research work closely related to this thesis. In Chapter 4 loading model is constructed and a stowage-planning model is developed. Discussion follows on constraints, tradeoffs, and performance goals. Chapter 5 introduces and examines the lower bound techniques. In Chapter 6 different sets of algorithms and techniques used to manage the container information in loading planning are set forth. Chapters 7 and 8 summarize the contributions and results of our work, and indicate some possible future research directions that may be taken.

Chapter 2: Problem Statement

2.1 Loading Characteristics

In this research, the primary interest is the category of cellular containerships. These ships are designed from keel up solely for container transportation. They have fixed cellular construction and the lift-on, lift-off method of handling is used. Containers are loaded from bottom to top of a ship, tier by tier. Container cells are grouped into “bays”. A bay is either “on-deck” or under-deck”. Cell guides facilitate lowering of containers to their proper storage positions and resist horizontal loads exerted by containers as a vessel rolls sideways during its voyage. Under-deck bays are usually dedicated to a specific container size, either 20 feet or 40 feet in most cases. The on-deck bays allow mixes of different container sizes. Refrigerator container (Reefer) can only be stowed in areas of ship with electric outlets, either on-deck or under deck. All on-deck containers must be properly secured to the deck, which can minimize container movements, with possible damages, under vessels’ roaring.

Total container weight in a stock must not exceed a certain deck strength limit. This restriction forces the empty containers or lightweight containers to be selected for on-deck stowage. Also, the total weight of all containers cannot exceed the maximum weight capacity of the containership.

2.2 Ship Stability

This section provides detailed discussion of the vessels stability and safety, which are very important components in the stowage planning. Before going into details of the problem, it is essential to have a basic understanding of the terminology used in vessel design and characteristics. This section presents an overview of the requisite naval architectural terms used in this formulation, along with their definitions, and a brief discussion of the stability and safety issues.

Definitions

Maximum Beam: The maximum molded width of the vessel measured to the outside of the hull frame angle of the channel but inside of the shell plating.

Molded Beam: The maximum breath of the hull measured to the inboard surfaces of the side shell plating of the flush-plated vessels, or between the inboard surfaces of the inside strakes of lap seam-plated vessels.

Deadweight: The carrying capacity of a vessel at any draft and water density. This includes the weights of the cargo, fuel, lubricants, oil, fresh water, stores, passengers, crew, and their effects.

Maximum Depth: The modified distance between the vessel's baseline and the underside of the deck plating of the uppermost continuous deck, measured at the side of the vessel.

Molded Depth: The vertical distance from the molded baseline to the top of the freeboard deck beam at side, measured at mid-length of the vessel.

Light Displacement*:* The weight of the vessel including hull, machinery, outfit, equipment, and liquids in the machinery.

Loaded Displacement*: The* displacement of a vessel floating at the greatest allowable draft.

Freeboard: The distance from the waterline to the upper surface of the freeboard side.

Keel: The principal fore-and-aft component of a vessel's framing, located along the centerline of the bottom and connected to the stern and stern frames.

Knot: A unit speed, equaling one nautical mile per hour, the international nautical mile is 1852 m (6076 ft).

Length between perpendiculars: The length of a vessel between the fore and the other perpendiculars. The forward is a vertical line at the intersection of the fore side of the stern and the summer load line. The after perpendicular is a vertical line at the intersection of the summer load line and either the after side of the rudder post or the sternpost or the centerline of the stock if there is no rudder post.

Service Speed: The service speed is defined as the predicted average speed at which the vessel is expected to operate over its entire life at sea. The prediction takes into account such factors as: the environment, the weather, fouling, corrosion, and any other items that end to reduce a vessel's speed.

Waterline: The waterline is the line of the water's edge when the vessel is afloat.

Stability: The stability of a vessel is its tendency to remain upright or the ability to return to her normal upright position when heeled by the action of waves, wind, etc.

Metacenter: The center of buoyancy of a listed vessel is not on the vertical centerline plane. The intersection of a vertical line drawn through the center of buoyancy of a slightly listed vessel intersects the centerline plane at a point called the metacenter.

The Vessel Hull Form

Vessel hull form refers to the shape of the hull, especially the part of the hull that is covered by water in normal operating conditions. The properties are called hull form characteristics or hydrostatic properties because they pertain to the underwater form of the hull. When these properties are displayed in graphical form, the set of curves is referred to as the hydrostatic curves.

Properties Included in Hydrostatic Curves

The hydrostatic properties are included in hydrostatic curves that are provided by vessel personnel. In this kind of problem the vessel stability is important and since we are taking into account vessel stability as a constraint, it is useful to discus the hydrostatic properties.

1. **Displacement** (Δ)**:** In the United States measurement system, displacement is based on the weight of the vessel and its contents. It is equal to the volume of displacement times the weight density of the water in which the vessel floats. The displacement is calculated as follows:

   $\Delta = \rho * g * Disp$

   where:

   $\Delta =$ Displacement weight
   $\rho =$ Mass density of water
   $g =$ Acceleration of gravity
   $Disp =$ Displacement volume

2. ***Longitudinal center of buoyancy (LCB):*** The longitudinal center of buoyancy is the distance of the center of buoyancy from a specified transverse reference plane, usually the midship section of the vessel. The LCB units are in meters.

3. ***Vertical center of buoyancy (KB):*** This is the height of the center of buoyancy above the baseline or keel.

4. ***Longitudinal center of flotation (LCF):*** The longitudinal center of flotation of the vessel is the centroid of the waterplane about amidships (amidships is exactly halfway between the forward and the after perpendiculars).

5. ***Tons per inch immersion (TPI):*** The tons per inch immersion is defined as follows:

$$TPI = \frac{A_w}{420}(U.S.units)$$

where:

A_w = Area of waterplane shown in figure 5.

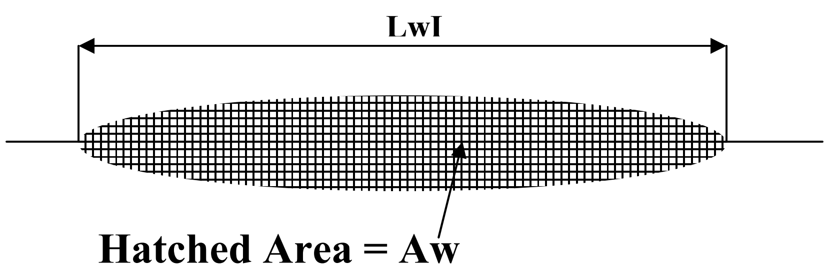

Figure 5: Vessel's waterplane

6. **Change in displacement per inch** $(d\Delta PI)$**:** It is defined as follows:

$$d\Delta PI = \frac{TPI * LCF}{LwI}$$

where:

TPI = Tons per inch immersion
LCF = Longitudinal center of flotation
LwI = Length, waterline

7. *Weight module:*

The lightship weight and its center of gravity are calculated using empirical relations given in literature. All weights are in metric tons, and the center of gravity is in meters.

Weight is broadly classified into three categories:

- Lightship
- Cargo
- Fuel and miscellaneous

The cargo weight is the product of the number of twenty-foot equivalent units (TEUs) and the weight per unit. We discretize the space available for container stowage in the lengthwise, beamwise, and the depthwise directions. The product of the number of TEUs in each direction and a stowage factor accounts for a geometry of the hull form and the space available for container stowage after accounting for the space occupied by the containers cell guides. The lightship weight is composed of:

- ✓ Hull steel weight
- ✓ Outfit and hull engineering weight
- ✓ Machinery weight

The empirical relation for weight is as follows:

The Hull Steel Weight is: (Schneekluth, 1987)

$$Ws = 5905.98 * \left(\frac{CN}{1000}\right)^{1.003} * [1 + 0.49532 * Cb) * [1 + 0.000928 * \left(\frac{Loa}{D} - 8.3\right)^{1.691}]$$

where:

CN = Cubic number = $\frac{Loa * B * D}{100}$
Loa = Length, overall
B = Beam, maximum

D = Depth at side

Cb = Block coefficient = $\frac{Disp}{LwI * B * T}$

Disp = Displacement, volume

LwI = Length, waterline

T = Draft, design

In the stowage-planning problem the stability is very important. A vessel becomes unstable if the vertical, transverse or longitudinal distribution of the vessel's weight is excessively unbalanced. Some stowage plans may result in the instability of the vessel. In these cases, changes of the stowage plans, i.e. rearrangements of containers, are necessary to regain the vessel's stability. While the vessel's stability is affected by various factors, we consider the following important factors:

- Transverse metacentre

Ship stability is a key requirement for safe ship operation and must be considered at the design stage. One of the major issues for ship stability is the metacentre. The position of the metacentre is found by considering small inclinations of a ship about its centerline, (Figure 6). For small angles the upright and inclined waterlines will intersect at point 0 on the centerline. The transverse moment with respect to the centerline must be zero or, at least, between very narrow limits around zero.

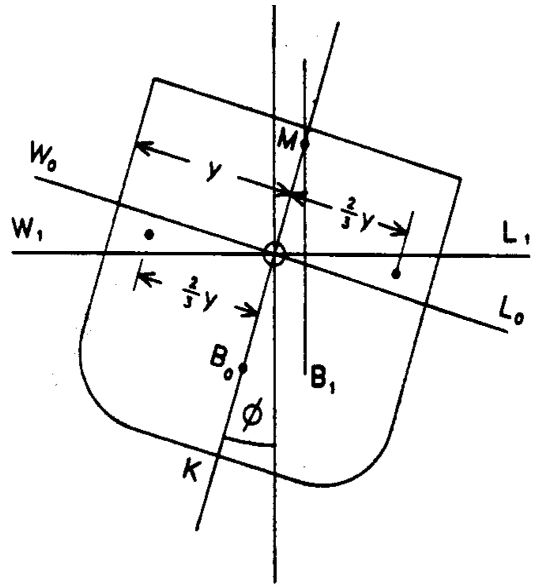

Figure 6: Shape of Transverse Metacentre.

For small angles the emerged and immersed wedges are approximately triangular (Tupper, 1993). The height of metacenter above keel is required to calculate the initial transverse stability.

Referring to Figure 6, KB is the height of the center of buoyancy above the keel. The difference between KM and KG (where G is the center of gravity) gives the metacentric height GM.

- Longitudinal Moment (Trim)

The principles involved are the same for transverse stability but for longitudinal inclinations, the stability is based upon the distance between the center of gravity and the longitudinal metacentre. In general, the trim must be based on specification that provides good performance and safety. The trim must be close to zero. In the case that trim is not close to zero stern trim is preferred to bow trim. The moment to change one inch is defined as follows:

$$MTI = \frac{\Delta * BM_L}{12 * LwI}$$

where:

MTI = Moment to change trim one inch

Δ = Displacement, weight

BM_L = Longitudinal metacentric radius

LwI = Length, waterline

- Metacentric Height (GM)

Metacentric height is the distance between the center of gravity of the ship (G) and the metacentre and symbolized with the letters GM or MG. The position of the metacentre is found by considering small indicators of a ship about its centerline. The position of the metacentre in relation to the center of mass of the ship determines the type of balance of the ship (Figure 7).

- ✓ When M is above the of center gravity (G), we have positive metacentric height and stability.
- ✓ When M is under the center gravity (G) , we have negative metacentric height and lack of stability
- ✓ When M is in at the same level with the center gravity (G) and we have neutral stability.

Satisfying this constraint implies placing the heavier containers at the lower rows. However, we cannot have very large metacentric heights because the righting lever becomes very high and causes the vessel to have a short rolling period. Quick rolling periods are very bad for the cargo and worst for the crew.

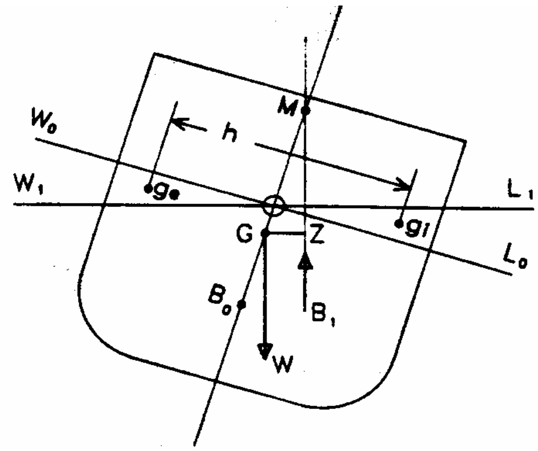

Figure 7: Metacentre and GM in Small Angle Stability.

Loading the heaviest container in the lower rows, may conflict with the objective of minimizing the container re-handling if the heaviest containers are those that are going to the nearest destinations. The minimum cost requires that the containers that will be unloaded first be placed at the upper rows.

- Structural stresses

The structural stresses allowed on the keel and on the deck are constrained to be less than the maximum ones approved for the ship by the ship's classification society.

- Deck Strength

It is possible that a stack of containers on deck weighs more than the deck structure can bear. In this case the number of containers per stack must be restricted.

- Raking Strength

The containers are aligned and stacked according to weight in order to avoid collapse. In stacking containers these collapse limits must be considered especially if they are placed on the deck.

- Refrigerated Containers

These containers carry refrigerated food and products. These containers are located in specific areas on vessels` near the vessels' power outlets. Usually the power outlets are on the deck in the lower rows.

- Container support

Containers of similar size and shape are stacked together so that they are supported on all four corners. This does not allow containers of different lengths to be stowed in the same stack.

- Chemical (hazardous) Container

A minimum distance between hazardous containers must exist.

In container loading not all the above constraints have the same importance. Furthermore, there may be constraints rising from different port facilities, which can restrict the possibility of using the full capacity of the vessel. In the era of 9000 TEU`s containerships certain ports might not be deep enough to handle these kinds of ships. Generally, the most important constraints are those related to the trim, stability and strength of the vessel. These constraints must be satisfied in any vessel's departure. In the past few years a few accidents in which those containerships broke in two were attributed to incorrect stowage planning and stability measurements. For instance, the containership "Han Se" capsized outside of South Korea on April 10, 2000 (Lloydlist, 2006)

2.3 Definition of Overstowage

Containerships make repeated tours of a series of ports according to their planned routes. At each port containers are unloaded and additional containers are loaded on board into stacks. A container is only accessible if it is on the top of the stack. Time duration required for loading and unloading depends on the arrangement of the cargo on board, referred to as the stowage plan (Aslidis, 1990), which specifies where each container is assigned on board. Stowage plans, if not prepared well enough, may cause unnecessary handling time, required for temporary unloading and re-handling of containers from or onto the vessel. Consequently, port efficiency and vessel utilization are largely affected by stowage plans. Overstowing is defined as follows. A container C destined to port $j+1$ of a column e is overstowed when it blocks the retrieval of another container C^* destined to port j and port $j+1$ is later on the schedule than destination port j of container C^* (Aslidis, 1989).

This research deals with the management of overstowage. In general, shifting is caused by overstowage, which denotes the situation when containers that should be unloaded at the current port are placed under other containers that should go further in the vessel's route. In this case, the latter containers should be temporarily unloaded in order for the former containers to be unloaded at the current port. These temporarily unloaded containers, commonly referred to as a overstowage, must then be re-loaded before the vessel departure from the port.

Also, movements of port cranes are affected by the distribution of containers on the containership. If containers with the same destination are spread over the containership in different bays it takes a longer time to unload the containers than the case in which those containers are placed as a group. A potential stowage plan for one section type is presented in Figure 8. For each column container information is specified.

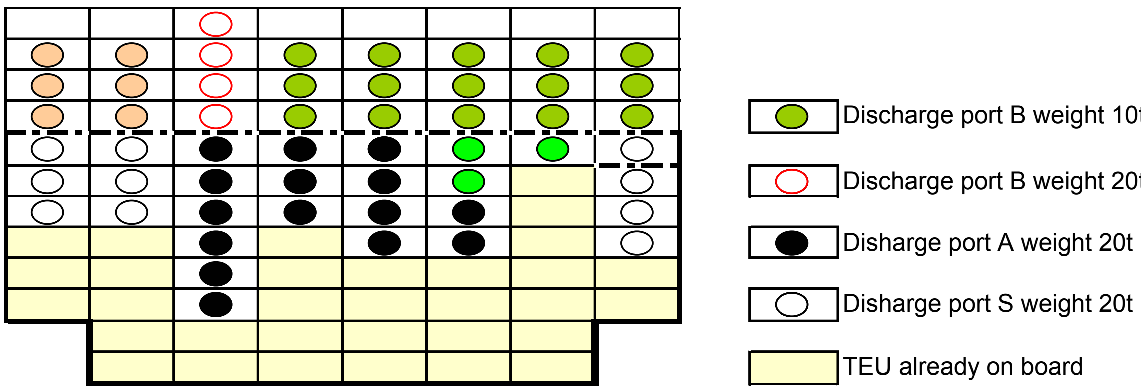

Figure 8: An Example for a Stowage Plan Provided by the Operational Office

Overstowage is a condition that arises in any stacking operations. The low cost of storing items in stacks is balanced by the limited accessibility of the items. Overstowage occurs when one item that is scheduled to be retrieved is under another item scheduled to be retrieved later. The item that has to be moved is overstow. Several reasons can be identified for overstowage:

- If containers become available for storage at different times
- If schedule of delivery is not known in advance
- Wrong stowage planning

In the first two cases it is very difficult for overstowage to be avoided. However, it can be minimized. Avriel et al., (2000) modeled the containership's single bay as an array with k rows and e columns. There are J ports. The following example demonstrates the main idea of the overstowage. In Figure 9 container A has to be retrieved in time T. However containers $B1$ and $B2$ have to be re-handled at that time so that A can be retrieved. The example set forth in Figure 9 demonstrates the basic concept that is what items have to be rearranged in order to minimize the total number of item rearrangements over a certain period.

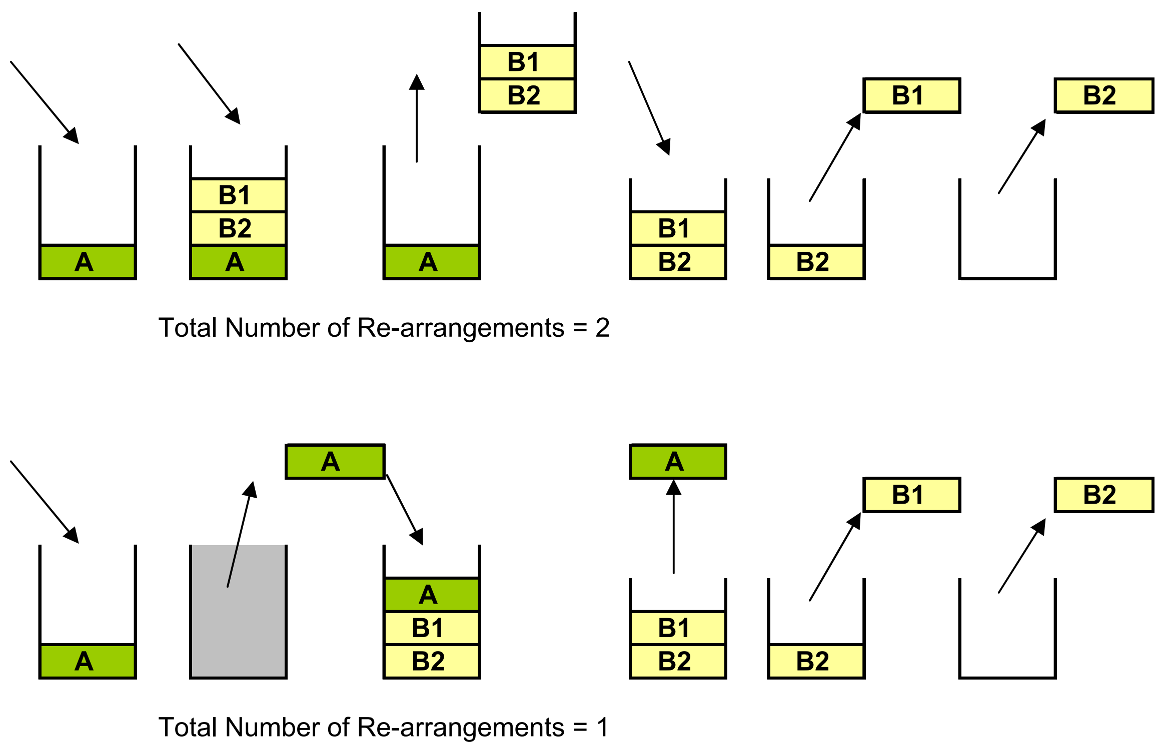

Figure 9: Items to be rearranged

It is worth mentioning in the above example that it is not logical to place container $B2$ above $B1$. Were the latter done then, an additional overstowage happens that is a wrong planning. It is apparent from the above that a usual place in which overstowage situations arises is stacking items in warehouses. However, this work is motivated by a different application, which is the field of containership operations. Other contexts in which overstowage happens are presented in the next section.

2.4 Other Causes for Overstowage

Container operation is not the only area facing the extra handling cost, called overstowage. Overstowage is present in all circumstances involving operations, in the industry or in routing/circuits on the telecommunication network. Stacking in marble factories and warehouses is another very common area where overstowage occurs (Schreiner, 2003).

The marble industry needs huge open storage areas for marble stock. It is very common to rearrange stock reflecting orders that each industry has. As a rule some gains can be made from blocking the rocks by color and point of origin. However, it is very common that the first rock at the lower level is needed to satisfy requirements for a particular order.

The operation of warehouses involves the arrival of purchases and their subsequent regaining later on (Christofides, 1989). Suppose that the next day's shipments are retrieved overnight and are placed in a standby area awaiting pickup. Similarly, assume that the items that arrive during the day are stored in the standby area as well. The latter area is placed in the warehouse main storage area during the night (Figure 10). This kind of operation resembles the one in which a vessel is visiting a series of ports. Imagine that the vessel is the warehouse, which "travels" in time and visits a series of "days" (ports) (Beasley, 1989). Fortunately, many of the constraints described in the containership (i.e. stability constraints, vessel constraints, etc.) operation do not apply.

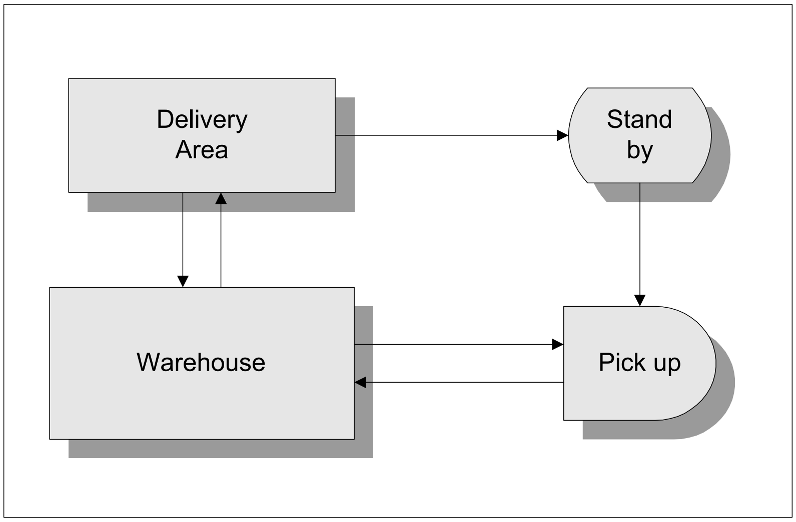

Figure 10: Warehouse model with overstowage

A case similar to a containership visiting a series of ports comes up when a truck visits a series of locations where it loads and /or unloads boxes stored in stacks. Of course, the scale of the problem is smaller (fewer stacks) and again most of the constraints that apply in containership problem, such as trim constraint, do not exist here.

The concept of stacking does not require the stack to be physically vertical. Any linear arrangement with only one access point may serve as a stack. A typical example is parking garage operation as shown in Figure 11.

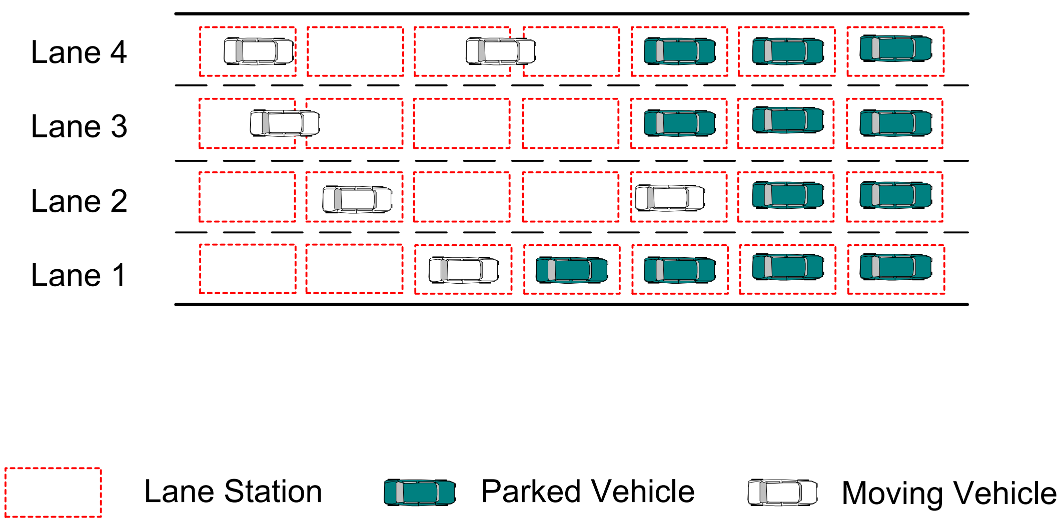

Figure 11: Horizontal storage example - parking garage

In this case the stacks are horizontal. Another example of horizontal stacking is in a railway transportation system. As in many other transportation systems, there are spatial imbalances in the freight flows. Intermodal facilities or terminals ship out a different amount of goods than they receive, and some receive more than they ship out. Therefore, the arrangement of train tracks in the storage yard is very important. The same situation may arise in container terminals that use chassis to move containers around. A somewhat different view of overstowage appears in the following situation. Suppose that there exist a number of tools, say, M. These tools are stored in a stack. Every time a tool is to be retrieved and used, all tools that block it have to be removed. After being used, the tool is restocked. Removing a tool costs a certain amount of time and money. If the frequency by which each is used is known, a natural consideration would be the order of items in the stack that minimizes the expected cost (time or money).

