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Scope

It is estimated that about 90% of all volume and about 70% of the value of all goods transported worldwide is carried by ships. It is perhaps the most essential form of transportation, yet until recent years has it received limited attention in the operations research literature within the academic community. The goal of this workshop is to bring together a combination of academic and industrial participants to discuss the challenges, solutions and ideas for operations research in the maritime transportation and port logistics field. Maritime fleet sizing and composition, terminal management problems and green logistics solutions are some areas of interest, but any topic that falls into the broad area of maritime transportation and port logistics can be considered. Ideally, the presentations and discussions will include different kinds of shipping markets (petroleum, LNG, bulk products, containers, etc.) and bring together a variety of approaches or technology such mathematical optimization, simulation, specialized software, and others.

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Conference Program

A stochastic programming model for strategic design of container yard under throughput uncertainty

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1 Introduction

Container yard layout and the corresponding equipment deployment significantly affect the investment and operational efficiency of a container terminal. Existing literature on container yard layout planning focused mainly on optimizing block (a basic unit of container yard) size for a given sized container yard [1], [2], [3] and [4]. In an effort of minimizing the total cost per TEU, Kim and Kim [5] developed a mathematical model that simultaneously considers the yard layout and its equipment deployment strategies. Their model assumes a fixed import container throughput. However, in reality container throughput is greatly influenced by several factors, such as weather condition, world economy, trade policy, supply and demand relation of the terminal, etc. The goal of this paper is to establish a modeling framework for strategic design of container yard under the uncertainty of container throughput.

In engineering practice, a common approach for handling uncertainty is to aggregate possible future scenarios to a single scenario, by taking the expected or the most likely value of an uncertain parameter, and then to solve the corresponding deterministic problem [6]. Deterministic approaches are usually conceptually and computationally simpler, but may generate unreliable (or sometimes even infeasible) solutions. In this study, we develop a stochastic programming model that hedges well against all possible future scenarios.

2 Problem statement

In this paper, we focus on parallel yard layout with transfer lanes as depicted in Fig. 1. The uncertainty of container throughput is represented by a set of discrete scenarios and their associated probabilities. The planning decision variables to be determined by the model include the depth of the yard, the length of each block, and the total number of yard cranes to be deployed. The operational decision variables involve the throughputs of containers stacked in design and neighboring yards. The objective is to minimize the total expected capital and operating costs of the container yard, which consists of the cost of yard space, the capital cost of yard cranes, and the operating costs of yard cranes and trucks.

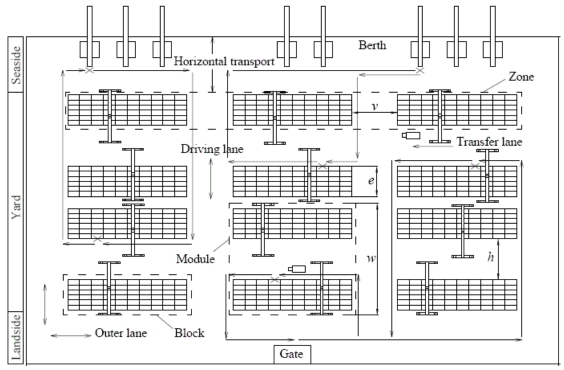

Fig. 1. An illustration of a parallel container terminal layout.

3 Mathematical model

3.1 Modeling assumptions

The model is based on the following key assumptions:

a. Each yard crane is assigned to only one zone of container yard.

b. Discrete throughput scenarios with their associated probabilities are given.

c. A certain number of containers can be stacked in neighboring yards with a higher handling cost.

