Reconfiguration Strategies for Mitigating the Impacts of Port Disruptions

FINAL REPORT

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Abstract

Marine terminals and ports are designed to meet expected demands during normal operations in order to facilitate the smooth and efficient movement of goods. Disruptive events may affect thes e normal operations, and terminals, ports and regions must be prepared to mitigate such disruptio ns in an effort to maintain the movement of goods.

In this project, we investigate methods of modeling and evaluating the port disruptions and develop mitigation strategies for reducing the impacts of disruptions. The types of disruptions we study in this work are assumed to occur at the local and regional levels. We show that disruptions at the local level can be modeled as terminal allocation problems (TAP). The multi berth allocation problem is viewed as a set partitioning problem, in which each partitioned problem consists of a single berth allocation problem (BAP). Berth allocation is an essential logistics operation, since, the deployment of other resources at a terminal have to be coordinated with the berth allocation plan. The BAP is an NP-hard problem, and consequently heuristic methods based on sub gradient and simulated annealing algorithms are developed to find a near-optimal solution within a reasonable amount of time. Numerous experimental scenarios are developed to evaluate the proposed BAP methodologies in the presence disruptions.

The problem at the regional level is to develop mitigation strategies so that the regional throughp ut in moving goods is affected by the disruption at a minimal level. We look into the U.S. west co ast region, consisting of multiple ports and the associated traffic network used for moving the go ods within and out of the region. The regional service network is defined at a high level of aggre gation, which includes the major ports and aggregated zones representing broad geographical des tinations and intermediate zones. The network under disruption is modeled as the minimum cost flow problem with binary constraints.

We demonstrated via examples that our methodology that relies on the use of optimization can m inimize the effect of disruption at all levels.

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Disclosure

Project was funded in entirety under this contract to California Department of Transportation.

List of Acronyms and Abbreviations

AGV: Automated Guided Vehicle

AP: Acceptance Probability

BAP: Berth Allocation Problem

B&B: Branch-Bound method

BOA: Berthed-On-Arrival

BTR: Berth-Time-Requested

CDF: Cumulative Distribution Function

ETA: Estimated-Time-Of-Arrival

AF: Assignment Formulation for the Berth Allocation Problem

FCSN: Fixed Cost Service Network Formulation

MCFP: Minimum Cost Flow Problem Formulation

MCFPB: Minimum Cost Flow Problem Formulation with Binary constraints

MILPF: Mixed Integer Linear Programming Formulation for the BAP Problem

RPF: Relative Positioning Formulation for the Berth Allocation Problem

SSST: Separating the Set of Slack Transportation links in the MCFPB

H1: Heuristic 1

H2: Heuristic 2

IP: Integer Programming

mH1 : Modified Heuristic 1

MILP: Mixed Integer Linear Programming

PCU: Passenger Car Unit

LRπ : Relaxed Problem using Lagrangian Multiplier

D: Dual of Problem LRπ

SA: Simulated Annealing

SG: Subgradient

SPP: Set Partitioning Problem

TAP: Terminal Allocation Problem

1 Introduction

In today's global economy, the oceans are becoming increasingly important for international trade. Currently, more than 80% of the world's trade travels by water. A very important component of this global economic chain is container transport, since about half of the world's trade by value, and 90% of the general cargo, are transported in containers.

Shipping is the heart of the global economy, but it is vulnerable to attacks. Trade passes primarily through a small number of hubs spread around the globe. Close to 75% of the world's maritime trade and half of its daily oil consumption pass through a handful of international straits and canals. Hence, the international commerce is at great risk from attacks at one of the major trading hubs or at one of a handful of strategic chokepoints [1],[2]. The adoption of a just-in-time delivery approach to shipping by most industries, rather than stockpiling or maintaining operating reserves, means that a disruption or slowing of the flow of almost any item can have widespread implications for the overall market, as well as upon the national economy.

Disruptions to the maritime transportation system could be due to natural causes, (such as hurricanes or earthquakes), or to man-caused activities (such as military surge or terrorism acts). Moreover, the disruptions can be classified as predictable/anticipated (such as the longshoremen strike), or unpredictable/unanticipated (such as a potential terrorist attack).

The location where the disruption occurs is a very critical parameter in determining the disruption's impact. For example, disruptions of operations in the ports on the west coast can have a national impact, since the combined port of Long Beach/Los Angeles handles 33% of the total container traffic in the US [3]. This huge volume moving through the local ports has very serious effects not only at the local and regional levels, but on a national scale as well. As a consequence the national economy has become heavily dependent on the smooth and reliable operation of the west coast ports. This fact became quite evident during the 2002 longshoremen strike at the Port of Los Angeles, which for 11 days crippled the nation at an estimated cost of $1-$2 billion per day [4].

In this study, we investigate methods of modeling and evaluating the effect of disruptions and develop mitigation strategies for reducing their impact on port operations. The types of disruptions we investigate are such that they can render a terminal partially or totally non-functional. These disruptions can be caused by equipment failure; physical damage to the terminal berths due to natural or manmade disasters; delays caused by increased demands as in the case of military surge, etc. Disruptions, caused by failure of one or more berths at terminals within a single port, are related to the berth allocation problem (BAP), as it is referred to in the literature. Berth allocation is an essential logistics operation for the management of container terminals. According to the berth allocation plans, terminal operators are required to coordinate the deployments of various resources within the ports so that containers are moved as smoothly and as quickly as possible.

When a disruption takes place, the terminals might be unable to meet the expected demand, due to partial or total loss of operational capabilities, or to a sharp rise in the demand (e.g. military surge). Furthermore, such a disruption could affect several terminals within a particular port. It is therefore critical to allocate berths to ships in such a way as to meet all demand, minimize the vessel berthing time and maximize berth utilization. In order to mitigate the impacts of disruptions, methods will be developed to re-route goods to different berths within the terminal, or to different terminals within the ports so that the overall port throughput is affected as little as possible. The question we will answer in this study is: how can we reassign ships to berths/terminals within the same port, such that the overall port throughput is maintained.

In this study, we first address disruptions that can be handled on the local level i.e. by the termina l itself via reallocation of resources or port level via reallocation of resources among terminals. D isruptions that cannot be handled on the local level are studied on the regional level alone or in c ombination with local level.

On the local level we consider the continuous BAP (as opposed to the discrete BAP), because it is more diverse and more practical as a way of allocating resources on the berth level in order to serve ships. Since the continuous BAP cannot be calculated in polynomially-bounded time [7], we develop and implement some heuristic procedures based on sub gradient and simulated annealing optimization methods, a set of systemic and efficient heuristics is implemented, in order to find an initial feasible solution and to update a current solution by exploring a sufficiently large solution space.

In addition to the BAP, we address the allocation of ships to multiple berths. This problem is referred to as the terminal allocation problem (TAP). We will see that the TAP can be viewed as a set partitioning problem, and hence it is an NP-hard problem. We develop a methodology based on simulated annealing algorithm to solve the TAP.

The objective at the regional level is to develop mitigation strategies so that the effect of disruption on the regional throughput is minimized. We consider the US west coast region, consisting of multiple ports and the associated traffic network used for moving the goods within and out of the region. The regional service network is defined at a high level of aggregation, which includes the major ports and aggregated zones representing broad geographical destinations and intermediary zones.

The flow of freight in the regional service network under normal operating conditions is modeled as a minimum cost flow problem in which the disruption level is low enough to be handled by ground transportation modes. When disruption occurs, the regional service network is reconfigured to deal with the situation. For example, if the LA port zone is rendered non-functional for a period of time, all services associated with the zone will either be discontinued or operate at a lower capacity, which will affect its throughput capacity. The re-configuration of the service network will involve opening sea transportation links between port zones. The regional service network under disruption is modeled as a minimum cost flow problem with binary (or, integer) constraints. It is solved by branch-and-bound method and a LP relaxation is performed on every leaf of the branch-and-bound tree.

This report is organized as follows: In Section 2, the berth allocation problem (BAP) is described and various formulations of the problem are presented. In Section 3, the BAP is modeled analytically and two solution methods are developed. In Section 4, an extension to the BAP, the terminal allocation problem (TAP), is studied. The TAP is modeled as asset partitioning problem, and solution methods are proposed. The service network optimization is explained in Section 5. In Section 6, the overall modeling and mitigation is demonstrated by an example. Finally, Section 7 presents the conclusions.

2 Container Terminals and the BAP

A container terminal is a facility where containerized cargo is trans-shipped between ships and land vehicles (trucks and trains). A terminal may have several wharfs (quays). Each quay consists of several berths, which in turn are divided into sections. Each quay corresponds to a linear stretch of space in the terminal. Container ships are moored at a berth of a terminal where they are unloaded and loaded by gantry or quay cranes. Quay cranes traverse along the quay to position containers at any point along the length of the ship. Quay cranes at berths load imported containers on in-yard trucks, straddle carriers, or automated guided vehicles (AGVs). Quay cranes also unload export containers from these vehicles into the ships. To maximize berth utilization and minimize ship-turn-around time, ships should be optimally assigned and allocated to berths. Hence, optimal allocation of berths to incoming ships will have a substantial impact on logistics cost and level of service.

Usually, carriers inform the terminal operator of their *estimated-time-of-arrival* (ETA), latest possible service completion (departure) time, and request a berthing time (called *berth-time-requested* or BTR) several days in advance [5]. A vessel is said to be *berthed-on-arrival* (BOA) if the mooring operation commences within 2 hours of arrival. The BOA statistics is often used as an indicator to gauge the quality of service provided by the port operator [6].

Based on the information received, a terminal operator tries to satisfy the requested departure times of every vessel by allocating one or more sections on a berth to calling vessels according to their ETAs, estimated departure times, and BTRs. However, in cases when the arrival rate of vessels is high, or unexpected arrivals occur, or any type of disruption happens at a terminal, it may not be possible to serve all the vessels before their requested service completion time. Thus, departures of some vessels may be delayed past the requested due time [5].

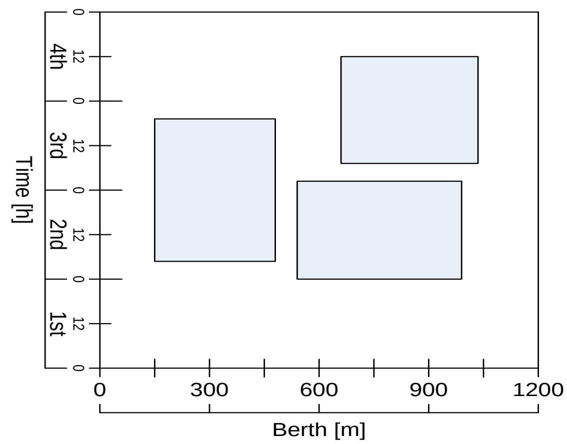


Figure 1: Space-time diagram for the berth allocation problem

Figure 1 illustrates the space-time diagram of a berth schedule. The horizontal axis represents the berth length, while the time is represented by the vertical axis. Note that, in Figure 1, a vessel is represented by a rectangle. The length of the vertical side of each rectangle represents the duration of stay of a vessel at the berth, while the length of the horizontal side represents the vessel length [5], [7]. Each calling vessel is characterized by its own space-time rectangle. These rectangles cannot overlap either in the space or in the time dimension. The Berth Allocation Problem (BAP) is to determine the optimal locations of those rectangles without overlaps [5]. In other words, the BAP consists of optimally allocating and scheduling the berth space to calling carriers such that the carriers are served within their time limits.

2.1 Classifications of the BAP

The BAP can be classified into the following two general categories:

1- *Discrete vs. Continuous BAP:*

In the continuous BAP, the berthing can be done in a continuum of locations along the berth [8], [9]. In contrast, in the discrete BAP, the entire quay is divided into a countable number of berths. In the discrete problem, it is assumed that, at each instant of time, at most one vessel can be served at each berth.

It should be noted that a discrete BAP can be modeled as an unrelated parallel machine scheduling problem, and the continuous BAP can be mapped into a two-dimensional cutting-stock problem, which is an NP-Hard problem [7]. The focus of this study is on the continuous BAP. The continuous BAP is more diverse and general. It can address the growing trends in ship sizes, as there is a need for more flexible berth allocation planning. For instance, mega-ships may sometimes moor across neighboring berths in order to enhance berth usage.

2. *Static vs. Dynamic BAP*

In Imai *et al.* [10], the static BAP refers to the problem in which all the ships are assumed to have arrived at the port prior to the beginning of the berths' scheduling. In contrast, the dynamic BAP takes into account not only the ships that have already arrived at the time of planning, but also those which will arrive later during the planning horizon. Furthermore, it is assumed that the arrival times of all the ships are known a priori, hence re-planning is not an issue.

In a general planning problem, however, the dynamic environment refers to the events whose occurrences may change in time. For example, in the work by Moorthy and Teo [6], the authors deliberately induce delays in the port stay time of vessels and increase the number of vessels to evaluate their dynamic policy in a rolling horizon framework. That is to say that the notion of dynamic BAP used in [10] is very limited and, therefore, we will use the second notion in which the occurrence of events may change in time.

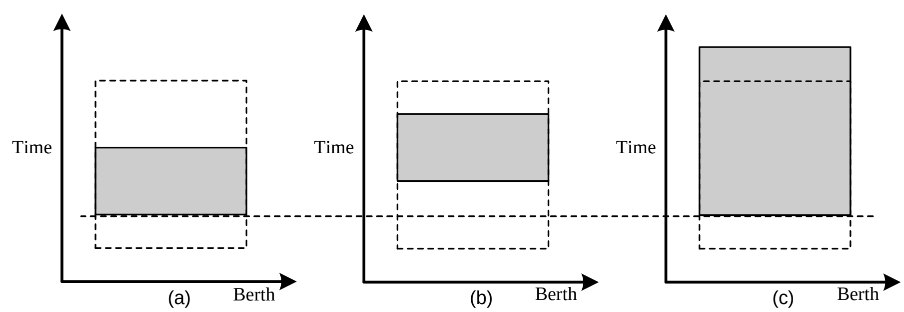


Figure 2: Changes in the original allocation due to changes in arrival time and service time. The original assignment of the ship, (b) delayed arrival time, and (c) delayed service time Resulting from the terminal's lack of resources (such as cranes and trucks)

Figure 2 demonstrates possible disruptions in an original berth allocation. These disruptions may have occurred due to delays in vessel arrival time (Figure 2b), or vessel service time (Figure 2c). If these unexpected delays make the original allocation plan unsatisfactory, re-allocation of vessels may be needed to maintain the same level of quality of berth performance. The re-allocation can easily be implemented by using a rolling horizon framework in such a dynamic environment. It should be noted that frequent re-planning is often undesirable and sometimes impossible as it has adverse impact on other terminal resources. So, the re-planning of a berth allocation should be carefully performed by considering the impact on all in-terminal resources.

2.2 Literature Review

Recently, berth allocation problems have been the focus of many research efforts. Imai *et al.* proposed a mixed integer programming formulation of the discrete berth allocation problem [10]. Two formulations are developed for static and dynamic variants of the problem. A Lagrangian relaxation methodology equipped as a heuristic method was developed to minimize the ships' waiting and handling times. Imai *et al.* in [11] developed a formulation and a solution methodology for the discrete berth allocation problem with priority considerations. In this work, they extended their previous work in [10] to serve calling vessels at various service priorities. A heuristic method based on genetic algorithms was developed to approximately solve the problem with less computational burden.

In [8], Imai *et al.* considered a continuous berth allocation problem in which a vessel can be moored across the designated quay boundaries. The authors developed a heuristic solution based on their discrete BAP solution in [10]. They used a series of local procedures to ensure the feasibility of the solution. The approach was based on the fact that an optimal solution to the BAP provides an upper bound, when the berth length is set to the maximum ship length, and provides a lower bound, when the minimum ship length is used. Guan and Cheung in [12] developed a composite heuristic for a BAP whose objective is to minimize the weighted completion time. A batch was defined as a group of ships whose total size is smaller than the overall berth space. As an exact solution method, a tree search procedure was proposed to solve small-sized problems. In the composite heuristic proposed, a pair-wise exchange was performed between batches. The tree search procedure was applied to enhance the solution of each batch.

Park and Kim in [5] addressed a BAP with a general objective that minimizes the costs resulted from the vessels delayed departure times. The objective function also consists of additional handling costs, which were resulted from deviated berthing locations. The BAP formulation is very practical since the cost related to the delayed departure times is explicitly minimized. In practice, penalties are imposed if the requested service cannot be done by the requested departure time. A subgradient optimization technique was applied to solve the proposed BAP formulation. A heuristic method was repeatedly used to update an upper bound. The method attempted to move overlapping schedules to feasible directions which yielded the minimum cost increase. Park and Kin in [13] proposed a simulated annealing based method to solve the BAP. Their heuristic resembled the tree search in [12] since it sequentially tried to locate each ship at lowest-cost point.

Moorthy and Teo in [6] studied the allocation of preferred berthing space to a set of vessels which arrive periodically in a weekly basis. The authors used the concept of sequence pair for defining search space. By defining the time and space constraint separately, cost estimation for each dimension was provided. Several neighborhood searches were employed by a simulated annealing method to modify or update a sequence pair. However, due to the periodicity of the weekly arrivals, the authors focused on reducing the overlaps between unfinished vessels rectangles in the current planning horizon and scheduled rectangles in the next horizon. Golias et al. in [14] considered simultaneous berth and quay cranes scheduling. They formulated the problem as an integer programming problem with objective of minimizing the costs resulting from delays. They used the genetic Algorithms optimization technique to solve the problem.

3 The Berth Allocation Problem (BAP)

In this section, we study the static continuous berth allocation problem which can be represented by a space-time diagram where the horizontal and vertical axes represent the berthing space and time, respectively. Figure 3 shows the representation of a berth in the space-time diagram. A vessel k with length l_k and width h_k can be defined by a rectangle in this diagram.