In another version, let's say that the sequence by which the tools are used is assumed known. Again, the question is "what is the order that minimizes the rearrangement cost?" These problems define the class of "use-and-restock" problems. This is to be contrasted with the type of problems introduced earlier (containership, warehouse) which define the class of "pickup-and-deliver" problems since the items come on a stack for a certain period of time, and then, go off for ever (Aslidis, 1990).

There are many variations of overstowage problems that can be constructed. All of them have a combinatorial nature. Consequently, their solution requires techniques from the field of combinatorial optimization. Undoubtedly, this class of problems is very interesting from both the theoretical and practical viewpoint. It appears that overstowage problems are hard in the general case (Wilson, 2000). Special or restricted versions of them can be solved efficiently, though.

A more promising way to handle the allocation of containers to stacks is to describe the list of items in each stack at a particular time. Items can still be individually identified. The problem can be expressed as a series of assignment problems of items to stack position at the time of interest. Inspired from the short description of the state of the stacks, solving the loading problem subject to the placement constraints (as in containership operations) appears to be a different task because of the knapsack nature of the problem. The objective of this thesis is to study the optimal loading on containership. The presence of side constraints may obscure the aspects of the pure loading problem and add difficulty. As the literature survey in the following chapter reveals, very little research has been done on this problem and on the problem of minimizing overstowage costs.

2.5 Problem Statement

Stowage planning is important in the design, load planning and techniques in the containerships and in maritime industry in general. While the users' demand for improved and more sophisticated models of inventory and allocation increases rapidly, improvements in stowage planning come at a slower place. Therefore, the possibility of designing a control function (such as stowage, and allocation mechanisms) in a way that takes into consideration safety and minimum overstowage, presents a novel opportunity.

This research is motivated by a stowage planning problem with integrated optimality criteria. The cost of stowage of the units (containers) is minimized when certain units are scheduled "close" to each other. For example, the units may overlap in the work needed to accomplish them and the design of effective stowage policies must take these overlap into consideration.

A crucial design in the maritime industry is that of stowage planning. Due to the importance of the container loading accounting for different container types over multiple container destinations may require better planning. On the other hand, multiple journeys could result in significant overhead and routing complexity along with utilization of a larger amount of network nodes (ports), thereby potentially increasing the overall complexity. The use of good heuristic procedures can give very good results in a reasonable computing time.

Motivation comes from containership operations that include the most difficult aspects of loading. The focus of this work is to develop an optimization method and algorithm for optimal loading of containerships to minimize the extra handling cost. Our objective is to minimize the extra and un-necessary container movements on board during the loading and unloading procedure. This translates into minimizing the time at port per vessel call.

With modern containerships carrying several thousands of containers (in the range of 8,000), margins for improvement exist. The containers on board are placed in stacks. Access to these stacks is possible only from the top. In fact access to stacks below the deck requires clearing the hatch (deck cover) that leads to the components below the deck. The stacks on board create the overstowage. Containerships visit (call at) ports in which they pick up and deliver containers. The time it takes to load and unload a container is usually two to four minutes. Therefore, if 50 to 150 re-handlings at each port can be eliminated, the amount of time saved in one year would be approximately three days. This represents about a 1% increase in the productivity of the vessel (measured in container miles per year).

In this research, we plan to develop an optimization model that includes a set of rules, guidelines, and constraints which must be met, including:

1. Strength requirements of the vessel structure. This requirement is extremely important for the strength limit of the vessel construction. In addition, this requirement accounts for the limit on the bending and shear stresses that are developed along the vessel.
2. Stability requirements of the vessel. These constraints are very important for vessel stability.
3. Cargo constraints: This requirement accounts for the fact that different containers must be placed in different positions. For instance refrigerated containers must be placed at positions supplied with power outlets.

4. Container stability constraints: these constraints account for the fact that the stack of containers must have a height limit, because the containers at the bottom should be able to carry the weight of the containers above them.
5. Cargo adjacency constraints: these constraints take into account regulations related to hazardous cargo. For example, reacting cargoes cannot be placed in adjacent positions.

A similar conclusion can be drawn from the perspective of port operation. The same saving of container re-handling corresponds to a greater percentage of port time. If 50 re-handlings are saved per ship call, and if the latter involves the pick up and delivery of 1000 to 2000 containers, then the savings may reach to 5% of port time. Generally, port time goes down in direct proportion to the number of container re-handlings saved.

The main difficulty of any mathematical model using real world constraints is the large number of variables used. For instance, if SV is the number of available positions on board and CV is the number of containers we want to ship, SV*CV variables should be defined. It is clear that with a vessel carrying more than 1000 TEU`s, the number of required variables is greater than 1,000,000. The number of variables relates solely to the assignment part of the problem. Figure 12 simplify the problem formulation by introducing the concept of virtual container (or blocks) as defined in the previous sections. Even this virtual representation of the container assignment in each station/bay shows the number of the possible variables. Therefore with this number of variables the use of any formulation to handle large-scale problems is virtually impossible. A heuristic is therefore introduced to produce a solvable model for medium and large-scale problems.

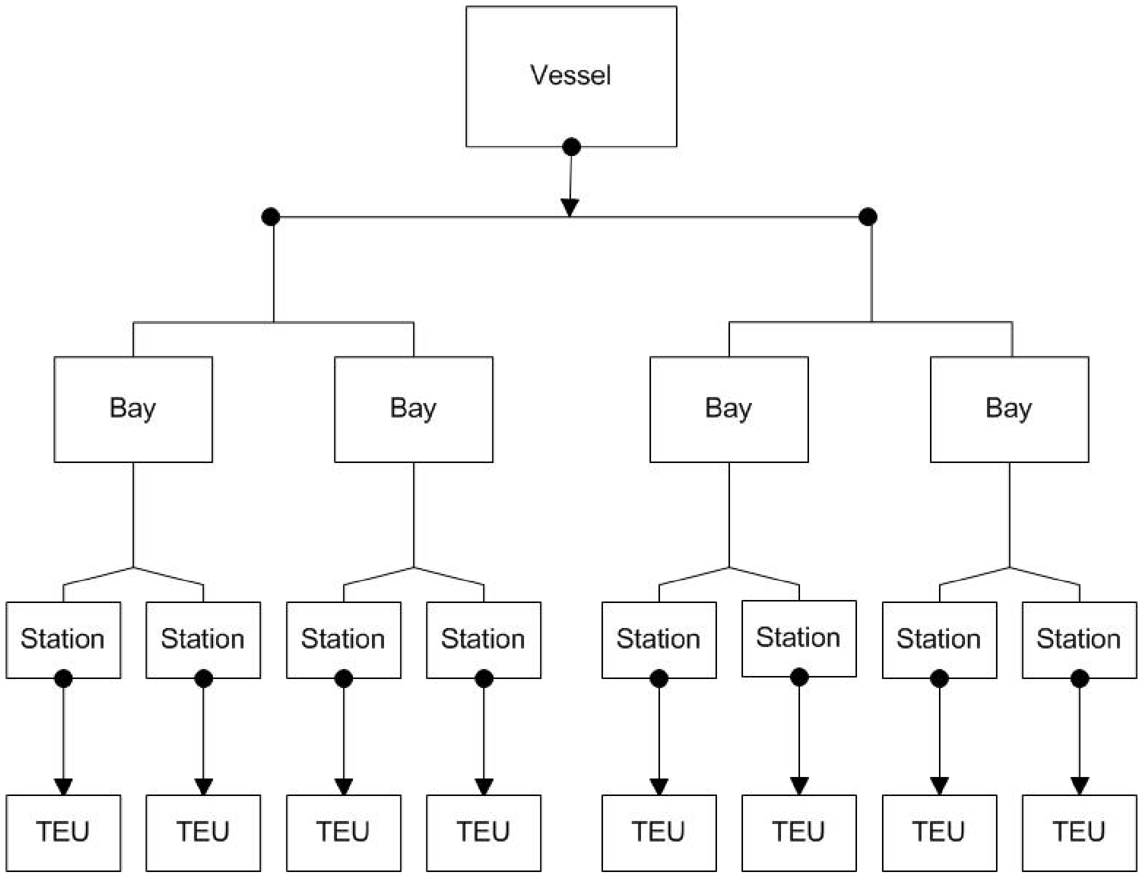

Figure 12: Virtual representations of the container assignment

In our research we use a fixed geometric configuration for ships. For instance, we are using the normal cross cutting configuration as shown in Figure 13. Note the stacks above and below the deck of the containership.

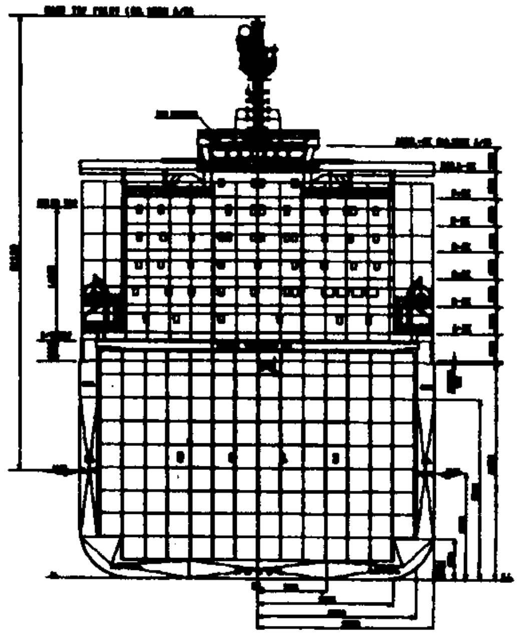

Figure 13: Containership cross-cut section for 5,500 TEU(Εφοπλιστης, 1999).

2.6 Research Objective and Scope

The major goal of this research is to formulate a realistic stowage planning problem and find an efficient solution algorithm for container loading as described in Section 1. In order to achieve the purpose of this research, the following objectives will be pursued:

- Development of a mathematical model for stowage planning model (container loading) stated in Section 4.4. This model will be used for finding the exact solution.
- Development of a heuristic algorithm for container loading. The heuristic algorithm must find a good solution to the problem within a reasonable time.

- Conducting extensive testing to examine the performance of the proposed model and solution approach.

2.7 Research Contributions

Driven by the ever-increasing demand for container transport, the lagging capacities of container loading procedures, and the capabilities of emerging operations in the network, this thesis broadly addresses the problem of container loading into the containership. It capitalizes on the scalability potential of container loading from the container terminal (Dock) to thousands of clients.

Stowage planning has been investigated by a few researchers, along with a number of related issues.[1] This thesis focuses on stowage planning for containership regulated by safety constraints. So far, every technique proposed for this planning follows a common thread: There is an assumption that the users are fully aware of the safety constraints used to produce a static data loading schema. The premise of these approaches is that users provide loading plans, which are compiled to derive the stability pattern. While this may be suitable in some instances, it is not applicable when the interests of the client changes and when the container load is huge and definitely require optimal solutions, at the appropriate time.

The key contributions of this dissertation are as follows.

- A mathematical model is developed which considers all operational constraints. After discussing the advantage of the model, we make test cases and we study the results.

[1] For a survey refer to Chapter 3

- The mathematical model is used to develop a procedure to obtain lower bounds for the optimal objective function values.
- A heuristic procedure is introduced that essentially disguises the problem of loading to the stowage-planning problem. The special properties of this planning are identified, a discussion of its performance is offered and basic management principles are set. The general goal of stowage planning is to minimize the unnecessary shifting of containers on board. Based on this algorithm, updates are made, which are intended to offer optimum guidelines with respect to safety, stability, and maritime law requirement.

All proposed algorithms and mathematical models are validated with experimental results drawn from a detailed model of the loading operation. In all cases, these results demonstrate the stability, flexibility, and efficiency of the model, and establish its potential as a versatile and practical method for large scale container loading.

Chapter 3: Related Work

3.1 Literature Survey

Stowage problems have been subject of research since the early 1970's and a small amount of literature has been created in this area. At the same time, starting with the first worst case analysis of the performance of an approximation algorithm in 1966, (Graham, 1996), there has been a significant progress in the development of methodologies for designing efficient algorithms for NP-hard problems. Recently there has also been much progress in our understanding of the extent to which near-optimal solutions can be efficiently computed for NP-hard problems. Despite the impressive amount of literature that exists in the area of heuristic algorithms for loading problems not much work has been done in solving loading problem in the containership (Wilson, 1999). Broadly, our work falls in general research area of container shipping industry. In the following I will outline the research that exists in related areas.

3.2 Literature in Container Loading

While the container-loading problem has now been explored for more than three decades, not many papers can be found in the literature. The first study about this problem was done by W.C. Webster and P. Van Dyke, of Hydronautics Inc. (Aslidis, 1989). Their work focused on the loading / unloading process and it was presented at the Computer Aided Ship Design Engineering Summer Conference at the University of Michigan in 1970. In their study, the stability constraints of the vessel are important. The flexibility one has in allocating the cargo on board is also given great attention. Through their work they hope to optimize the operation of the ship and the container system. The overall system is divided into components – the "ship" and the "container". Each component is assigned optimal goals. For the ship they include (a) having desirable longitudinal, vertical and transverse centers of gravity to satisfy stability or trim constraints; (b) the ballast must be as little as possible to satisfy the stability constraints; and (c) utilization of consumables while underway to maintain this desirable conditions.

The containers are grouped in blocks based on the destination port. The containers for further ports are loaded in lower rows. The paper has 3 steps: first, general characteristics and assignment of containers by destination, second, the schedule of container loading for the next route and third the decision of the loading and unloading sequence for the next route. This study does not follow the optimal solution procedure and the presented method was not tested. Also, it was the first in analyzing containership operations. However, the heuristic that was developed was simple and not completely tested and real results are not available.

The first major study came with the adoption of the Computer-aided preplanning system (CAPS) by American President Line (APL) in 1981. This system, explained by Shields (1984), uses simulation techniques and human interaction to provide possible vessel plans. This work took a completely different approach to the problem. Different loading patterns were randomly generated and analyzed. To minimize the possible large number of inefficient loading patterns the process was tweaked to produce favorable results. The criterion through which a specific loading was generated was selected randomly among a set of criteria.

Each pattern produced was evaluated based on the increase of time in handling of containers. Each increase was assigned a penalty. An even larger penalty was assigned to violations of constraints. Patterns with the least amount of penalties were selected (Shields, 1984).

Patterns for loading containers of the next port were developed using the strategy of starting points. The procedure was repeated at each port. At the end the least costly solution was adopted. This algorithm considers many parameters and satisfies them equitably well. However, it does not guarantee optimality. Moreover, the selected solutions at each port are not necessarily the best. This algorithm stays more in probabilistic view of the problem. The probability to find a better solution increases when we can run more combinations of loading patterns. However this requires greater processing time and power.

The PhD thesis by Aslidis in 1989 deals with the minimization of the overstowage cost in stacking operation. The one-stack overstowage is examined first. The algorithm is based on the property of the problems that decompose under certain assumption into smaller size problems. The algorithm runs in O (M^3) polynomial time, where M represents the number of ports for the containership problem. The multi-stack overstowage problem is examined in the second part of his thesis. His analysis leads to a set of heuristic algorithms. These heuristics try to solve the container case without stability or placement constraints. He also looked at other stacking operation that he tried to solve under certain assumptions.

Botter and Brinati (1992) developed a mathematical model for the stowage problem. While the model shows the complexity of the problem it has many limitations. Therefore, it cannot be guaranteed that an optimal solution can be found for a vessel in a reasonable time.

A simplified mathematical model for the stowage-planning problem was presented by Avriel and Penn in 1993. They developed a 0-1 binary linear formulation that can find the optimal solution. The model used the General Algebraic Modeling System GAMS software, but they found out that using this model is quite limited because of the large number of binary variables that were needed for the formulation. In addition, the authors developed several heuristics algorithms to solve the problem. The one presented here is based on a reduced transportation matrix. The model tries to minimize shifting without considering stability constraints.

Todd and Sen in 1997 developed an algorithm for container loading. The authors compared the containership-loading problem to the Traveling Salesman Problem (TSP). They concluded that unlike the TSP problem the numbers of containers are usually less than the numbers of possible locations and this makes the problem more complex. The model is tested in simplified versions of the problem. The authors used a genetic algorithm to solve the problem. Several of the objectives were combined to form a single criterion and others were omitted. The GA is able to produce a range of configurations with generally good properties. However, the nature of the algorithm prevents it from being able to deal with a single mis-positioned container.

Avriel et al. (1998) treat the stowage-planning problem as a two-dimensional stacking problem, and give a heuristic procedure called the suspensory heuristic procedure for the objective of minimizing the number of shifting operations. However, they assume that there is only one large cargo bay in a vessel without considering constraints related to batch covers and the stability of the vessel.

Kaisar, in his MS thesis in 1999, examined a simplified version of containership operation. He assumed that a vessel visits a series of ports of which, at the first port the vessel is totally empty. The mathematical model presented addresses the complexity by considering many factors, such as longitudinal moment, trim, and metacentric height (GM). This model does not take into account any other hydrostatic requirements. The model deals with containers with same dimensions, but considers a variety of different weights. The model first assigns containers to available positions. If the GM and the trim are not within the specifications, then the containers are re-assigned. Positions are assigned through column interchanges taking into account that the water ballast must be kept to a minimum. Iterations continue until requirements are met.

The proposed formulation is tested in a variety of example problems using different networks of ports. It provides good results in a reasonable computational time. This mixed integer-programming model is based on minimizing the extra container handling cost (Kaisar, 1999).

Wilson and Roach (1999) presented a methodology for generating automated solutions to the containership stowage problem. Cranes were taken into account, with tests assuming two cranes being available at the berth. They developed a tabu search combined with a packing heuristic based on the conceptual processes employed by human planners. They summarized their results and highlighted how incorporating modern heuristics (such as Tabu search) in a traditional heuristic can give good results even if the solution is not optimal. The standard heuristic for crane usage is to make sure that any port specific crane limitations are taken into account and to make sure that cargo for a given port is blocked in such a way that crane usage is maximized.

Steenken et al. (2001) considered the ship planning problem at maritime container terminals where containers are loaded onto and discharged from containerships using cranes. The container transport between the containerships and the yard positions in the terminal is carried out by a fleet of straddle carriers. Based on a stowage plan provided by a shipping company, the dispatcher assigns containers to specified positions. Then, subject to operational constraints, he schedules containers in order to avoid waiting times at the quay cranes. They considered the cranes in their model. Based on the availability information of cranes, a crane split can be computed by solving a partitioning problem with some operational side constraints. They presented computational results based on real-world data of a German container terminal. Moreover, they discussed some real-time and online influences on the daily dispatch situation.

Also, Imai, et al. (2002) studied the problem from two different points of view. First, they consider the ship stability and second the number of necessary container re-handling. The paper did not give an inferior solution set for the containership loading. They developed two types of mathematical formulations: a linear and an integer programming. The authors did not guarantee that their model always obtains feasible solution in terms of GM, and the computational time is reported to be very high.

Dubrovsky et al. (2002) used a genetic algorithm for solving the stowage planning problem of minimizing the number of container movements. They used parallel implementation for their research. The GA approach is ideal for parallel implementation. Using parallel processors in their research they were able to speed up the process considerably. A compact and efficient encoding of solutions is developed, which reduces the search space significantly. The efficiency of the suggested encoding is demonstrated through an extensive set of simulation runs. This algorithm is much more suitable for handling real life containership stowage problems and may be further developed to include all ship constraints.

Kim et al., (2002) focused on the stowage problem with the objective of minimizing the time that containerships spent in port terminals, or equivalently, a weighted sum of the number of shifting operations and the frequency of required crane movements, which are major factors that influence the time. In this study the stowage planning problem is partitioned into two sub-problems, the problem of assigning container groups to holds and that of determining specific positions or slots for the containers assigned to each hold. The container group denotes a set of containers with the same port of origin and the same destination and the same weight, but it includes the time required to move crane from one bay to another. In this study the sub-problem referring to assigning the cargo in holds is formulated as a mathematical program which is similar to that of the fixed change transportation problem. The other sub-problem referring to the cargo to the particular slot is defined and solved based on a tree search method. Although, the authors considered several aspects or characteristics of cargo handling operations at ports to make the research practical, there are still more to be done. In this study they considered only one standard type of containers, but there are containers of various sizes.

Ambrosino et al., (2004) proposed a linear programming model for a bay plan problem that is the problem of finding optimal plans for stowing containers into a containership, with respect to a set of structural and operational restrictions. They presented a heuristic approach that relaxes some relations from the model and gives prestowage rules to solve this combinatorial optimization problem. In particular, they split the set of available locations of the ship into different subsets and focus the stowage of containers within them depending on their features and handling operations. Also, this linear programming model is aimed at defining the stowage planning only for standard containers.

Finally, Ambrosino et al., (2006) presented a decomposition approach that allowed them to assign a priori the bays of a containership to the set of containers to be loaded according to their final destination, such that different portions of the vessel are indecently considered for the stowage. They checked the global vessel stability of the overall stowage plan and look for its feasibility, by using an exchange algorithm which is based on local search techniques. However, in the proposed approach they assumed that the vessel starts its journey in the problem for which they are studding the problem, and visits a given number of other ports where only unloading operations are allowed that is they are only concerned with the loading problem at the first port.

3.3 General Literature on Loading and Re-handling Problems

3.3.1 Bin-Packing Problem

The loading problem is now well recognized in the literature and has become widely used in a variety of transportation operations. Most of this work has been done for container loading (as bin packing problem). A few papers from the bin-packing are reviewed here. Some of the papers formulated the problem as a zero-one mixed integer-programming model. They include the consideration of multiple containers, multiple cartons sizes, and carton orientations.

Scheithauer in 1992 considers three-dimensional problem of optimal packing of container with rectangular pieces. The author proposes an approximation algorithm based on the forward state strategy of dynamic programming. A good description of packing is developed for the algorithm, and some computational experience is reported.

Tarnowski, et al., in 1994 developed a polynomial time algorithm for solving the two-dimensional cutting stock problem where all small rectangles are of the same dimensions. The authors tried to solve the major problem by decomposing it into three subproblems. The authors used dynamic programming to solve two of the sub-problems in polynomial time, and the third used a search algorithm (TINOS). The reason that the authors used a polynomial time algorithm is because the algorithm that they developed requires the minimization of linear modulo functions.

Scheithauer, and Terno in 1996 developed a new heuristic for the two-dimensional pallet-loading problem. The heuristic structure tries to generalize the structure of packing patterns, which requires the same organization of packed boxes within each box. The heuristic gives optimal solution and solves all instances where at most 50 boxes are contained in optimal packing. The algorithm runs in polynomial time.

Faroe, et al., in 1999 developed a heuristic for three-dimensional bin packing problem. The presented algorithm decreases the number of bins. Each time the search for a feasible packing of the boxes was guided local search (GLS). The procedure terminates when a given time limit is reached or the upper bound matches a precomputed lower bound. The algorithm can be applied for two-dimensional problem as well.

3.3.2 General Literature on Re-handling Problems

In order to speed up the loading operations of export containers onto vessels, the rearrangement operation is very important. The re-handling work influences the performance of transfer cranes significantly in a container terminal. There are very few research results published about the re-handling operation. Cho (1982) developed a methodology for containership load planning. McDowel et al. (1985) analyzed container handling operations and focused on re-handling problem. Watanabe (1991) suggested a simple method to estimate the number of re-handles. Kim (1997) proposed a methodology to estimate the expected number of re-handles to pick up an arbitrary container. In addition, the author estimated the total number of re-handles to pick up all the containers in a bay for a given initial stacking configuration. Kim and Bae (1998) proposed a methodology to convert the current bay layout into a desirable layout by moving the fewest possible number of containers and in the shortest travel distance. The authors divide the problem into three sub-problems including the bay matching, the move planning, and the task sequencing. In addition the authors suggested a basic mathematical model for each sub-problem.

3.4 Balanced Loading

An important consideration for loading is balance. Currently, load planners rely on rules of thumb for loading vessels, trucks, and aircrafts. Computerized systems such as those described by Cochard and Yost (1985) and Martin-Vega (1985) are used to help solve the higher-level problem of assigning cargo on planes. Zhang, Amiouny, Bartholdi III, and Vande Vate (1992) developed a heuristic for a problem motivated by the loading of aircraft or trucks: pack blocks into a bin so that the center of gravity is as close as possible to a target point. The heuristic also works when non-homogeneous blocks are loaded into a bin of nonzero and possibly non-homogeneous mass (Zhang, et al., 1992). Mathur in 1998 presents an efficient algorithm for a one-dimensional loading problem. The goal is to pack homogeneous blocks of given length and weight in a container in such a way that the center of gravity of the packed blocks is as close to a target point as possible. The proposed algorithm is based on the approximation of this problem as a Knapsack problem. This algorithm performs better on randomly generated problems (Mathur, 1998).