3.2 Model formulation

In yard layout problem, the planning decisions, such as yard size and the deployment of yard cranes, need to be made before the uncertainty is revealed. These decisions are usually capital intensive and cannot be easily adjusted once implemented. The operational decisions, such as the amount of containers stacked in and out of design yard, can be adjusted (with a recourse cost) depending on the actual realization of uncertain parameters. To distinguish the different natures of planning and operational decisions, we adopt a two-stage stochastic programming model presented as follows.

$$\min_{M,N,n} \quad c_a a(M) + c_f nM + E_\xi Q(M, N, n, y, w, \xi) \tag{1}$$

$$\text{s.t.} \quad M/2, N, n \square Z_+ \tag{2}$$

with

$$Q(M, N, n, \xi) = \min_{y,w}\{f_1(M, N, n, y)\gamma y + f_2 \gamma w\} \tag{3}$$

$$\text{s.t.} \quad y \leqslant V \tag{4}$$

$$y + w = \xi \tag{5}$$

$$y, w \geqslant 0 \tag{6}$$

where decision variables M, N, n, y denote the number of rows of blocks, the number of columns of blocks, the number of yard cranes deployed per row of blocks, the number of containers stacked in design yard, respectively. Variable w is a recourse decision allowing containers to be stacked in neighboring yards at a higher cost, if needed. Symbol ξ represents the uncertain container throughput of the terminal. Cost terms $c_a a(M)$ and $c_f nM$ mean the cost of yard space and the capital cost of yard cranes, respectively. c_a and c_f are given parameters, and function a is the area of the yard. Hence, the objective (1) minimizes the total cost, including the first-stage and expected second-stage costs. Constraint (2) requires that M be even, since blocks are usually laid out in the unit of module, i.e. a combination of two blocks. Expression (3) calculates the second-stage cost, i.e. the operating cost of containers stacked in and out of design yard (denoted by f_1 and f_2). f_1 can be computed referring to references [1], [5] and [7]. For simplicity, f_2 is set as f_1 by a multiplier. Parameter γ converts TEU to the number of containers. Constraint (4) sets the capacity of the container yard. Constraint (5) states that all containers must be stored either in design yard or its neighboring yards.

4 Case study: the second phase terminal of Yangshan Port

4.1 Model input

The second phase terminal of Yangshan Port in Shanghai, China, is used as a real world case study to show the applicability of the proposed model. Sixty discrete demand scenarios based on the historical data of monthly throughput from year of 2007 to 2011 are considered, with equal probabilities. Rubber-tyred gantry cranes (RTGs) coordinated with trucks are used for transporting containers. Operational parameters, such as average cluration of containers, height of stacks, travelling speed of RTGs and trucks, etc., involved in the proposed model and cost assessment are provided. The value of f_2 is assumed to be 10 times of that of f_1.

4.2 Results and sensitivity analysis

4.2.1 Yard layout and cost

The optimal solution to the stochastic model is M=14, N=4, and n=3, which leads to a total of 42 RTGs in the yard. The resultant total system cost is 1,255×10^4 yuan/month, of which about 38% is attributed to space cost of yard, less than 14% to capital cost of RTGs, and 48% to the expected operating cost.

4.2.2 Comparison and analysis

The proposed M is the same as the real value 14, while the proposed N is slightly smaller than the real one 5. As for the total amount of RTGs, the real value 60 is more than the suggested number 42. The possible reason is that our model is based on the average performance of terminal operation which means peak time operation is not taken into account.

4.2.3 Stochastic vs. deterministic solution

The performance of stochastic programming (SP) and deterministic solutions are evaluated. Each wait-and-see solution is based on a single scenario, as if we were able to observe what would happen in the future before we make a decision. The expected-value solution is from a deterministic model where only the expected value of the container throughput is considered. The yard layout decisions from different models differ significantly. Variables M, N and n vary between 8 and 16, 2 and 9, 2 and 3, respectively. In particular, the solution to the expected-value model is M=12, N=7 and n=3. The performance of SP solution, expected-value solution, and a few representative wait-and-see solutions are illustrated in Fig. 2. As expected, the SP solution provides the lowest total system cost on average. It also gives the smallest expected value of perfect information (EVPI), which means the SP model is less sensitive to imperfect model inputs. The value of stochastic programming solution (VSS) is 228.37×10^4 yuan. Compared with the expected-value scenario, the relative gain is 15.4%.