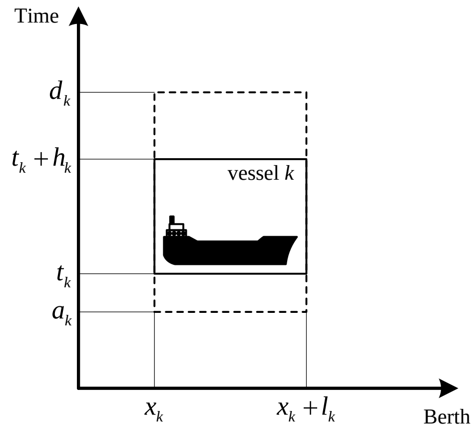


Figure 3: Defining a vessel in the space-time diagram

3.1 The BAP Formulations

The following notation is used throughput this section for the various formulations of the BAP that will be presented.

M Number of sections along the berth (length of the berth)

T Time horizon

K Number of vessels to be scheduled

a_k Estimated arrival time of ship (vessel) k

d_k Desired departure time of ship k

h_k Estimated handling time needed for ship k

w_k Priority factor (weight) assigned to ship k

l_k The length of ship k in terms of the number of sections along the berth

x_k The section of the berth for which the left bottom corner of ship k is assigned

t_k The time at which berthing of ship k starts

δ_{kl} The relative horizontal position of ship k with respect to ship l. It is 1 if ship k is completely to the left of ship l, and 0 otherwise

σ_{kl} The relative vertical position of ship k with respect to ship l. It is 1 if ship k is completely placed below ship l, and 0 otherwise

α The minimum space required between two ships moored at the same time at the berth (i.e., safety allowance)

τ The minimum time needed between a ship departure time and the next ship berthing time at the same location (i.e., time stability factor)

The mathematical formulation for the BAP can be either represented by the relative position of vessel rectangles, or by the space covered by the vessel rectangles.

3.1.1 The Relative Positioning Formulation for the BAP

The *relative positioning formulation*, which hereafter is called formulation *RPF*, considers the relative positioning of vessel rectangles. The objective function (1) minimizes the penalty incurred by not satisfying the desired departure times requested by vessels. The notation $(\cdot)^+$ in (1) is used with the following meaning: $y^+ = \max\{0, y\}$.

$$\min \quad \sum_{k=1}^{K} w_k (t_k + h_k - d_k)^+ \tag{1}$$

$$\text{s.t.} \quad [x_l - (x_k + l_k) - \alpha] \cdot \sigma_{kl} \geq 0 \qquad \forall k, l, k \neq l \tag{2}$$

$$[t_l - (t_k + h_k) - \tau] \cdot \delta_{kl} \geq 0 \qquad \forall k, l, k \neq l \tag{3}$$

$$\sigma_{kl} + \sigma_{lk} + \delta_{kl} + \delta_{lk} \geq 1 \qquad \forall k, l, k \neq l \tag{4}$$

$$\sigma_{kl} + \sigma_{lk} \leq 1 \qquad \forall k, l, k \neq l \tag{5}$$

$$\delta_{kl} + \delta_{lk} \leq 1 \qquad \forall k, l, k \neq l \tag{6}$$

$$x_k \in [1,\ M - l_k + 1] \qquad \forall k \tag{7}$$

$$t_k \in [a_k,\ T - h_k + 1] \qquad \forall k \tag{8}$$

$$\sigma_{kl} \in \{0,1\} \qquad \forall k, l, k \neq l \tag{9}$$

$$\delta_{kl} \in \{0,1\} \qquad \forall k, l, k \neq l \tag{10}$$

Constraints (2) are to ensure the space requirement if a vessel is completely placed to the left of another vessel. Constraints (3) are to guarantee the time requirement if a vessel is completely placed below the other vessel. Constraints (4)-(6) ensure that no vessel rectangles are overlapping. Constraints (7) are the space constraints, (8) are time constraints, and (9), (10) are binary constraints.

3.1.2 The Assignment Formulation for the BAP

The *assignment formulation*, which hereafter is called formulation *AF*, is based on partitioning the space-time diagram into grid tiles which are covered by vessel rectangles as shown in Figure 4. A block (i, j) is referred to as a grid space whose left bottom corner is located at (i, j) for $i \in [1, M]$ and $j \in [1, T]$. As an example, the vessel rectangle k covers the consecutive blocks from (i, j) to $(i + l_k - 1, j + h_k - 1)$.

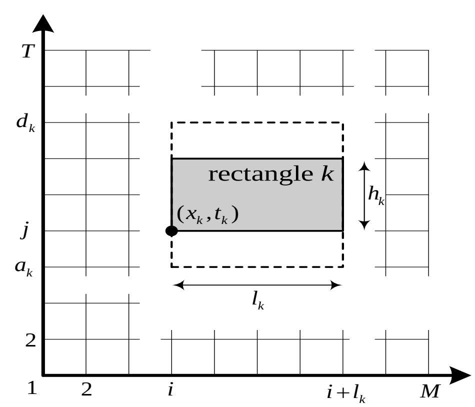


Figure 4: Vessel-berth allocation in grid spaces

Additional notation used here to represent the assignment formulation:

z_{ijk} : 1, if the left bottom corner of rectangle k is located at (i, j); 0, otherwise

y_{ijk} : 1, if rectangle k is covering block (i, j); 0, otherwise

Similar to (1), objective function (11) minimizes the penalty incurred by not satisfying the desired departure times requested by vessels. However, in contrast to (1), the minimization in (11) is not performed on a continuum but a discrete number of time periods (tiles) representing the unmet requested departure time.

$$\min \quad \sum_{k=1}^{K} \sum_{i=1}^{M-l_k+1} \sum_{j=a_k}^{T-h_k+1} z_{ijk} \cdot w_k (j+h_k-d_k)^+ \tag{11}$$

$$\text{s.t.} \quad \sum_{k=1}^{K} y_{ijk} \le 1 \qquad \forall i,\ j \tag{12}$$

$$z_{ijk} l_k h_k - \sum_{m=i}^{i+l_k-1} \sum_{n=j}^{j+h_k-1} y_{mnk} \le 0 \qquad \forall i=1,\cdots,M-l_k+1,\ j=a_k,\cdots,T-h_k+1,\ k \tag{13}$$

$$\sum_{i=1}^{M-l_k+1} \sum_{j=a_k}^{T-h_k+1} z_{ijk} = 1 \qquad \forall k \tag{14}$$

$$y_{ijk} \in \{0,1\} \qquad \forall i,\ j, k \tag{15}$$

$$z_{ijk} \in \{0,1\} \qquad \forall i=1,\cdots,M-l_k+1,\ j=1,\cdots,T-h_k+1,\ k \tag{16}$$

Constraints (12) imply that a block is covered by at most one vessel rectangle. Constraints (13) ensure that blocks covered by a vessel rectangle must be consecutive. Constraints (14) imply that each vessel has only one berthing coordinate. Constraints (15) and (16) are binary constraints.

3.1.3 The Mixed Integer Linear Programming Formulation for the BAP

The following formulation, which hereafter is called formulation *MILPF*, is equivalent to the BAP formulation in *RPF* and is the mixed integer linear programming formulation for the BAP. Similar to (1), the unmet desired departure times requested by vessels are minimized in (17).

$$\min \quad \sum_{k=1}^{K} w_k \beta_k^+ \tag{17}$$

$$\text{s.t.} \quad t_k + h_k - d_k = \beta_k^+ - \beta_k^- \qquad \forall k \tag{18}$$

$$x_l - (x_k + l_k) - \alpha - N(\sigma_{kl} - 1) \ge 0 \qquad \forall k, l, k \ne l \tag{19}$$

$$t_l - (t_k + h_k) - \tau - N(\delta_{kl} - 1) \ge 0 \qquad \forall k, l, k \ne l \tag{20}$$

$$\beta_k^+, \beta_k^- \ge 0 \qquad \forall k \tag{21}$$

and Constraints (4)-(10).

The objective function in (17) minimizes the penalty cost resulting from the delay in the departure time of vessels. A method for dealing with $(t_k + h_k - d_k)^+$ variables is to introduce new variables β_k^+ and β_k^-, constrained to be nonnegative, and let $t_k + h_k - d_k = \beta_k^+ - \beta_k^-$. It is intended to have $t_k + h_k - d_k = \beta_k^+$ or $t_k + h_k - d_k = -\beta_k^-$, depending on whether $t_k + h_k - d_k$ is positive or negative. Then the original problem (*RPF*) can be formulated as a MILP by adding a corresponding constraint (18) to (21).

For an optimal solution to the problem, and for each value of k, we must either have $\beta_k^+ = 0$ or $\beta_k^- = 0$. That is true since otherwise we could have reduced both β_k^+ and β_k^- by the same amount while preserving feasibility. In other words, we could have reduced the cost, which is in contradiction to optimality. Constraints (19) and (20) are to enforce the definitions of σ_{kl} and δ_{kl}, and N is a large positive number.

3.1.4 Some Notes on Alternative Objective Functions

The objective function used in (1) minimizes the penalty associated with the violation of the desired departure times requested by the vessels. A generalized alternative for this objective function is one that rewards early service operations. The following function is a possible choice for generalized objective function, which is a linear combination of penalized late departure time and rewarded early service operation.

$$\mathrm{J}_2 = \sum_{k=1}^{K} \left\{ w_k^1((t_k + h_k) - d_k)^+ - w_k^2(d_k - (t_k + h_k))^+ \right\} \tag{22}$$

where $w_k^1 > 0$ is the penalty weight, and $w_k^2 > 0$ is the reward weight. We require that $w_k^1 \geq w_k^2$.

The setback is that J_2 may assume both negative and positive values. To make J_2 non-negative, the possible maximum value of the second term is added to J_2 as an offset. Hence, a better choice for the generalized objective function would be

$$\mathrm{J}_3 = \sum_{k=1}^{K} \left(w_k^1((t_k + h_k) - d_k)^+ - w_k^2(d_k - (t_k + h_k))^+ + w_k^2(d_k - (a_k + h_k)) \right). \tag{23}$$

The objective function J_3 can also be rewritten as

$$J_3 = \sum_{k=1}^{K} \begin{cases} w_k^2(t_k - a_k), & \text{for } (t_k + h_k) - d_k < 0 \\ w_k^1((t_k + h_k) - d_k) + w_k^2(d_k - (a_k + h_k)), & \text{for } (t_k + h_k) - d_k \geq 0 \end{cases} \quad (24)$$

J_3 tries to minimize the delayed departure times while maximizing the temporal margin after completion of the service. A very interesting special case of J_3 - which has been considered by other researchers [6], [8], is the one in which $w_k^1 = w_k^2$. This special case will result in

$$J_4 = \sum_{k=1}^{K} w_k^1 (t_k - a_k) \quad (25)$$

The objective function J_4 minimizes the delayed mooring time only. Furthermore, by adding a fixed offset $w_k^1 h_k$ to J_4, the choice of the objective function will be as follows

$$J_5 = \sum_{k=1}^{K} \left(w_k^1 (t_k - a_k) + w_k^1 h_k \right) = \sum_{k=1}^{K} w_k^1 (t_k + h_k - a_k) \quad (26)$$

The objective function J_5 minimizes the delayed mooring and handling times. This choice of objective function was considered by Guan and Cheung [12] and Imai *et al.* [10].

Figure 5 shows two different final solutions, when J_4 or J_5 is used. The two solutions are both optimal if w_k^1 is the same for all the ships. However, if we consider a more general situation in which a delayed departure disturbs the successive assignments, the first solution cannot be optimal. In such a case, we can introduce the generalized objective function and can penalize the delayed departure time with a higher penalty weight to get an optimal solution.

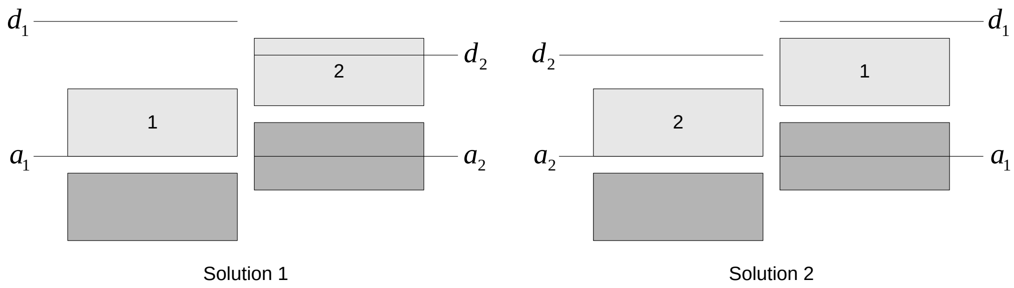


Figure 5: Possible optimal solutions under different cost functions

3.2 Solution Methods for the BAP

Since the continuous BAP is an NP-hard problem, in this section, we develop two approximation methods to find good solutions in a reasonable amount of time. Without loss of generality, formulation MILPF, described in section 3.1.2, is used to illustrate the solution methods. In the sequel, we will focus on this formulation.

3.2.1 The Lagrangian Relaxation Method for the BAP

Many hard integer problems can be viewed as an easy problem complicated by a relatively small set of side constraints. Dualizing side constraints produces a Lagrangian problem which is easy to solve and whose optimal value is a lower bound for minimization problems on the optimal value of the original problem. This method was termed "Lagrangian relaxation" by Geoffrion [20], who developed a systematic methodology to construct the lower bounds as a means of exploiting special problem structure.

The problem (MILPF) can be converted into a relaxed problem using the Lagrange multipliers $\pi_{ij} \geq 0$, $\forall i, j$, as follows:

$$z_{LB}(\pi) = \min\left(\sum_{k=1}^{K} \sum_{i=1}^{M-l_k+1} \sum_{j=1}^{T-h_k+1} z_{ijk} \cdot w_k (j + h_k - d_k)^+ + \sum_{i=1}^{M} \sum_{j=1}^{T} \pi_{ij} \left(\sum_{k=1}^{K} y_{ijk} - 1 \right) \right) \qquad (\text{LR}\pi)$$

s.t. Constraints (13)-(16).

where $\pi = [\pi_{ij}]$, $i = 1, \cdots, M$ and $j = 1, \cdots, T$, is a matrix of Lagrange multipliers.

The dual problem of the relaxed problem (LRπ) becomes

$$z_{LB} = \max_{\pi} z_{LB}(\pi)\,, \tag{D}$$

where $z_{LB}(\pi) = \min \sum_{k=1}^{K} \sum_{i=1}^{M-l_k+1} \sum_{j=1}^{T-h_k+1} z_{ijk} \cdot w_k (j + h_k - d_k)^+ + \sum_{i=1}^{M} \sum_{j=1}^{T} \pi_{ij} \left(\sum_{k=1}^{K} y_{ijk} - 1 \right)$

s.t. Constraints (13)-(16), and $\pi_{ij} \geq 0$.

If we ignore the last constant term in (*D*), then $z_{LB}(\pi)$ is equivalent to

$$\min \sum_{k=1}^{K} \sum_{i=1}^{M-l_k+1} \sum_{j=1}^{T-h_k+1} z_{ijk} \cdot w_k (j + h_k - d_k)^+ + \sum_{i=1}^{M} \sum_{j=1}^{T} \pi_{ij} \sum_{k=1}^{K} y_{ijk} \tag{27}$$

When $z_{ijk} = 1$, we have $y_{ijk} = 1$ for $m = i, \cdots, i + l_k - 1$ and $n = j, \cdots, j + h_k - 1$. Therefore, for a vessel k, the second term becomes

$$\sum_{i=1}^{M} \sum_{j=1}^{T} \pi_{ij} y_{ijk} = \sum_{m=i}^{i+l_k-1} \sum_{n=j}^{j+h_k-1} \pi_{mn} \tag{28}$$

Then, this implies that the relaxed problem (LRπ) can be considered as

$$\min \sum_{k=1}^{K} \sum_{i=1}^{M-l_k+1} \sum_{j=1}^{T-h_k+1} z_{ijk} \left(w_k (j + h_k - d_k)^+ + \sum_{m=i}^{i+l_k-1} \sum_{n=j}^{j+h_k-1} \pi_{mn} \right) \tag{29}$$

s.t. Constraints (14)-(16)

The solution to (LRπ) can be obtained since (29) is separable in k. The optimal coordinate for each sub-problem is calculated by setting $z_{ijk} = 1$.

$$\min_{i,\, j \geq a_k} w_k (j + h_k - d_k)^+ + \sum_{m=i}^{i+l_k-1} \sum_{n=j}^{j+h_k-1} \pi_{mn} \tag{30}$$

To optimize dual functions in Lagrangian relaxation, we use the subgradient method (SG) for separable integer programming problems. All sub-problems are solved optimally to obtain a subgradient direction. The subgradient method is an adaptation of gradient methods, in which gradients are replaced by subgradients. For further discussion on subgradient methods see [21].

Given an initial value $\pi_{ij} = 0$, a multiplier is generated by the following rule:

$$\pi_{ij} = \max\left\{0,\ \pi_{ij} + s\left(\sum_{k=1}^{K} y_{ijk} - 1\right)\right\} \tag{31}$$

where y_{ijk} is from an optimal solution to (LRπ) and s is a positive scalar step size. We use the following step size which has been commonly adopted in practice [22].

$$s = \frac{\lambda\left(z_{UB} - z_{LB}(\pi)\right)}{\|\sum_{k=1}^{K} y_{ijk} - 1\|^2} \tag{32}$$

where λ is a scalar satisfying $0 < \lambda \le 2$ and z_{UB} is the best known feasible (upper-bound) solution value obtained by applying a heuristic to formulation (MILPF).

We use a general rule, which is to set $\lambda = 2$ for some fixed number of iterations. This number is called *maxIter* hereafter. At each iteration, we successively halve both the values of λ and *maxIter* until the value of *maxIter* reaches some threshold (here, number 4). Note that, alternatively, the procedure can be stopped when λ reaches a threshold.