3.5 Heuristic Algorithms for Stowage Problem

Not many heuristic methods have been applied to this problem. For stowage problem once an efficient estimation is obtained for the performance of the system, a search of the parameter space to find the optimal values will be required. This section presents the modified algorithms that could be used, taking into account the complexity of the system.

3.5.1 Simulated Annealing

Simulated annealing is a technique that first became very popular in the mid of 1980`s (Kirkpatrick et al., 1982). The simulated annealing technique can be viewed as a general approach for solving hard combinatorial optimization problems through controlled randomization problems (Eglese, 1990). In addition, simulated annealing adopts the analogy between the physical annealing process of solids and that of solving combinatorial problems. This technique is similar to local search with the added advantage of not being trapped in local optima. The local search strategy starts with an initial solution, which is then perturbed in an attempt to improve it. It works by allowing for the escape from local optima, with the possibility of reaching a global optimum, by allowing uphill moves. In addition the algorithm allows moves to inferior solutions under the control of a randomized scheme. Specifically, if a move from one solution x to another neighboring but inferior solution x' results in a change in value $\Delta\varepsilon$, the move to x' is still accepted if:

$$\exp\left(-\Delta\varepsilon / T\right) < R$$

where T is a control parameter, and R is a uniform random number between (0,1). The parameter T is initially high, allowing many moves to be accepted, and it is slowly reduced to a value where inferior moves are nearly always rejected. There is a close analogy between this approach and the thermodynamic process of annealing in physics. Simulated annealing is a simple procedure to apply. However, there are several decisions to be made in applying it. Usually, simulated annealing can be implemented in combinatorial problems by using a simple neighborhood solutions, a starting temperature suggested by some small scale initial experiments, and a simple cooling schedule, and then makes further improvements.

3.5.2 Tabu Search

Several schemes for incorporating nonimproving moves in improving search without undo cycling have proved effective on a variety of discrete optimization problems. One is called Tabu search and was first introduce by Glover in 1993 and has been used to solve many practical problems that arise in real world applications.

The basis for Tabu search is described by Glover. Given a function $f(x)$ to be optimized over a set, X , Tabu search begins in the same way as an ordinary local search, proceeding iteratively form one point (solution) to another until a given termination criterion is satisfied. Each $x \in X'$ has an associate neighborhood $N(c) \subset X$, and each solution $x \in N(x)$ is reached from x by an operation called a move.

The quality dimension refers to the ability to differentiate the merits of the solutions visited during the search. Quality is a foundation for incentive-based learning. The flexibility of these memory structures allows the search to be guided in a multi-objective environment. In tabu search, a neighborhood of current solution is generated through different classes of transformations. Unlike classical local search heuristics, Tabu search does not stop at the first local optimum when no improvement is possible. The best solution in the neighborhood is always selected, even if it is worse than the current solution. This approach allows the model to escape from local optima and explore a larger fraction of a feasible region (Glover, 1997).

To avoid cycling, transforming to solutions recently visited during the search are forbidden. To achieve this goal, a data structure known as a Tabu list stores the recent search trajectory.

3.5.3 Genetic Algorithms

Another method for avoiding optima in improving search is known as genetic algorithm and it has been used in container loading (Dubrosky et al, 2001). The original aspiration for genetic algorithms comes from the population genetics. The metaheuristic genetic algorithm uses a collection of solutions, from which using selective breeding and recombination strategies, better and better solutions can be produced. Simple genetic operations such as a crossover and mutation are used to construct new solutions from pieces of old ones, in such a way that for many problems the population steadily improves. It many applications, the component vector or chromosome is simply a string of 0`s and 1`s. Goldberg (1985) suggests that there are significant advantages if the chromosome can be structured.

The best single solution encountered so far will always be part of the population, but each generation will also include a spectrum of other solutions. Ideally all will be feasible, and may be nearly good as the best abstraction in terms of the objective function. New solutions are created by combining pairs of individuals in the population. Local optima are less frequent because this combining process does not center entirely on the best solution. In order to generate automatically strategic stowage plans and explore the application of artificial intelligence to cargo stowage problem, Wilson et al., (2001) used a genetic algorithm (GA) approach.

3.6 General Literature

Another area of research in which the loading procedure is of great interest is the Traveling Salesman Problem. Many researchers have studied this problem in different ways and approaches. Ladany and Mehrez (1984) considered a form of the Traveling Salesman Problem in which overstowage costs are also included. This problem is very common in large delivery corporations that deliver merchandise door to door (Ladany and Mehrez, 1984). Researchers have taken different approaches based on dynamic programming. These approaches can be regarded as extensions of the Christofides

(1981) state space relaxation method to problems with time windows. Problems with up to 15 customers have been solved to optimality.

Usually trucks carry the load in stacks. For this problem loading capacity is to be maximized while the total time of the operation is to be minimized. This consists of the traveling time between the pickup and delivery points, and the time spent at each of the above locations.

The number of stacks is a function of the number of boxes that are unloaded from or loaded onto the truck. Obviously the fewer is the number boxes that are re-handled at each location the lower is the total operation time. Given the sequence by which the locations are visited, a minimum rearrangement plan may be derived. If the sequence of visits is not specified and is to be decided, then there are two traveling salesman problems that need to be solved. However, the two TSPs are linked through the requirement of minimization of the rearrangement time. This is a generalization of the TSP problem and consequently it is very difficult. In fact it can be easily proven that the problem belongs to the class of NP complete problems (Aslidis, 1989).

Laporte (1997) considered an arc routing problem that can be modeled and solved as traveling salesman problem. Computational results indicate that the approach works well on low-density graphs containing few edges. It constitutes also the approach for solving Stacker Crane Problem to optimality (Laporte, 1997).

Christofides and Collof (1989) have published a paper on finding the optimal way of rearranging items in a warehouse. The rearrangements are necessary in warehouses for good service and "fast moving". Usually, the most common items have to be at the "front" end of the warehouse while slow moving ones must be moved towards the rear.

The paper gives a two-stage algorithm that produces the sequence of item movements necessary to achieve the desired rearrangement and incur the minimum cost (or time) spent in the rearranging process (Christofides et al., 1989).

Finally, papers from different areas such as airline and paper industry were reviewed such as George (1993) and Cochard et al., (1985). A common idea to provide a solution approach that provides the loading procedure focusing on reducing cost.

3.7 Other Container Problems

3.7.1 General Literature on Rearrangements Problems

Containerized liner trades have been growing steadily since the globalization of world economy intensified in the early 1990s. However, these trades are typically unbalanced in terms of the number of inbound and outbound containers. As a result, the relocation of empty containers has also become a major problem. The earliest description of using models of empty container relocation can be dated back to 1972. White (1972) introduced the problem. Florez later in 1986 formulated the problem as a deterministic network problem (Florez, 1986). Crainic, Gendreau, and Dejax worked on this problem from different point of view (Dejax, et al., 1991). Crainic, Gendreau, and Dejax (1993) further developed a model to minimize the total inland transportation costs. Lai, Lam, and Chan used a simulation model to represent the problem and developed heuristic search techniques to find the lowest cost option (Chan, et al., 1995).

3.7.2 General Literature about Vessel Design

Vessel design, in general is a multifaceted activity requiring the efficient utilization of resources to meet some functional requirements. A slender hull form is preferred for minimizing resistance, whereas maximizing cargo volume results in a fuller hull form.

Ericson (1991) presented a mathematical model for containership design optimization that considers operating costs incurred at container port terminals and for land transportation. In this research the author discovered that the objective function is found to be flat in the neighborhood of the optimum point and further reductions of the stepwidths did not improve the value of the objective function by more than 0.2 percent.

Crhyssostomidis (1996) proposed an optimization approach to containership design in which the carrying containers and the speed is fixed during the design process. A random search optimization technique is employed, for many cases until a near least-cost design is achieved.

Recently, Neu et al., (2000) developed a prototype tool with a multidisciplinary optimization approach to ship design. A containership is used as a test case and the problem formulation treats the carrying capacity (numbers of containers) and the speed as variables in the design process. In this research, the weight-displacement equality is enforced through a decomposition approach that speeds up the design process.

3.7.3 General Literature about Container Terminal

Another area in which containers have significant effect is in container terminal operation. There is a significant amount of container port literature available, but only a small fraction of it deals with relatively new services such as intermodal containerized cargo. The limitations of these methods became evident when new technologies were introduced and ports grew in complexity and importance, spurring new interest in port and rail research.

A number of authors have developed analytical models for the analysis of port related problems. One of the most comprehensive contributions from a systems analysis viewpoint was by Imakita (1978). Also, Castilho and Daganzo (1991) examined the trade-off between container storage and handling efforts for different operating strategies (Castilho and Daganzo, 1991). The operations of modern container terminals are described by many authors (for example Atkins, 1983). Ballis and Abacoumkin (1995) introduce a computer simulation model for a container terminal equipped with straddle carriers. The proposed model was used to examine the differences between "the observed" operation strategy and the strategy dictated by the operational rules of the port of Piraeus. The results show that "the observed" strategy leads to shorter truck service time but increases the traffic conflicts in the terminal internal transport networks.

The efficiency of container ports is of great importance to the shippers, ship-owners, and ports. Because the time that a ship spends in a port is very crucial, port facilities need to minimize queuing delays to ships. Several researchers have tried to optimize the number of berths in a port by minimizing the port cost and ship delay (Schonfeld and Sharafeldien, 1985). Siberholz in 1989 developed a simulation program to transfer containerized cargo to and from vessel. The model addresses this complexity by stochastically simulating many functions, such as work crew schedules and vessel capacities. The model allows owner to analyze cost and service times incurred at the facility. Also the model permits port operators to examine throughput rates, total costs and overhead costs.

There are a few more container-related problems with which researchers have been dealing including truck loading. Brown and Ronen in 1997 developed an interactive system based on a mathematical optimization model that is used by a major US manufacturer to consolidate customer orders into truckloads (Brown and Ronen, 1997). Since the thesis topic is more focused on loading, we do not need to go deeper in containerization problems.

Following the review of the container loading problem we realize that the container loading has some particular characteristics. Because of these characteristics, the general heuristic methods are not appropriate for this problem. A new approach is needed that accounts for realistic constraints. These include constraints related to ship stability and loading requirements. A realistic model should also be able to handle containers in different sizes in producing a loading scheme.

In this research, we propose a new formulation for the optimal container loading, and develop a new algorithm to solve the problem. The proposed model has the following characteristics.

1. The model can deal with containers with different dimensions as well as containers that have specific loading requirements such as: refrigerated and hazardous material containers.
2. The model can adjust the number of containers to minimize the cost for extra handling.

3. The heuristic solution method can solve large problems with acceptable gaps in reasonable solution time.

Chapter 4: A Mathematical Model

4.1 The General Problem

The loading / unloading procedure of containers in the vessel is an important activity in the maritime industry. The container loading can be classified as the three dimensional (ED) rectangular packing problem, in combination with an assignment problem, and it is a NP-hard problem. Because the number of different packing patterns increases exponentially with the number of units (containers), results for solving problems of small size are reported in literature only for heuristic algorithms (Wilson, 1999). These algorithms make many assumptions that result in an over-simplification of the problem.

The loading problem is one of the most common and difficult problems in the maritime industry. A survey and classification about bin-packing problem is available in Drychoff (1990). The problem also arises in warehouses, trucking industry and any storage area such as: in the marble industry. In this thesis we focus on containership loading, however, the developed models and algorithms can be applied in other problem contexts as well. In containership operations the preferred situation is to have the best possible arrangement of containers that minimizes the total number of extra handlings of containers in ports, and then the cost will be as low as possible.

4.2 Assumptions

The assignment of containers to locations in the containership is a major issue in shipping industry. In an attempt to achieve tractability, a few assumptions are made that are necessary for developing the model:

1) The route of the vessel's tour is given, as the origin and the destination port of the network is given as well.
2) We are going to optimize the loading procedure with respect to cost. The cost of horizontal crane movements is significantly smaller than the overstowage cost and can be ignored. However, the algorithm offers the option to choose between "blocking" and "nonblocking" the containers for the same destination.
3) The stations, columns and rows on the deck are fixed.
4) The (un)loading schedule is known before the ship starts the trip from the first port till the final destination. This is very hypothetical because it is very difficult to know the complete loading schedule at the beginning of the voyage. For instance, for a network of twelve to fifteen ports for which the voyage takes three or more weeks it is very difficult to know the final schedule of loading at the beginning of the journey. Usually, the officers on the vessel receive the schedule of loading a day (or maybe a few hours) before the ship arrives at the port because the number of containers that have to be loaded changes very often.

5) The structural stresses on the containers are not taken into account. The structural stresses require a more detailed analysis and are beyond the scope of this research.
6) Containers have the same height

4.3 Problem Characteristics

The problem of efficiently operating a fleet of container vessels serving a network of ports is composed of several sub-problems, among them finding the optimal sizes and the optimal routing of the vessels. In addition, container assignment on the dock is very important for smooth and efficient operation. Nevertheless loading cargo is still one of the major issues in the maritime industry. The transfer of containers to and from the vessel has to be carried out rapidly and efficiently. With the very large vessels of today, requiring thousands of container movements to load and discharge, it is quite difficult to achieve such efficiency. Also, the variety of cargo and regulation imposed by the port authorities has significantly increased the complexity of loading problem. Inefficient loading schedules could result in the increase of ship operating cost. Therefore the container-loading (stowage-planning) problem is a very important issue in the shipping industry.

Since the transfer of containers to vessel is critical in port facilities, it becomes very important that it be carried out rapidly and efficiently. For any shipping operation to be cost-effective it is essential to optimize the utilization of the vessel itself by arrangement of the cargo on board the vessel. The cost includes the lifting of containers from the deck and putting them in the assigned “slots” (Cells) on the vessel. The crucial cost depends of the rearrangement that will be necessary during the loading procedure. Container to vessel cell assignments is of one-to-one type. Whereas most stowage plans are based on port efficiency and general loading, the subject of our study is to create a plan that reduces as much as possible the number of shifting operations while including all real world constraints**.** This nature of the assignment easily leads to the 0-1-integer program as a possible model structure for solving the containership load-planning problem.

Aslidis in his work presented a polynomial-time algorithm for the stowage planning problem that solves the single column case (Aslidis, 1989). In this work we address the computational complexity of this optimization problem including multi-column cases. In the solution procedure suggested in this work, the stowage-planning is partitioned in two sub-problems: the problem of assigning container groups to holds and that of determining specific positions or slots for the containers assigned to each cargo hold. The container group denotes a set of containers with the same characteristics (origin port, destination port, type, and weight).

Let us consider a containership consisting of bays for container stowage. Each bay has d stations, and each station has vertical columns labeled e, where $e = 1,2,.....,E$ (column 1 is the first column on the left). Each column has k cells, where $k = 1,2,.......F$ (cell 1 is the bottom cell). Since each column in the station has a finite number of cells, the bay is referred to as a capacitated bay.

Speaking in maritime terms, we assume that the vessel (containership) is scheduled to visit a series of ports $0,1,2,3,.....,M, M+1$. We assume that the ship starts its service route at port 0 with its bays empty of containers, and sequentially visits ports

1, 2, 3,……M, M+1. In each port $l = 0,1,2,...,M$ containers can be loaded to destination $l+1,.....M+1$. In the last port $M+1$, the vessel is emptied of all remaining containers and starts the route in the opposite direction. Also, in each port j the vessel discharges containers with destination. j Containers with the same origin and destination belong to the same group of containers. Containers with the same destination and characteristics belong to the same group of class containers. The placements of containers in a section-bay when the vessel leaves port j have to be unchanged until arrival at port $j+1$. Let $T = [T_{lj}]$ be the $(M)*(M)$ *transportation matrix,* where T_{lj} is the number of containers originating at port l with destination j, $j = i = 1,.....,M$. Thus, $T_{lj} = 0$ for all $l \geq j$. Note, that the indices of the diagonal of T are $T_{l,j+1}$. A stack is in "in-order" condition if the containers of the stack are placed in ascending order of destination from top to bottom, or it is grouped for a section-bay. Assume that the stack is 'in-order" as the vessel arrives at port j. Also, that the transportation matrix is known before the vessel starts its service route or at least before each departure.

A container i is a $j-container$ if its destination is port j. The set of all $ij-containers$ is referred to as an $ij-group$. The problem of finding a stowage plan with the smallest number of shifts, is referred to the minimum shift problem (Avriel et. al, 1993). The minimum shift problem is part of the problem which in general called stowage planning problem. A binary variable X_{ijk} from the $ij-group$, could be designed to describe the assignment of the containers to the loading cells that are available on the ship.

$$X_{ijk} = \begin{cases} 1 & \text{if container i from the port j is assigned to cell k} \\ 0 & \text{otherwise} \end{cases}$$

Therefore, the loading problem with the assignment cost of the containers on board could be expressed as:

$$Min \sum_{i=1}^{n} \sum_{j=1}^{M} \sum_{k=1}^{q} C_{ijk} X_{ijk} \qquad \text{a)}$$

The following notation is used for the above expression:

i : index for containers; $i = 1,2,............,n.$
j : index for ports; $j = 1,2,3..........,M.$
k : index for cells; $k = 1,2,3,.........,q.$

Where:

C_{ijk} = the handling cost of the container i in the port j, which it is assigned in the cell k.

Since stowage plan at a port is affected by those made at previously visited ports, one has to make stowage plans at all ports included in a tour of containerships simultaneously. As it will become clear in the sequence of ports, multiple-stack overstowage problems are much harder to solve than their single-stack case. Exact efficient algorithms cannot be developed even for very simplified versions of multiple-stack problems (Aslidis, 1989). The sequence of ports during the containership voyage and the different loading schedules in each port can make the stowage-planning problem very difficult. Avriel et al., (1998) described and studied this problem as a traveling Salesman problem but it is a more difficult problem because of the specific locations to which the containers have to be assigned.

Eventually, with the large vessels of today requiring literally thousands of container movements to load and discharge, this operation with "Jumbo" vessels can be very difficult to achieve. So, we can represent cell (K) in three dimensions; section, column and row. Because in the loading procedure we do not avoid station interchanges, it would be better if we introduce index for a station in our formulation. Figure 14 shows a simple station configuration of the vessels cross section that proves the benefit of the new cell representation.

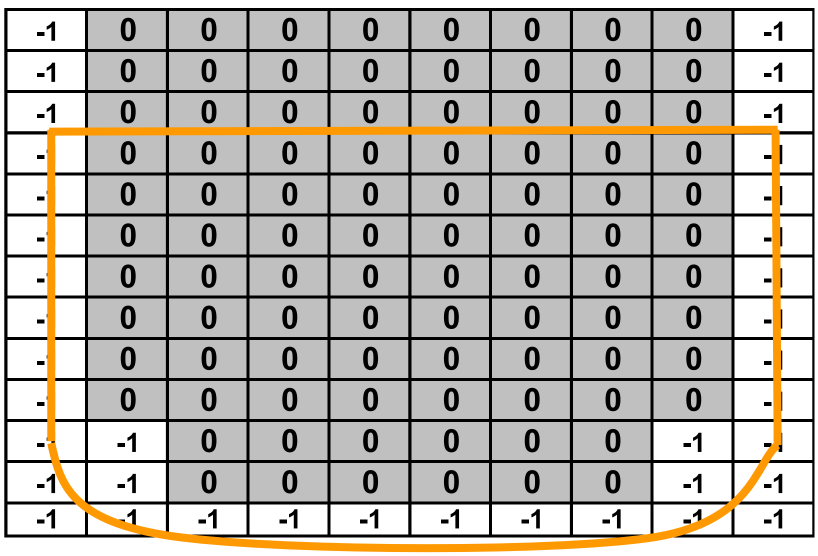

Figure 14: A simple station configuration of a vessels cross section

In Figure 14 the negative numbers (-1) represent the cells in which we are not allowed to assign any container. These particular cells are for the geometric of the ship. Because the stowage-planning problem deals with a huge number of variables it is necessary to represent the cell in a different way. Furthermore, we could represent the cell by column and row in different stations. Now we are sure that containers should be assigned column by column, which can change the whole loading procedure. This is an entirely new “feature’ in the problem (Aslidis, 1990). In this approach containers should be assigned to the group. In the case that we have to “re-arrange” containers in the group are treated as deliveries to that port plus an equal number of pickups from that port with destination the same as those considered delivered.

The following example demonstrates that rearrangement and the bigger picture of the model. The network has as many components (nodes) as destinations, which is $M+1$. Suppose that a container of group (i, j) needs to be rearranged at the port Ω, and addition is switched from the stack it is on as the containership enters port Ω, stack A to stack B. Then the situation is like having a container of group (Ω, j), in stack A and a container of group (j, Ω) at stack B. The above observation reduces an assignment problem with bin-packing constraints (for stability). Let us consider a container of group. It can be assigned to any of the groups at port i. Suppose that Ω is the first port where its get re-arranged. At port Ω though it gets off that stack and can be re=assigned to any stack, again. Figure 15 shows how much a container switches. It becomes clear from Figure 15 that when a container gets re-arranged it essentially joins the group of containers of the same destination with that originated at the port of re-arrangements.

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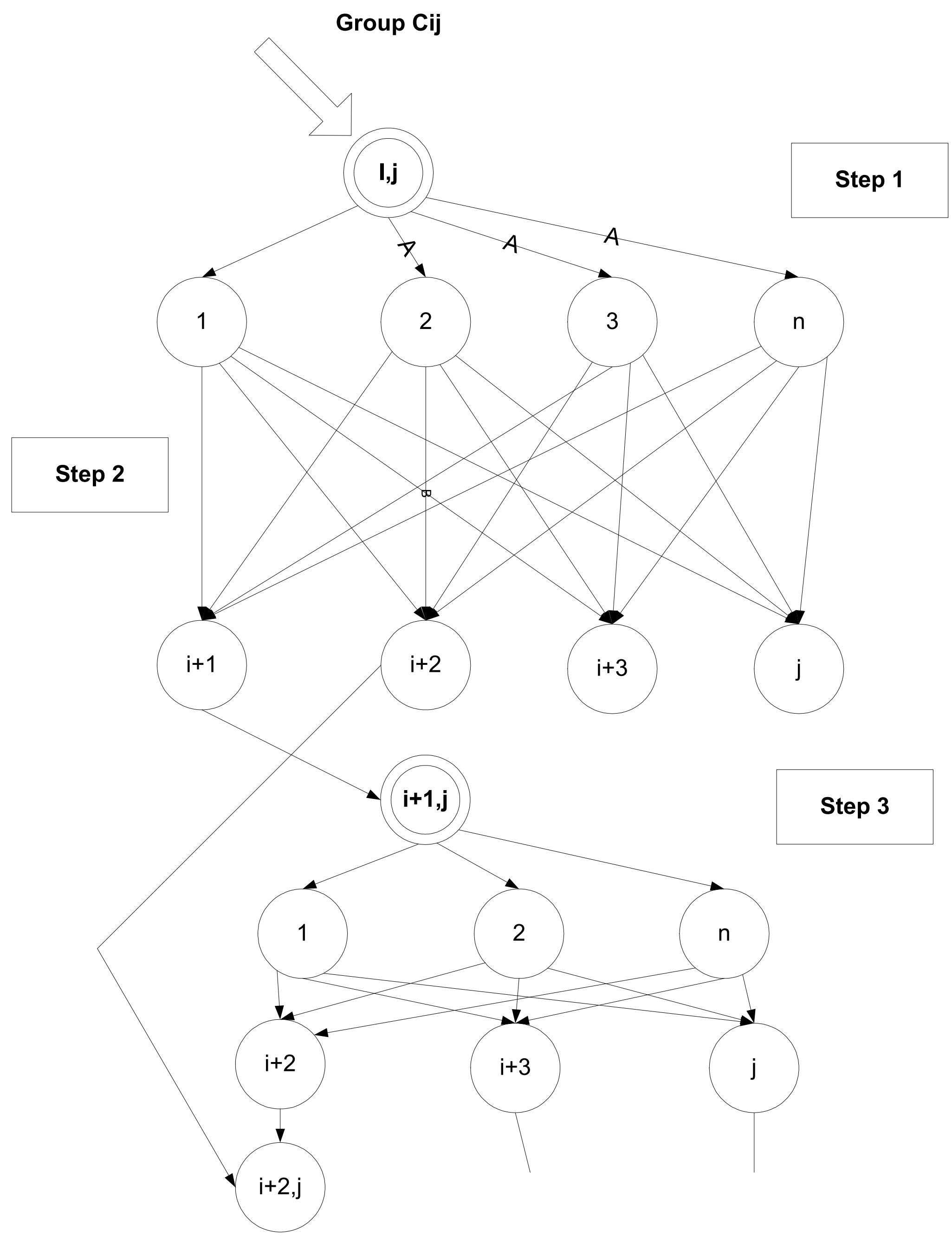

Figure 15: The Network Representation of Rearrangements (Aslidis, 1989, Modified by Kasar, 2006)

The representation of the problem as a network is not new; a few researchers have represented the problem as a network flow problem. First, Aslidis in his thesis studied the problem as a flow problem with capacity constraints, and Avriel et al studied the connection to the coloring of circle graphs (Aslidis, 1989, and Avriel, et al., 1993)

The objective of the network representation of the problem is to minimize the flow along the arcs at the step 3, because the flow of containers along these arcs gives the direct count of the container movements on and off board. Obviously, the flows on all arcs must be integer; otherwise the solution does not correspond to a physical situation. Unfortunately, previous studies did not lead to an efficient algorithm. In fact, it appeared that this problem is particularly hard in terms of finding the optimal solution (Avriel, et. al., 1998).