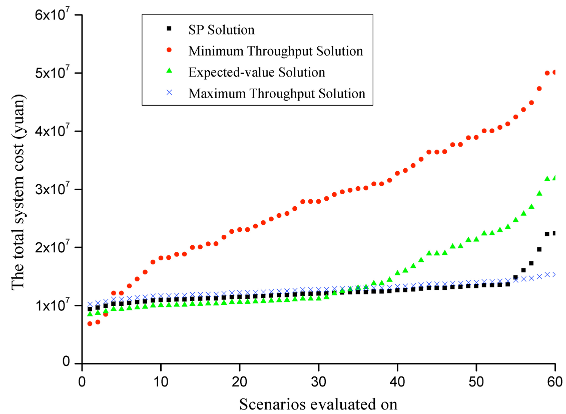

Fig. 2. Performance evaluation of stochastic and deterministic solutions.

4.2.4 Sensitivity analysis

The impacts of critical parameters on yard layout and system cost are evaluated through sensitivity analyses. The results indicate that the average cluration of containers has larger impact on both yard depth and system cost, and the travelling speed of RTGs mainly affects the total number of RTGs deployed.

5 Conclusions and discussions

The key contribution of this study to the literature is on the development of an integrated modeling framework that can be used to support future container yard system planning under uncertainties. Based on a case study of the second phase of Yangshan Port, it was found that different throughput scenarios had more impact on both the depth of the yard and the length of each block rather than the number of yard cranes deployed in each block. Some potential extensions include focusing on peak time operation, extending the two-stage SP model to a multistage one, and incorporating carbon emission to the objective function.

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Berth and Quay Crane Allocation Problems: Dynamic Modeling and Nested Tabu Search

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1 Introduction

At container terminals, the water-side berthing area and quay cranes are key resources. Each calling vessel will occupy space along the berth and will use assigned quay cranes for container unloading and loading until these container processing tasks are completed. Terminal operators must properly assign limited berth and crane resources to arriving vessels to maximize productivity while meeting customer expectations. Berth and/or quay crane allocation problems are generalizations of the resource constrained project scheduling problem, and are complicated in part by practical constraints such as the contiguity of multiple berth segments assigned to each vessel and the dependency of vessel completion time on the number of assigned quay cranes. Bierwirth and Meisel (2010) provide an excellent overview of optimization models and solution approaches that have been proposed to tackle these important and complex scheduling problems.

In this research, we first study the container terminal berth allocation problem (BAP) with fixed vessel processing times and deterministic arrival times, and an objective of minimizing total dwell time with vessel lateness penalties. A polynomial lower bounding procedure is introduced that yields a tighter bound than the linear programming relaxation to a two-dimensional packing mixed-integer programming model. An effective tabu search algorithm is proposed for large-scale instances of this problem; the algorithm proposes a useful solution encoding procedure, and uses a nested neighborhood search to find high quality solutions. We then extend the berth allocation problem framework in two directions. We consider a dynamic berth-crane allocation problem (DBQCAP), where vessel processing times depend on crane assignments and vessel arrival times may be uncertain. A two-stage approximation model is proposed, and the nested tabu search algorithm is adapted to this problem generalization.

2 Berth Allocation

We first present a BAP problem for a single continuous berth, where both the berth and time dimensions are discretized; see Ak (2008). Given vessel lengths and fixed processing times, the problem can be viewed as packing vessel rectangles in the time-space berthing rectangle, while ensuring each rectangle lies to the right of its vessel arrival time and that no rectangles overlap. This *NP*-hard BAP can be formulated using two alternative mixed integer programs: the Position Assignment Formulation, or the Relative Position Formulation. A lower bound for the BAP is developed using a relaxation based on a parallel machine scheduling problem *P* that can be solved by bipartite minimum weight matching; we show that this bound is tighter than the linear programming relaxation bounds.