To describe our developed subgradient optimization procedure for the BAP, the following notation is used.

z_{LB} maximum lower bound from Lagrangian relaxation

z_{UB} minimum upper bound

z_{H1} initial upper bound found by Heuristic ***H1*** (it is described in section 3.2.3)

z_{H2} updated upper bound found by Heuristic ***H2*** (it is described in section 3.2.4)

minUB best upper bound so far

maxLB best lower bound so far

maxIter maximum number of iterations

The following procedure, named ***BAPsg procedure***, describes our developed subgradient optimization method.

BAPsg Procedure (Berth Allocation Problem- Subgradient Method)

1. Calculate the initial upper bound using ***H1***, $z_{UB} = minUB = z_{H1}$

   Set $z_{LB} = maxLB = 0$, $\lambda = 2$, $\pi_{ij} = 0$, and $maxIter = 2K$
2. If $\lambda < 0.005$, then stop. Otherwise, continue.
3. Update the lower bound z_{LB}.

   If $z_{LB} > maxLB$, then $maxLB = z_{LB}$, $\lambda = 2$, and $Iter = 1$. Otherwise, $Iter = Iter + 1$.
4. Update the minimum upper bound using ***H2***, $z_{UB} = z_{H2}$

   If $z_{UB} < minUB$, then $minUB = z_{UB}$.

   If $z_{LB} = 0$, then stop. Otherwise, continue.
5. If $Iter > maxIter$, then $\lambda = \lambda \times 0.5$, $maxIter = \max\{4, maxITer \times 0.5\}$, and $Iter = 1$.
6. Update the step size s and the multiplier π_{ij}. Go to step 2.

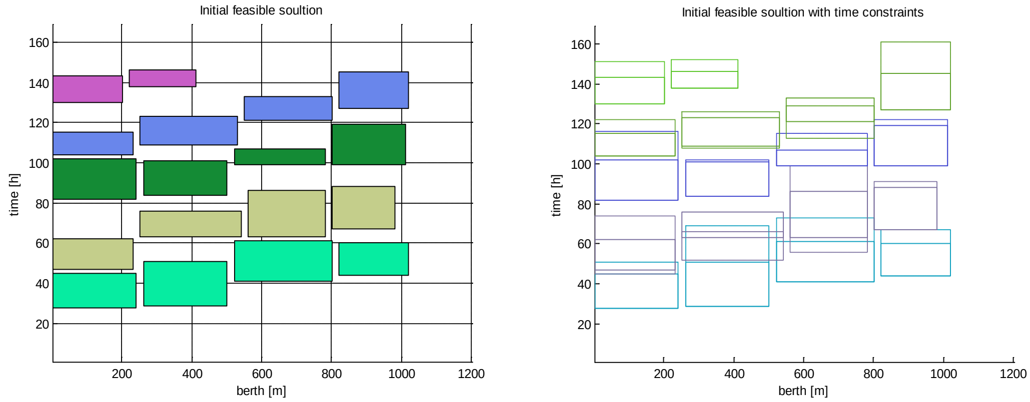
In Step 3 of the ***BAPsg*** procedure, the lower bound z_{LB} is acquired by solving each sub-problem (30). Then, the heuristic ***H2*** is applied to find a feasible solution in Step 4. Details about heuristics ***H1*** and ***H2*** will be provided in sections 3.2.3 and 3.2.4. In the end, the procedure returns the best feasible solution (the minimum upper bound) and the maximum lower bound. At the end of each iteration of the procedure, an optimal solution to (*D*) may be still infeasible for (*MILPF*), which means that vessel rectangles may be overlapping. However, as the multipliers corresponding to vessels with infeasible berthing are increased, the cost of (*D*) is increased. This ensures that the solution associated to z_{LB} gets close to a feasible solution of the original problem (*MILPF*).

Figure 6 demonstrates an instance of a BAP with initial and final solutions which were obtained by the above procedure. In the figure, each batch is represented by a distinct color. A batch is defined as a set of rectangles in the space-time domain, where the sum of their lengths, including safe distances between them, is less than or equal to the berth length *M*. The batch concept is fundamental to our heuristic methods which will be described later. The left figure is a berth allocation plan represented by color-filled rectangles. The figure on the right shows the corresponding plan along with time constraints. The time constraints of each vessel are represented with a dotted rectangle. The height of a dotted rectangle is determined by the vessels' arrival and desired departure times and the width is equal to the vessel's length.

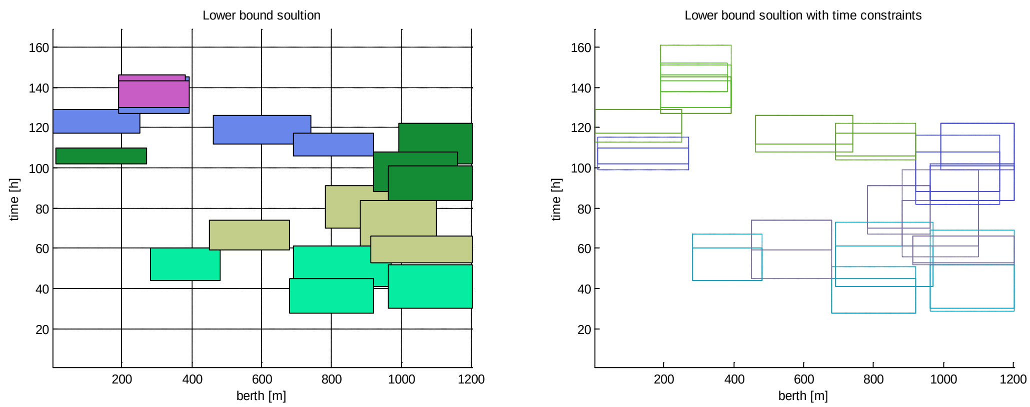
If a vessel rectangle is not fully enclosed by its (dotted) constraint rectangle, it will results in a cost increase. As shown in Figure 6(a), the initial feasible solution indicates that two rectangles (A and B) are not completely enclosed by their constraint rectangles. Figure 6(b) shows the final lower bound solution, which is still infeasible, since several rectangles overlap. Finally, the final upper bound solution is shown in Figure 6(c). In this specific example, the procedure yields an optimal solution to (MILPF) without penalty cost associated with waiting times.

Various port disruption events can be graphically described by using a vessel rectangle and its constraint rectangle. The disruption can result in changes to either the vessel rectangle or to the constraint rectangle. For example: (a) If, because of equipment break-down, the service time h_k is delayed by ω hours, then the height of the vessel rectangle is lengthened by ω hours. That is, the vessel rectangle could change. (b) If the arrival time a_k is delayed by ω hours, because of delays due to an unexpected event, the constraint rectangle should be adjusted and, also, the berthing time should be adjusted so that $t_k \geq a_k + \omega$. That is, both the vessel rectangle and its constraint rectangle could change.

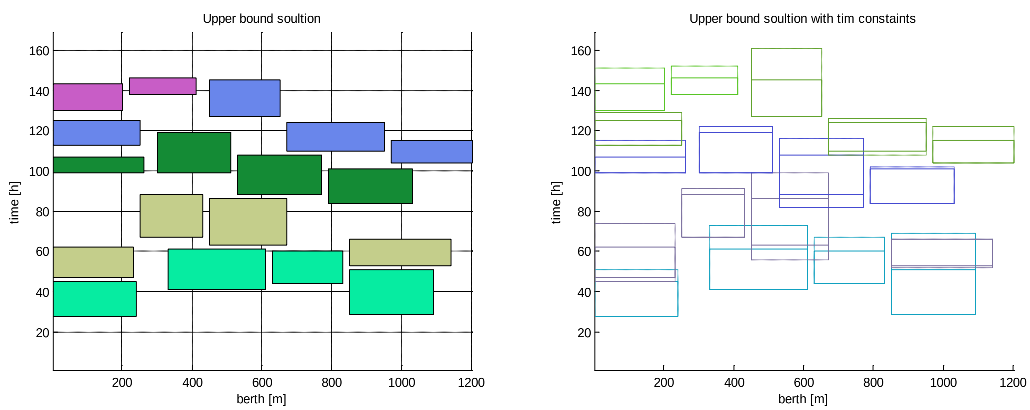
In both cases above, we can graphically detect whether the changed rectangles (resulting from a disruptive event) disturb an original allocation plan or not. If the original allocation plan is disrupted, and the disturbance occurs in batch b, we will reallocate vessel rectangles in the later batches ($b+1, b+2, \cdots$).



(a) Initial feasible solution



(b) Lower bound solution (infeasible)



(c) Upper bound solution

Figure 6: Initial and final solutions found by applying subgradient method

3.2.2 The Simulated Annealing Method for the BAP

The second methodology developed is based on simulated annealing (SA) to find good solutions to the BAP. The SA methodology was independently presented by Kirkpatrick *et al*. [23] and

Cerny [24]. The SA algorithm resembles the annealing process in metallurgy. In each step of the algorithm, the current state (solution) is replaced, with some probability, by a randomly generated neighboring state. This probability depends on the difference between the current state energy (cost) and generated neighbor energy, as well as, on a global parameter T (temperature) which is gradually decreased using a scheduled parameter r (cooling rate). The SA algorithm is such that it makes the system ultimately move to lower energy states (called downhill movements). Also, uphill movements prevent the algorithm from staying at local minima.

Before describing the methodology in detail, we start by defining the variables and parameters, neighbor search function, and acceptance probability function for our SA procedure.

3.2.2.1 Notation and Definitions

The following notation is used in this section.

sc	current state
sn	new state
sb	best state
ec	energy (cost) of current state, ec=E(sc)
en	energy of new state, en=E(sn)
eb	energy of best state, eb=E(sb)
T_0	initial temperature
r	cooling rate

3.2.2.2 Neighbor (candidate move) Search Procedure

A new state (solution) sn is obtained by exchanging a pair of consecutive vessel rectangles in the current state sc. The current state $sc = (1,\cdots,K)$ is defined as a sequence of vessel rectangles.

BAPneighbor Procedure

1. Choose a rectangle k, where $k \in \{1,\cdots,K-1\}$
2. Exchange the order of the pair $(k, k+1)$ in the current state sc
3. Update to a new state sn by applying heuristics ***H1*** and ***H2***

Details about heuristics ***H1*** and ***H2*** are provided in sections 3.2.3 and 3.2.4.

3.2.2.3 Acceptance Probability Function

A probability of making the transition from the current state to a candidate state is specified by an acceptance probability function. We adopt the following acceptance probability (*AP*) function, as described in [23].

$$AP(ec,en,T)=\begin{cases}1, & en<ec\\ \exp\left((ec-en)/T\right), & \text{otherwise}\end{cases} \tag{33}$$

where parameter T is a designed parameter (temperature in metallurgy).

3.2.2.4 Simulated Annealing Procedure

The following procedure implements the simulated annealing heuristic for the BAP, starting from the state generated by the initialization routine ***BAPinit***. The call ***BAPneighbor***(*sc*) generates a randomly chosen neighbor for a current state sc. The annealing schedule is defined by calling $AP(ec,en,T)$, which use the temperature to apply, given the fraction r of the time budget that has been expended so far.

BAPinit Procedure

1. Sort vessels according to their arrival times so that $a_1 \le \cdots \le a_k \le \cdots \le a_K$
2 . Generate a current state sc by applying ***H1*** and ***H2***
3. Set $ec=bc=E(sc)$

The following procedure, named ***BAPsa Procedure,*** describes our developed simulates annealing optimization method.

BAPsa Procedure (Berth Allocation Problem-Simulated Annealing Method)

```
1   set i = 1, flag = 1, and T = T_0
    while i ≤ i_max and T ≥ 1
        for j = 1 : 2K
            sn = BAPneighbor(sc), en = E(sn)
            if en < eb,
                then sb = sn, eb = en, and flag = 1
```

elseif $AP(ec, en, T) > rand(1)$,

then $sc = sn$ and $ec = en$

End

End

set $T = rT$

if $flag = 1$,

then $i = i + 1$ and $flag = 0$

End

End

3.2.2.5 Initial Temperature and Cooling Rate

The choice of the initial temperature T_0 and the cooling rate r affects the quality of the solutions obtained by the simulated annealing procedure. To be able to determine the right values for T_0 and r, we generated ten instances of the BAP problem whose size are randomly varied from 16 to 21 vessels. Details about generating an instance of the BAP are given in a later section. Each BAP was solved 700 times using different combinations of T_0 and r. In our experiments, T_0 was varied from 10 to 130 by a step of 10, whereas r was changed from 0.5 to 0.95 by a step of 0.05. For each T_0 and r, the results were averaged and shown in Figure 7.

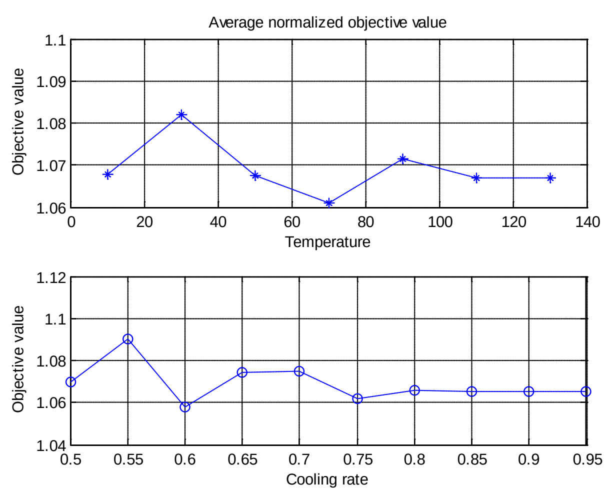


Figure 7: Normalized objective values

In Figure 7 each normalized value represents the ratio of the corresponding objective value to the lowest objective value. On average, the minimum objective value was found at the initial temperature 70 and the cooling rate 0.6. These values are used in the succeeding experiments.

Figure 8 shows the average number of iterations to reach final solutions (a) and the number of minima (b). Note that the minima of each combination were selected over 10 repeated tests as described above.

As seen from Figure 7, a combination of a higher temperature and a higher cooling rate, generally, yields better solutions. However, such combination requires higher number of iterations too, which means more running times. The actual required running time of a certain combination can be deduced from the figure. It shows that our choice ($T_0 = 70$ and $r = 0.6$) needs less than 300 iterations to reach to final solutions. Also, the quality of solutions with respect to the parameters can also be estimated from Figure 2.8b. It indicates that our chosen parameters yield a higher number of minima (about 6.5). Therefore, the chosen parameters are expected to produce good solutions within reasonable time.

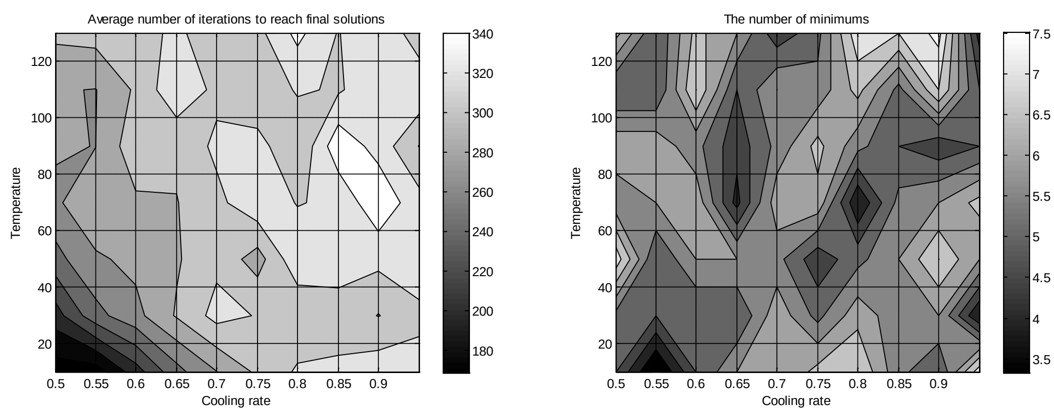


Figure 8: (top) Density plot, showing the average number of iterations to reach final solution; (Bottom) Number of minima. Both graphs are parameterized by the cooling rate and Temperature.

3.2.3 H1: Heuristic Method for an Initial Feasible Solution

Although methods based on subgradients with Lagrangian relaxation and methods based on simulated annealing have been used in the literature to solve the BAP and similar allocation problems, our heuristic procedures are quite different from any procedures reported previously in the literature. As already mentioned, our heuristics implement a set of systematic and efficient methods in order to find an initial feasible solution and to update a current solution by exploring a sufficiently large solution space.

To find and update feasible solutions for both subgradient (SG) and Simulated Annealing (SA) algorithms, two heuristic methods are developed. The first method is called Heuristic ***H1*** and is developed to generate an initial feasible solution. Using ***H1***, each vessel rectangle is sequentially placed on the solution space according to its arrival order. Heuristic ***H2*** is developed to repeatedly improve the feasible solution, using pair-wise swaps between neighboring rectangles within a batch or over neighboring batches. A batch is defined as a set of rectangles where the sum of their lengths including safe distances between them is less than or equal to the berth length *M*.

Under any combination of rectangle movements and swapping operations, Heuristic ***H2*** tries to create rooms (temporal spaces) for rectangles to be berthed to the earliest possible time (pushed down).

3.2.3.1 Algorithm for an Initial Feasible Solution

The following notation is additionally used to describe the heuristic procedures.

S_p the set of rectangle indices in a batch p

B the number of batches in a berth, that is $p=1,\ldots,B$

q_p the number of rectangles in a batch p, that is, $|S_p|=q_p$

Heuristic Procedure *H1* (Algorithm for an initial feasible solution)

1. Construct a batch of rectangles by assigning their berthing locations

   set $x_1 = 1$, $p = 1$, and $S_p = \{1\}$

   for $k = 2 : K$

   $x_k = x_{k-1} + l_{k-1} + \alpha$

   if $x_k + l_k \le M$, then $S_p = S_p \bigcup k$

   else, $x_k = 1$, $p = p + 1$, and create $S_p = \{k\}$

   end

2. Assign a feasible berthing time with the earliest possible berthing time

   for $k = 1 : K$

if $k \in S_1$, then $t_k = a_k$

else, $t_k = \max\{a_k, \ t_s + h_s + \tau\}$ for all $s \in S_{p-1}^k$

end

where S_{p-1}^k is a subset of S_{p-1}, satisfying $x_s < x_k + l_k + \alpha$ and $x_s + l_s + \alpha > x_k$ for $s \in S_{p-1}$ and $k \in S_p$. In other words, s represents a rectangle in S_{p-1} whose berthing space overlaps with rectangle k.