Let us consider the network flow representation of the problem, and keep at the beginning of this study the assignment of containers to the bay/section as the only decision. During each voyage the vessel picks up containers from each port, or discharge containers at this port, and distributes them to the ports on its route. In this era that we have Transatlantic and Transpacific routes of trade, with more than ten ports, containership corporations consider the origin, the intermediate and the destination ports as the major ports in the trade routes (for "Jumbo" ships) with major container movements. The objective of our study is to minimize the incurred extra container handling cost with respect to ship safety regulations. The cost associated with placing the container at a certain location depends on the necessary rearrangements of cargo. The loading problem is a combination of an assignment problem, bin-packing problem and knapsack problem. In addition, with respect to ship stability and safety the problem becomes more difficult.

Therefore, the binary variable X_{ijk} can be redefined as follow:

$$X_{ijhdek} = \begin{cases} 1 & \text{if container i from port j to port h is assigned to station d in column e and row k.} \\ 0 & \text{otherwise} \end{cases}$$

The cell is now represented by three co-ordinates: station, column and row. Therefore, we can deal with this problem as a part of a pure assignment problem.

Let us consider a single bay for container stowage. The bay has one section with horizontal rows that represents cells $k = 1,2,3,....,F$, and vertical columns labeled $e = 1,2,3,.......,E$ It is assumed that in each column of the station there is room for EK_F containers. Such a bay is called a rectangular bay. Without loss of generality, we consider the columns arranged in a single line, therefore we are forming 'two-dimensional" section/bay, although in reality a bay is always three-dimensional.

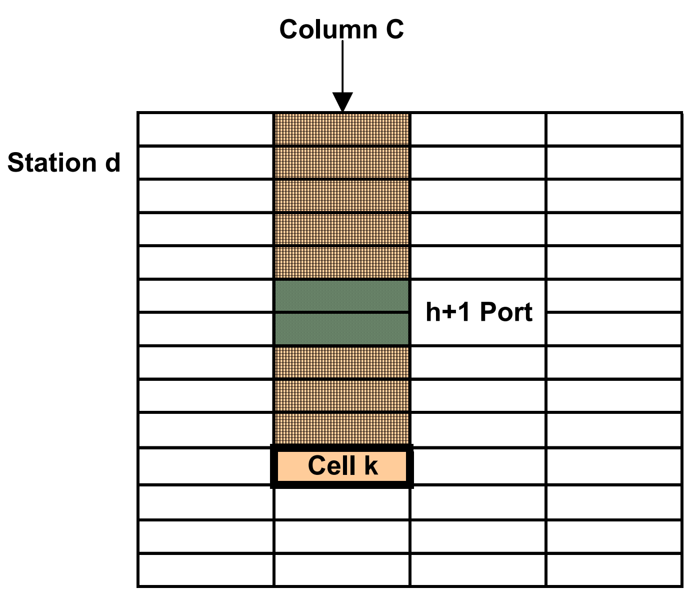

Figure 16: Column Overstowage Represantation

The placement of containers in a bay/section when the vessel leaves port j remains unchanged until arrival at port $h = j + 1$. Let $T = T_{jh}$ be the transportation matrix, where T_{jh} is the number of containers which originate at j with destination h. Transportation matrix is said to be feasible if all the containers can be stowed in any given cell. Figure 16 along with the shipment matrix constitute the input for the version of re-shifting problem to be formulated in this chapter.

There are two stack operations that are performed at every port. First, delivery of containers with destination at the current port, and secondly, placement on board the stack of the containers to be shipped out of the current port. Along with the above, there exists some containers that are quay, although neither are destined to nor originating from the current port. These are containers are blocking the delivery of those to be delivered (see figure 16) and consequently have to be taken off the place on board temporarily. However, these 're-handled" containers need to be placed back onto the stack along with the new containers. In fact, there is no reason to treat them differently from the latter. Therefore, all the containers of the same origin j, and destination h should be grouped together and experience the same methodology in terms of rearrangements.

4.4 Notation and Variables

We define the data sets and constants used in the formulation before we present the mathematical model. We also define the decision variables used in the model formulation.

Indices

i : index for containers; $i = 1,2,3,......,N$

j : index for origin ports; $j = 1,2,3,........,M$

h : index for destination ports; $h = 1,2,3,........,H$

d : index for stations; $d = 1,2,3,........,D$

e : index for columns ports; $e = 1,2,3,........,E$

k : index for cells; $k = 1,2,3,........,F$

Data Sets

N : total number of containers

D : section sets

E : column sets

F : cell sets

Constants

DS : deck strength limit

SH_k : stack height limit

W_c : total weight of containers

Y_k : Y-axis location of the center of gravity of cell k

H_y : magnitude of maximum allowable CG_y deviation

CG_y : center of gravity for loaded containers in athwartship direction

X_d : X-axis location of the center of gravity of station d from the midship

P_l : Desirable position of CG_x from the midship

D_x : Maximum allowed deviation of CG_x from P_l

X_e : Z-axis location of the center of gravity of cell e from the keel

P_v : Desirable vertical location of CG_z from the keel

D_z : maximum allowed deviation of CG_z from its desirable position

C_{dek} : rearrangement cost of container i from the position dek

Decision Variables

X_{ijhdek} = 1, if container i from port j to port h is assigned to station d in column e and row k

= 0, otherwise

$$Y_{dek} = \begin{cases} 1 & \text{if there is a container on top the container with later destination} \\ 0 & \text{otherwise} \end{cases}$$

4.5 Objective Function

The objective of this problem is to minimize the total re-handling cost in a rolling port horizon. As we mentioned in the previous chapters, we do not have to consider the fixed loading cost of containers on board. We would like to minimize the un-necessary container movements on board within the total available number of containers. Therefore, the objective function of the stowage-planning problem could be expressed as:

$$\min \sum_{d=1}^{D} \sum_{e=1}^{E} \sum_{k=1}^{F} Y_{dek} C_{dek}$$

4.6 The Constraints

The constraints of the model consist of three categories: container constraints, stability constraints, vessel constraints and other constraints. The detailed explanations of the constraints are as follows.

4.6.1 Container Constraints

There are several constraints related to the containers. These constraints are relatively simple compared to the stability constraints. Every container has to be assigned in a particular cell at once and discharge in the proper destination port. Also, a few cells are limited by capacity constraints and must be assigned before the regular cells. These constraints are expressed in the following equations.

The containers can be assigned in any cell on board. In equation (1), dek represents the cell position on board. In the port h, container/s with destination $h+1$ above the cell (node) dek has to be rearranged prior to discharge the container underneath.

$$Y_{dek} = \sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{h=h+1}^{H}\sum_{k=k+1}^{F} X_{ijhdek} \qquad \forall\ \mathrm{d,e,k} \qquad (1)$$

Constraint (2) is the well known assignment constraint forcing each container to be stowed only in one ship location. This constraint is very important especially for the containerships built with cells auxiliary tools in which containers are lashing in particular space.

$$\sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{k=1}^{H} X_{ijhdek} \le 1 \qquad \forall\ \mathrm{i} \le \mathrm{d,e,k} \qquad (2)$$

Constraint (3) is also the well known assignment constraint which is explains that the container for particular origin port that is going to delivered port must be assigned to one and only one cell

$$\sum_{d=1}^{D}\sum_{e=1}^{E}\sum_{ki=1}^{F} X_{ijhdek} = 1 \qquad \forall\ \mathrm{i} \le N, \mathrm{J}, \mathrm{H} \qquad (3)$$

The containers can be assigned to any cell on board. However, constraint (4) ensures that the containers are stacked on top of each other that is, if a location *dek* is occupied all other cells under it must also be occupied.

$$\sum_{i=1}^{N} X_{ijhdek} - \sum_{i=1}^{N} X_{ijhde(k+1)} \ge 0 \qquad \forall\ \mathrm{d}, \mathrm{e}, 1 \le \mathrm{k} \le (\mathrm{F}-1) \qquad (4)$$

Containers that are scheduled to be loaded have different lengths. Equation (5) is the size constraint, as they have been described in Section 2. In particular this expression ensures, respectively, 40' containers to be stowed in even bays, and 20' containers to be in odd bays. Also this constraint expression makes infeasible the stow of 20' containers in those odd bays that are contiguous to even locations already chosen for stowing 40' containers.

$$\sum_{k=1}^{K} X_{ijhvdek} + \sum_{k=1}^{K} X_{i'jhdek} \le 1 \qquad \forall\ \mathrm{i} \in D_2, \mathrm{i'} \in \mathrm{D}_1, \mathrm{j}, \mathrm{h}, \mathrm{d} \qquad (5)$$

Containers have different destinations. The destination constraints (6) avoid positioning containers that have to be unloaded first, below those containers that have a later destination port. Also, in each column e the containers are vertically stowed with the one above the other for containers with the same length and same destination in decreasing order of weight

$$\sum_{i=1}^{N} W_i X_{ijhdek} \geq \sum_{i=1}^{N} W_i X_{ijhde(k+1)} ....\forall j, h, d, e \leq k \leq (F-1) \qquad (6)$$

Constraint expression (7) is the assignment constraints for special containers such as reefer container by forcing them to be stowed only in a specific location on board.

$$X_{ijhdek} = 0 \qquad (7)$$

4.6.2 Stability Constraints

Stability is very important in stowage planning, and incorporates bin-packing elements. At present, the only known methods for producing optimal packing involve examining essentially all possible packing and choosing the best one. Constraint expressions (8), (9), (10) ensure the ship's stability in terms of the trim, heel, and GM respectively.

Horizontal Stability

Constraint (8) is the horizontal equilibrium condition, stating that the difference in weight between the anterior and posterior bays must be at most $\pm H_y$ tons.

$$-H_y \leq \sum_{k=1}^{N} \sum_{e=1}^{E} y_k \frac{W_i}{W_c} X_{ijhdek} \leq H_y ....\forall d, l \leq k \leq (F-1) \qquad (8)$$

Longitudinal (trim) stability

The longitudinal center of gravity must be within certain limits from a desirable position. Thus, we have:

$$P_1 - D_x \leq \sum_{i=1}^{N}\sum_{ki=1}^{F}\frac{W_i}{W_c}X_{ijhdek} \leq P_1 + D_x \text{..........}\forall d, e \tag{9}$$

Vertical stability

Upper and lower limits of a vessel's metacentric height (GM) for a given vessel displacement can be translated to the following constraints on its vertical center of gravity:

$$P_v - D_z \leq \sum_{i=1}^{N}\sum_{d=1}^{D}\frac{W_i}{W_c}X_{ijhvdek} \leq P_v + D_z \text{....................}\forall e, k \tag{10}$$

4.6.3 Vessel Constraints

The vessel constraints ensure that only a specific number of containers can be assigned in any column, and enforce the height limitation for safe navigation. Constraint (11), explains that the stock of either 20' or 40' containers cannot exceed the value DS that usually correspond to 125 and 166 tons; note that such constraints verify the corresponding tolerance value in all occupied columns in the same section, as required by the weight constraints described in Section 2.

$$\sum_{i=1}^{N}\sum_{e=1}^{E}W_i X_{ijhdek} \leq DS \text{..........................}\forall j, h, d, k \tag{11}$$

The height constraints (12), avoid positioning containers above specific height limits in upper deck, and ensure better stability and safe navigation.

$$\sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{h=1}^{H}\sum_{k=1}^{F} HX_{ijhdek} \leq SH_k ....\forall d, e \qquad (12)$$

Finally, in (13) the binary variables of the problem are defined.

$X_{ijh\delta\varepsilon\kappa}$ = 0,1 binary variables. (13)

Note that in the formulation of the problem we assume that the ship start its journey in the port for which we are studying the problem and successively visits a given number of other ports.

4.7 Summary

In this chapter, we proposed the formulation of the stowage planning problem as a mixed integer linear programming problem. The objective of the problem is to minimize the total re-handling cost in a rolling port horizon. The constraints of the problem consist of container constraints, stability constraints, vessel constraints and other constraints.

As we discussed in previous chapters, the stowage planning problem is a NP-hard problem and it very hard to obtain an exact solution. Moreover, the formulated problem is more complicated because it is the stowage problem with the additional stability constraints. When we consider a very small problem with 100 cells and 100 containers the number of binary variables is 10,000. When we increase the number of cells to 1,000 with the same number of containers the number of binary variables is 100,000. We can recognize how rapidly the number of binary variables increases.

We use the proposed formulation to solve as large a problem as possible exactly. A heuristic procedure is proposed in the following chapters to solve larger problems. The proposed formulation will be used for developing an approach to generate lower bounds on the value of the objective function as well.

Chapter 5: Lower Bound for Stowage Planning Problem

A stowage planning problem is a combinatorial problem that generally can be categorized under the umbrella of discrete optimization problems. Discrete optimization problems are defined by a finite set of solutions and objective function values associated with these solutions (Jacobson et al, 1997). The goal when addressing such problems is to determine the solution for which the objective function is optimized.

Garey et al., (2000) present an in-depth discussion on the complexity of discrete combinatorial problems, which can be classified as easy (i.e., solvable in polynomial time in the size of the problem instance) or hard (i.e. in the class NP-hard). The stowage planning problem is an NP-hard problem (Avriel, 1993). Algorithms are typically formulated to address combinatorial problems with the hope of finding good and near optimal solutions as we are going to address in the next chapter.

In addition to a good solution we would like to have some guarantee on the quality of the solution found. Such a guarantee can be given through a lower bound on the value of the objective function. In general, lower bounds can be obtained by solving relaxations of the original problems. Then the optimal solution of the relaxed problem gives a valid lower bound for the value of the objective function of the original problem. Different relaxations provide different lower bounds. The main goal is to find relaxation problems for the stowage planning problem that can be solved efficiently and which give lower bounds as tight as possible.

There are no lower bound methods for stowage planning problems in the literature, although there are a few lower bound methods for bin-packing problems. For the stowage planning problem, which it is a combination of knapsack, bin- packing, and assignment problems, obtaining a good lower bound would be very difficult. The difficulty of finding a lower bound algorithm suggests that we should focus on the characteristics of the problem. The nature of the constraints is such that even the lower bound method still has conflicting constraints that make the implementation very hard to find a bound. Although doing this will limit our method, the ideas behind the method may be applied to general stowage problems also.

5.1 Branch and Bound Strategies

Branch and bound algorithms are commonly applied to integer programming problems. The effectiveness of a branch and bound is heavily influenced by its lower bounds. Such bounds are useful when they are tight and easy to compute. The characteristics of the stowage planning problem suggest that we may use the branch-and-bound method to obtain the lower bound. Because of the special requirements of the field operations, we can reduce the branch and bound tree significantly by imposing these special requirements (constraints). In the next sections, we will discuss several strategies to take advantage of different special characteristics of the problem. The size of branching tree is significantly reduced and good or acceptable lower bounds may be found in a reasonable time.

5.1.1 The Basic Scheme

In a branch-and-bound scheme there are two important question: how to split a problem into subproblems and which node is to be processed next. To a branching variable we apply the most infeasibility rule. This rule chooses a variable with the fractional part closes to 0.5. For node selection, the following strategies are tested:

Best first search. A node is chosen with the weakest parent lower bound (promising the best solution). The goal in this search is to improve the global lower bound, which is the minimum of local bounds of all unprocessed leaves. However, when the state space is large this approach may prove costly in terms of time.

Depth first search . This rule chooses one of the deepest nodes in the tree, The advantage of this search are the small size of the search tree and fast re-optimization of the subproblem. Also a good feasible solution is found very quickly that it is so important in a stowage planning problem.

Consider the search tree for our model. Node $\varnothing$ represents the null assignment. Every other node represents a partial assignment $C = \left(C_{(1)},\ldots\ldots\ldots.C_{(s)}\right)$, indicating that container C_g is assigned in g^{th} position on each bay s. Any permutation σ of the set of misplaced containers defines a complete assignment for containers C_N when C_N is the total containers that has to be loaded in the vessel from port j: $C\sigma = \left(C_{(1)},\ldots\ldots\ldots.C_{(s)},\sigma_{(1)},\ldots\ldots.\sigma_{(N-s)}\right)$. By placing any misplaced containers C_{mis} back in to position $de(k+1)$, we produce a descendant node $\sigma_{C_{mis}} = \left(\sigma_{(1)},\ldots\ldots.\sigma_{(\sigma)},C_{mis}\right)$. In our model we have to incorporate a best-bound rule.

Begin

Initialize C

The initial state is made up of the available cargo-space referring as a cargo space, and an ordered list of containers comprised of all containers to be loaded at current loading port

While (not termination-condition) **do**

Remove best section $C \to D_i$

New solutions are generated that reflect every possible placement into a block of the first group of containers. Then in this phase we remove from the search space S all potential locations that a priori are not to be considered for stowing container $c, \forall c \in C$. If after expanding a partial solution a feasible solution found, then it is set

Reduce or subdivide $D_i \to D_i^l$

Each of the candidates locations on board produced during the branching process is sorted according to its fitness value and the number containers within associated list of containers that needs to be loaded

Update f_{bound}

$C \leftarrow C \cup D_i^l$

For all $D_i \in C$ **do**

If $F(D_i) > f_{bound}$ then remove D_i from C

end

Therefore for stowage planning problems, it is very hard to get a good lower bound using a pure branch-and-bound. For a set of examples, where the optimal solution was known, the Branch and Bound had an average gap of 17.64% from the optimal solution value. Other methods must be explored, In the next section we will discuss another popular lower bound method Lagrangian relaxation, to find the lower bound.

5.2 Lagrangian Relaxation Approach

An approach to solving the integer programming problems is to take a set of "complicating" constraints into the objective function in a Lagrangian fashion. This approach is known as Lagrangian relaxation. By removing the complicating constraints from the constraint set, the resulting sub-problem is often considerably easier to solve. The bound found by Lagrangian relaxation can be tighter than that found by linear programming. Lagrangian relaxation requires that one understands the structure of the problem being solved in order to relax the constraints that are "complicating" (Fisher, 1981). A related approach which attempts to strengthen the bounds of Lagrangian relaxation is called Lagrangian decomposition (Guignard and Kim, 1987). This approach consists of isolating sets of constraints so that one can obtain separate, easy problems to solve over each of the subsets. The dimension of the problem is increased by creating linking variables, which link the subsets.

Most Lagrangian-based strategies provide approaches that deal with special row structures. Other problems may process special column structure, such that when some subsets of the variables are assigned specific values, the problem reduces to one that is easy to solve. Bender's decomposition algorithm fixes the complicating variables, and solves the resulting problem. Since each of the decomposition approaches provide a bound on the integer solution, they can be incorporated into a branch and bound algorithm, instead of the more commonly used linear programming relaxation.

In following section, we describe a solution method based on a Lagrangian relaxation within a branch-and-bound framework. Lagrangian relaxation in combination with branch-and-bound is often used for NP-hard problems. Because this approach has been successfully applied to the Knapsack and bin packing problems, it is interesting to investigate this method in stowage planning problems as well. The Lagrangian relaxation for the stowage planning problem must be designed in such a way that it results in easily solved sub-problems and yield lower bound tight enough to an optimal solution. Consequently, we optimize a relaxed problem, which contains the original problem as a special case. The basic idea of this method is to change the original NP-hard problem to an "easy" and solvable problem. Notice the lagrangian relaxation keeps variables discrete. Integrality requirements of the original model have not been dropped (Fisher, 1985).

Even when the given model is an integer liner problem, the strongest practical relaxation may not be the LP relaxation. Lagrangian relaxation, which proves stronger for some model forms, adopt a completely different strategy. Furthermore, information communicated between the Lagrangian relaxation and the bounding process serve to improve the performance of both processes. When the branch-and-bound algorithm accumulates sufficient fathoming information so that permanent (or even temporary) decisions can be made on the solution matrix, these decisions are communicated to the lagrangian and serve to improve the lower bound calculations. An advantage of the relaxation is that in a branch-and-bound algorithm it produces feasible solutions, without having to progress through all the branches of the tree to their outermost tips.

To perform a Lagrangian relaxation, a suitable constraint set is chosen to be relaxed. Considering the stowage planning formulation in the previous chapter, the two main alternatives are to relax either the stability (Bin-packing) constraints (8), (9), or (10), or the grouping constraints (5) and (6). To maintain the problem structure in the relaxation, one might prefer to choose the second relaxation related to grouping constraints. In choosing to relax the grouping constraints the cost is going to be higher and the result is not tight to the exact solution. The reason behind is because the solution now is in a wider neighborhood.

For proof of this result see Bourjolly and Rebetez (2003), where also they analyze a lower bound for the bin-packing problem. Also, see Gendron and Grainic (1994) where the Lagrangian relaxation is compared with an LP relaxation. In the computational tests in Gendron and Grainic, sub-gradient optimization methods are run for a certain number of iterations. The conclusion is that the second relaxation regarding the grouping constraints does not provide a good lower bound.

In this study we use the first type of Lagrangian relaxation, obtained by relaxing the stability constraints. The main advantage of this relaxation is that it yields a very simple separable sub-problem as shown later in this section. In addition, relaxing the stability constraints yields a quicker procedure and most of the time the resulting bound is significantly good. A significant improvement is obtained by strengthening the formulation of the model. This benefits both the straightforward use of branch-and-bound, and the Lagrangian relaxation.

The strategy of the lower bound solution procedure for the stowage planning problem is to find a way that minimizes the number of integer variables. In the previous chapters, we note that the value of the Y_{dek} depends on the assignment and stability (knapsack, and bin-packing) constraints through the variable X_{ijhdek}. Moreover, the part that is involved in stability constraints can be identified as a special case of the linear Bin-packing problem in which all the variables have coefficient 1. This fact suggests that we can relax the horizontal and longitudinal constraints (8) and (9) of the stability constraints group. Also, we notice that in this model the condition related to the vertical equilibrium given in the previous sections can be dropped since it becomes redundant due to the group (weight related) constraints.

As we discussed, instead of dropping integrality requirements we relax a couple of the main linear constraints of the model. By relaxing the constraints set (8), and (9) using multiplier μ_1 and μ_2 we obtain the following Lagrangian:

$$\min \sum_{d=1}^{D} \sum_{e=1}^{E} \sum_{k=1}^{F} Y_{dek} C_{dek} + (\sum_{k=1}^{N} \sum_{e=1}^{F} y_k \frac{W_i}{W_C} X_{ijhdek} - H_y)\mu_1 + (\sum_{i=1}^{N} \sum_{k=1}^{F} \frac{W_i}{W_C} X_{ijhdek} + P_l + D_x)\mu_2$$

Subject to:

$$Y_{dek} = \sum_{i=1}^{N} \sum_{j=1}^{J} \sum_{h=h+1}^{H} \sum_{k=k+1}^{F} X_{ijhdek} \qquad \forall\, \mathrm{d,e,k} \qquad (1)$$

$$\sum_{i=1}^{N} \sum_{j=1}^{J} \sum_{k=1}^{H} X_{ijhdek} \leq 1 \qquad \forall\, \mathrm{i} \leq \mathrm{n,d,e,k} \qquad (2)$$

$$\sum_{d=1}^{D} \sum_{e=1}^{E} \sum_{ki=1}^{F} X_{ijhdek} = 1 \qquad \forall\, \mathrm{i} \leq n, \mathrm{j,h} \qquad (3)$$

$$\sum_{i=1}^{N} X_{ijhdek} - \sum_{i=1}^{N} X_{ijhde(k+1)} \geq 0 \qquad \forall\, \mathrm{d,e}, 1 \leq \mathrm{k} \leq (\mathrm{F-1}) \qquad (4)$$

$$\sum_{k=1}^{K} X_{ijhvdek} + \sum_{k=1}^{K} X_{i'jhdek} \leq 1 \qquad \forall\, \mathrm{i} \in D_2, \mathrm{i'} \in \mathrm{D}_1, \mathrm{j}, \mathrm{h}, \mathrm{d} \tag{5}$$

$$\sum_{i=1}^{N} W_i X_{ijhdek} \geq \sum_{i=1}^{N} W_i X_{ijhde(k+1)} \ldots\ldots\ldots\ldots \forall j, h, d, e \leq k \leq (F-1) \tag{6}$$

$$X_{ijhdek} = 0 \tag{7}$$

$$P_v - D_z \leq \sum_{i=1}^{N} \sum_{d=1}^{D} \frac{W_i}{W_c} X_{ijhvdek} \leq P_v + D_z \ldots\ldots\ldots\ldots\ldots\ldots\ldots \forall e, k \tag{8}$$

$$\sum_{i=1}^{N} \sum_{e=1}^{E} W_i X_{ijhdek} \leq DS \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \forall j, h, d, k \tag{9}$$

$$\sum_{i=1}^{N} \sum_{j=1}^{J} \sum_{h=1}^{H} \sum_{k=1}^{F} HX_{ijhdek} \leq SH_k \ldots\ldots\ldots\ldots\ldots \forall d, e \tag{10}$$

$X_{ijh\delta\varepsilon\kappa}$ = *0,1* binary variables. (11)

A close look at the remaining constraints in Lagrangian relaxation will reveal it conforms to requirement. Also, dropping linear constraints in a Lagrangian relaxation cannot eliminate any solutions. That is, Lagrangian relaxation parallels property in having every solution feasible in the full model still feasible in the relaxation. The optimal value of any valid Lagrangian relaxation of a minimized model yields a lower bound.