To solve larger instances pragmatically, we introduce a nested tabu search algorithm with two neighborhood search layers. Each feasible berth schedule solution *X* can be encoded by a vector pair (*L*, *B*), where *L* is a vessel berthing priority list and *B* is a set of vessel berthing positions. The outer layer TS_1 uses a randomized neighborhood generated by vessel swap moves, where each new *L* decodes to an initial solution *X* and *B* using a first-fit vessel packing strategy. The inner layer TS_2 searches for best vessel positions *B* given a priority list *L*. For computational efficiency, the search is limited to a special subset of berth schedule solution candidates that is shown to contain an optimal solution.

Computational experiments on test instances show that for small instances, the proposed nested TS is faster than solving the Relative Position Formulation directly using a commercial MIP solver, and delivers equivalent or better solutions. For larger instances that are not solvable exactly, TS improves the initial optimality gap by 70% on average, while the parallel machine lower bound is tighter than the best lower bound found during the MIP search.

3 Berth-Crane Allocation

We next study a DBQCAP extension of the BAP, where vessel processing times depend on the number of assigned quay cranes and vessel arrival times may not be known when planning. We use a two-stage approximation model in a rolling horizon procedure similar to that in Zhang et al. (2011) for this multi-stage stochastic optimization problem.

The DBQACP discretizes time into shifts, and decisions will be made at the beginning of each shift. Each vessel arrival time becomes known no later than the shift prior to its actual arrival. To enable effective yard operations, each vessel's berth position is finalized at the beginning of the shift prior to its arrival shift. Since cranes can roam, we allow the number of cranes assigned to a berthed vessel to change at the beginning of each shift.

At decision epoch *k*, we define three vessel subsets: V^{A} are vessels berthed at *k* but still being processed; V^{B} are vessels not berthed at *k* but will arrive before *k*+1; and V^{C} are vessels with an uncertain arrival time between shift *k*+1 and shift *k*+*s*, where *s* is the second-stage decision horizon. Different decisions are made for different vessel types. For V^{A}, the number of cranes c^{A} to be assigned is the only decision (first-stage). For V^{B}, we first set a binary delay indicator u^{B}, which indicates whether this vessel is berthed prior to *k+1* or not. For V^{B0} vessels to be berthed prior to *k+1*, we also decide the berthing time t^{B0} and crane number c^{B0}; for V^{B1} vessels, we determine scenario-dependent start time t_{ω}^{B1} and crane number c_{ω}^{B1} as recourse decisions. For V^{C}, we determine a unique berthing location b^{C} along with scenario-dependent start times t_{ω}^{C} and crane numbers c_{ω}^{C}. The objective is to minimize the sum of fixed and expected recourse decision costs, measured by total dwell times, written as $\min f(x_k)+E_w[\tilde{f}(x_{k+1}\,|\,x_k)]$, where $x_k=\{c^{\mathrm{A}},u^{\mathrm{B}},t^{\mathrm{B0}},c^{\mathrm{B0}},b^{\mathrm{C}}\}$, $x_{k+1}=\{t_{\omega}^{\mathrm{B1}},c_{\omega}^{\mathrm{B1}},t_{\omega}^{\mathrm{C}},c_{\omega}^{\mathrm{C}}\}$.

We formulate a two-stage stochastic MIP for this problem, and propose a nested 3-layer tabu search extending ideas from the BAP. TS_1 searches a neighborhood defined by a berthing priority list L, TS_2 searches a neighborhood defined by assigned vessel crane numbers C given a 1st stage decision X which has been decoded from L, and TS_3 searches for a best 2nd stage decision Y_ω for each individual scenario ω, by moving in the neighborhood defined by a partial berthing priority list L_ω^2.