3.2.4 H2: Heuristic Method for an Improved Feasible Solution

The heuristics H2 uses a series of rectangle movement functions, which consist of all possible directional movements and swapping operations. The heuristics H2 procedure is used to improve an initial feasible solution in the initialization stage and to improve current feasible solutions in both subgradient (SG) and simulated annealing (SA) procedures for the BAP.

Heuristic Procedure *H2* (Algorithm for improving the feasible solution)

1. Set z_{H2} with the minimum of known feasible solution value
2. Find z_{H2}^{new} by running **SWAPb, SWAPt, RIGHT,** and **LEFT**
3. Update and return z_{H2} if $z_{H2}^{new} \le z_{H2}$

Given a feasible solution, a slightly different combination of rectangle movements might work better for some problem instances.

3.2.4.1 Rectangle Movement Operators

For the sake of clarity we introduce here the rectangle movement operators. These operators define all the possible movements of a rectangle in time-space, and will be the basis of the rectangle movement functions in the next section.

Table 1: The rectangle movement operators

Operator	Purpose	Procedure	Notes
Push − Up	Moves a rectangle k up to the allowable limit	for $r=1:N$ if $t_k+h_k+r \le T$, then $t_k=t_k+r$ if $t_k<t_s$ and $t_k+h_k+\tau>t_s$, then $t_k=t_k-1$, stop end	N big number $k \in S_p$, $s \in S_{p+1}^k$
Push − Down	Moves a rectangle k down to the allowable limit	for $r=1:N$ if $t_k-r \ge 1$, then $t_k=t_k-r$ if $t_s<t_k$ and $t_s+h_s+\tau>t_k$, then $t_k=t_k+1$, stop end	$k \in S_p$, $s \in S_{p-1}^k$
Push − Right	Moves a rectangle k right to the allowable limit	for $r=1:N$ if $x_k+l_k+r \le M$ then $x_k=x_k+r$ if $x_k<x_s$, $x_k+l_k+\alpha>x_s$, then $x_k=x_k-1$, stop end	$k,s \in S_p$ satisfying $t_s<t_k+h_k+\tau$, $t_s+h_s+\tau>t_k$
Push − Left	Moves a rectangle k left to the allowable limit	for $r=1:N$ if $x_k-r \ge 1$ then $x_k=x_k-r$ if $x_s<x_k$, $x_s+l_s+\alpha>x_k$, then $x_k=x_k+1$, stop end	$k,s \in S_p$ satisfying $t_s<t_k+h_k+\tau$, $t_s+h_s+\tau>t_k$
Swap − Pair	exchanges consecutive rectangles u and v, $x_u < x_v$, if space is allowable	set $x_u^t=x_v$, $x_v^t=x_v+v_v-l_u$, $t_u^t=t_v$, and $t_v^t=t_u$ if $t_k^t>t_s$, $t_k^t \ge t_s+h_s+\tau$ for $\forall$ $k=\{u,v\} \in S_p$, $s \in S_{p-1}^k$ and if $t_k^t<t_s$, $t_k^t+h_k+\tau \le t_s$, for $\forall$ $k=\{u,v\} \in S_p$, $s \in S_{p+1}^k$, then $x_u=x_u^t$, $x_v=x_v^t$, $t_u=t_u^t$, and $t_v=t_v^t$.	

3.2.4.2 Rectangle Movement Procedure

The rectangle movement functions are designed to generate a better solution by moving each rectangle down to its allowable limit which is defined by the arrival time or the neighboring rectangles.

SWAPb (SWAPt) function exchanges a pair of neighboring rectangles in the same batch, which starts from the bottom batch (or, from the top batch). These functions eventually try to swap all the possible combinations of rectangle pairs in the same batch using the repetition scheme, although Swap-pair operator is designed to exchange of the positions of consecutive rectangles.

SWAPb (SWAPt) Procedure

```
1.  for p = 1:P ( p = P:1 )
        for q = 1:q_p − 1
            if p < P , then
                Push-Up k ∈ S_{p+1}
        Swap-Pair q and q + 1
        Push-Down k ∈ S_p ∪ S_{p+1}
            else
                Swap-Pair q and q + 1
        Push-Down k ∈ S_p
            If the cost increases, then restore their positions
        end
    end
```

RIGHT (*LEFT*) function pushes a rectangle $S_p(q)$ to the allowable limit or to the next nearest rectangle on the right (or, on the left) in the same batch.

RIGHT (LEFT) Procedure

```
1.  for p = 1:P
        for q = q_p − 1
            if p < P , then
                Push-Right q (Push-Left q )
        Push-Down k ∈ S_p ∪ S_{p+1}
            else
                Push-Right q (Push-Left q )
        Push-Down k ∈ S_p
.           if the cost increases, then restore their positions
        end
    end
```

The following figures show how the combination of several rectangle movement functions can reduce the allocation cost. Each allocation plan for a vessel is represented by a shaded rectangle along with its arrival time and requested departure time (dotted box). Also, darker shade represents the region which causes a penalty cost due to the violation of the desired departure time.

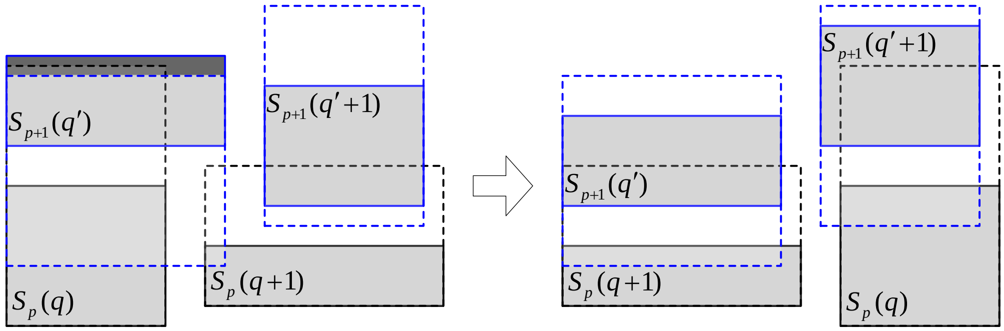


Figure 9: Reduction by SWAPx resulting from Swap-Pair between $S_p(q)$ and $S_p(q+1)$ followed by Push-Down $S_{p+1}(q')$.

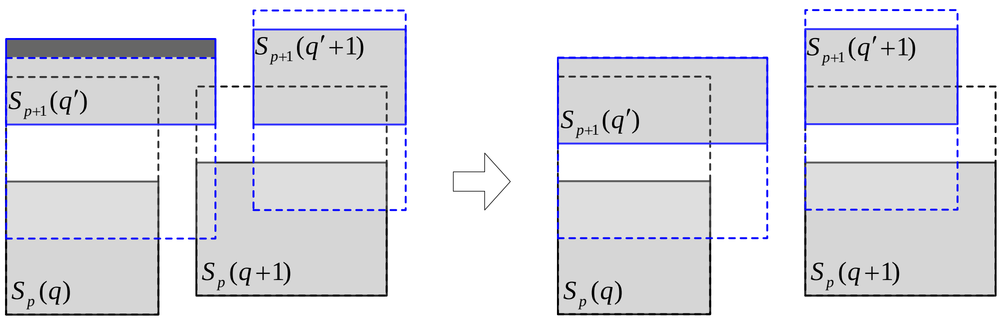


Figure 10: Reduction by RIGHT resulting from Push-Right of $S_p(q+1)$ followed by Push-Down $S_{p+1}(q')$.

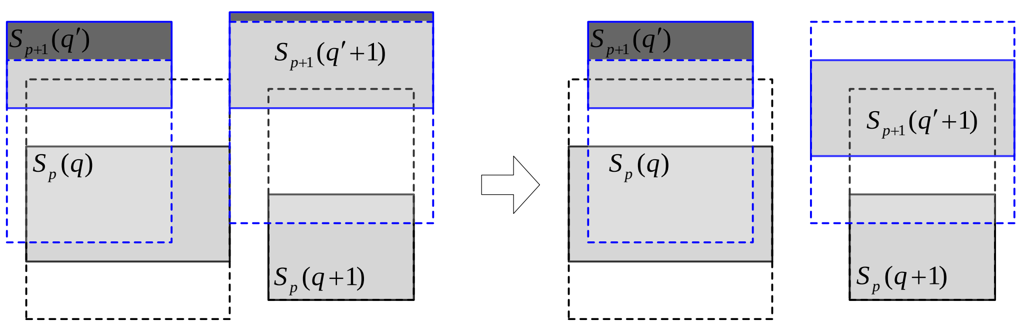


Figure 11: Reduction by LEFT resulting from Push-Left of $S_p(q+1)$ followed by Push-Down $S_{p+1}(q'+1)$.

3.3 Computational Experiments for the BAP

A disruption at a berth may result in changes in the space-time diagram as compared to the baseline plan. The disruption may alter the diagram in the time dimension, the space dimension, on in both dimensions. Usually, disruptions in the time domain are caused by delayed arrival times, delayed berthing times, or longer service times. Disruptions in the space domain are less frequent yet their impact is more severe on the port operations. They may be the result of anticipated events (e.g., construction, scheduled maintenance, pre-planned military surge, etc.), or unanticipated events (e.g., terrorist acts, earthquakes, hurricanes, etc.).

In this section, we will consider disruptions caused by delays, i.e., disruptions affecting only the time dimension of the space-time diagram. Disruptions affecting the space dimension will be studied in Section 4, where we introduce partially operational berths and the Terminal Allocation Problem. Here we assume that the delays are caused by an increase in the number of calling vessels on the berth. This increase in the number of vessels to be serviced could be for example a direct consequence of physical break-downs in adjacent berths within the same terminal/port, due to unanticipated events. Because of the increased number of vessels, we may not be able to serve all the vessels within their requested time frames. The objective is to minimize the total delay incurred for all the vessels. We will show, via several computational experiments that our developed subgradient and simulated annealing optimization techniques will be able to deal with this type of disruptions by finding the best allocation for the calling vessels such that the total delay is minimized. The CPLEX MIP solver is used to find exact solutions for small size problems, enabling us to evaluate the quality of the solutions generated by our methodologies for such problems.

3.3.1 CPLEX MIP: Computational Experiments

The computational experiments are conducted using realistic data obtained from Park and Kim in [5], and Kim and Moon in [13]. In order to generate random instances, we use a discrete uniform distribution whose Cumulative Distribution Function (CDF) is given by

$$F(x;a,b)=\frac{1}{b-a+1}\sum_{i=1}^{n}H(x-x_i) \qquad (34)$$

where the Heaviside step function $H(x-x_i)$ is the CDF of the degenerate distribution centered at x_i. Table 2 shows the range of parameters a and b assumed in our simulation experiments to generate l_k, h_k, a_k, and d_k. For instance, h_k is generated randomly using the given CDF for $a=7$ and $b=23$. Upon choosing h_k, the value of a_k is randomly generated using the same CDF with parameters $a=1$ and $b=T-h_k+1$. Note that d_k is chosen so that $h_k \le d_k - a_k \le 2h_k$. In our simulation experiments, we set $M = 1200[m]$, $T = 168[h]$, $\alpha = 20[m]$, and $\tau = 2[h]$.

Table 2: Ranges of parameters *a* and *b*

Parameter	l_k [m]	h_k [h]	a_k [h]	d_k [h]
a	170	7	1	$a_k + h_k$
b	290	23	$T - h_k + 1$	$a_k + 2h_k$

We assume that the weight w_k in (1) is equal to the area covered by the vessel rectangle, i.e., $w_k = l_k \cdot h_k$. This choice of w_k imposes higher penalties to be paid to ships with possibly higher workloads, if the requested departure times are not met.

Using the specifications given in Table 2, we generate 500 random instances of the BAP. Table 3 compares the performance of the CPLEX MIP solver (IP), the subgradient optimization method (SG), and the simulated annealing method (SA).

Table 3: Comparison between the BAP solutions using IP, SG, and SA methods

K	r_{OC}	Cost					Average time[s]			Maximum time[s]		
		z_{IP}	z_{SG}	z_{SA}	z_{IP}/z_{SG}	z_{IP}/z_{SA}	t_{IP}	t_{SG}	t_{SA}	m_{IP}	m_{SG}	m_{SA}
11	0.19	10.7	32.4	14.3	3.03	1.34	0.0	2.0	2.1	10.6	115.4	178.0
12	0.21	23.5	46.7	41.5	1.99	1.77	0.2	3.4	6.6	25.4	130.8	254.1
13	0.22	34.0	112.8	52.8	3.31	1.55	0.8	5.5	8.5	236.5	106.2	252.0
14	0.24	71.2	187.1	115.9	2.63	1.63	1.7	11.2	20.0	468.8	183.8	444.6
15	0.26	89.8	310.0	170.1	3.45	1.89	28.8	13.7	21.5	6781.0	238.1	367.8
16	0.27	89.7	299.2	137.6	3.34	1.53	16.7	19.1	31.0	1486.2	234.2	481.8
17	0.29	230.4	606.4	307.6	2.63	1.33	156.8	30.5	61.8	24739.6	260.4	639.6
18	0.31	244.0	683.4	389.7	2.80	1.60	361.1	38.7	76.9	38798.5	239.3	617.6

In Table 3, z_{IP}, z_{SG}, and z_{SA} are, respectively, the average cost of the best solutions found by the IP, SG and SA. The average and the maximum running times for different methodologies are also shown in the table. It indicates that the cost ratio of SA to IP (i.e., z_{IP} / z_{SA}) is rather small which means that SA yields good quality solutions. The cost ratio z_{IP} / z_{SG} is much higher than z_{IP} / z_{SG}. To improve the solution quality of SG, one can increase the number of iterations of ***H2***.

The occupation ratio of a berth, denoted by r_{OC}, is defined as the sum of the vessel rectangles divided by the entire space

$$r_{OC} = \sum_{k=1}^{K} h_k l_k / (MT) \qquad (35)$$

The occupation ratio is an indicator of the berth utilization. As indicated by Table 3, as r_{OC} increases, more time is needed to find the best solutions.

As it can be seen from Table 3, the IP can solve the problem instances up to K =18. However, comparing to the heuristics, as K increases, the IP needs considerable amount of time to find the exact solution. We noticed that for K >18, we will not be able to find the exact solutions in a reasonable amount of time. This limitation will be more pronounced as we move toward the *dynamic BAP* and the *multiple BAP*, which are discussed in the following sections.

3.3.2 Heuristic Methods: Computational Experiments

We assume that the number of vessels calling on a berth is between 12 to 20 vessels. This number is close to the numbers of vessels considered in real-life scenarios in [5], [13].

In Table 3, we have observed that the exact method is able to find the optimal solution, in a reasonable amount of time, for $K \leq 16$. However, the running time of the exact method is abruptly increased when $K \geq 17$. In this subsection and in order to evaluate and compare our developed heuristic methods, we consider instances of the BAPs with $17 \leq K \leq 21$. We adopt the generalized objective function J_3 in (23) with $w_k^1 = 10 l_k$ and $w_k^2 = l_k$. These values are chosen so that we can impose higher penalties on delayed departure times. The values of w_k^1 and w_k^2 are directly proportional to the length of the vessel k, l_k. Hence, higher priority is given to larger vessels which, most probably, carry higher volume of loads.

Table 4 shows the performance of the SG and SA optimization methods over various sizes of problems. Among randomly generated instances, 20 instances are selected as long as they have a non-zero initial feasible solution. Each result in the table is averaged over 20 such independent trials.

Table 4: Performance comparison between SG and SA methods

K	r_{OC}	Subgradient optimization					Simulated Annealing			z_{SA}/z_{UB}
		z_{LB}	z_{UB}	g_{SG}	t_{SG}	c_{SG}	z_{SA}	t_{SA}	c_{SA}	
17	0.29	145.2	380.3	1.6	590.4	227.1	322.1	133.3	148.1	0.85
18	0.32	403.2	737.4	0.8	742.5	281.6	532.8	183.1	195.4	0.72
19	0.33	525.8	897.9	0.7	711.0	268.6	569.3	154.7	183.4	0.63
20	0.35	428.6	899.7	1.1	845.4	304.8	545.9	261.1	289.0	0.61
21	0.36	729.5	1951.2	1.7	822.8	268.6	1409.1	248.5	261.4	0.72

In the table 4, r_{OC} is the occupation ratio of a berth, z_{LB} is the maximum lower bound from Lagrangian relaxation model, z_{UB} is the minimum upper bound (best feasible solution by the SG method), g_{SG} is the duality gap between z_{LB} and z_{UB}, defined as $g_{SG} = (z_{UB} - z_{LB}) / z_{LB}$, t_{SG} is the computational time of the SG method, c_{SG} is the number of iterations of ***H2*** in the SG method, z_{SA} is the best feasible solution by the SA method, t_{SA} is the computational time of the SA method, and c_{SA} is the number of iterations of ***H2*** in the SA method. The duality gap g_{SG} implies the maximum deviation of the final lower bound from the best feasible objective value. The duality gap ranges from 70% to 170% which means that the SG produces good approximations of optimal solutions.

In Table 4, in order to improve the solution quality of the SG methodology, we may increase the number of iterations of ***H2***. It is noted that step 4 in ***BAPsg*** doesn't need to be executed every iteration. We noted that the step should be executed when $z_{LB} < maxLB$ or $z_{LB} \leq maxLB$.