The simplest lower bound is to set $\mu = 0$, which means that the relaxation constraints are simply ignored. By changing Lagrangian multiplier μ, if we can find a certain $\mu:(\mu_1-\mu_2)$ that the decrease in objective function valued due to part B of the objective function (Part B: $(\sum_{k=1}^{N}\sum_{e=1}^{F}y_k\frac{W_i}{W_C}X_{ijhdek}-H_y)\mu_1+(\sum_{i=1}^{N}\sum_{k=1}^{F}\frac{W_i}{W_C}X_{ijhdek}+P_l+D_x)\mu_2)$ is smaller than the increase due to part A of the objective function is the original objective function (Part A: $\sum_{d=1}^{D}\sum_{e=1}^{E}\sum_{k=1}^{F}Y_{dek}C_{dek}$), and then a better lower bound is found.

We have observed from the literature that many researchers have used the Lagrangian relaxation fior problems related to container loading (e.g. one-dimensional, two-dimensional). For stowage planning problem, it is very hard to get a very good lower bound using any technique. Lagnangian relaxation is a very promising technique to get a lower bound in very reasonable time. As far as we can compare the lower bound with the exact solution, the Lagrangian relaxation method provides excellent results within a short time. Table 2 below shows the comparison of a few test problems of the exact solution and the lower bound. From the Table it is obvious that the gaps are less than 4% for 150 to 1050 TEUs test problems

Table 2: Comparison of the Exact Solution and Lower Bound

Problem	Size			Exact		Lower Bound	
	Ports	TEU	Special	Result	Time	Result	Time
1	3	150	5	25	14	25	12.5
2	4	300	15	52	14	50	15.6
3	5	500	50	74	19	70	16.5
4	4	750	100	170	32	167	21
5	6	500	25	120	25	110	27
6	5	750	50	375	30	120	18.5
7	5	1000	43	1555	168	1478	12
8	5	1050	25	1378	167	1367	19.5
9	5	1000	70	1390	169	1360	19
10	5	1000	150	1760	178	1705	11
12	5	750	25	203	70	188	19
13	5	800	200	403	85	383	18.2
14	4	500	10	241	38	215	16
15	5	900	100	397	218	378	16.4

The key requirements of a suitable relaxation are the quality of its solution with respect to the optimum of the original problem and its efficient solvability. Precisely, there should exist a fast algorithm that solves the relaxed problem. Therefore, we propose a first relaxation, which can be solved using AMPL optimization software and run in CPEX environment

.

Chapter 6: A Solution Method for the Stowage Planning Problem

6.1 Philosophy Behind the Heuristic Algorithm

Prior to this chapter, we have dealt with mostly every aspect of the stowage-planning problem. We have explained the problem (in Chapter 2), we have developed the mathematical model including all practical constraints (in Charter 4), and examined alternative formulations for the lower bound (in Charter 5). In this chapter, we describe a solution method for the stowage planning problem.

The container stowage-planning problem is concerned with the suitable placement of container units in the vessel (usually a cellular containership) on the multi- port journey, such that each container placement has one assignment at any subsequent ports. Considering that stowage planning is NP-hard and formulating it as a binary integer program does not provide much hope to obtain results in a reasonable time, developing a heuristic procedure is necessary (Avriel, 2000). The container stowage planning problem is a combinatorial optimization problem, its size depends upon vessel capacity (given by the number of TEU units) and the container loading schedule at each origin-destination port (POD). Formulation of the combinatorial optimization problem is complicated by the need to consider stowage across a number of ports, with respect to a vessel's stability and its restrictions. Even for the smallest cases, container stowage planning is a large-scale problem due to the extensive number of variables. For instance, for a medium-sized containership of 2000 TEU being huge (approximately 3.3 times ten to 5735th power (Wilson, 1999, and Dillingham, 1986).

There are two possible sources of difficulty in this complex problem. First of all, we should account for the problem of assigning containers to cells. Since the cost of the one-stack overstowage problem is not a linear function of the cost C_{ij}\`s $(i = 0,....m; j = i+1,.....M+1),$ the assignment alone can make the problem very difficult (Aslidis, 1989). Secondly, in the multi-port journey, it is possible to switch a container from one cell to another.

As discussed in previous chapters, formally, the stowage planning problem involves determining how to stow a set C of N containers of different types, dimensions, and weights into a set at S of F available locations (cells) within a containership. This study focuses on how those N containers can be grouped and then left unmoved or when necessary, shifted minimally, before the discharge at the destination port. This must be accomplished subject to constraints on structural and safety constraints, whilst minimizing the re-handling cost and loading/un-loading time. Most existing heuristic methods have drawbacks in that they do not consider the stability of the vessel, and/or the stowage plans at subsequent ports do not account for container characteristics. Initial attempts at understanding the problem components and deriving some rules for determining good container stowing plans were based on work reported in Kaisar (1999) and Wilson et al., (2000). In this chapter, complexity issues are reviewed and the stage is set to develop a heuristic algorithm.

6.2 Iterative Development of the System-Level Models.

Re-arrangement is a situation arising in all types of stacking operations and it is not restricted in applications found in the maritime field. Stacks can be defined as three-dimensional storage systems with one access point at the top. Each stack consists of containers that are stowed one on top of another. In each one, the end point is close to the access point and the bottom of the stack is the least accessible end. In stacking operations, the last item put in is the first one to be taken out.

There are two types of stack operations that are performed at each port. First, is the delivery of containers with a destination at the current port, and second, is the placement of the containers to be shipped out of the current port on board, onto the stack. Furthermore, there exist containers that end up on the quay that have nothing to do with the current port. These are containers that block movement and consequently must be removed from the stack temporarily. These "re-handled" containers must be placed back onto the stack along with the ones from the current port.

Although we do not have a measure of disorder for a given arrangement of the containers of a current stack for any stack storage system, we can easily compare two arrangements with the same characteristics. Speaking in maritime terms, we assume that a containership is scheduled to visit a series of ports $(0,1,2,......j,p,.........H,H+1)$. Suppose the vessel is at port j and has already discharged the containers destined for that port. Figure 17 shows the arrangement of a section in which containers are blocked. It is obvious that there are two containers in Figure 17 (a) that need to be "re-arranged", but in Figure 17 (b), these two containers are not blocked relative to the containers with destination $(j+p+t)$. The arrangement in Figure 17 (b) is not worse than the arrangement in Figure 17 (a).

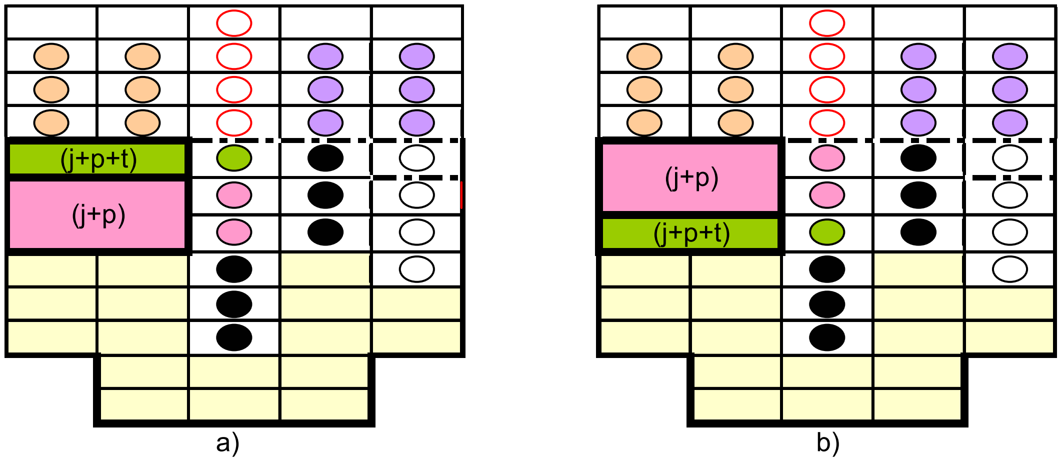

Figure 17: Different Stack Arrangements / Same Section

The rearrangement of containers with destination $(j+p+t)$ in Figure 17 (a) would not be optimal if the rearrangements happen to be in any port before the destination port $(j+p)$ (Aslidis, 1989). As we have seen in Chapter 3, the term re-arrangement is used both when it is voluntary and forced. Since there are no containers going to previous ports, below the container with destination $(j+p)$, no such container is blocked by containers with destination $(j+p+t)$. Therefore, the arrangement of containers in Figure (b) does not result in more re-arrangements under the same loading plan. This is because $(j+p)$ and $(j+p+t)$ either move or stay together, including at $(j+1)$ and $(j+p-1)$. Hence, the arrangements (a) and (b) of Figure 17 can be thought of as the initial stack for a vessel starting at port $(j+1)$ and going to $(H+1)$. It is clear that these containers should be placed in descending order, according to their destination.

In addition, for any bay and section, containers of origin j and destination h should be grouped together and treated the same in terms of re-arrangement. Otherwise, grouping them together can always decrease the number of re-arrangements. In his thesis, Aslidis (1989) showed that an optimal re-arrangement policy treats containers of the same group in the same manner. The optimal re-arrangement policy at any port, h, involves re-arrangements of all containers that block them (Aslidis, 1989). However, in the multi-destination case, when a group with an intermediate destination is delivered, any improvement in the stability and cost, from re-arrangements in the previous port, is lost. This means that the re-arrangement policy depends on what containers are on board at port h. Based on the above discussion, we can understand that the design of the solution approach for stowage planning problem is generally complex, and that there is a high possibility that subtle error will cause stability issues and erroneous behavior.

To overcome the difficulties associated with producing a good solution for the stowage planning problem we propose that the process be decomposed into two sub-processes. The first is the ***general planning phase*** for assigning container groups to the bay-section cargo spaces, and the second is the ***cell-planning phase*** for determining a loading pattern for containers assigned to specific cells within each blocked bay-section space. These two sub-processes are solved iteratively using information obtained from the solution of the other. Due to this iterative procedure, we may assume the interdependency of the two stages. For instance, if a solution of the loading pattern to each bay results in "re-arrangement" at a particular iteration, then the number of containers that can be stowed in the same hold can be limited to a certain number of container groups that can prevent the "re-arrangement" in the next iteration.

6.3 Solution Approach

The stowage-planning problem, as we mentioned earlier in this chapter, is very complex and typically contains millions of decision variables and thousands of constraints. Modeling techniques are now routinely used to transform this problem, with nonlinear constraints and objectives, to one with a linear constraint and objective. A specialized branch and bound technique and simulated annealing with heuristics embedded within the optimization algorithm are used to exploit the problem structure and speed up the solution process. In this study, the stowage-planning problem is portioned into two sub-problems: the problem of ***general planning*** and the ***cell-planning process.*** In the general planning process the bay-section cargo space on board S was split into different partitions, in order to be able to solve separately the stowage-planning problem for each portion of the vessel. Simulated annealing can be used in cell planning process used to produced a stowage plan and to guide any process that employs a set of moves for transforming one solution plan to another. The following sections explain how the stowage planning is decomposed into sub-problems to simplify the overall process (see Figure 18).

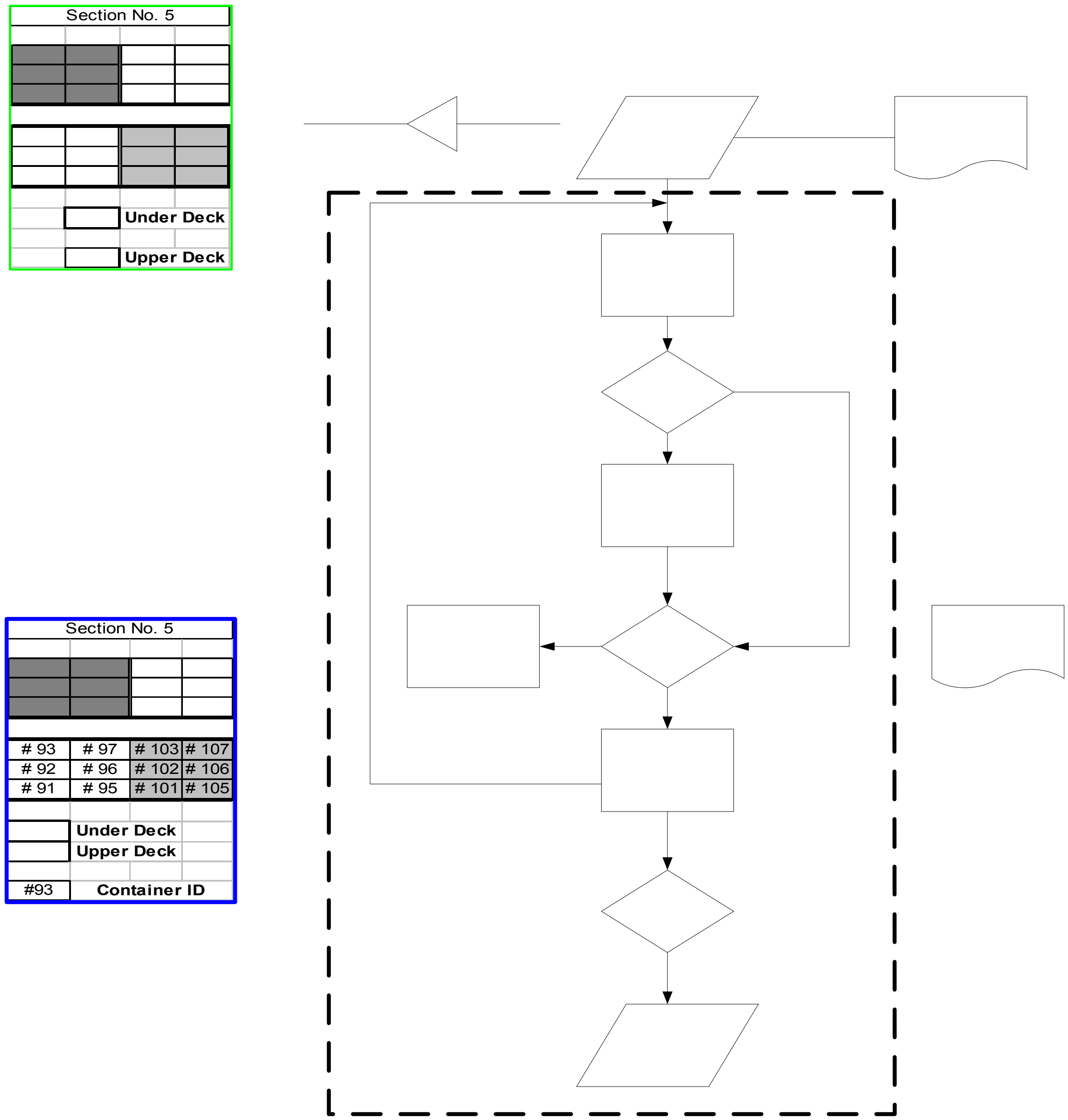

Figure 18: Heuristic Procedure Split it in two Sub-processes.

6.3.1 General Planning

Assigning Containers to Section Cargo Space

The *first* sub-problem, which will be described in more detail later in this section, is the *general planning* phase, aimed at tightening the constraints of the model and reducing the feasible region of each container $c_i \in N$ on board. We sort the data related to the available containership locations on board according to their bay-section address, in order to look at the container assignment on board, with respect to indices $d, e, and\ \ k$.

In this phase, we allocate groups of containers on board the containership according to destination, length, and type. The container's assigned position depends on the availability of containers with the same characteristics. The presence of the existing cargo, on board, is crucial in the decision making process because it indicates to which bay-section the containers that are being loaded will be allocated.

Also, at this stage it is possible to allocate containers to more specific areas along the bay-section, such as above or below deck cells. A further consideration when using this procedure is the particular container position on board with regard to the bay-section address. A specific container is not necessarily allocated to a particular cell, but instead to a general location. The final solution at this stage is a picture of the loaded containership in general. The assignment of a containers group to particular cells is associated with the cell-planning process.

A potential stowage planning for a bay-section is presented in Figure 19.

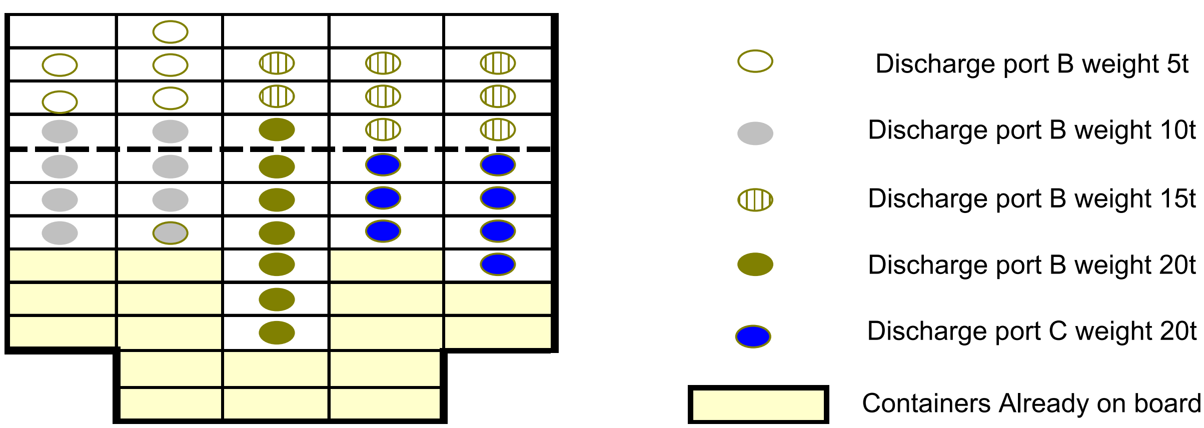

Figure 19: An Example of Potential Stowage Planning

A container type is specified for each bay section position. The required size of a container is defined by the bay-section's characteristics. Usually, the bay is restricted to handle 20' containers or 40' containers. It is very common for a 40' section to contain two 20' containers, with the loading restriction that only a 40' container can be stored above the two 20' containers. The on-deck positions can also accommodate 45-foot containers in specific cells. It is assumed that the under-deck bay will be used to store the entire refrigerated, 20-foot and 40-foot containers. The hazardous container is only permitted to be stored under deck in the stern bay.

The steps to determining to which special bays that hazardous cargo and other special containers are assigned are a part of the general planning process. Vessel stress and stability can be calculated during this process, using the bin-packing constraints that we discussed in Chapter 4. Appropriate longitudinal center of gravity (LCG) and vertical center of gravity (VLC) values are tested as well. This sub-process provides a plan for distributing containers at the end of the loading/unloading process, which is used at every subsequent port.

6.3.2 Cell Planning

After the general planning process has produced a plan, containers allocated to each bay-section block are assigned to available cells in the bay-section cargo area. In the *cell- planning process,* we consider the set Δ of available locations, split into different blocks with respect to their bay-section address. During the cell planning phase, specific allocations of containers to cell location within the bay are recorded on the stowage plan. This stowage plan can be determined for each bay-section cargo area because the groups of containers that should be loaded and unloaded from each hold at each port were determined by the solution of the general planning process. Therefore, those loading plans at port j should be made while considering the loading/unloading plans of the other ports. Figure 20 shows an industry example of a section plan, in which the numbers correspond to the weight, origin and destination port of certain containers.

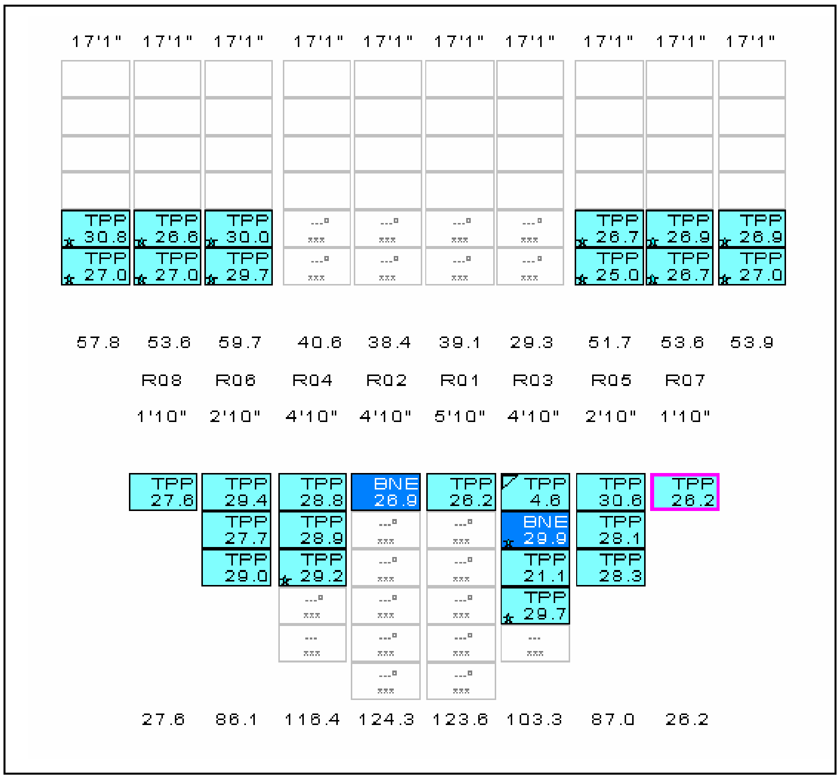

Figure 20: Sample by-Section Plan

This process determines the exact cell occupied by each container at the current port. The generalized stowage pre-plan of the cell stowage planning process is used to direct these specific placements of containers to cells. Additionally, we ensure that all constraints, such as reefer placement, upon container assignments are satisfied, during this stage. The cell-planning process then helps to optimize the stowage plan throughout an entire voyage by reducing the number of container moves within the same cargo space and/or the entire containership.

6.3.4 Obtaining an Initial Solution

We have seen that the size of real world problems (i.e. the stowage planning problem) can grow very large, as the number of variables in the problem increases. Recall that there are $(M-1)/2$ different solutions for the stowage planning problem, where M is a port series length in the particular route (Aslidis, 1990). Exhaustive search is out of the question for a large M, so it would be helpful to have a process that eliminates parts of the search space and minimizes the computational time.

An initial examination of the stowage-planning problem, based upon discussion with maritime personnel, resulted in research focusing upon cellular containerships. Examination of a number of cellular containership structures revealed the fact that a vessel can be divided into a few bays where all sections share a common set of vertical center of gravity (VCG`S) (Ganesan, 1999). Each bay is divided into a number of sections, usually of the same level and size

The hatch-lid can be used as a reasonable separator for upper-deck and below-deck cargo holds. Load restrictions applied to upper deck bays are different from those applied to the under deck bays. In addition, upper deck cargo can be placed across two sections of the lid, creating groups of cargo cells that have a partnership with these sections of hatch-lids. Thus, grouping the cargo space of the containership would reduce the number of options for specific container placements available at any stage of the general planning process. Since the containers have been allocated to certain groups, the general planning process can now proceed to assign the containers to groups within each bay. Constraints (8), (9), and (10) from Chapter 4 must be satisfied; that is, it becomes necessary to distribute the containers between the latitudinal groups associated with each longitudinal group as well. Only containers with particular characteristics are allocated to their corresponding groups. The vessel stress constraint (11) relating to the lateral distribution of weight limit can be calculated to an acceptable level of tolerance.

Therefore, we first sort the data related to the available containership location according to their bay-section address, and then create a load list, taking advantage of the container descriptions. The generated load list of containers grouped into different classes of containers. For instance, all the 40' containers destined $j+2$ would be placed in the same class. Each of these classes (groups) would then be sorted in ascending order of weight. When classes (groups) consist of a large quantity of containers with large spaces within the cargo bay-section, more than one container would be placed. The number of containers placed could possibly start out large and be reduced at each branch of the search tree.

The method that is used most often to solve integer programs that minimize the search space is called branch and bound. Branch and bound is the method usually used to solve integer programs. It does so by minimizing the search space. This is an enumerative procedure that examines all possible values of the integer variables, either implicitly or explicitly, in the search of the optimum solution (Jensen, 2003). Because every bounded integer program has a finite number of solutions, it is conceivable that one could examine each solution with an exhaustive enumeration procedure and then choose the feasible solution. Also, branch and bound is a technique that works on the idea of successively portioning the search space, and can be applied to the general planning process to allocate all containers to individual cargo bay-section spaces. We first need some means of obtaining a lower bound on the cost of any particular solution. If we have a solution with a cost of *C* units and we want to minimize the objective function, then if we know that the next solution to be tried has a bound greater than *C*, we do not have to compute its specific value. We can skip it and move on to the next feasible solution (Michalewicz, 2000).

In the general planning, where the cargo-space is divided longitudinally into different blocks, the algorithm for performing the search would be as follows: First, we sort the loading information (container destination, type, and characteristics), and group the containers into classes. Each of these classes would then be placed into ascending order, according to weight, and used to generate the load list. Containers would be placed sequentially, generating a number of different stowage configuration combinations. When classes of containers consisting of many containers with large available cargo spaces, more than one container would instead be assigned. The number of containers assigned could start out large and be reduced at each branch of the search tree. Therefore, at the first port, we start out with an immense search space, which gets smaller as cargo accumulates.

This process is illustrated in Figure 21 (a), where large group spaces at the beginning of the search imply that there are many possible moves (container assignments) to the new state. As space fills up, the number of possible assignments decreases. The above process produces many different stowage configurations for a single port. Figure 21 (b) is a simple example that shows the loading pattern representation scheme used in this research.