We can also observe that, on the average, the SA algorithm still yields a non-inferior solution, which ranges from 61% to 85% of the corresponding upper bound found by the SG algorithm. This might have resulted from the fact that the range for swapping operations in the SA method is little wider. Considering the superiority of the solution quality and the running time of the SA methodology, in the following sections we will only use the SA methodology to find the best solutions to other variants of the BAP namely the *dynamic* BAP, and *multiple* BAP.

4 Terminal Allocation Problem (TAP)

Usually certain berthing locations (home berths) are preferred due to the long-term contracts with carriers, the depth of water, differing wave heights, etc [5]. In this section, we assume that for some predicted or unpredicted scenarios (disruptions) a calling vessel cannot moor at its home berth location and that other berth locations (within the same terminal or adjacent terminals) can accommodate the vessel. This leads to a more complex, yet general, variant of the BAP which, hereafter, is referred to as the terminal allocation problem (TAP).

In the TAP, we assume that we have N disjoint berths. The disjoint berths could belong to the same or to different terminals, and because they are disjoint, a vessel can utilize only one such berth (i.e. a vessel cannot moor across two or more such berths). The disjoint property will enable us to model a partially functional terminal (e.g., a terminal consisting of N disjoint berths, of which $N_1 \le N$ have been rendered non functional due a disruptive event, hence there are only $N - N_1$ remaining functional berths). We assume that the length of berth n is M_n and that the time horizon for all berths is T. Figure 12 illustrates the TAP graphically in a space-time diagram.

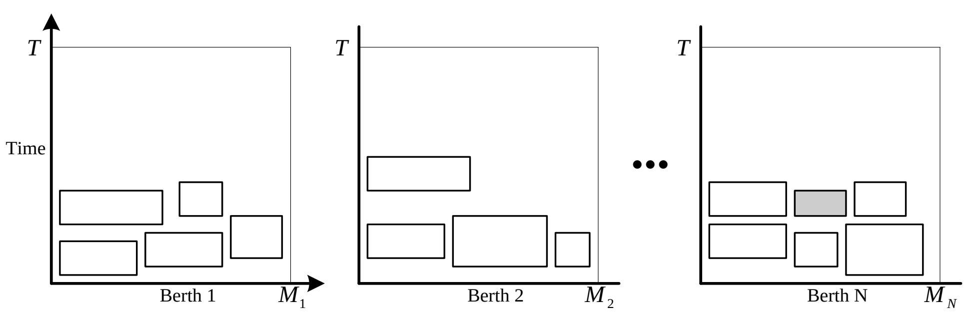


Figure 12: Space-time diagram for the Terminal Allocation Problem

The TAP can be stated as follows: Determine the least-cost assignment of K vessels to N disjoint berths such that each vessel is assigned to exactly one berth and no two vessels are overlapping (in the space-time domain), while all the vessels' constraints (arrival times, service times, etc.) are met. Therefore, the TAP consists of two intertwined problems: (1) A set partitioning problem (SPP), and (2) A number of individual berth allocation problems (BAPs).

4.1 Set Partitioning Problem

Given a collection of feasible subsets of a certain ground set, one can formulate the problem of finding the best collection of subsets such that the cost associated with these subsets is minimized. This problem is called the set partitioning problem (SPP).

Let y_j be 1 if berth j is functional and at least one vessel is assigned to it, and zero otherwise. Let c_j be the cost of berth j which is computed as the aggregated costs of serving all the vessels assigned to that berth. Let also a_{ij} be 1 if vessel i is assigned to berth j, and zero otherwise. The SPP can be formulated as follows:

$$\min \quad \sum_{j=1}^{N} c_j y_j \tag{36}$$

$$\text{s.t.} \quad \sum_{j=1}^{N} a_{ij} y_j = 1, \qquad i = 1, \cdots, K \tag{37}$$

$$y_j \in \{0,1\}, \qquad j = 1, \cdots, N \tag{38}$$

Almost every heuristic approach, for solving general integer programming problems, has been considered and applied to the set partitioning problem. For instance, in [15], some greedy algorithms and interchange approaches were applied to the SPP problem. Other heuristic approaches such as genetic algorithms; probabilistic search, simulated annealing, and neural networks have also been studied and applied to the problem. In addition, heuristics are embedded within exact algorithms so that one iteratively tightens the upper bound and at the same time attempting to get a tight approximation to the lower bound for the problem [16], [17]. Unfortunately, there has not been a comprehensive and comparative test across such methods to determine under what circumstances a specific method might perform best.

It should be noted that the SPP is known to be NP-hard [19]. As described above, the TAP can be mapped into the SPP; hence, the TAP is an NP-hard problem too. Moreover, the TAP consists of a collection of BAPs, where each BAP is an NP-hard problem [7].Therefore, as the number of the berths and vessels in the TAP increases, finding an optimal solution will be computationally too expensive. In the following, we develop an approximation methodology to find good solutions to the TAP in a reasonable amount of time.

4.2 Solution Method for the TAP

Figure 13 demonstrates our approach toward the TAP. The approach is based on a typical set partitioning procedure. Assuming that the terminal consists of N disjoint berths, the TAP is partitioned into N BAPs. Each BAP is solved separately using the previously developed heuristics **H1** and **H2** as described before. Based on our computational results and findings presented in Section 3.3, we will use the simulated annealing methodology for each BAP sub-problem.

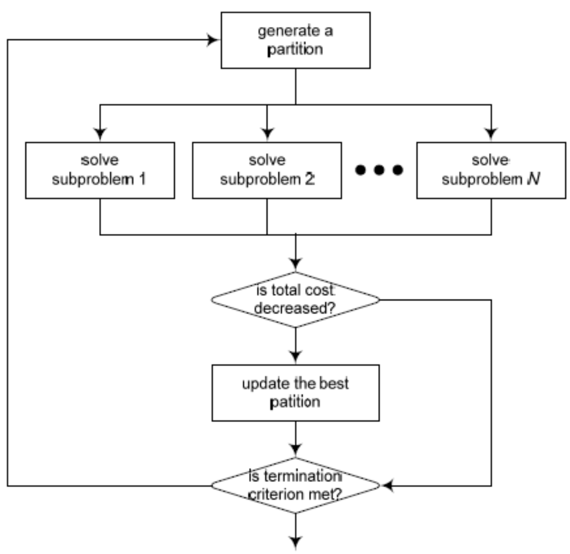


Figure 13: The TAP as a set partitioning problem

Initially, a specific number of vessels, calling on the port is assigned to each berth. This number is proportional to the area of the space-time diagram of each berth. If a vessel has specifically requested to be served at a particular berth, it will be assigned to that berth, unless other restrictions at the berth prohibited this assignment.

Recall from Section 3.1.2 that a block (i, j) is referred to as a grid space whose left bottom corner is located at the point (i, j). The overlapping value of block (i, j) at berth n, denoted by c_{ijn}, is defined as the number of overlapping vessels at block (i, j) at that berth. The maximum of this value is $c_{\max,n} = \max_{i,j} \{c_{ijn}\}$, $i = 1, \cdots, M_n$ and $j = 1, \cdots, T$.

Let Bn be the set of vessels assigned to berth n. Assume vessel $k \in Bn$. The vessel k overlapping index, denoted by IV_k, is defined as the number of blocks whose values are $c_{\max,n}$ within the vessel rectangle k. The overlapping index of berth n, denoted by IB_n, is defined as the sum of the block values in that berth.

$$IB_n = \sum_{i=1}^{M_n} \sum_{j=1}^{T} c_{ijn} \tag{39}$$

Figure 14 illustrates a simple example to demonstrate how to find a vessel's and a berth's overlapping indices. The right figure shows berth n containing two overlapping vessel rectangles k and k'. For this example $c_{\max,n} = 1$, $IB_n = 2$, and $IV_k = IV_{k'} = 2$.

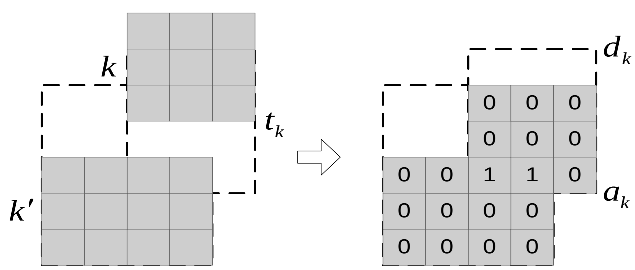


Figure 14: Value of the block

Before describing the SA methodology for the TAP in details, we define the variables and parameters used in our SA methodology.

4.2.1 Notations and Definitions

A vessel rectangle k, denoted by v_k, is defined by a 9-tuple as follows.

$$v_k = \left(n_k, l_k, h_k, a_k, d_k, w_k^1, w_k^2, x_k, t_k\right) \tag{40}$$

where

n_k is the assigned berth index for vessel rectangle k

l_k is the length of vessel k

h_k is the estimated handling time of vessel k

a_k is the estimated arrival time of vessel k

d_k is the requested departure time of vessel k

w_k^1 is the penalty weight assigned to vessel k

w_k^2 is the reward weight assigned to vessel k

x_k is the assigned mooring location to vessel k

t_k is the assigned mooring time to vessel k

Let B_n be the set of vessels assigned to berth n. That is,

$$\mathsf{B}_n = \left\{ v_k \mid v_k = \left(n_k, \ldots, t_k \right), n_k = n,\ k = 1, \ldots, K \right\}, \qquad n \in \left\{ 1, \cdots, N \right\} \qquad (41)$$

where K is the number of vessels to be scheduled, and $\left| \mathsf{B}_n \right| = K_n$ is the cardinality of the set representing the number of vessels assigned to berth n. A state $\mathbf{s}$ is formed by aggregating all B_n in a single set, i.e.

$$\mathbf{s} = \left\{ \mathsf{B}_1, \cdots, \mathsf{B}_N \right\}. \qquad (42)$$

The cost of the state $\mathbf{s}$ is defined as the sum of the costs of all the individual berths B_n forming $\mathbf{s}$. Recall that the cost of each berth is defined in (1). Alternative costs were discussed in 3.1.4.

In addition, the following notation is defined and used in this section.

sc current state

sn new state

sb best state

ec cost of the current state $\mathbf{sc}$, $\mathbf{ec} = E(\mathbf{sc})$

en cost of the newt state $\mathbf{sn}$, $\mathbf{en} = E(\mathbf{sn})$

eb cost of the best state $\mathbf{sb}$, $\mathbf{eb} = E(\mathbf{sb})$

In the set partitioning algorithm, we construct a single aggregated state $\mathbf{sc}$ to easily perform an interchange operation. The new state $\mathbf{sn}$ is obtained from the current state $\mathbf{sc}$ by exchanging a pair of vessel rectangles across different berths. After interchanging vessels across different berths, the optimization procedure is sequentially applied to the sub-problems. Each sub-problem by itself is a BAP. The BAP optimization algorithms were discussed extensively in the previous section. The policy for choosing the pair of vessels to be exchanged is represented in lines 2 to 5 of the following procedure.

NewPartition

1. Order the rectangles of a current state **sc** by arrival times.
2. Choose (randomly when tie) a berth b_1 having $\max IB_n$.
3. Choose (randomly when tie) a vessel k_1 having $\max IV_k$ where $k \in \mathrm{B}_{b_1}$.
4. Choose the first k_2 such that $a_{k_1} < a_{k_2}$ and $n_{k_1} \neq n_{k_2}$.
5. If k_2 cannot be found, go to step 2

   Else, exchange the berth indices of v_{k_1} and v_{k_2}.
6. Divide into sub-states $\mathrm{B}'_n = \{v_k \mid n_k = n\}$ and sort by arrival times.
7. Generate an initial solution for each BAP by applying ***H1*** and ***H2***.
8. Update each state $\mathrm{B}_n = \boldsymbol{BAPsa}(\mathrm{B}'_n)$ and return a new state $\mathbf{sn} = \{\mathrm{B}_1, \cdots, \mathrm{B}_N\}$.

4.2.2 TAP Procedure

The proposed solution procedure for the TAP is referred to as ***TAPproc***. In the procedure, the sum of IB_n s under i th partition is denoted by sIB_i (line 3 in the following procedure description). This procedure is terminated when the best objective function value of the TAP or the sum of the berth overlapping indices sIB_i reaches zero (line5).

TAPproc (Terminal Allocation Problem Procedure)

1. Initialize $\mathbf{bc} = \mathbf{sc}$ by ***TAPinit***, $\mathbf{eb} = \mathbf{ec} = E(\mathbf{sc})$, $i = 1$, and $r = 0$.
2. while $i \le i_{\max}$
3. $\mathbf{sn} = \boldsymbol{NewPartition}(\mathbf{sc})$, $\mathbf{en} = E(\mathbf{sn})$, and $sIB_i = \sum_n IB_n$
4. if $\mathbf{en} < \mathbf{eb}$, then $\mathbf{sb} = \mathbf{sn}$ and $\mathbf{eb} = \mathbf{en}$;
5. if $\mathbf{eb} = 0$ or $sIB_i = 0$, then stop
6. for $j = 1 : i - 1$
7. if $sIB_j = sIB_i$, then $r = r + 1$
8. End
9. if $r = r_{\max}$, then stop
10. End

The TAP optimization algorithm starts by a feasible solution generated by ***TAPinit***. Vessels are alternately assigned to berths according to their arrival times. However, in the presence of a partially functional berth (which will be defined later), the initial subsets will be assigned based on the ratio of the operational region in the space-time domain.

TAPinit

1. Sort the order of rectangles of a current state $\mathbf{sc}$ by arrival times
2. Assign a berth index to each vessel $n_k \equiv k \pmod N$
3. Divide into sub-states $\mathsf{B}'_n = (v_k \mid n_k = n)$
4. Generate an initial solution by applying ***H1*** and ***H2***
5. Update each state $\mathsf{B}_n = \boldsymbol{BAPsa}(\mathsf{B}'_n)$

4.3 Port Disruptions Resulting in Partially Functional Berths

A berth is said to be functional (or fully functional) if the entire berth is available to be used by the calling vessels for the entire planning horizon. A berth is partially functional if some sections along the berth are not operational for some periods of time. These non-operational regions may be caused by anticipated events (e.g. construction; scheduled maintenance; pre-planned military surge etc.), or by unanticipated disruptions (e.g. terrorist acts; earthquakes; hurricanes etc.).

Recall that a port disruption will result in changes of the space-time diagram as compared to the baseline plan. A partial region in the space-time diagram is termed a *cell*. A non-operational region is regarded as a cell termed a *non-operational cell*. The remaining region in the space-time diagram can be divided into several *operational cells* based on its shape. These cells are all mutually disjoint and exhaustively cover the space-time diagram. Figure 15 illustrates the space-time diagrams for three different examples of partially functional berths.

To decompose the time-space diagram into operational and non-operational cells, we can employ a simple coverage type algorithm [18]. This is similar to grid-based coverage algorithms used in mobile robot applications, such as demining, lawn mowing, and floor cleaning tasks. These algorithms require complete coverage of an unstructured environment with obstacle avoidance. Our non operational regions in the space-time domain are comparable to obstacles in the mobile robot applications. Both our operational non-operational regions are rectangular in shape, hence we can easily employ a grid-based coverage algorithm.

Subsequently, our developed heuristics are modified to incorporate the terminal allocation problem when a berth is only partially functional. A cellular decomposition scheme is incorporated into the heuristic **H1**, which was developed to generate an initial feasible solution. The modified heuristic is referred to as heuristic **mH1**. Once the vessels are assigned to batches, heuristic **H2** will be deployed to improve the current solution. Recall that a batch is defined as a set of rectangles where the sum of their lengths including safe distances between them is less than or equal to the berth length M. The cellular decomposition scheme is done in two stages in the modified heuristics. At first, the solution space is roughly decomposed into cells that allow some overlapping with neighboring operational cells. Figure 15 shows some examples of the decomposed cells from the first stage. The space-time diagrams are divided into several operational and non-operational cells. The cells are mutually disjoint and exhaustively covering the space-time diagram. An operational cell r is defined by the coordinate of its lower-left corner and the projected distances of its upper-right corner along both axes: (x^r, t^r, M^r, T^r), where the total number of operational cells is R, i.e., $|r|=R$

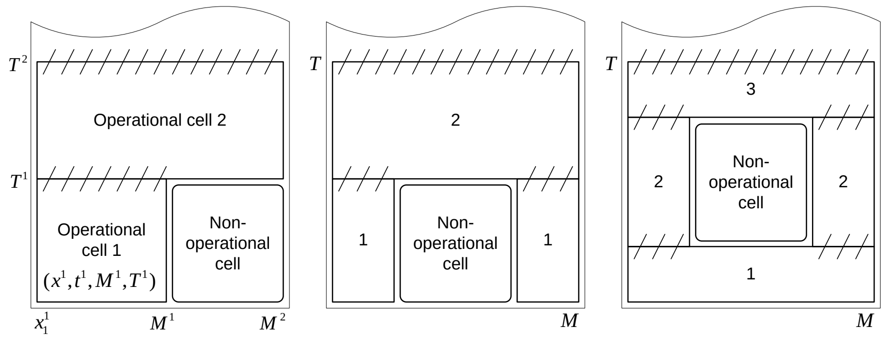


Figure 15: Examples of partially functional berths

In the second stage, any overlapping is removed since the upper cells are adjusted by the allocation plan of lower cells. Then, the cells are mutually disjoint and exhaustively cover the solution domain. In the modified procedure for an initial feasible solution, the cells are decomposed and allocated in two stages by the following procedure in a bottom-up fashion.

Heuristic procedure, mH1 (Algorithm to generate an initial feasible solution for TAP)

1. Define the operational cells with (x^r, t^r, M^r, T^r) for $r = 1, \cdots, R$
2. Set $k^1 = 1$, $p = 1$
3. for $r = 1 : R$
4.   set $k = k^r$, $x_k = x^r$, create $S_p = \{k\}$
5.   for $k = k^r + 1 : K$
6. $x_k = x_{k-1} + l_{k-1} + \alpha$
7.   if $x_k + l_k \le M^r$, then $S_p = S_p \cup k$
8.   else, $x_k = x^r$, $p = p + 1$, and create $S_p = \{k\}$
9.   end
10.   for $k = k^r : K$
11.   if $k \in S_1$, then $t_k = a_k$
12.   else, $t_k = \max\{a_k, t_s + h_s + \tau\}$ for all $s \in S_{p-1}^k$
13.   end
14.   for $k = k^r : K$
15.   if $t_k + l_k + \tau > T^r$,
16.   if $k \in S_q$ and $q = p$, then return
17.   else, set $k^{r+1} = S_{q+1}(1)$, $p = q + 1$, delete S_{q+1} for $q < p$, and break
18.   end
19. end

where S_{p-1}^k is a subset of S_{p-1}, satisfying $x_s < x_k + l_k + \alpha$ and $x_s + l_s + \alpha > x_k$ for $s \in S_{p-1}$ and $k \in S_p$.

In lines 4-9, each batch of rectangles is constructed by assigning their berthing locations. The first rectangle of operational cell r is denoted as k^r and is allocated at the beginning section of the cell, x^r. In lines 10-13, a feasible berthing time is assigned as the earliest possible berthing time. Finally, in lines 14-18, a batch that overrides with the next cell is determined as the last batch of the current cell. The contour of the next cell is adjusted according to the allocation plan of the current cell. Eventually, the entire functional region can be decomposed into independent cells occupied by a feasible berthing plan. If an overlapping takes place in the last batch, it implies that the remnant of the current scheduling will stay for the next planning horizon.

However, in a rolling horizon framework, we can easily generate a feasible solution by considering the next planning horizon as a neighboring cell.
The contour of the next cell is adjusted according to the allocation plan of the current cell. Eventually, the entire functional region can be decomposed into independent cells occupied by a feasible berthing plan, as shown in Figure 16.

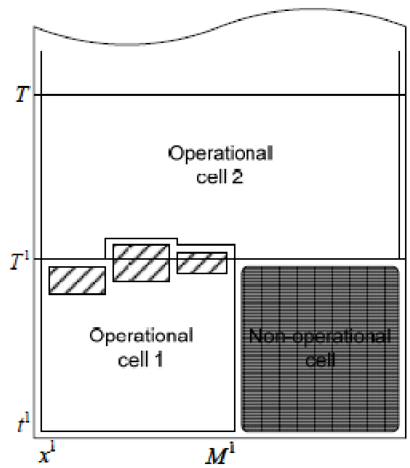


Figure 16: Allocation on decomposed operational cells

By repeatedly applying the steps used in ***H1***, this modified procedure generates an initial feasible solution when a non-operational cell exists in a berth space-time domain.

Therefore, in the case of a partially functional berth, the heuristic ***mH1*** replaces ***H1*** in procedures ***BAPneighbor***, ***BAPinit***, and ***BAPsa***. Subsequently, the procedures for the mBAP should be properly modified to handle a situation where a partially functional berth exists among multiple berths. We assume that all ships can be allocated to any berth, possibly, allowing for extra penalty if the ship does not moor at its home berth. Again, in the presence of a partially functional berth, the heuristic ***mH1*** replaces ***H1*** in the procedure ***NewPartition***.

In particular, vessel rectangles are distributed according to the proper occupation ratio in the initialization procedure, which is referred to as ***mTAPinit***.

In the presence of a non-operational region, the occupation ratio of berth n, $r_{OC}(n)$, is redefined as the sum of the vessel rectangles and the non-operational area of A_n divided by the entire space.

$$r_{OC}(n) = \left(\left(\sum_{k|v_k \in \mathsf{B}_n} h_k l_k\right) + A_n\right) \Big/ M_n T \quad (43)$$

mTAPinit

1. Sort a current state $\mathbf{sc} = \{\mathsf{B}_1, \cdots, \mathsf{B}_N\}$ by arrival times
2. Assign a berth index to each vessel: $n_k \equiv k \pmod N$
3. Randomly substitute berth indices so that

   $$K_n = \frac{1 - r_{OC}(n)}{\sum_{n=1}^{N} (1 - r_{OC}(n))} K \text{ where } \sum_{n=1}^{N} K_n = K$$

   Divide into sub-states $\mathsf{B}_n' = \{v_k \mid n_k = n\}$
4. Generate a feasible solution by applying ***mH1*** and ***H2***
5. Update each state $\mathsf{B}_n = \boldsymbol{BAPsa}(\mathsf{B}_n')$

4.4 Computational Experiments for the TAP

In this section, we perform several computational experiments are performed to evaluate our developed methodology for the TAP. Our computational experiments consist of both functional and partially functional berths. Here, we consider vessels with both flexible and inflexible berthing locations and departure times. To evaluate our develop techniques, under different experimental scenarios, we use the cost function J_6 defined as

$$\mathsf{J}_6 = \min \left[\mathsf{J}_3 + \sum_{k=1}^{K} w_k^3 \left| n_k - m_k \right| \right], \quad (44)$$

where J_3 is the cost function defined in (23), m_k the desired (home) berth location for vessel k, and w_k^3 the spatial penalty for vessel k. The penalty w_k^3 is applied to a vessel which cannot be moored at its desired berth. The last term in J_6, in fact, penalizes the difference between the assigned and the desired berthing location for vessel k.

In our computational experiments, and without loss of generality, we assume the following values for w_k^1, w_k^2 and w_k^3.

$$w_k^1 = \begin{cases} Q, & \text{if } f_k^d = 1 \text{ and } t_k + h_k > d_k \\ 10 l_k, & \text{otherwise} \end{cases}$$

$$w_k^2 = l_k \tag{45}$$

$$w_k^3 = \begin{cases} Q, & \text{if } f_k^b = 1 \text{ and } n_k \neq m_k \\ 2 l_k, & \text{otherwise.} \end{cases}$$

where Q is a big positive real number

$$f_k^d = \begin{cases} 1, & \text{if the departure time of vessel } k \text{ is not flexible} \\ 0, & \text{otherwise} \end{cases} \tag{46}$$

$$f_k^b = \begin{cases} 1, & \text{if the berthing location of vessel } k \text{ is not flexible} \\ 0, & \text{otherwise} \end{cases}$$

In the following, we will consider various scenarios to evaluate our developed methodologies under different circumstances.

4.4.1 Case I: Vessels with Flexible Berthing Locations and Departure Times

Here, we assume that the calling vessels have flexible berthing locations and flexible departure times (i.e., $f_k^d = 0$ and $f_k^b = 0$). By flexible berthing locations, we mean that the vessels do not have any restrictions on the section of the berth they will be assigned to. However, these vessels may be willing to moor at any other berth within the terminal or may only choose a specific berth.

In our experiments, and without loss of generality, we assume that $N = 3$, $M_n = M = 1200m$ for $n = 1, \cdots, 3$, and $T = 168h$. We also assume that the number of vessels mooring at each berth is initially uniformly distributed between 16 to 21.

Scenario 1: In this scenario, all three berths are functional and the vessels are not flexible to change their berths. In fact, this scenario can be viewed as three disjoint BAPs.

Scenario 2: In this scenario, the vessels in Scenario 1 are flexible in changing their berths. This scenario, in fact, represents an instance of the TAP with three berths.

We randomly generated 20 instances of the problem are randomly generated with general specifications as described above. Each instance is comprised of three BAPs such that at least one BAP has a non-zero cost (i.e., the value of the objective function generated by **H1** is non-zero).

In order to evaluate the proposed heuristics for Scenarios 1 (BAPs) and 2 (TAP), a series of ***BAPprocs*** and ***TAPproc*** are successively applied to each instance. The results are averaged and summarized in Table 5.

Table 5: Experiment results for Scenarios 1 and 2

r_{OC}	Scenario 1			Scenario 2				g_{12}
	z_{S1}	t_{S1}	c_{S1}	z_{S2}	t_{S2}	c_{S2}	p_{S2}	
0.31	2796.0	967.7	491.8	27.3	7700.7	4558.0	13.5	0.99

In Table 5, r_{OC} is the occupation ratio of the terminal which is defined as the statistical mean of $r_{OC}(n)$ in (41). z_{Si} is the value of the best solution in Scenario i, t_{Si} the computational time in seconds, c_{Si} the number of iterations of procedure ***H2*** by calling ***BAPneighbor***, p_{Si} the number of iterations of the set partitioning by calling ***NewPartition***, and g_{ij} the cost reduction as a solution gap between Scenarios i and j, i.e., $g_{ij} = (z_{Si} - z_{Sj}) / z_{Si}$.

As seen from the table, due to the flexibility of vessels in choosing different berths, the total allocation cost of Scenario 2 is reduced by 99% (g_{12}=0.99) compared to Scenario 1. The table also shows that the running time for scenario 2 is almost 8 times larger than that of scenario 1.

The following scenarios 3 and 4, are similar to scenarios 1 and 2, under the additional condition that one of the berths in the terminal is now only partially functional.

Scenario 3: Consider Scenario 1 again. Here, berths 2 and 3 are fully functional while berth 1 is partially functional. We assume that berth 1 has a non-operational cell between 600-1200*m* in space and 1-100*h* in time in the space-time diagram.

Scenario 4: Consider Scenario 2 again. Similar to Scenario 3, we assume that berths 2 and 3 are fully functional while berth 1 is non-operational between 600-1200*m* in space and 1-100*h* in time.

Using the same problem instances generated for Scenarios 1 and 2, Scenarios 3 and 4 are created by assuming a non-operational cell in first berth, respectively.

Table 6 summarizes the average results over 20 problem instances, Comparing Table 6 and Table 5, we can easily observe that the non-operational cell increases the occupation ratio from 0.31 to 0.41 and it increases the cost of BAPs by more than 10 times. It indicates that, even in the presence of a partially functional berth, the allocation cost can still be reduced by using multiple berths. It is found that the cost is decreased by 93% (g_{12}=0.99).

Table 6: Experiment results for Scenarios 3 and 4

r_{OC}	Scenario 3			Scenario 4				g_{34}
	z_{S3}	t_{S3}	c_{S3}	z_{S4}	t_{S4}	c_{S4}	p_{S4}	
0.41	32232.0	1241.0	504.8	2266.8	41036.8	26338.5	44.7	0.93

4.4.2 Case II: Vessels with Strict Berthing Locations and Departure Times

Hence, we assume that the departure times and/or the berthing locations of some vessels cannot be violated (i.e., $f_k^d = 1$ and/or $f_k^b = 1$ for some vessels). Accordingly, the set of vessel rectangle v_k assigned to berth n, B_n, is divided into two subsets:

$$\begin{aligned} &\mathrm{B}_n^{free} = \left\{ v_k \mid v_k = \left(n_k, \ldots, t_k\right), n_k = n,\ f_k^b = 0, k = 1, \ldots, K \right\},\ \text{and} \\ &\mathrm{B}_n^{fixed} = \left\{ v_k \mid v_k = \left(n_k, \ldots, t_k\right), n_k = n,\ f_k^b = 1, k = 1, \ldots, K \right\} \quad n \in \left\{1, \cdots, N\right\} \end{aligned} \tag{47}$$

The procedures for generating an initial feasible solution and an updated partition are respectively modified to handle the inflexible requests by vessels. First the rectangles from the first subsequence B_n^{free} are distributed over N berths according to the initial occupation ratio $r_{OC}(n)$ and then the assigned rectangles are combined with the rectangles from the second set B_n^{fixed}.

In the set partitioning procedure ***NewPartition***, only the rectangles from the set B_n^{free} are selected for swapping operation. The following four scenarios 5-8 are used to evaluate the proposed algorithms when some vessels have requested strict berthing locations and departure times.

Scenario 5: We assume that all three berths are functional and that vessels are not flexible in changing their berths. Additionally, we assume that 30% of the vessels in each berth have strict departure time requests. In fact, this scenario represents three BAPs having strict berthing time requests.

Scenario 6: In this scenario, we assume that some vessels in Scenario 5 are flexible in changing their assigned berths, However, 30% of the vessels in each berth have requested strict berth location. In fact, this scenario represents a TAP having strict requests on berthing times and berthing locations.
Again, we randomly generated 20 instances. Each instance is comprised of three BAPs such that at least one BAP has a non-zero initial objective function value generated by ***H1***. In order to evaluate the proposed heuristics over scenarios 5 (BAP) and 6 (TAP), a series of ***BAPproc***s and ***TAPproc*** are successively applied to each instance. The averaged results are summarized in Table 7.

Since the BAPs in Scenario 5 have the strict requests on departure times, some vessels' rectangles, probably with lower priority, may not be allocated in the current time horizon (possibly placed over two consecutive planning horizons). The number of these undesirable allocations in Scenario i is denoted by e_{Si}.

According to the results, if vessels are allocated to the single integrated terminal with multiple berths, the allocation cost can be reduced by 63% even with the strict requests on berthing locations and departure times. Note that the average number of vessels having the inflexible departure times is 5.55 for 3 berths. These vessels having higher priority could make some allocations undesirable. However, by implementing the TAP, the number of undesirable allocations can also be reduced from 0.27 to 0.09. Table 7 also shows that the running time is increased from 0.19 to 2.24 hour.

Table 7: Experiment results for Scenarios 5 and 6

r_{OC}	Scenario 5				Scenario 6					g_{56}
	z_{S5}	t_{S5}	c_{S5}	e_{S5}	z_{S6}	t_{S6}	c_{S6}	p_{S6}	e_{S6}	
0.31	31258.1	666.4	489.9	0.27	11442.2	8052.1	6916.6	10.8	0.09	0.63

Furthermore, additional scenarios are prepared to compare the BAPs and TAP in the presence of a partially functional berth. Using the same problem instances generated for scenarios 5 and 6, scenarios 7 and 8 are prepared by adding a non-operational cell in the first berth, respectively.

Scenario 7: Consider Scenario 5 again. Assume that berth 1 has a non-operational cell between 600-1200*m* in space and 1-100*h* in time while berths 2 and 3 are fully functional.

Scenario 8: Consider Scenario 6 again. Similar to Scenario 7, we assume that berths 2 and 3 are fully functional while berth 1 has a non-operational cell between 600-12000*m* in space and 1-100*h* in time.

Table 8 shows the benefit of implementing the single integrated terminal in the presence of a partially functional berth when vessels have both strict requests on berthing locations and departure times.

A comparison between Table 6 and Table 7 indicates that, although the presence of the non-operational cell increases the cost of BAPs by more than 700%, the allocation cost is still reduced to 57%. In addition, the number of undesirable allocations is reduced from 1.91 to 0.82, on average. Table 8 also shows that the running time is increased from 0.24 to 6.03 hours.

Table 8: Experiment results for Scenarios 7 and 8

r_{OC}	Scenario 7				Scenario 8					g_{78}
	z_{S7}	t_{S7}	c_{S7}	e_{S7}	z_{S8}	t_{S8}	c_{S8}	p_{S8}	e_{S8}	
0.41	221176.1	872.3	599.2	1.91	95818.3	21724.5	21444.5	33.5	0.82	0.57

5 Disruption Mitigation at the Regional Level

Logistics service providers or carriers consolidate their freight in a network of hubs and terminals and build up regular services. The design of such services requires decisions about the frequency, mode, and route of the service and the corresponding schedule and routing of freight. Planning decisions for such networks are made on a tactical level and have a direct impact on customer services and costs. These kinds of tactical planning problems are generally referred as a service network design [25].

5.1 Service Network Design

Railways, less-than-truckload (LTL) motor carriers, mail/package delivery services, airlines, intermodal shipping lines are typical examples of such systems that require tactical planning of operations. Service network design is increasingly used to designate the set of main tactical issues and decisions relevant to the described carriers: the selection and scheduling of the services to operate, the specification of the terminal operations, the routing of freight, the empty balancing strategy, etc. The corresponding models usually takes the form of network design formulations, a class of the mixed-integer network optimization problems for which no efficient exact solution method exists, except for special variants [26].

In this section, we describe a general service network design problem containing decisions regarding the service selection and the traffic distribution. In the service selection, the routes which services are offered and the characteristics of services are defined. In the traffic distribution, the paths between origins and destinations are determined to move every demand.

Network design formulations are defined on graphs containing nodes connected by links. The objective is to select links in a network, along with capacities, eventually, in order to satisfy the demand for transportation at the lowest possible system cost computed as the total fixed cost of the selected links, plus the total variable cost of using the network. Consider a graph $\mathsf{G}=(\mathsf{N},\mathsf{A})$ which represents a physical network, where N is a set of node and A is a set of links.