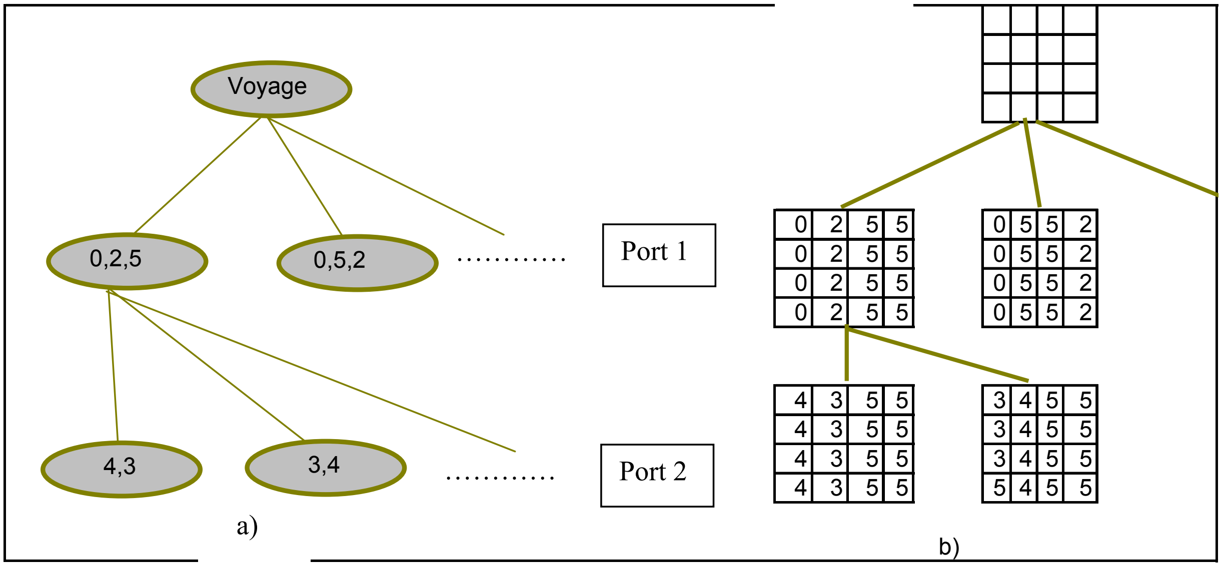

Figure 21: a) A Partition of the Search Space *S* of the Tree, b) the Loading Pattern Associated with the Tree

It is important to remember that each of the solutions passed on for consideration at the next port are starting points from which a large number of solutions will be generated. From these, the best solutions are chosen and passed on. Each solution will be then be ranked according the cost associated with the "re-arranged" containers.

Furthermore, in order to avoid investigating wrong branches, we proposed a combination of best first search, and depth first search. It first selects the most promising node to explore, akin to a best-first strategy. Then, it explores one of its branches using a depth-first approach, without backtracking. Once this branch has been explored, it returns to the best-first approach to select another promising node (loading pattern), and explores one of its branches in a depth-first fashion and so on. The solution process stops when a good feasible solution is found Thus, the branch and bound procedure to obtain an initial solution is as follows:

Procedure "Initial Solution"

Begin

Initialize C
Initialize f_{bound}
While (not termination-condition) **do**
Remove best section $C \rightarrow D_i$
Reduce or subdivide $D_i \rightarrow D_i^l$
Update f_{bound}
$C \leftarrow C \cup D_i^l$
For all $D_i \in C$ **do**
  If $F(D_i) > f_{bound}$ then remove D_i from C

end

For the stowage planning problem, the branch and bound algorithm is specialized as follows:

Step 1: The initial state involves the available cargo-space, referred to as bay–sections, and an ordered list of all the containers to be loaded at current port. The total number of containers to be loaded at each port Δ split into subsets ΔC_j where $j = 1,2,3,.....,M$. where $j > 1$ is the number of different ports visited by the containership. We associate subset ΔC_j where $j = 1,2,3,.....,M$. with sections $d \in D$, depending the on the size of ΔC_j, the value of j, and the subsets $D\Delta_j$ of all sections on board. Devoted to the stowage of containers $c, \forall c \in \Delta_j$. The reefer and the hazmat containers are ordered on the list, according to which ones are to be placed first. We consider the specifications for both types of containers by setting to one the corresponding variables (e.g. hazmat and special constraints). Then, the groups of containers with the furthest destinations are placed in the sequence.

Step 2: New solutions are generated, which reflect every possible placement into a block of the first group of containers. Then in this phase we remove from the search space S, all potential locations that a priori are not to be considered for stowing container $c, \forall c \in C$. If after expanding a partial solution, a feasible solution is found, then it is set aside.

Step 3: Each of the candidate locations on board produced during the Step 2 process, is sorted according to the number of containers associated with the bay-section cargo space. Containers from the loading list are sorted as well. According to the size constraints, we can a priori remove all variables related to both odd bays for 40' containers and even bays for 20' ones.

Step 4: A single bay D_i is selected and removed from the candidate set C during every iteration**.** There are many methods for choosing which section to remove, but one common method is to select a section with a smallest bound. We then try to reduce the size of D_i or to eliminate it altogether. If this utilized for some dimension i, then the section is reduced to a single point, along with the dimension on the boundary of the section. Then, in this algorithm, we remove from the set S all potential locations that a priori are not to be considered for stowing container $c, \forall c \in C$ in the blocks.

Constraints related to special cargo types can be stored in each cargo space and will be used to prune branches from the search tree. Each of the newly generated states is then examined to ensure that no constraint has been violated. Metacentric height and trim will be calculated for each final solution for a given port, starting with the most promising, until all constraints are satisfied. Another important point of consideration at this stage is the fixed data, such as the dead weight and light ship condition. The trim limits are also checked, due to changes from one voyage to another. In addition, the file contains the total number of sections and bays to load. The longitudinal moment (LM) and vertical moment (VM) on board prior to loading are also included.

We obtain the following notations:

W : Total ship displacement, including containers and equipment

MTC : Moment to change trim by $1cm$ at a given displacement

KM : Keel to metacenter distance

LCB : Longitudinal center of Buoyancy

VM : Total vessel vertical moment

LM : Total vessel longitudinal moment

FS : Free-surface effect moment by liquid stores

LBP : Length of vessel between two perpendiculars

The most important characteristic for the loading is the longitudinal moment (LCB) that is given by the vessel's builder. The LCB is different for each vessel. Knowing the characteristics of the containers that are going to be loaded, the LCB can be calculated. Usually, the longitudinal moment is somewhere around the middle of the ship.

The trim is another important coefficient. We prefer to have zero trim, but when this is not possible we prefer to have stern trim. Especially if the ship is not fully loaded, then it can have negative trim. This is the ideal case, because the propeller is immersed in the ocean, providing greater fuel economy and better navigational control.

Therefore, the relationship to compute a containership's GM and trim is:

$$GM = KM - (VM + FS)/W$$

The model calculates the upper and lower limits of applicable moments due to the current set of containers to be loaded. To calculate the load, we input the light vessel's condition, the constant load, liquid stores, and the weight of containers that are already loaded. The model is called to check if the GM and trim have intersects feasibility. If not, the model is reviewed for possible modifications. Again, the model checks for stability through the (8), (9), and (10) constraints.

The vast combinatorial problem described in Chapter 2 has been reduced in size by analyzing the problem in two sub-processes. The purpose of the general planning phase is to arrange containers in such a way that the number of cells occupied by each destination and the number of cargo blocks occupied by containers are minimized.

Now that all containers have been allocated to a block within the cargo space, the next step is to allocate specific stowage locations for each of the containers placed there. This is accomplished by adopting a two-stage procedure for planning the stowage configuration, which is done for each of the cargo bay-section blocks. Stage one of the proposed stowage procedure uses heuristics to generate an initial stowage configuration. Stage two of the proposed methodology uses simulated annealing to optimize the initial configuration. The following section describes this proposed two-stage procedure.

6.3.5 Cell Planning Procedure

The previous section described how the general planning phase would be implemented. The overall solution also requires the implementation of the cell-planning phase, which we are going to discuss in this section. In the cell planning phase, we are considering the general planning process where groups of containers are allocated to bay-section locations as input. At this point, we should use a heuristic approach that makes individual assignments based on three-dimensional bin-packing problem.

The cell planning phase uses the best solution found in the general planning phase. The solution assigns all containers that are to be loaded to blocks. At this stage, we prepare an initial specific solution using the following heuristic approach. The heuristic is used to load the cargo bay-section space depending upon where the block is located and the special requirements, if any, associated with the grouped containers.

The blocks under the hatch usually have restrictions that limit the length of containers that can be placed there. Hazardous containers are more likely to be stowed in the upper deck area, typically in the extreme bay or starboard. As we mentioned earlier, before containers can be allocated to particular cells, we need to sort the containers to be loaded by standard size, destination, and weight. Then, depending on which cargo bay-section space is being filled, containers are sequenced into the blocked cargo space using the following heuristic.

Assume that group G is the set of containers i from the same class and that they still need to be assigned to a place on board. The algorithm searches for the first candidate location to be filled. Usually, if the vessel is empty or partially empty, the group G has to be assigned close to LCB, which is the center of the loading vessels' area. At this point, the procedure also assigns other containers that need special assignment on board. The basic steps of the heuristic approach are as follows:

Step 1. The set of bays B on board are sorted and a cargo- space to consider is chosen.

Step 2. Choose a stacking order for the cargo-space under consideration

Loading starts: stern to bow and from centre outwards

Step 3. Find the first bay-section space that it is not full

Step 4. Find the next container from the loading list (database)

Step 5. If there are still containers to be loaded, then find a stack S that it is not full the top container i on the stack or all the containers on the stack have the same destination port as the candidate container. Place the container into stack S.

Step 6. If there is still a container i to be loaded, go to Step 3.

Step 7. If there are containers with different destinations/characteristics, either find a different stack S where the assigned containers in the stack have the same destination with the candidate container to be placed or attempt to relocate. If they can be legally relocated, then do so and place the removed container back into the load-list.

Step 8. If there are still containers with different destinations/dimensions go to Step 7

Step 9. If there are containers in the load list, go to Step 3

Step 10. Check the stability and loading restrictions. Stop.

Using this heuristic, all containers will be allocated a relative location in the cargo bay-section space such that;

- Overstows are minimized (since containers with the furthest destination are the first to be loaded onto stack
- Heavier containers are stowed lower than lighter ones
- Stacks usually have containers of the same group

The number of containers assigned to a stack at any port cannot be larger than the capacity of the stack. The stability and loading restrictions are checked with the load plan obtained by the algorithm. The sums of weights and both moments (vertical and longitudinal) prior to the loading are part of the input data. The vertical and longitudinal moments' contribution by each bay load is computed. The resulting GM and trim values are checked against their upper and lower limits. The total weight stacked in each on-deck column is checked against the limit applied to the bay. Any violation is reported and the model rearranges the containers in such a way that satisfies the GM and Trim conditions.

The heuristic, which is given in this section, is sufficient to demonstrate the applicability of this approach and generate a starting point for the optimization process. The heuristic used to place containers into the cargo bay-section space could produce a good stowage solution. However, this solution is unlikely to be optimal. The solution found at this stage, therefore, is used as a starting point for an optimization process, which rearranges the containers in the cargo bay-section space. This optimization process is explained in the next section by using Simulated Annealing.

6.3.6 Simulated Annealing Approach

Simulated Annealing is similar to tabu search. As we mentioned earlier, it is a stochastic neighborhood search process. In each stage, L randomly chosen candidate solutions in the neighborhood of the current solution are evaluated. If a candidate solution improves on the current solution, then it is accepted. Otherwise, there is a probability of $P(T,\Delta) = e^{-\frac{\Delta}{T}}$ that it is accepted, which depends on a control parameter

T and the amount Δ, by which a move worsens the current solution. This relation ensures that the probability of moving to a poor solution is very small. This is accomplished in the algorithm below, in steps 5 and 6. At the completion of each stage the temperature T at the beginning of the process, the probability of accepting non-improving moves is fairly high. As the process continues, the temperature decreases and the probability of choosing a non-improving moves decreases. The search is continued until there is evidence to suggest that there is a very low probability of improving on the best solution found so far. At this stage, the system is considered to be frozen.

The simulated annealing search process is initialized with a starting solution x^1. Afterwards, set the iteration counters $l = 1$, $k = 1$, the best known solution $x^* = x^1$. Furthermore, choose the initial temperature T, a stage length L, a cooling rate r and a stopping rule. These choices are discussed in further detail below. In addition, let $U[0;1]$ denote a uniform distribution, from which random numbers are drawn. The procedure can then be described as follows :

Simulated annealing method

Step 1: Is the stopping rule satisfied?

If yes: Stop X^* is the best known solution

If no: Go to step 2

Step 2: Is $l = L + 1$? If yes: Go to Step 8

If no: Go to Step 3

Step 3: Randomly choose $x' \in N(x^k)$ and compute the cost change $\Delta = z(x') - z(x^k)$

Step 4: Is $\Delta \geq O$ (is non-improving move)?

If yes: Generate a random variable p and go to Step 5

If no: Go to Step 6

Step 5: Is $p \leq e^{-\frac{\Delta}{T}}$? If yes: Go to Step 6

If no: Set $l := l + 1$ and go to Step 2

Step 6: (Accept the move) *Set* $x^{k=1} := x'$ and $k = k + 1$

Step 7: Is $z(x^k) < z(x^*)$? If yes set $x^* = x^K, l = 1$ and go to stop 8

If no set $l = l + 1$ and go to step 8

Step 8: Set $T = rT$, and $l = 1$ and go to step 1

The loading heuristic generated a stowage configuration that will require changes, since it is unlikely to be optimal and may have illegal relationships between containers, it would require containers to be moved to other locations. Simulated annealing (SA) is a stochastic computational technique derived from statistical mechanics for finding close by, globally optimum solutions to large optimization problems. It was developed by Metropolis (1953) to simulate the annealing process of crystals on a computer and was first proposed by Kirkpatrick et al., (1982) and Cerny (1985). Kinrkpatrick adapted this methodology to an algorithm exploiting the analogy between annealing solids and solving combinatorial optimization problems. The simulated annealing search process attempts to avoid becoming trapped at a local optimum by using the stochastic computational technique to find global or nearly global optimal solutions to combinatorial problems.

Simulated annealing requires a valid solution to begin with, hence the need for first generating a stowage planning solution by the heuristic. The task of the optimization process is to re-arrange the containers until no further improvement is expected. The key to the optimization process is determining a neighborhood of moves from the current state that are admissible. The neighborhood, in the context of the stowage planning problem, is the set of permissible moves within a single block of cargo bay-section space. The basic step that we used in stowage planning problem follows:

Step 1. Cargo space is optimized by re-arrange containers along the containership until the number of re-handling has been reduced to a minimum. At this stage the neighborhood of the search process is the set of all moves of all containers within the particular cargo space regarding their destination.

Step 2. Cargo bay-section space is optimized by moving containers around until as many blocks as possible have the same length and characteristics of container stowed there.

Step 3. Within each block, arrange containers with the same destination so that heavier containers are stowed below lighter ones. The neighborhood is limited to the same destination containers stowed in the same block.

Step 4. Cargo bay-section space is optimized by re-arrange containers until the weight distribution, satisfying the stability issues. The re-arrangements at this stage occurred only for containers with the same destination.

In summary, the experimentation with simulated annealing search applied to the optimization of the stowage containers, within pre-assigned blocks, resulted in the rapid generation of optimal stowage configurations. When bays have been assigned, then the section part is called to make individual container-cell assignments according to the generated routing plan. Stability and loading restrictions, such as the number of high cubes and weight on-deck are checked on this load from the vessel information. Any violated constraints and locations are identified as well. At this point, the heuristic calls the vessel information to compute the most favorable values of GM and trim. When the algorithm reaches the last step, it performs iterations towards feasibility. Each iteration consists of a pairwise exchange of assignments. At the conclusion of the check, the algorithm calls back the stability function and recomputed stability figures.

Chapter 7: Experiment and Results

7.1 Experiment

In the previous chapters, a mathematical model, improvement methods and heuristic procedures were developed. Since we design these methods for different route and port networks, the algorithms can be applied to different variation of the stowage-planning problem. In this chapter, we will test the proposed algorithm with fixed and randomly generated examples for the algorithm parameter calibration. Many factors had to be considered and evaluated to make the experiment both realistic and interesting. The routing plan is an optimal plan for a situation at a particular period.

In this chapter we present results, which are performed on a 1.40 GHz CPU with 512 MB Memory. The algorithms are implemented in Visual Studio .Net on windows platform. The experiments were varied with vessel capacity and numbers of ports considered, and in the presentation of the experiments, time measurements as well as loading parameters are expressed in terms of container units.

The goal of this chapter is to verify that the proposed algorithm can produce good stowage planning and it works well in a loading procedure of a given port network.

7.2 Performance Analysis

The test problems are based upon today's shipping operations, which are used by different maritime companies. All test problems are for direct port networks, and are classified into two types: problems with low-density networks (partial loading), and problems with very dense or complete networks (almost full loading).

We generated fixed and random test problems that were used to compare the performance of the proposed algorithm with the exact solution and the lower bound of the solution. There are three ranges of problem sizes, which are each in terms of the number of demand nodes. Demand nodes represent the cells on the containership.

The first is a small range with 100 to 500 TEUs, including special containers. For these small problems, we can have an exact solution, lower bound solutions and algorithm solutions. The second is a mid-size range of problems with 501 to 3500 TEUs, which also includes special containers. It is quite difficult to solve this kind of network within a reasonable time. When the number of special containers increases, the difficulty of the problem increases as well. These problems were used to compare the results of the algorithm solution procedure to the lower bounds solutions and on occasion, to the exact solutions. The third range is used for the large networks, for which the exact solution is difficult to obtain. However, the proposed algorithm can give results within a reasonable time. A few problems are used for the analysis at the end of this chapter.

In summary, various scenarios are generated for each combination of port networks and the number of containers to be loaded/unloaded during the voyage. Therefore, the total number of test problems gives a complete overview of the stowage problem and solution procedures. Each scenario has several variables associated with it, including the stability requirements and the container capacity of each bay/section. The number of containers is randomly generated using different fluctuating patterns during a planning period. The random number generator is based on a uniform distribution between $[1, M]$, where M is the maximum capacity of any variables that we need for initialization.

The purpose of this chapter is to verify the proposed heuristic solution procedure, by comparing its result with the exact solution and/or the lower bound solution. The first solution's results are those obtained by directly solving the mixed integer formulation (MIP). We used AMPL Plus version 1.50 with CPLEX 6.5 and/or CPLEX 8.1 solver for the exact solution procedure. It is quite difficult to solve the IP formulation in a reasonable time by using the existing IP solver software for large problems. The commercial software helps us to establish the formulation and is intended to verify the effectiveness of the proposed heuristic algorithm for optimal container loading. Also, we run the LaGrangian relaxation lower bound procedure. In this procedure, we tried several approaches, as discussed in the previous chapters. In this chapter, we present the results that are efficient and reasonable; also, we use AMPL Plus version 1.50 with CPLEX 8.1 solver. The third set of results is from the heuristic solution procedure. We applied the proposed algorithm, which we introduced in the previous chapter, to each set of different scenarios. A summary of the experimental scenarios is shown in Tables 3 and 4. Note that if we want to achieve a good solution, it should be in the vicinity of the local optima. Tables 3 and 4 contain the combinations of approaches that are implemented in each case.

Table 3: The Expected Result from Each Problem Size

Number of	Number of Ports							
Containers	1	3	4	5	7	8	10	12
100	E, LB, H	E, LB, H	E, LB, H	E, LB, H				
200	E, LB, H	E, LB, H	E, LB, H	E, LB, H				
350		E, LB, H	E, LB, H	E, LB, H	E, LB, H			
500		E, LB, H	E, LB, H	E, LB, H	E, LB, H	E, LB, H	E, LB, H	E, LB, H
750		E, LB, H	E, LB, H	E, LB, H	E, LB, H	E, LB, H	E, LB, H	LB, H
1000		E, LB, H	E, LB, H	E, LB, H	E, LB, H	LB, H	LB, H	LB, H
1250		E, LB, H	E, LB, H	E, LB, H	LB, H	LB, H	LB, H	LB, H
1500		E, LB, H	E, LB, H	LB, H	LB, H	LB, H	LB, H	
2000		LB, H	LB, H	LB, H	LB, H		LB, H	
2500	LB, H	LB, H	LB, H	LB, H				
3300	LB, H	LB, H						
4500								
5200								
mega						*	*	*

□) H: Heuristic solution, L: Lower bound solution, E: Exact solution

Table 4: Expected Result from Different Problem Size

Number of	Number of Ports										
Containers	Port 5	Port 6	Port 7	Port 8	Port 9	Port 10	Port 11	Port 12	Port 13	Port 14	Port 15
3000	LB.H	LB.H	LB.H	LB.H	LB.H	LB.H					
3500	LB.H	LB.H	LB.H	LB.H	LB.H	LB.H	LB.H				
4000			LB.H	LB.H	LB.H	LB.H	LB.H	LB.H			
4500			LB.H	LB.H	LB.H	LB.H	LB.H	LB.H			
5700			LB.H	LB.H	LB.H	LB.H	H	H			
6500			LB.H	LB.H	LB.H	H	H	H			
8300		H	H	H	H	H	H	H	H	H	
9350			H	H	H	H	H	H	H	H	H

□) H: Heuristic solution, L: Lower bound solution, E: Exact solution

7.3 Test Environment and Procedure

Experiments of different loading scenarios have been created to test the model. The computational time is one of the major issues in our stowage problem. In addition, in our study, we test the effectiveness of the algorithm using actual load sets of vessels, which visited a series of ports. Containerships commonly carry containers of many other companies, in addition to their own. They ordinarily make cross-Atlantic and cross-Pacific voyages. In our test problems we are going to use cellular containerships, which can carry both 20-foot and 40-foot containers. We also have special cases for 45-foot containers, which are tested using the heuristic solution.

7.4 Comparison of the Results

In this section, we describe the results from the three solution procedures, namely the exact solution method, the L.B. solution procedure, and the heuristic solution procedure. As is shown in Tables 4 and 5, we cannot have all results from all three solutions for each test problem. The gaps between the exact solution (E), the L.B, and the heuristic solution are calculated as follows.

- Total cost gaps between He. and Exact solution = (He – E)/He. * 100
- Total cost gaps between He. and L.B. solution = (He. – L.B.) / L.B. * 100
- Total cost gaps between L.B. and Exact solution = (E - L.B.) / L.B. * 100
- Ratio of calculation time between He. and Exact solution = E / He.
- Ratio of calculation time between He. and L.B. solution = L.B. / He.
- Ratio of calculation time between L.B. and Exact solution = E / L.B.

Test results are summarized in several tables. The results offer feasible load plans, which had acceptable stability indicators. The allowable limits in GM and trim for any vessel in our tests range from 1.0M to 2.0M in both categories, with 0.1M excess in trim tolerated in certain situations.

Unlike other real-world problems with many variables, the stowage problem requires that each container be treated as an identity and its exact shipboard assignment produced by the model. When handling containers, shipside cranes and yard transtainers move in discrete steps. For a pair consisting of port crane and a transtainer, the work sequence is the same for both pieces of equipment. In our model, we had to take the transtainer move distance (TMD) as an assumption. The TMD is constant and can be studied at a future time. Nevertheless, grouping the containers in advance (i.e. at the dock) helps immeasurably with the loading procedure. The container has to be transferred to the dock near to the vessel ready for loading.

Statistics for the number of containers to be picked up per stage and the number of ports are shown in the tables. The vessels we used are typical containerships (cellular or otherwise), which can carry different amounts of containers. The number of refrigerator containers comprises a small percent of the total, while the special containers usually represent less than 1% percent of the total in our tests. We had cases with a large number of refrigerators and special containers, which required a designated storage area for proper ventilation.

We have exact solutions for less than 1500 demand node problems (TEUs) in 5 port network combinations, and less than 2250 demand node problems (TEUs) in 7 port network combinations. A total of more than 50 cases are used for the comparison between the exact solutions and the heuristic. To the extent that we can compare the heuristic and the exact solution results in very small problems (less than 750 TEUs), the heuristic produces excellent results, with short calculation times. However, there are huge differences in the calculation times as the number of TEUs increases. As far we as we can compare the heuristic procedure with the exact solution of medium and large problems, the gap increases. To get the exact solution, we spent tremendous amount of time compare with the heuristic solution. Even in the small cases. The following tables give us the flavor of results for a small cell-network, which is still considered to be a big problem with a huge number of variables. Table 5 below shows the results for a very small problem for a 100-TEU (TEU: Twenty Foot Equivalent Unit) vessel (or barge). In table 6 Loads of TEUs means the vessel's capacity, and Exact(E) represents the exact solution obtained from CPLEX. L.B represents the lower bound solution using CPLEX, and He. is the solution obtained from the heuristic procedure.