FORMULATION *FCSN*. The following formulation, which hereafter is called formulation *FCSN*, is equivalent to the fixed cost service network.

$$\text{Min} \quad \sum_{(i,j)\in \mathsf{A}} f_{ij} y_{ij} + \sum_{(i,j)\in \mathsf{A}} \sum_{(i,j)\in \mathsf{P}} c_{ij}^{p} x_{ij}^{p} \tag{48}$$

$$\text{Subject to} \quad \sum_{j\in \mathsf{N}} x_{ij}^{p} - \sum_{j\in \mathsf{N}} x_{ji}^{p} = d_{i}^{p} \qquad i \in \mathsf{N},\ p \in \mathsf{P} \tag{49}$$

$$\sum_{p\in \mathsf{P}} x_{ij}^{p} \le u_{ij} y_{ij} \qquad (i,j) \in \mathsf{A} \tag{50}$$

$$x_{ij}^{p} \ge 0 \qquad (i,j) \in \mathsf{A},\ p \in \mathsf{P} \tag{51}$$

$$y_{ij} \in \{0,1,2,\cdots\} \qquad (i, j) \in A \qquad (52)$$

where

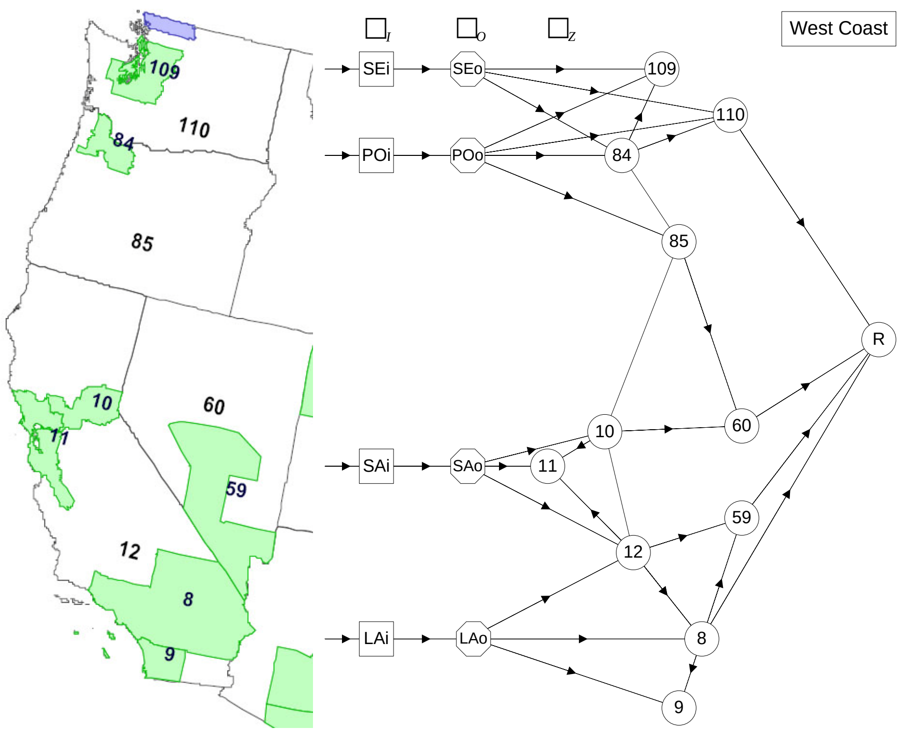
- f_{ij} is the fixed cost incurred by opening service on link (i, j) per service unit
- y_{ij} is the discrete decision variable which represents the number of service units (e.g. trucks) offered on link (i, j)
- c_{ij}^{p} is the transportation cost per unit flow of product p on link (i, j)
- x_{ij}^{p} is the flow decision variable indicating the amount of flow of commodity p using link (i, j)
- d_i^p is the demand of product p at node i
- u_{ij} is the capacity of link (i, j).

The objective function (48) minimizes
the cost of all relevant decisions, i.e., the service selection and the traffic distribution. Constraint (49) is the flow conservation and demand satisfaction requirements. Constraint (50) is the capaci ty restriction of the flow on each link. Constraints (51) and (52) ensure the variables are nonnega tive and the design variable is an integer.

5.2 Service Network for the U.S. West Coast Region

The focus area for developing mitigation strategies at the regional level, is the region consisting of the entire west coast of the United States. The region contains multiple marine ports and the associated ground transportation network, through which goods move within the region and in and out of the region. The basic question at the regional level is: “what is the impact of appropriate mitigation measures if one of the ports in the region becomes partially or fully non-functional for a specific period of time?”

The existing service network is defined at a high level of aggregation, which includes the major ports and aggregated terminals (zones) representing broad geographical destinations and intermediary terminals. To define the regional network at an appropriate level of resolution, the 2002 Origin-Destination data from the Freight Analysis Framework (FAF) of U.S. DoT FHWA (Federal Highway Administration) is used [27]. Using the FAF data, the service network of the west coast region, including the state of Nevada, is constructed. This region consists of 11 zones. In addition, the remainder of the U.S. is considered as one zone and four major combined ports (Los Angeles and long beach, San Francisco, Portland, and Seattle) are also added in the network. Then, the regional service network consists of 20 nodes as shown in Figure 17. The zoning of the FAF is represented in Figure 17(a) and the corresponding network is shown in Figure 17(b).



(a) FAF's zoning (b) constructed network

Figure 17: Service network for the U.S. west coast region

Sine each zone in the FAF data represents an aggregated location of demands, it is modeled as a node (N_Z). A port of disembarkation is not represented as a zone in the data. However, each port node is added to supply the zones. Also, in order to assign the capacity to a port node, it is split into an inbound node (N_I) and outbound node (N_O). In this level of aggregation, a link does not imply a specific freeway or railway between two corresponding nodes. Rather, it represents an aggregated path by possible ground transportation modes (trucks and trains). This distribution network for import freight is assumed to handle an aggregated single commodity. Then, N is a set of node comprised of port nodes and zone nodes ($\mathsf{N} = \mathsf{N}_I \cup \mathsf{N}_O \cup \mathsf{N}_Z$) and A is a set of links comprised of port and ground links ($\mathsf{A} = \mathsf{A}_P \cup \mathsf{A}_G$),

where, $\mathsf{A}_P = \{(i, j) \mid i \in \mathsf{N}_I, j \in \mathsf{N}_O\}$ and $\mathsf{A}_G = \{(i, j) \mid i \in \mathsf{N}_O, \mathsf{N}_Z, j \in \mathsf{N}_Z, i \neq j\}$

Formulation *MCFP*. If all links are activated to move freight, the regional service network can be modeled as a minimum cost flow problem, which hereafter is called formulation *MCFP,* is showed in the following:

$$\text{Min} \quad \sum_{(i,j)\in\mathsf{A}} c_{ij} x_{ij} \tag{53}$$

$$\text{Subject to} \quad \sum_{j\in\mathsf{N}} x_{ij} - \sum_{j\in\mathsf{N}} x_{ji} = d_i \qquad i \in \mathsf{N} \tag{54}$$

$$x_{ij} \leq u_{ij} \qquad (i, j) \in \mathsf{A} \tag{55}$$

$$x_{ij} \geq 0 \qquad (i, j) \in \mathsf{A} \tag{56}$$

where

- c_{ij} is the transportation cost per unit flow in link (i, j)
- x_{ij} is the flow decision variable indicating the amount of flow using link (i, j)
- d_i is the demand at node i
- u_{ij} is the capacity of link (i, j)

Classical pseudopolynomial-time algorithms, such as, cycle-canceling, primal-dual, out-of-kilter, and relaxation algorithms can be applied to solve this problem. These algorithms have some commonalities in that they all repeatedly solve shortest path problem. They frequently provide the essential building blocks and core ideas used in more efficient algorithms. Also, it can be solved by a linear programming method. Note that a linear program with 0-1 incident matrix can be transformed into a minimum cost flow problem [28].

5.3 Mitigating Disruptions at Regional Level

When a disruption occurs at the regional level, the regional service network may need to be reconfigured. For example, consider the U.S. west coast region presented in Figure 17. If the LA port node is rendered non-functional for a period of time, all services originating from the node will either be discontinued or be operated at lower capacity. The reconfiguration of the service network is performed by installing a sea transportation mode between ports. Figure 18 shows the possible sea transportation links (dotted arrows) from the LA port node to other port nodes.

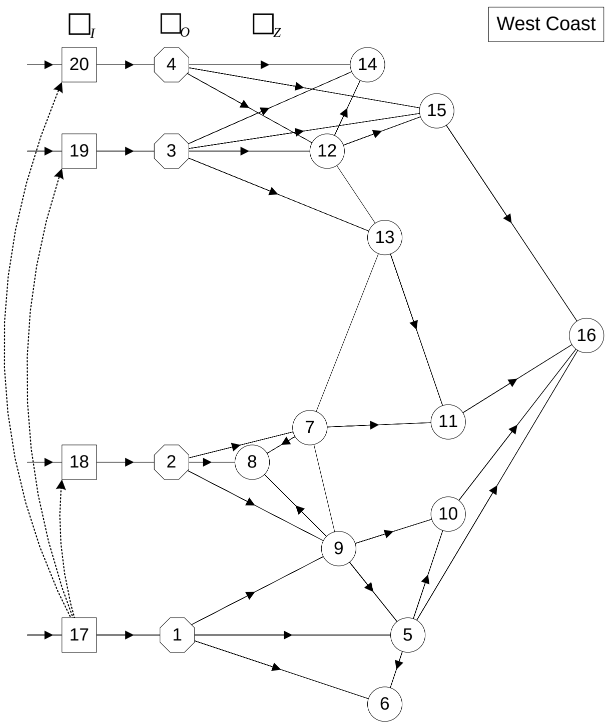


Figure 18: Reconfiguration of the regional service network

The choice of sea transportation links will determined by an optimization procedure, which minimizes a generalized cost while satisfying the transportation demands. Our solution provides the data about the amount of goods that can be distributed by sea links and the corresponding alternative ground links. Due to capacity constraints of links, some amounts of goods may not be distributed although all the available sea links are activated. The amount of goods may remains at the disruptive port waiting to be distributed in the next planning horizon.

Formulation *MCFPB*. The set of links A are differentiated into port operation links A_P, ground transportation links A_G and sea transportation links A_S, where, $\mathsf{A}_S = \{(i, j) \mid i \in \mathsf{N}_I,\ j \in \mathsf{N}_I,\ i \neq j\}$. Then, the service network formulation which can mitigate disruptions is modeled as a minimum cost flow problem with binary constraints. The following formulation is called formulation *MCFPB.*

$$\text{Min} \quad \sum_{(i,j)\in \mathsf{A}_S} f_{ij} y_{ij} + \sum_{(i,j)\in \mathsf{A}} c_{ij} x_{ij} \tag{57}$$

$$\text{Subject to} \quad \sum_{j\in \mathsf{N}} x_{ij} - \sum_{j\in \mathsf{N}} x_{ji} = d_i \qquad i \in \mathsf{N} \tag{58}$$

$$x_{ij} \le u_{ij} y_{ij} \qquad (i, j) \in \mathsf{A}_S \tag{59}$$

$$x_{ij} \le u_{ij} \qquad (i, j) \in \mathsf{A}_P, \mathsf{A}_G \tag{60}$$

$$x_{ij} \ge 0 \qquad (i, j) \in \mathsf{A} \tag{61}$$

$$y_{ij} \in \{0,1\} \qquad (i, j) \in \mathsf{A}_S \tag{62}$$

where

- f_{ij} is the activation cost of sea link (i, j)
- y_{ij} is the discrete decision variable of sea link (i, j)
- c_{ij} is the transportation cost per unit flow in link (i, j)
- x_{ij} is the flow decision variable indicating the amount of flow using link (i, j)
- d_i is the demand at node i

- u_{ij} is the capacity of link (i, j)

If the maximum flow saturates all the links from the source, the minimum cost flow problem is feasible. That is to say, when the supplies/demands at the nodes satisfy the condition $\sum_{i \in \mathrm{N}} d_i = 0$, the minimum cost flow problem has a feasible solution. To make this problem feasible by ensuring $\sum_{i \in \mathrm{N}} d_i = 0$, we add a set of slack transportation links between port-inbound nodes and zone nodes. The set of slack transportation links defined as $\mathrm{A}_K = \{(i, j) \mid i \in \mathrm{N}_I,\ j \in \mathrm{N}_G\}$. Then, the set of links are redefined as $\mathrm{A} = \mathrm{A}_P \cup \mathrm{A}_G \cup \mathrm{A}_S \cup \mathrm{A}_K$. These slack links will provides information how much of goods cannot be delivered to each demand nodes.

FORMULATION *SSST*. Formulation (*MCFPB*) can also be rewritten by separating the set of slack transportation links and in that case it will be called formulation *SSST*.

$$\text{Min} \quad \sum_{(i,j) \in \mathrm{A}_S} f_{ij} y_{ij} + \sum_{(i,j) \in \mathrm{A}_P, \mathrm{A}_G, \mathrm{A}_S} c_{ij} x_{ij} + \sum_{(i,j) \in \mathrm{A}_K} \omega_{ij} x_{ij} \tag{63}$$

$$\text{Subject to} \quad \sum_{j \in \mathrm{N}} x_{ij} - \sum_{j \in \mathrm{N}} x_{ji} = d_i \qquad i \in \mathrm{N} \tag{64}$$

$$x_{ij} \le u_{ij} y_{ij} \qquad (i, j) \in \mathrm{A}_S \tag{65}$$

$$x_{ij} \le u_{ij} \qquad (i, j) \in \mathrm{A}_P, \mathrm{A}_G, \mathrm{A}_K \tag{66}$$

$$x_{ij} \ge 0 \qquad (i, j) \in \mathrm{A} \tag{67}$$

$$y_{ij} \in \{0, 1, 2, \cdots\} \qquad (i, j) \in \mathrm{A}_S \tag{68}$$

where ω_{ij} is the penalty to undistributed goods which could be greater than the cost related to the alternative sea link choice.

This problem is solved by a branch-and-bound (B&B) method and a linear programming (LP) relaxation is performed on every leaf of the branch-and-bound tree. The Simplex algorithm is applied to solve the relaxed LP problem. The Simplex algorithm is defined by the pivot rule. This rule defines the way that decides with vertex of polyhedron is selected when there are many basic feasible solutions (BFSs) to choose from [29]. Suppose that the pivot rule is always to move the adjacent to BFS which there is at least increase in the objective function value. Under this pivoting rule, the Simplex algorithm requires $2^n - 1$ pivoting steps before terminating. More precisely, in a standard form, the time complexity of LP is $O(mn2^n) = O(n2^n) = O(2^n)$ where, m is the number of rows and n is the number of columns of the incident matrix. In a worst case, since a B&B could generate all leafs on the tree and it solves a relaxed LP on every leaf, it takes exponential time $O(p_a \cdot (p-1) \cdot 2^n)$ to solve our problem, where p_a the number of ports in which activated sea links are originated and p is the number of all ports in the network.

As described above, the Simplex algorithm has exponential time complexity. Its average behavior and worst case behavior have been studied and explained by Borgwardt [30] and Klee and Minty [31], respectively. There is no deterministic pivot rule under which the Simplex algorithm is known to take a sub-exponential number of iterations. However, the numerical behavior is conflict with theoretical analysis [32]. That means that it is efficient in practice, while having no polynomial time worst-case complexity, although there are no satisfactory theoretical explanations of its excellent performance. Therefore, the running time in solving our problem is governed by the term $p_a \cdot (p-1)$.

The B&B method explores the set of feasible integer solutions. However, it uses bounds on the optimal cost to avoid exploring certain part of the feasible set. The developed algorithm follows the typical B&B strategies, with few implementation strategies which are listed below.

- It always branches a non-convergent sub-problem unless it is a leaf of the B&B tree.
- To break a sub-problem, it chooses a variable x_i which is not integer and creates two sub-problems by adding either of the constraints $x_i \le \lfloor x_i^* \rfloor$ or $x_i \ge \lfloor x_i^* \rfloor$.
- The lower bound of the optimal cost of a sub-problem is obtained by the linear programming relaxation using the simplex method.
- The upper bound is updated with the best feasible integer solution so far.

- As a way of choosing an active sub-problem, it uses depth-first search with back-tracking.

5.4 Computational Experiments

As we described earlier, our regional service network is constructed based on zoning and data from 2002 FAF. The service network of the US west coast region including the state of Nevada is constructed, which consists of 11 zones for the interested region, 1 zone for the remainder of the US, and four imaginary zones for the major combined port areas (Los Angeles, San Francisco, Portland, and Seattle). In order to assign the capacity to a port zone, each port node is split into an inbound node and outbound node. Therefore, the regional service network consists of 20 nodes as shown in Figure 18.

The freight demands (in tons) are extracted from multi-dimensional matrices which consist of origin, destination, commodity, mode, and port of disembarkation. Originally, origins and destinations consist of 114 regions and 7 international regions. We extracted the freight from the international regions to the interested ports in the west coast regions. Among all freight, we selected freight whose transportation modes are truck, train, and a combination of truck and train. Based on this information, the west coast service network is constructed as shown in Figure 18 and the corresponding demands are defined in Table 9.

Table 9: Import Freight Distribution (ton/day) via Major West Coast Ports

node	z8	z9	z10	z11	z12	z59	z60	z84	z85	z109	z110	zR	Supply
LA	113667	5651	444	2457	4926	1369	61	239	159	757	233	12969	142932
SA	385	8	454	10508	1112	24	59	32	26	76	68	681	13433
PO	321	44	58	34	120	3	25	6643	661	526	1325	935	10695
SE	710	3	31	77	83	1	1	994	670	21861	2525	2819	29775

It summarizes the supplies and demands of four independent distribution networks originating ea ch combined port complex. First column represents ports of the west coast region and first row re present zones in the region. Columns 2 to 13 represent demand d_i^{XX} of zone i supplied by port X X, independently. Then, $d_i = -d_i^{LA} - d_i^{SA} - d_i^{PO} - d_i^{SE}$. The last column represents the supply to each port. Following table describes the legends and indices used in above table and figures.

Table 10: Legends and numbers of nodes describing FAF zones

Legend	FAF acronym	Zone	Node
LA	CA Los A	Los Angeles/Long Beach port areas	17, 1
SA	CA San J	Oakland port area	18, 2
PO	OR Portl	Portland port area	19, 3
SE	WA Seatt	Seattle/Tacoma port areas	20, 4
z8	CA Los A	Los Angeles-Long Beach-Riverside, CA	5
z9	CA San D	San Diego-Carlsbad-San Marcos, CA	6
z10	CA Sacra	Sacramento-Arden-Arcade-Truckee, CA-NV	7
z11	CA San J	San Jose-San Francisco-Oakland, CA	8
z12	CA rem	Remainder of California	9
z59	NV Las V	Las Vegas-Paradise-Pahrump, NV	10
z60	NV rem	Remainder of NV	11
z84	OR Portl	Portland-Vancouver-Beaverton, OR-WA	12
z85	OR rem	Remainder of Oregon	13
z109	WA Seatt	Seattle-Tacoma-Olympia, WA	14
z110	WA rem	Remainder of Washington	15
zR	-	Remainder of West Coast Zone	16

The activation cost f_{ij} of link $(i, j) \in \mathsf{A}_S$ can be defined by 'the running cost' of a ship during the entire trip including the loading at $i \in \mathsf{N}_I$, and the unloading at $j \in \mathsf{N}_I$. The transportation cost c_{ij} of link $(i, j) \in \mathsf{A}_S$ is defined as 'the price per ton' since the distance is already considered in the opening cost. Following relations are used to calculate the opening cost and transportation cost of sea links, especially from LA to other ports.

Fuel cost (FC) = (*Loading and Unloading time*) $\times$ *Fuel per day at port* + *Transit time* $\times$ *Fuel per day at sea*

Running Cost = *Daily running cost* $\times$ *Total time* + *fuel cost* + *port cost*

Price per ton = (*Daily profit* $\times$ *Total times* + *Running Cost*) / *Total tons*

Besides the distance information between port nodes, several assumptions are made to calculate these costs in Table 11.

- Average ship speed is 25 knot.

Transit time (17-18) = 368/25/24 = 0.6133 hour

- Loading/unloading time is 1 hour.

- Fuel consumption per day at port and at sea is 2 ton and 34 ton, respectively.

- Fuel price per ton is $100.

Fuel cost (17-18) = $(1 \times 2 + 0.6 \times 34) \times 100 = 2240$

- Daily running cost of a ship is $5000 and each port cost is $3000.

Activation cost (17-18) = $5000 \times 2.6 + 2240 + 3000 \times 2 = 21240 = f_{17,18}$

- Daily profit required is $1000.

- Maximum load of a ship is $10000.

Price per ton (17-18) = $(1000 \times 2.6 + 21240)/10000 = 2.384 = c_{17,18}$

Table 11: Activation and transportation cost of sea links

Sea link	Distance	Transit time	activation cost	Price per ton
i-j	(nautical miles)	(h)	f_{ij}	c_{ij}
17-18	368	0.6	21240	2.384
17-19	976	1.7	25480	2.818
17-20	1127	1.9	27160	3.006

According to [33], the price per ton-mile of ground transportation modes (truck and train) is roughly 22 times higher than that of sea transportation mode. Since our price per-tone mile of sea links is about $0.004, we can proportionally assumed that the price per ton-mile of our ground transportation link is about $0.1. Then, the ground transportation cost per unit ton is $c_{ij} = 0.1m_{ij}$, where m_{ij} is distance in miles of link $(i, j) \in \mathrm{A}_G$.

The maximum capacity of link is assumed to be high enough to distribute current demands found in the FAF data. First, the maximum capacity of port link $(i, j) \in \mathrm{A}_P$ is defined by increasing the current optimal flow which is an optimal solution to (MCFP).

$$u_{ij}^m = x_{ij}^* / r_p, \qquad (69)$$

Where, u_{ij}^m is the maximum capacity, x_{ij}^* is the optimal solution to (MCFP), and r_p represents the capacity utilization ratio ($0 < r_p \leq 1$). Without any disruption, a higher r_p is given to the LA port node. However, we will generate a disruption in LA node by reducing it's r_p in the experiments.

Table 12 shows the maximum capacity of each link and the residual capacity u_{ij}^r which will be used in PART I of the experiments, later.

Table 12: Estimating capacity (ton) of port links

Port Link	Optimal flow	r_p	Maximum capacity	Residual capacity
17-1	142932	0.9	158813	158813
18-2	13433	0.5	26866	13433
19-3	10695	0.5	21390	10695
20-4	29775	0.6	49625	19850

Secondly, the capacity of ground link $(i, j) \in A_G$ is defined by increasing the current optimal flow which is an optimal solution to (MCFP).

$$u_{ij}^m = x_{ij}^* / r_g \,, \tag{70}$$

where u_{ij}^m is the maximum capacity, x_{ij}^* is optimal solution to (MCFP), and r_g represents the capacity utilization ratio. A higher r_g is given to links whose destination has more demand as shown in Table 13.

Table 13: Estimating capacity of ground links

Zone	r_g	Links
LA Metropolitan area	0.9	1-5,1-6
Other Metropolitan area	0.6	2-7,2-8,3-12,3-14,4-12,4-14
Other than above	0.5	Other than above

5.4.1 Distributions of Freight from LA Port Node

In this part, it is assumed that, if some of freight which cannot be processed in the LA node, they are distributed through other port nodes. Therefore, higher priority is given to the supplies of those nodes. That is, the distributions between the other nodes to zones are performed a priori. That is, $u_{ij} = u_{ij}^r$ for $(i, j) \in A_P$ and $u_{ij} = u_{ij}^m$ for $(i, j) \in A_G$. Assume that a disruption occurs in LA port. As a result of the disruption, we assume that the capacity of link 17-1 is reduced from 90% to 70% in 5% decrements. Table 14 shows the performance of our mitigation strategy summarized in terms of the cost of distribution and the amount of remaining freight.

Table 14: Freight distribution from LA port by activating sea links

Capacity	Capacity	Base Case (MCFP)		Reconfiguration Case (SSST)				
(%)	(ton)	RGoods	Cost (LA)	SA	PO	SE	RGoods	Total Cost
90	142932	0	3.53e+6	2962	1388	0	0	3.36e+6
85	134991	7941	1.91e+6	6457	1484	0	0	3.42e+6
80	127050	15882	6.74e+5	6457	4658	4767	0	3.61e+6
75	119110	23822	5.11e+5	6457	8499	6101	2765	3.78e+6
70	111169	31763	4.45e+5	6457	8499	6101	10706	3.72e+6

The first column represents the current capacity of LA port link with respect to the maximum capacity. The second column shows the corresponding capacity in tonnage. Cost (LA) is the optimal cost of distributed goods supplied to the LA node. RGoods is the amount of remaining goods at LA node due to capacity insufficiency of the overall service network. Suppose that the optimal solution to (MCFPB) or (SSST) is (x_{ij}^*, y_{ij}^*). Then,

$$\text{PCost} = \sum_{(i,j)\in A_S} f_{ij} y_{ij}^* + \sum_{(i,j)\in A_P, A_G, A_S} c_{ij} x_{ij}^* . \quad (71)$$

$$\text{RGoods} = x_{ij}^*, \ (i, j) \in A_K \quad (72)$$

When the current capacity is down to 90%, all the freight from LA node can be distributed using only ground links. However, by activating two sea links, the computational result indicate that the distribution cost originating LA node can be further reduced under our assumptions regarding costs. If the current capacity of LA node is reduced to less than 90%, the part of freight supplied to LA node cannot be distributed in (MCFP). When the capacity is reduced to 85% or 80%, the freight supplied to LA zone can still be distributed by opening some of the sea links in (MCFPB). However, if the capacity of LA node is reduced to 75%, we have excess freight of 2765 ton even though all the possible sea links from LA are activated.

6 Overall Disruption Modeling and Mitigation

Mitigation strategies have been developed at the terminal, port and regional levels and several scenarios were discussed to demonstrate the best mitigation strategies to be followed at each level. It is important that these strategies be integrated with each other, in order to optimize the routing of ships, trucks and trains and to dissipate the disturbance caused by a disruption at any level.

Our overall methodology is developed based on minimizing the total cost at all levels. The regional level takes inputs from the terminal and port levels and the results are used as a new input to the port level using heuristic methods to optimize the routing of goods to their destinations as explained in detail in previous chapters. In the following, a computational experiment is discussed to evaluate the overall methodology applied to a combination disruptions at all levels.

In the following scenario, we have focused on the port of LA/LB which consists of 15 container terminals and the adjacent road network. A major portion of the goods from the port complex are delivered to zone 8 which includes the Los Angeles, Long Beach and Riverside regions. Trucks take I-710, I-110, 47 and 103 roads to distribute the goods in zone 8 as shown in the Figure 19.

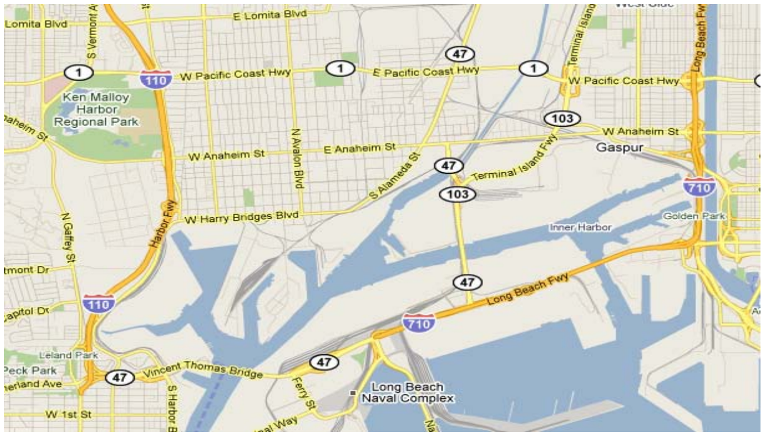


Figure 19: Port (LA/LB) complex and adjacent road network.

For the simulation of cargo movements inside terminals we use the macroscopic terminal model TermSim that was developed under a previous METRANS project and was modified to handle disruptions under this project. For the simulation of traffic flow in the road network adjacent to the twin ports we use the commercial software VISSIM to develop and tune a microscopic traffic simulation model.

The VISSIM based microscopic traffic simulation model is integrated with the macroscopic terminal model in order to calculate the number of trucks entering and leaving the terminals.

Locations of terminals are shown in Figure 20 and the capacity of each terminal is presented in Table 15.

Figure 20: Location of container terminals

Table 15: Capacity of terminals

Terminal#	Normal Capacity (ton/day)	Maximum Capacity
1	11149	6133
2	8290	9133
3	15437	17106
4	7004	7809
5	4145	4609
6	12578	13871
7	4145	4626
8	28015	32150
9	13864	17220
10	8290	12010
11	5717	6985
12	4145	6100
13	5717	7810
14	11149	14905
15	2287	2536

Baseline traffic flow on the adjacent roads prior to applying the scenario assumptions is shown in Figure 21.

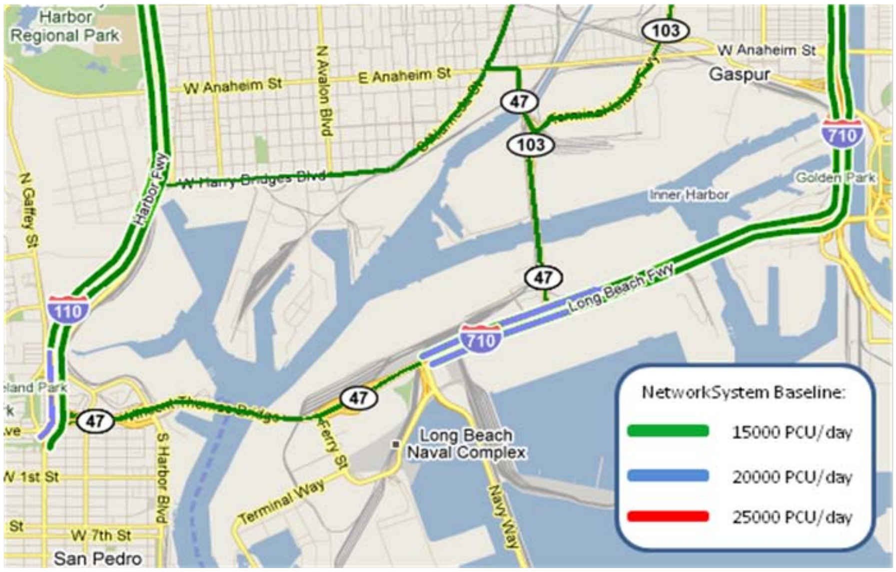


Figure 21: Baseline traffic flow

(PCU -Passenger Car Unit, 1 truck=2.5 PCU, 1 car=1 PCU)

In our disruption scenario terminals 1, 2, 3 and 4 are partially functional due to a military surge (the disruption scenario assumes that the terminals operate at 50% capacity). Therefore, 21100 ton/day is left to be redistributed to the other terminals.

In the following, we provide a comparison of using our methodology, i.e. a combination of the terminal allocation problem (TAP) and service network optimization, versus separately optimizing each one.

6.1 TAP and Service Network Optimization (separately)

In this part, the goods are distributed among other terminals. Table 16 shows the performance of TAP mitigation strategy summarized in terms of distribution of goods in terminals.

Table 16: TAP optimization, container distribution

Terminal#	Normal Capacity	Maximum Capacity
1	5575	6133
2	4151	9133
3	7775	17106
4	3549	7809
5	4332	4609
6	12803	13871
7	4362	4626
8	32115	32150
9	16467	17220
10	11096	12010
11	8642	6985
12	6085	6100
13	7785	7810
14	14746	14905
15	2501	2536

Figure 22 shows traffic flow in the adjacent network. Traffic congestion is observable in I-110 and 47 highways.

Figure 22: Service network optimization, traffic flow

6.2 Combination of TAP and Service Network Optimization

In this part, the impact of the adjacent road network traffic is added to the cost function. As a res ult, terminals 2 to 8 receive more containers compared to the previous part to relieve the traffic fl ow on I-110. This is shown in Table 17.

Table 17: Combined optimization, container distribution

Terminal#	Normal Capacity	Maximum Capacity
1	5575	6133
2	4151	9133
3	7775	17106
4	3549	7809
5	6190	4609
6	14621	13871
7	6297	4626
8	29921	32150
9	15674	17220
10	10009	12010
11	7514	6985
12	5075	6100
13	7514	7810
14	12963	14905
15	4311	2536

As an outcome of considering service network optimization and TAP, the traffic flow shown in Figure 23 is less congested than traffic flow of Section 6.1.

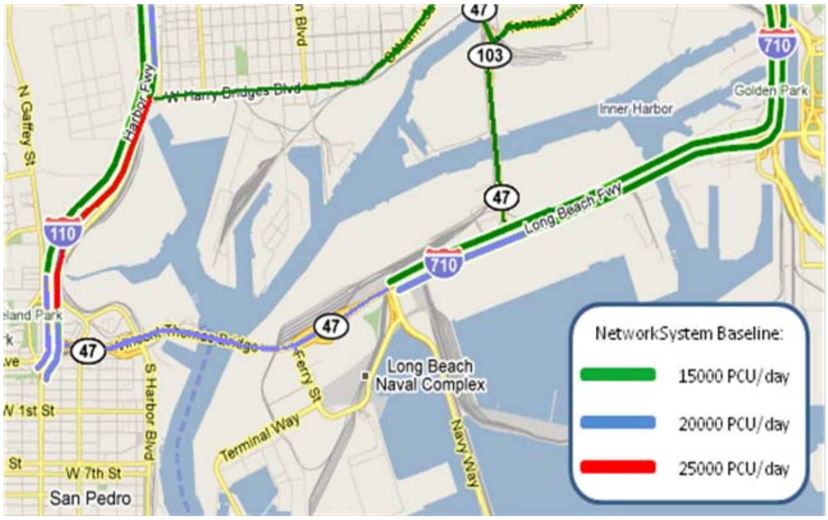


Figure 23: Combined optimization, traffic flow

Figure above demonstrates the improvement of the traffic flow in the network and the total travel time is reduced by using the combined optimization.

7 Conclusions

Shipping is the heart of the global economy, but it is vulnerable to disruptions. Disruptions at marine terminals and ports may cause long delays and long queues at the terminals which may have enormous adverse impacts on the economy. Disruptions may be the result of anticipated events (e.g., construction, scheduled maintenance, pre-planned military surge, etc.), or unanticipated events (e.g., terrorist acts, earthquakes, hurricanes, etc.). In this project, we developed strategies to mitigate the effects of such anticipated or unanticipated disruptions in an effort to maintain port operations and productivity. We investigated methods of modeling and evaluating port disruptions, at the terminal, port and regional levels.

At the terminal level disruptions were analyzed within the framework of the Berth Allocation Problem (BAP). Since the BAP, which can be viewed as a rectangle packing problem, is an NP hard problem, two heuristic optimization techniques based on the sub gradient (SG) and simulated annealing (SA) optimization methods were developed. Simulation results show that the developed methodologies are able to find a near-optimal solution in a reasonable amount of time.

At the port level the disruptions were analyzed within the framework of a Terminal Allocation Problem (TAP). In the TAP, vessels calling on a port were represented by rectangles in the space-time diagram. Disruptions may alter the diagram in the time, space, or both time and space domains. Usually, disruptions in the time domain are caused by the delays in arrival times, delays in berthing times, longer service times, etc. Disruptions in the space domain are less frequent yet their impacts are more severe on the port operations. They may be caused by construction, scheduled maintenance, military surge, terrorist acts, etc. When a disruptive event occurs at a berth, other berths within the terminal may be utilized to further mitigate the impact of that event. To be able to consider a very general TAP, we defined concepts such as a partially functional berth which can be used to represents any type of disruptions in the space-time diagram. We show that the TAP can be viewed as a set partitioning problem, in which each partitioned problem is a BAP. Since the TAP is also an NP hard problem, a heuristic method based on the simulated annealing algorithm was developed to find a good solution in a reasonable amount of time. Numerous experimental scenarios were developed to evaluate the developed TAP solution method in the presence of disruptions. We show that when multiple berths are utilized to accommodate calling ships, the impact of disruptions, either anticipated or unanticipated, can be mitigated significantly using the developed methodologies.

At the regional level disruptions were analyzed within the framework of a service network. The service network optimization is modeled as a minimum cost flow problem with binary (or, integer) constraints. Computational experiments showed that the possible cost reduction acquired under the maximum utilization of the network capacity. The focus was on the entire west coast region of the US, consisting of multiple ports and the associated transportation network. The regional service network is defined at a high level of aggregation. Under a disruptive event, the network is reconfigured by opening sea transportation mode between ports.

In the combined methodology (TAP and service network optimization), the traffic flow in the road network adjacent to the port is less affected by the disruption in one terminal or multiple terminals. The road network in Figure 23 shows less traffic congestion in the area and as the result the total travel time is reduced. Therefore, the total cost is decreased by considering the combination of disruption mitigation methodologies at all levels.

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