Table 5: Experimental Result for 100TEU on Different Port Networks

Ports	TEUS	Load of TEUS	Exact(E) Result	Exact(E) Time (Hr)	L.B Result	L.B Time (Hr)	He. Result	He. Time (Hr)	E & L.B. Result (%)	E & L.B. Time (rt)	E & He. Result (%)	E & He. Time (rt)	L.B & He. Result (%)	L.B & He. Time (rt)
3	100	100	75	8	75	0.3	75	0.15	0	26.7	0	53.3	0	2
4	100	100	75	10	73	0.5	75	0.1	2.74	20	0	100	2.74	5
4	50	100	19	6	19	0.15	20	0.1	0	40	5.263	60	5.26	1.5
4	90	100	60	8	59	1	62	0.15	1.695	8	3.333	53.3	5.08	6.67
4	100	100	75	8	75	1	76	0.2	0	8	1.333	40	1.33	5
5	90	100	60	12	59	1	62	0.15	1.695	12	3.333	80	5.08	6.67
5	100	100	75	14	73	1.15	77	0.2	2.74	12.2	2.667	70	5.48	5.75
6	100	100	85	14	84	1.15	89	0.2	1.19	12.2	4.706	70	5.95	5.75

For TEUs larger than 100, we also compare the Exact solution, the Heuristic solution and the L.B. solution. We have the exact solutions for 200 and 350 TEU problems and we could compare the L.B. solution and the exact solution results. In these small problems, we have a gap ranging from 0.27 to 1.7% between the L.B. and the exact solutions for the 200 TEUs case problems. For 350 TEU case problems, the gap ranging from 1.3 to 4.4 % between the L.B. and the exact solutions. When we consider the gaps between the L.B. and the exact solutions, we can anticipate the gaps between the Heuristic solution and the exact solution for 30 demand node problems to be less than 4.5%.

Table 6 below shows the result of a 200 TEU containership capacity with a small percentage of special containers. These special containers are hazmat containers.

Table 6: Experimental Result for 200TEU

Ports	TEUS	Load of TEUS	Exact(E) Result	Exact(E) Time (Hr)	L.B Result	L.B Time (Hr)	He. Result	He. Time (Hr)	E & L.B. Result (%)	E & L.B. Time (rt)	E & He. Result (%)	E & He. Time (rt)	L.B & He. Result (%)	L.B & He. Time (rt)
3	200	200	364	24	363	2	367	0.15	0.275	12	0.824	160	1.1	13.3
4	80	200	135	16	135	2	138	0.1	0	8	2.222	160	2.22	20
4	100	200	100	24	100	1	104	0.1	0	24	4	240	4	10
4	100	200	117	26	115	1	120	0.1	1.739	26	2.564	260	4.35	10
4	120	200	235	30	231	1	236	0.1	1.732	30	0.426	300	2.16	10
4	150	200	247	30	245	2	251	0.15	0.816	15	1.619	200	2.45	13.3
4	180	200	378	35	375	1.5	382	0.2	0.8	23.3	1.058	175	1.87	7.5
4	200	200	358	30	357	3	361	0.2	0.28	10	0.838	150	1.12	15
5	100	200	105	20	104	1	109	0.15	0.962	20	3.81	133	4.81	6.67
5	160	200	236	26	235	2	237	0.2	0.426	13	0.424	130	0.85	10
5	150	200	400	49	398	2	403	0.2	0.503	24.5	0.75	245	1.26	10
5	155	200	277	30	275	2	277	0.2	0.727	15	0	150	0.73	10
5	200	200	360	50	358	2.5	362	0.2	0.559	20	0.556	250	1.12	12.5
6	100	200	123	28	121	2	124	0.2	1.653	14	0.813	140	2.48	10
6	105	200	169	32	168	2	172	0.2	0.595	16	1.775	160	2.38	10

Table 7 below displays a sample of results for a 350 TEU, in most of the sample cases the vessel is partial loaded.

Table 7: Experimental Result for 350 TEU

Ports	TEUS	Load of TEUS	Exact(E) Result	Exact(E) Time (Hr)	L.B Result	L.B Time (Hr)	He. Result	He. Time (Hr)	E & L.B. Result (%)	E & L.B. Time (rt)	E & He. Result (%)	E & He. Time (rt)	L.B & He. Result (%)	L.B & He. Time (rt)
3	350	350	157	24	155	3	157	0.15	1.29	8	0	160	1.29	20
4	100	350	145	16	144	2	147	0.1	0.694	8	1.379	160	2.08	20
4	200	350	340	24	335	2	349	0.1	1.493	12	2.647	240	4.18	20
4	200	350	313	26	308	2	322	0.1	1.623	13	2.875	260	4.55	20
5	200	350	311	20	305	4	325	0.15	1.967	5	4.502	133	6.56	26.7
6	300	350	593	26	585	4	603	0.2	1.368	6.5	1.686	130	3.08	20
7	100	350	670	49	660	4	693	0.2	1.515	12.3	3.433	245	5	20
7	200	350	268	30	262	3	274	0.2	2.29	10	2.239	150	4.58	15
7	200	350	280	50	268	4	284	0.2	4.478	12.5	1.429	250	5.97	20

In the small problems, the results are quite interesting. For 500 TEU, we have the exact solutions for any network in our test cases (12 ports). The results are fairly good, with the lower bounds and the exact solutions having an average gap of 3.46%. The heuristic results are also good. However, the differences in the calculation times grow very large, as the number of demand nodes increases (TEU that has to be loaded). To get the exact solution, we spent about 200 times longer than was required for the heuristic solution. For instance, in the case with 3 ports, with 200 TEU loading, the computational time is 114 hours, but with very good results. The gap for both cases is below 3%. Table 8 below displays the results of the exact solution, the lower bound, and the heuristic approach for 500 TEU case problems.

Table 8: Experimental result for 500 TEU

		Load	Exact(E)		L.B		He.		E & L.B.		E & He.		L.B & He.	
Ports	TEUS	of TEUS	Result	Time (Hr)	Result	Time (Hr)	Result	Time (Hr)	Result (%)	Time (rt)	Result (%)	Time (rt)	Result (%)	Time (rt)
3	200	500	280	114	274	24	280	2	2.19	4.75	0	57	2.19	12
4	400	500	345	168	338	28	349	2	2.071	6	1.159	84	3.25	14
5	200	500	260	150	253	20	264	1	2.767	7.5	1.538	150	4.35	20
5	320	500	310	175	308	29	312	2.5	0.649	6.03	0.645	70	1.3	11.6
6	200	500	250	140	241	24	256	1	3.734	5.83	2.4	140	6.22	24
6	300	500	290	185	282	28	291	1	2.837	6.61	0.345	185	3.19	28
7	300	500	410	154	406	21	416	2	0.985	7.33	1.463	77	2.46	10.5
10	200	500	240	120	235	19	249	2	2.128	6.32	3.75	60	5.96	9.5
12	200	500	275	160	270	17	276	2	1.852	9.41	0.364	80	2.22	8.5

Table 9 below displays the result of a 750 TEU containership capacity. The lower bounds and the exact solutions have an average gap of 3.08 %. The heuristic results are also good. As we mentioned in the previous cases, there are huge differences in the calculation times as the number of container increases. To get the exact solution, we spent a lot of time more than the time required for the heuristic solution.

Table 9: Experimental result for 750 TEU

Ports	TEUS	Load of TEUS	Exact (E) Result	Exact (E) Time (Hr)	L.B. Result	L.B. Time (Hr)	He. Result	He. Time (Hr)	E & L.B. Result (%)	E & L.B. Time (rt)	E & He. Result (%)	E & He. Time (rt)	L.B. & He. Result (%)	L.B. & He. Time (rt)
3	**750**	**500**	240	32	235	6	246	0.2	2.0833	5.333	2.5	160	4.6809	30
4	**750**	**450**	285	95	277	7	293	0.2	2.807	13.57	2.807	475	5.7762	35
5	**750**	**550**	620	120	594	9	641	0.3	4.1935	13.33	3.3871	400	7.9125	30
7	**750**	**500**	785	130	758	9	805	0.3	3.4395	14.44	2.5478	433	6.2005	30
8	**750**	**600**	832	150	818	9	843	0.3	1.6827	16.67	1.3221	500	3.0562	30
10	**750**	**500**	925	135	903	11	972	0.35	2.3784	12.27	5.0811	386	7.6412	31.43
12	**750**	**550**	950	170	923	12	989	0.35	2.8421	14.17	4.1053	486	7.1506	34.29

Table 10 below displays the results for 1000 TEUs case problems. In this set of experiment runs, it is obvious that the number of variables is growing enormous, which affects the computational time. In addition, from this point, the gaps between the lower bound and heuristic solution (LB - He.) and the heuristic solution and exact solution (He. - E) increase, but remain in an acceptable range (5 to 10% gap). This could be caused by a number of different constraints that are interacting with each other or the stability issues, which are very sensitive components.

Table 10: Experimental result for 1000 TEU

Ports	TEUS	Load of TEUS	Exact (E) Result	Exact (E) Time (Hr)	L.B. Result	L.B. Time (Hr)	He. Result	He. Time (Hr)	E & L.B. Result (%)	E & L.B. Time (rt)	E & He. Result (%)	E & He. Time (rt)	L.B. & He. Result (%)	L.B. & He. Time (rt)
3	600	1000	1325	360	1290	29	1335	1.5	2.71	12	0.75	240	3.49	19
4	400	1000	1305	320	1280	31	1324	1	1.95	10	1.44	320	3.44	31
5	300	1000	1270	325	1210	24	1291	2	4.96	14	1.63	163	6.69	12
5	500	1000	1350	380	1265	36	1370	1	6.72	11	1.46	380	8.30	36
5	850	1000	1770	420	1685	54	1805	2.5	5.04	8	1.94	168	7.12	22
6	550	1000	1306	310	1255	42	1342	1	4.06	7	2.68	310	6.93	42

Previous tables indicate that by using the algorithm, we obtain a desired solution and that the overall gap percentage over the lower bound is approximately less than or around 5%, at least for the small and medium cases. We note that in most of the cases, the algorithm produces good solutions. However, in a few cases we have slightly different results. This happens most commonly when we have special containers.

For a 1250 TEU containership with 7 bays, thirteen rows, and thirteen columns (eight is in the hold and five in the upper deck, respectively), we tested our model and heuristic solution by referring to the 15 cases, reported in Table 11 below. It is clear, such cases differ from each other by the number of containers to load (ranging from 588 to 1250), their size, type, and the number of ports to be visited (ranging from 5 to 10). Column "Full" gives the vessel occupation level (in percentages) when all containers are loaded. A 100% occupation level is allocated when 1250 TEU containership are loaded for the second case. Usually, a few cells on board are always kept free for security and possible emergency reasons (Ambrosino, et al., 2004).

Table 11: Data of the 1250 TEU Case Under Consideration

Case	Container					Size	Full (%)
	TEUs	General	Reefer	Hazmat	Destination		
1	1234	925	306	13	10	1250	98.72
2	1250	845	392	13	10	1250	100
3	1008	742	256	10	10	1250	80.64
4	1008	802	196	10	10	1250	80.64
5	1214	909	302	3	8	1250	97.12
6	1200	1007	180	13	5	1250	96
7	960	662	288	10	5	1250	76.8
8	1092	745	336	11	7	1250	87.36
9	882	649	224	9	5	1250	70.56
10	896	663	224	9	5	1250	71.68
11	1120	913	196	11	7	1250	89.6
12	972	674	288	10	5	1250	77.76
13	588	414	168	6	5	1250	47.04
14	1230	1003	214	13	10	1250	98.4
15	1152	884	256	12	10	1250	92.16

The computational results related to the cases described in Table 12 are displayed in Table 12 below. As before, Table 13 gives the value (He.) by solving the stowage planning model, the lower bound (L.B.), and the objective function value (Exact) by applying the mathematical model presented in Chapter 4, as well as their relative optimality gaps, as described in previous Section (Section 7.3). The objective function is very close to lower bound, and differs from it by an average of 4.02%. The good performance of the heuristic solution can be observed in column “Result (%)” that reports the optimality gap as a percentage difference, between the optimal solution and both the relaxed and the heuristic one, given by the ratios $(He. - E)/E$ and $(E - LB)/LB\%$. The computational times are in hours corresponding to the above solutions.

Table 12: Experimental Results for 1250 TEU Case

Case	Container		Ports	Exact (E)		L.B.		He.		E & L.B.		E & He.		L.B. & He.	
	Size	TEUs		Result	Time (Hr)	Result	Time (Hr)	Result	Time (Hr)	Result (%)	Time (rt)	Result (%)	Time (rt)	Result (%)	Time (rt)
1	1250	1234	10	795	205	762	48	813	0.6	4.2	4.27	2.26	342	6.7	80
2	1250	1250	10	780	192	734	46	800	0.8	5.9	4.17	2.56	240	9.0	58
3	1250	1008	10	683	180	652	40	715	0.5	4.5	4.50	4.69	360	9.7	80
4	1250	1008	10	665	170	645	42	688	0.7	3.0	4.05	3.46	243	6.7	60
5	1250	1214	8	735	190	698	45	750	1	5.0	4.22	2.04	190	7.4	45
6	1250	1200	5	690	165	665	38	715	0.7	3.6	4.34	3.62	236	7.5	54
7	1250	960	5	625	140	602	44	646	0.8	3.7	3.18	3.36	175	7.3	55
8	1250	1092	7	645	146	615	36	674	0.6	4.7	4.06	4.50	243	9.6	60
9	1250	882	5	445	124	420	28	457	0.3	5.6	4.43	2.70	413	8.8	93
10	1250	896	5	420	130	408	26	460	0.5	2.9	5.00	9.52	260	12.7	52
11	1250	1120	7	515	154	489	34	554	0.3	5.0	4.53	7.57	513	13.3	113
12	1250	972	5	453	130	438	24	470	0.3	3.3	5.42	3.75	433	7.3	80
13	1250	588	5	375	136	368	24	394	0.2	1.9	5.67	5.07	680	7.1	120
14	1250	1230	10	815	235	785	56	870	0.9	3.7	4.20	6.75	261	10.8	62
15	1250	1152	10	751	222	725	46	779	0.7	3.5	4.83	3.73	317	7.4	66

The computational times in the three cases are also graphically reported in Figure 22, which outlines the impressive reduction of the computational time when our solution is used.

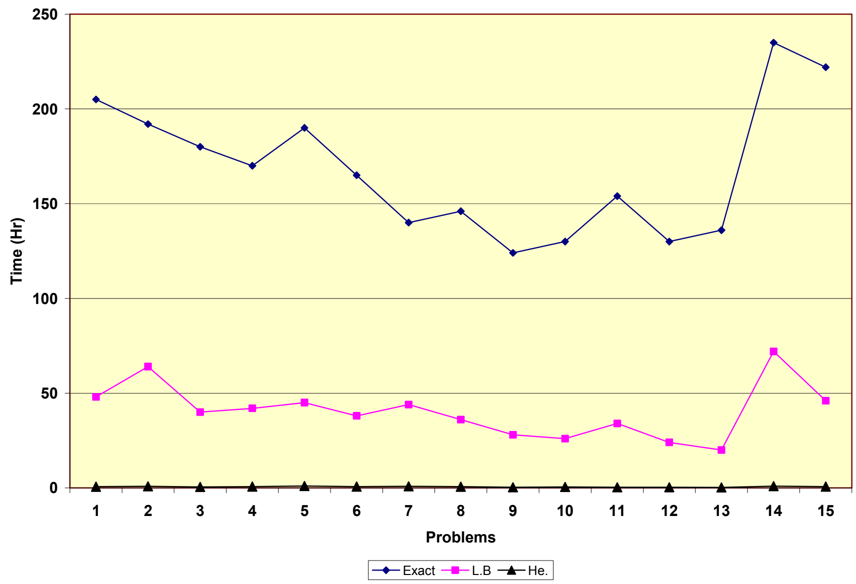

Figure 22: Trend of the Computational Time for the 15 Cases

7.5 Experimental Results for Different Port Networks

As a comparison and evaluation of the mathematical models and solution we have generated a few classes of small and medium sized scenarios, for the same port number of ports network, with containers having different destination, weight and size. All computational experimental experiments have been performed on the same platform as before. The results are shown in Tables 14, and 15. The heading as follows: TEU give for each problem size; "Exact" is the objective function value using CPLEX, L.B. is the value of the relaxed model without a couple of the bin-packing constraints, and He. Is the value obtained by applying our heuristic solution to the problem resolution. Also, the headings *Constraints, Non-zeros* have been generated from CPLEX runs for each case.

Table 13 below shows the results for 5 ports network for different loading schedules. TEU represents the capacity of the vessel. Constraints and non-zeros are generated from the CPLEX. The containerships which services the route is designed to satisfy container demand in each port. Less than 4% special containers are considered in problem 4 for 750 TEU.

Table 13: Experimental Results of 5 Ports Network

Port Network 5									
Problems	TEU	Constraints	Non-zeros	Exact (E)		Lower Bound		Heuristic	
				Result	CPU	Result	CPU	Result	CPU
1	100	122899	16419170	60	12	59	1	62	0.1
2	200	129904	18945621	231	26	230	5	232	0.1
3	350	165439	20239548	289	36	289	1.5	294	0.2
4	750	186654	34129870	210	29	207	2.1	213	0.2
5	1000	367104	42189751	301	124	299	2	307	0.2
6	1250	394512	48099189	294	176	290	2	299	0.2
7	1500	431981	57312540	345	201	339	2.3	351	0.2
8	2000	495533	63902430	510	230	499	2.1	519	0.3
9	2500	563299	70349012	555	230	551	3	563	0..2

Table 14 shows the results for 7 ports network for different loading schedule. Each bay of the containership consists of two sections. Also, in these problems the empty containers consists the 20% of loaded containers. For problems 7 to 12 we were not able to obtained values for the exact solution using CPLEX.

Table 14: Experimental Results of 7 Port Network

Port Network 7									
Problems	TEU	Constraints	Non-zeros	Exact (E)		Lower Bound		Heuristic	
				Resutl	CPU	Resutl	CPU	Resutl	CPU
1	500	180349	21349192	155	40	153	1.5	160	0.1
2	750	219745	29117234	185	48	185	2	189	0.2
3	900	223491	45858127	325	68	319	3	333	0.2
4	950	271219	49651938	274	80	269	4	278	0.3
5	1050	288346	58632931	293	88	290	3	300	0.3
6	1100	319812	64823953	343	92	340	3.1	347	0.4
7	1500	377873	72904822	*	-	451	5	465	0.4
8	2000	418451	78969319	*	-	565	4.5	574	0.5
9	3200	449347	82796990	*	-	578	4	589	0.4
10	4500	500349	88010429	*	-	596	5	603	0.4
11	5700	532009	94675672	*	-	640	6	652	0.6
12	6500	632581	98389193	*	-	*	-	695	0.5

The computational results related to the 5 port network cases described in Table 15. The heading in the Table 16 are as follows: columns Vessel Capacity and TEUs give for each class of scenario the specification of the set of containers to be loaded on the vessel. Again, column Exact (E) is the objective function value, L.B. is the relaxed model, that it is our lower bound, and He. is the value obtained by applying our proposed solution to the problem.

Table 15: Experimental Results for 5 Port Network

Problem	Port	Vessel Capacity	TEUs	Number of constraints	Solution		
					Exact (E)	L.B.	He.
1	5	100	100	12569	170	165	172
2	5	200	180	245632	265	230	272
3	5	350	200	437129	385	365	405
4	5	350	300	481546	355	330	380
5	5	500	420	410456	555	578	580
6	5	750	500	554398	750	730	795
7	5	750	540	559183	740	725	794
8	5	750	650	572345	885	825	915
9	5	900	450	639843	1140	1085	1195
10	5	900	700	682574	1180	1120	1220
11	5	900	800	693485	1160	1115	1705
12	5	1000	500	547634	1315	1280	1375

7.6 Computational Results

The goal of this section is to verify that the proposed heuristic works well in any port network that has loading schedule variation during the voyage when dynamic demand information is available in the database. To investigate the performance of the heuristic procedure suggested in this study, computational tests were done on many fixed and randomly generated problems. Test problems developed for each port network (i.e.

3, 6… 15), levels of the vessel capacity (i.e. 1000, 3000…, 8100) and a few levels for the number of container weights. These parameters values used for problem generation were selected so that resulting test problems reflected real stowage planning problems in maritime industry. The allowable limits in GM and trim for the containerships varies but for many cases were from 1.0M to 2.0M with 0.1M excess in trim tolerated in certain situations. Different loading and special loading schedules must be dealt with. We tested our algorithm for different loading scenarios on the same network, including four different types of containers, general, refrigerators, hazardous and empty containers.

In a real world situation, the loading plan for a vessel is generated based on consideration of all demand and loading schedules received from previous days. Prior to the vessel's arrival in a port the operational office prepares the loading plan. After the vessel call, new containers can arrive. There are two ways to deal with the newly arrived demands. One is to postpone all new demands that arrive until the next voyage, while the other is to accept the new demands that arrive and re-schedule the container-loading plan for the new arrivals if there is adequate notice. In our study we considered that the loading list is completed for each port.

For our study we generated a basic network that represents a service region consisting of different ports. The port characteristics and the vessel design speed are also generated for this research by approximating the real world situation. All the container weights are between 5 to 25 tons. As mentioned earlier, the capacity of the vessel can be translated in the number of TEU's, and into the number of tons.

To give an idea of the type of the problem that can come up, let us present an example concerning a stowage plan of the containership, where we have a load of general containers split between 20' and 40' with weight ranging from 5 to 25 tons. These containers have to be loaded for a 4 port network. The containership consists of 4 odds bays, namely 01, 03, 05, and 07. The bay has 10 rows, namely R01, R02… R10, and seven columns denoted by 06, 04, 02, 0.0, 01, 03, 05. The containership has a capacity of 15000 dwt. The number of plugs under deck is 25.

The vessel has sections separated into 20' and 40'. As a rule the 20' cells are next to each other, which make up that particular 40' bay see Figure 23.

Bay A

9	19	29
7	17	27
5	15	25
3	13	23
1	11	21

Bay A+1

10	20	30
8	18	28
6	16	26
4	14	24
2	12	22

Sequence of Cells loading

Figure 23: Section Configuration (partial)

We solve the problem using CPLEX and the optimal solution is 235, which it was obtained in 2 hours and 35 minutes. The formulation of the problem according to model results in 24200 variables, and 39546 constraints. While using the heuristic approach proposed in Chapter 6 the minimum oversotwage cost is 238, corresponding to an optimality gap of 0.85 %. Figure 24 below shows an example of a partial departure bay-section plan giving container destination, origins and type.

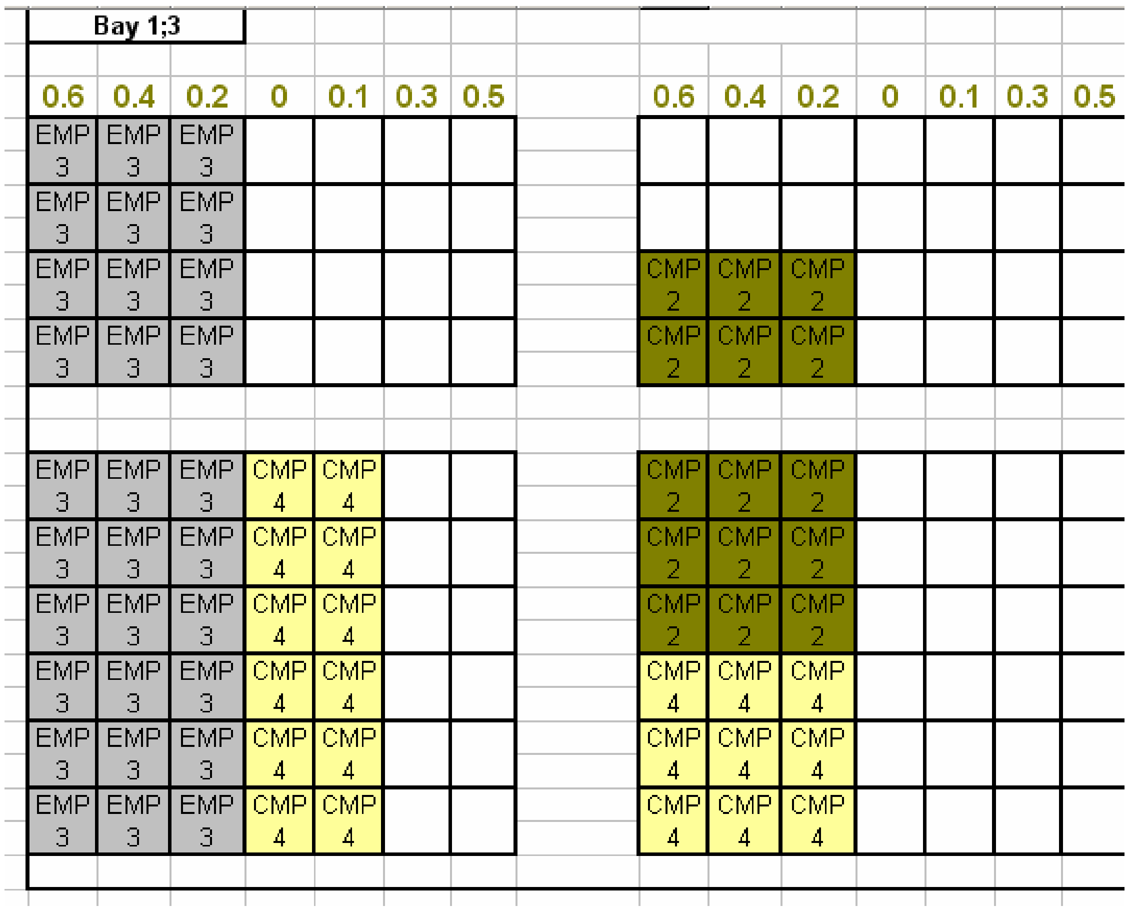

Figure 24: Stowage Plan for the Bay-Section

Let us consider another example with a containership capacity of 700 TEUs, with 11 sections, 8 columns and 8 rows. Again we have general containers split between 20' and 40' with weight ranging from 5 to 25 tons. The loading schedule is for 8 port network. The vessel is 75 % full loaded. The vessel has sections separated into 20' and 40'. The number of special containers constituted only 0.9 percent of the total. Table 16 below displays an example of loading plan for different ports in the same route. For instance, in Port HDE the loading list includes containers from APL, and MSC lines

(APL and MSC are shipping and logistics companies). G describes the general and R the refrigerator containers.

Table 16: Example of loading schedule

	APL					MSC					TOTALS
	20'		40'			20'		40'			
	G	R	G	R	H	G	R	G	R	H	
HDE			12	20		9		76	5		122
KHG	15		173	9		21	5	51			274
PCT	2		40	1		10		29			82
PCO	7		13	1		8		105			134
UME	11		97					34	3		145
	35	0	323	11	0	39	5	219	3	0	635
TOTALS	35		334			44		222			
	369					266					

The stability check for trim violations was effectively used to reduce the trim in most of the cases. The formulation of the problem according the mathematical model results of in 90500 variables, and 436578 constraints. The optimal solution, corresponding the objective function value is 413 and it was obtained in 4 hours. While using the heuristic approach the minimum cost is C: 418 corresponding to an optimality gap of 1.21 %.

A complete set of section plans, optimized with respect to container allocation was generated using the heuristic procedure that an example of which is shown in Tables 17 and 18. Note that in Tables 18 and 19: X Marks the empty cells, PCT is an earlier port of destination that PCO. Also, containers numbered 4020 are 40’ in length and ones labeled 2010 are 20’ in length.

Table 17: Departure Section Plan # 5 Giving Container Destination, and Characteristics

X	Por3/Por4 10T 4020	X	Por1/Por4 10T 2010	X	X
Por3/Por4 20T 4020	Por3/Por4 20T 4020	Por1/Por4 20T 2010	Por1/Por4 10T 2010	X	X
Por3/Por4 20T 4020	Por3/Por4 20T 4020	Por1/Por4 20T 2010	Por1/Por4 20T 2010	X	X
Por3/Por4 20T 4020	Por3/Por4 20T 4020	Por1/Por4 20T 2010	Por1/Por4 20T 2010	Por1/Por4 20T 2010	X
Por3/Por4 20T 2010	Por3/Por4 20T 2010	Por1/Por4 20T 2010	Por1/Por4 20T 2010	Por1/Por4 20T 2010	X
Por3/Por4 20T 2010	Por3/Por4 20T 2010	Por1/Por4 20T 2010	Por1/Por4 20T 2010	Por1/Por4 20T 2010	X
Por3/Por4 20T 2010	Por3/Por4 20T 2010	Por1/Por4 20T 2010	Por1/Por4 20T 2010	Por1/Por4 20T 2010	X

Table 18: Departure Section Plan # 6 Giving Container Destination, and Characteristics

X	Por3/Por4 10T 4020	X	X	X	X
Por3/Por4 20T 4020	Por3/Por4 20T 4020	X	Por1/Por4 10T 2010	Por1/Por4 10T 2010	Por1/Por4 10T 2010
Por3/Por4 20T 4020	Por3/Por4 20T 4020	Por1/Por4 10T 2010	Por1/Por4 10T 2010	Por1/Por4 10T 2010	Por1/Por4 10T 2010
Por3/Por4 20T 4020	Por3/Por4 20T 4020	Por1/Por4 10T 2010	Por1/Por4 15T 2010	Por1/Por4 20T 2010	Por1/Por4 20T 2010
Por3/Por4 20T 2010	Por3/Por4 20T 2010	Por1/Por4 10T 2010	Por1/Por4 15T 2010	Por1/Por4 20T 2010	Por1/Por4 20T 2010
Por3/Por4 20T 2010	Por3/Por4 20T 2010	Por1/Por4 10T 2010	Por1/Por4 20T 2010	Por1/Por4 20T 2010	Por1/Por4 20T 2010
Por3/Por4 20T 2010	Por3/Por4 20T 2010	Por1/Por4 20T 2010	Por1/Por4 20T 2010	Por1/Por4 20T 2010	Por1/Por4 20T 2010

The results we have presented and discussed in this chapter indicate that the algorithm works well. The idea behind the model philosophy is to assign containers on board according to overstowage cost.

7.7 Sensitivity Analysis

In this section, sensitivity analyses for the problem parameters that can be very critical for the model were performed. The intent is to examine the performance of the proposed model with respect to changes in the input parameter values. The parameters for sensitivity analysis that were studied in this section are as follows:

- Different loading patterns for the same number of ports network
- Different percentage of the number of special containers
- Different percentage of the order of 20 and 40 foot containers

The minimum overstowage cost changes win particular, were examined when the changes were made in the elements of the shipment matrix. In order to perform the sensitivity analysis, different scenarios of the problem was tackled. The containership that was examined for the most tests has a capacity of 350 containers, which are placed across five bays and seven columns up the ship's configuration. The containership also has split hatches covering pairs of bays along the length of the ship. This means that if containers under the deck need to be removed all of the containers on the hatch must be removed first. In our examples to follow it is clear that we kept the port network constant and the containers weight ranging from 5 to 25 tons.

Port network with four ports were considered and different loading scenarios of different cases were tested. These cases have different container distribution among the ports. The first study is related to the four port network with 20% container distribution from the network's first port (Port 1). Also, these tests included 20% of 40 foot containers and less than 10% refrigerator containers. The computational results for the 4 port network with 25% container distribution are described in Table 19 below.

Table 19: Test Problems for Twenty Percent Containers from Port 1

Case	Container					Object.
	Ports	Variables	Constraints	Non Zeros	Clique	
1	4	35350	1255	369097	410	555
2	4	35350	1254	368417	410	580
3	4	35350	1260	372863	410	595
4	4	35350	1253	367885	410	575
5	4	35350	1247	364765	410	560
6	4	35350	1257	370005	410	565
7	4	35350	1248	365373	410	570
8	4	35350	1254	368607	410	570
9	4	35350	1258	370617	410	575
10	4	35350	1254	371305	410	575

Table 19 above shows the number of problems (cases: 100_350) defined by the parameters' combinations using 20%.

Table 20 below shows the number of problems defined by the parameters combinations using 50%. The re-arrangement cost in Table 20 obtained slightly lower value compared with the cases in Table 19. This result was expected because the loading schedule plans from Table 20 has more containers to be distributed t the next port than the loading schedule plans from Table 19. Therefore, containers have been assigned to the bay-section cargo space on board regarding the next destination port.

Table 20: 100_350_A Cases for Fifty Percent Container from Port 1

Case	Container					Object.
	Ports	Variables	Constraints	Non Zeros	Clique	
1	4	77685	34652	2917234	410	535
2	4	77685	34558	2784531	410	580
3	4	77685	34761	2850912	410	520
4	4	77685	34034	2734053	410	580
5	4	77685	34200	2669097	410	555
6	4	77685	34983	2930134	410	540

As recognized from the Tables above, the re-arrangement cost varies and all these examples have the same total number of containers on board while the container distribution to each port changes. Therefore, it would be interesting to see the loading pattern of these two cases. Figure 25 below compares the two different loading patterns between cases in Tables 19 and 20. This example will only cover the Bay 5 departure from the first Port.

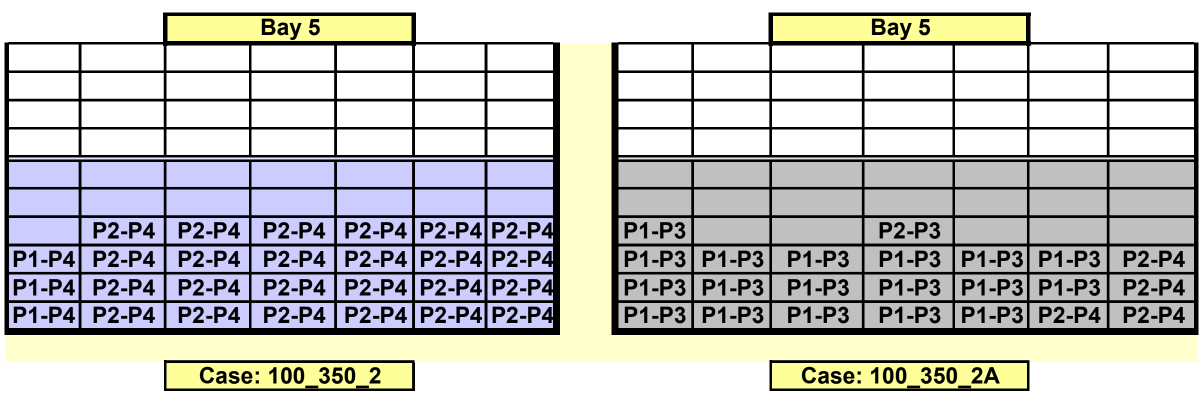

Figure 25: Departure Plan from Port 1 Giving Origin-Destination

Note that in Figure 25, for example, P1-P2 marks the origin and destination port of the container that has been assigned to this particular cell. It is relevant to note how the containers have been assigned in this particular Bay, because the stability constraints have to be satisfied

In the case of the special containers in Figure 26 below the re-arrangement cost increased when the number of special container increases. In the second test the cost is 710 with 36% of the total being special containers including a combination of 20-and-40 foot containers (see Figure 26). Figure 26 also, shows the re-arrangement cost for different cases in the same port network. The results are given for different loading plans.

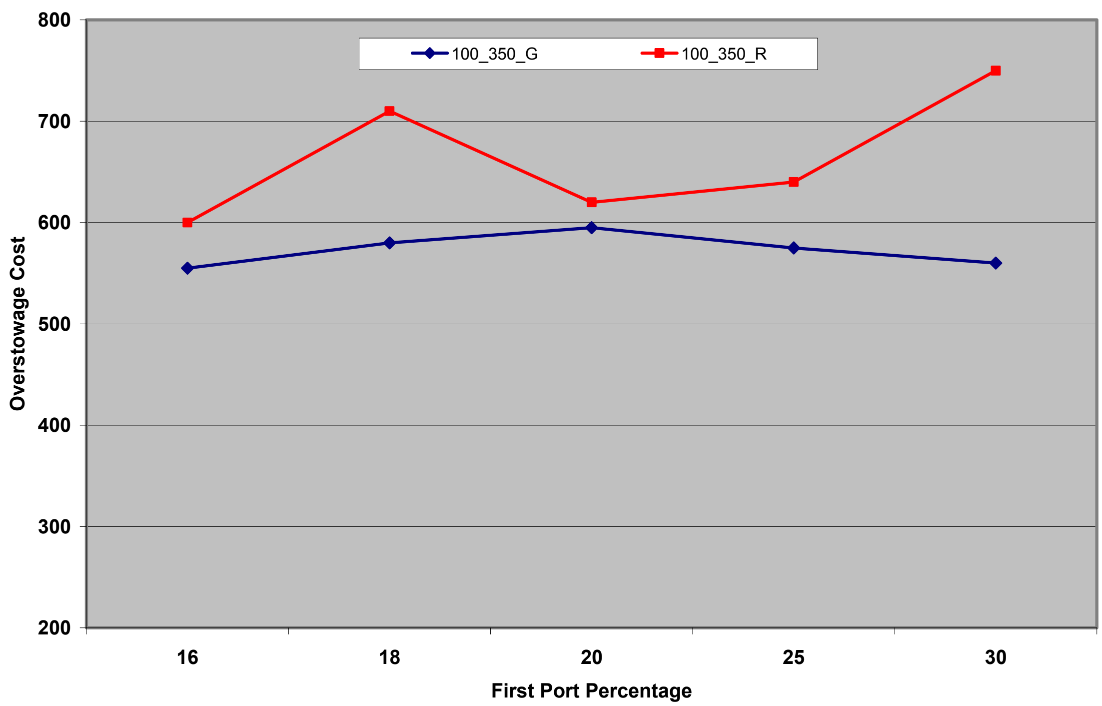

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Figure 26: Cost for 100_350_R and 100_350_G Cases for four Port Network

Table 21 below shows the sensitivity analysis result for 350 TEU cases with a mix different container dimensions. The table shows examples of the combinations in the different loading plans for 20-and-40 foot containers. The cost slightly increased when combination of 20-and-40 foot containers were loaded was taken into consideration.

Table 21: 100_350_D Cases for a Mix Dimension

Case	Container					Object.
	Ports	Variables	Constraints	Non Zeros	Clique	
100_350_D	4	35350	1245	363579	450	535
100_350_D1	4	35350	1240	360919	450	580
100_350_D2	4	35350	1246	364107	450	520
100_350_D3	4	35350	1230	360383	450	580
100_350_D4	4	35350	1257	369963	450	555

Figure 27 below shows the loading pattern of two different test cases with different loading combinations resulting in different loading plans for the partial load vessel. Example 100_350_D represents case with a mix dimension when the 40-foot containers are 30% and the example 100_350_7 consist of 10% 40-foot containers

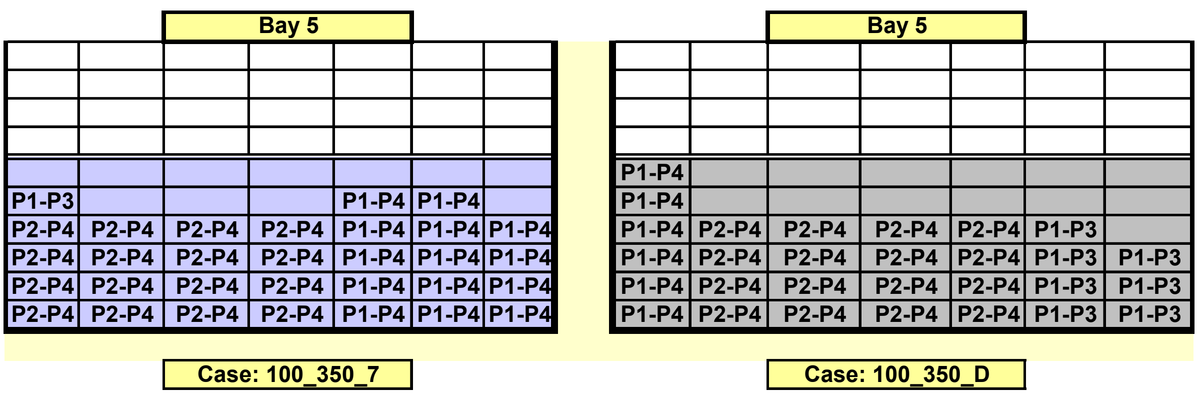

Figure 27: Departure Loading Plan at the Port 1

Another parameter that was tested in the container weight, particularly empty containers. Empty containers are a very prominent problem for the maritime industry. More than 40% of the world's container transportation refers to empty containers (Kaisar, 1999). Figure 28 below shows a loading plan example of container assghmnets in Bay 3 which has different loading plans. Case 100_350 has 10% empty containers when case 100_350_D has more than 50 % empty containers. This result could be different if there were a different loading plan or/and a full loaded vessel, because the empty containers should be assigned on the upper deck.

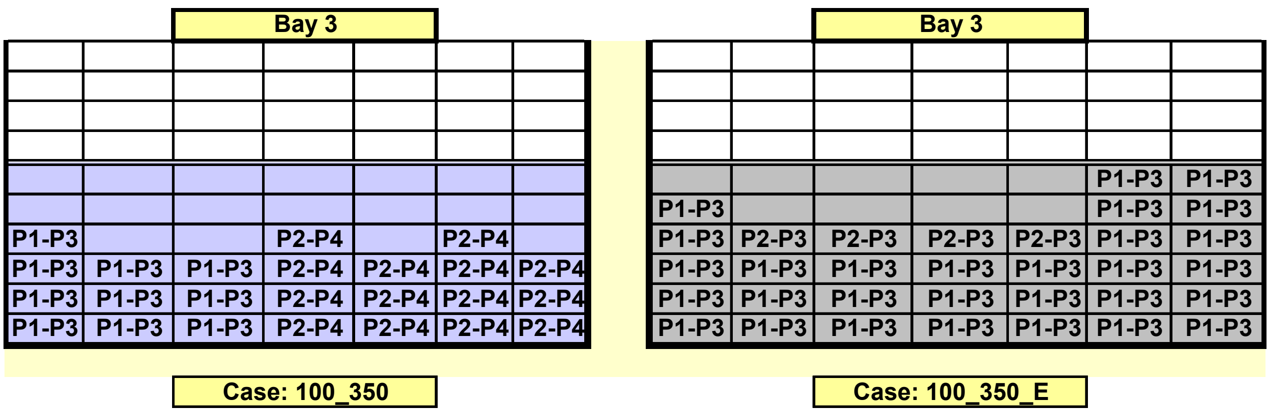

Figure 28: Loading Plans Departure First Port

The sensitivity analysis was presented with respect to model parameters, and was performed with respect to the re-arrangement cost. The results indicated that the proposed model performed as expected with respect to changes in these parameters.

Chapter 8: Conclusion and Future Research

An extensive research effort was necessary for this study to create and validate the optimization model presented in this thesis. This chapter provides a summary and conclusions as well as recommendations for future research.

8.1 Summary and Conclusions

In this research we proposed a new formulation for a stowage-planning program that can deal with real life constraints. A stowage-planning mathematical model is developed which considers all real life constraints and considering loading/unloading along the voyage. In addition, the formulation allowed all related loading parameters to be specified. The focus of the thesis has been the overstowage problem that has been examined in an order of increasing difficulty. This model was created to specifically to deal with the problem subsets, since the stowage problem is a combination of the assignment, three dimensional bin packing, and knapsack problems. The formulation proposed in this thesis deals with containership operations, but in reality the problem also arises in many other applications.

The stowage planning is a combinatorial problem with the number of possible stowage configuration for a containership of 2000 TEU being huge (approximately 3.3 times ten to 5735th power (Wilson, 1999, and Avriel 1993) and can be described as being NP-hard (Avriel, 1998). This means that an exact optimal solution cannot be found in a reasonable time using any available computer and software, and a heuristic solution algorithm is needed to solve problem of reasonable size.

The design of efficient approximation algorithms for this problem requires deep insight into its mathematical structure and inherent complexity. The problem is really complex due to large number of variables, such as vessel stability, reefer and hazardous cargo assignment on specific cells on board. To overcome the computational difficulties associated with producing a solution for the stowage-planning problem the problem was decomposed into two subproblems namely:

1) A ***general planning process*** involving the assignment of containers to a blocked bay-section space.
2) A ***cell planning process*,** which involves the assignment of the containers to specific cells within their assigned blocked bay-section space.

The solution of the general planning process gives a picture of the containers stowage distribution at each port at the end of the loading/unloading process. This approach reduces the combinatorial size of the problem and retains its characteristics at the same time. Blocking the available cargo space at each port of loading determines the number of options available at any stage of the stowage planning process. Stress and stability can be calculated for this phase using the stability and the vessel constraints from the model.

In the cell-planning process specific containers are assigned and/or re-arranged to specific cells within the blocked bay-section area. In this phase, the neighborhood is reduced to the moves within the same blocked area, and avoids the combinatorial difficulties.

A literature search was performed to survey the existing loading and heuristic models. This led to a good understanding of container loading and what research scholars in the field had already performed. We reviewed heuristic techniques such as the branch and bound that we used to allocate all the containers on board into individuals bay-section cargo areas. We reviewed the general simulated annealing (SA) background and structure. We also reviewed the application of SA's for the Bin-packing problem as well as developed a Simulated Annealing to solve the formulated problem. We modified the simulated annealing random keys and characteristics to fit our problem. We also tested the parameters used in the SA, including the number of multiple runs, the stopping criteria, and etc. The tests showed that the SA gave the appropriate results.

To verify the performance of the proposed heuristic, we compared the results from the heuristic solution procedure to the exact solution and a lower bound. The problem sizes that could be solved by different solution procedures are different. In the case of the exact solution procedure, we could get the results for problems with less than 1500 containers. For small problems, the heuristic produced very good results compared with the exact solution procedure within a very short period of time. The comparison between the exact solution and the heuristic solution shows that the heuristic produced good results quickly.

For larger problems, we designed a method to obtain lower bounds. We were able to obtain lower bounds for problems with up to 4500 containers. The difference between the heuristic solutions and the lower bounds were less than 4% except for the 5000 container problems that have gaps less than 6-7%. When we consider that the lower bound solutions had less than 4% gaps with the exact solutions, the proposed heuristic produced acceptable solutions.

In summary:

- Data from the maritime industry were used to calibrate the optimum-loading model. The results from the heuristic procedure using this data indicate that the proposed heuristic procedure works well.
- The analysis of the results of the experiment presented in this thesis showed that we could improve on loading operations at the port.
- The ability to define all of the model's parameters such as GM, trim, stability, etc makes the model very useful for loading planners as well as port authorities who deal with the day-to-day operations of the port.
- The heuristic has the advantage of requiring minimal computational time compared with the methods that we discussed in the literature review.
- The model is useful in the assignment of containers on containerships, optimizing costs, and improving productivity.
- It would be really good for this model to compare the results with the real world situation, if we can get data from any containership company. The problem here is that the companies do not release any information because of their business strategic plans.

8.2 Future Research and Performance Enhancements

Although this thesis explores container-loading patterns and the development is quite elaborate and realistic, it is clear that some aspects of this research suggest areas for future work. For instance, additional factors, such as quay crane movements during the loading/unloading process would result in container load sequence that minimizes total cost and time from the container terminal perspective. One extension to our model of special interests would be the additional constraint on loading sequence. How the containers have been distributed on board and how many quay cranes have assigned to the vessel for each port is really important. As mentioned earlier, for each section position, the stowage plan model assigns a container type with respect to the stability and vessels constraints along the route. However, a feasible stowage plan does not guarantee that the vessel will spend the minimum time at the port. Consequently, only a careful assignment of transportation duties to quay cranes will optimize the overall loading process. A quay crane requires between 80 and 120 seconds to load a single container to its section position. Also, the quay cranes should not be too close because they can interfere with each other. Loading/Unloading time increases if there are more shifting operations caused by over stows or if there are more longitudinal movements of cranes. Moving distance or time required for the movement is proportional to the number of sections where containers are to be loaded or unloaded. A more or less regular sequence of loading events ensures a smooth loading process that helps to avoid waiting times.

Another area of extension is the consideration of probabilistic shipment matrix. It is useful to extend the analysis to incorporate more general assumptions about when the containers of the shipment matrix become known and how the stowage planning is affected. Optimal decision-making can be achieved through perfect information. Unfortunately, in many cases in the maritime industry, complete container information is not available to the decision makers. Probability theory will allow decision makers to rationalize their decisions in the circumstances and determine a course of action. Therefore, decision support systems that try to optimize decisions made by practitioners by determining relationships between supply and demand should present predictions in terms of probabilities. Aslidis (1989) made a first step towards this direction by assuming that one of the elements of the shipment matrix is known only up to its probability distribution

Another extension to the problem is the consideration of container dock assignment, equipment assignment and periodic shipment requirements among a finite set of ports. High operating costs for vessels and container terminals and also high capitalization of the vessels, containers and port equipment demand a reduction of unproductive time at port. Therefore, the potential for cost savings is high. A key to efficiency is the automation in container terminal, storing, and stacking to increase the terminal throughput and decrease ship turnaround time at the terminal. One of the most important issues regarding terminal automation is the lack of appreciation of the usefulness of existing optimization techniques to improve the efficiency of operations. An automated system should reduce such preparation time to a minimum. Additional factors, such as container and crane movement during the loading process, factored into the evaluation of a stowage plan, would result in container loading procedure that minimize cost from the terminals point of view.

For containership that is loading / unloading, containers have to be transported from the storage area or from the dock to the containership and vice versa. Transport optimization at the quayside not only means a reduction in transport times, but also the synchronization of the transport with the loading/unloading process of the quay cranes. A general aim is to enhance crane productivity and containership turnaround time. The real performance at operation is in the range of 22-30 containers/hr moves. However, crane productivity can be even higher according to technical data. The reduced productivity comes from unnecessary shifts, moves of hatch covers, and lashing equipment. Additionally, more transport vehicles provoke further costs and containership operation becomes less economic. Concerning logistics, a gain in containership productivity cannot be necessarily achieved by enhancing the number or the speed of transport vehicles operating at the quayside. This is because the possibility of congestion at the cranes and in the yard increases more than proportionally with the number of vehicles or their speed. Therefore, an optimization system also has to cope with the minimization of port congestion.

In the area of heuristic algorithm design and analysis, there are several research efforts that can be undertaken both from the analytical and computational viewpoint. Testing of the proposed heuristic is as necessary as further development of the theoretical analysis of the stowage-planning problem. It is also worth examining alternative approaches such as Genetic Algorithm (GA), and neighborhood search with tabu search. Some research is devoted to developing GAs that can be implemented in parallel machines. To implement a parallel GA, we need to study the way to re-distribute information among the sub-populations. Parallel computing is another area of extension that is the simultaneously execution of the same task on multiple processors in order to obtain results faster. The idea is based on the fact that the process solving a problem usually can be divided into smaller tasks, which may be carried out simultaneously with some coordination.

Finally, we can take under consideration the different container height constraint. Today, containerships are dealing with two (2) to three (3) different height types of container and it would be interesting to see what effect this has on stowage planning. This type of constraint definitely affects the maximum number of containers per stack especially on deck or abroad a cargo ship going from one location to another. It also determines its location, size, and weight and the actual time it takes to load and unload.

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