To generate week-long test instances, we use guidelines proposed by Meisel and Bierwirth (2009). We assume a shift length of 24 hours, and a 2nd stage decision horizon of 24 hours. Arrival times are uniform on a range of +/- 3 hours around expected arrival time, and we approximate the second-stage expectation using a sample pool with 20 scenarios. In Table 1, we compare results with the best available solutions under posterior information (shaded items), and also with solutions obtained by using expected arrival times instead of sampled scenarios. The easy cluster has 9 small and 7 medium instances, each of which can be solved to optimality *a posteriori*. Using the proposed sample-average TS algorithm, the optimality gaps are within 2% and smaller than the gaps with expected information. The hard cluster has 1 small, 3 medium and 8 large instances, for which CPLEX finds no feasible solution within 10hr, while a rolling horizon CPLEX approach can provide upper bounds within hours. Using the proposed approach, the gap increment (now measured to the best posterior upper bound) is within 3%. Although using CPLEX and the expected arrival times can lead to smaller gap increments, much more computation time is required. The harder cluster has 2 large instances that can only be solved by TS with both posterior and expected information. The relative gap increment is 1.3% using the sample-average TS, much smaller than the one with expected information. These results show the efficiency of proposed method, its closeness to posterior results, and the value of its sampled stochastic information.

Table.1 Solution comparison with posterior, sampled and expected information (cpu in s, gap by %)

Cluster	V	Posterior						Sample		Expected			
		Cplex		Rolling Cplex		TS		TS		Cplex		TS	
		opt	cpu	gap or ub	cpu	gap or ub	cpu	gap	cpu	gap	cpu	gap	cpu
Easy	40			0.1	27	0.3	8	1.2	16	2.8	30		
	60			0.1	106	0.2	25	2.0	77	3.6	71		
Hard	40	-	-	211	15010	1.4	79	2.4	135	0.0	17837		
	60	-	-	258	4095	0.9	200	2.2	425	2.1	1492		
	80	-	-	307	10717	0.8	356	2.6	1459	3.7	4208		
Harder	80	-	-	-	-	340	731	1.3	4412	-	-	4.8	43

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Pro-active and Reactive Methods to Solve the Berth Allocation Problem with Stochastic Arrival and Handling Times

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1. Introduction

Maritime transportation is a major channel of international sea trade which has increased significantly over the past few decades. From the past research, it is well established that operations research methods and techniques can be successfully used to optimize port operations and enhance terminal efficiency. The large number of uncertainties involved in port operations which can potentially disrupt the normal functioning of the port and require quick real time action, also need to be considered at the planning level.

Through our collaboration with the biggest bulk port in the Middle East, SAQR port in Ras Al Khaimah, UAE, we have identified some key issues and possible sources of disruption. The issues identified at the port call for proper planning and management of port operations; a primary issue that needs to be taken into account during the planning phase is the enormous amount of uncertainty involved in the arrival times and the handling times of the vessels berthing at the port. In this research, we address the problem of accounting for the uncertainty in the operations, while minimizing the total realized costs of the berthing schedule..

2. Research Objectives

The primary aim of this research is to develop reactive and pro-active methods to account for the stochasticity in the arrival times and the handling times of the vessels berthing at the port. The objective is to minimize the total realized costs of the updated schedule as the actual data is revealed in real time.

The underlying model is the dynamic, hybrid berth allocation model for bulk ports by [5]. In container terminals, there have been few studies on robust planning methods for seaside operations planning problems. In the existing literature on seaside operations planning, primarily two types of approaches have been used to address the problem of pro-active robustness in planned schedules. The first approach in pro-active robust methods is to define surrogate problems that inherit the stochastic nature of the original problem. For example, robustness of a schedule is measured by the total slack time or buffer times in the tactical baseline schedule as they can absorb vessel delays to some degree and prevent delay propagation through the schedule. [4], [8], [6] and [3] are few examples of such works. The second approach in pro-active robust methods is based on stochastic programming. [7] use a meta-heuristic approach to solve a two-stage decision model for BAP under uncertainty in which a set of realized scenarios is explicitly defined and the objective is to minimize the total cost of baseline schedule and expected cost of recourse. [2] use a simulation based genetic algorithm approach to solve the integrated berth and quay crane scheduling problem with uncertainty in vessel arrival and operation times.

We propose to develop a two stage model for the berth allocation problem to capture the uncertainty in the arrival information and the handling time information of the vessels. To the best of our knowledge, two stage robust optimization models for the berth allocation problem have not been studied in the context of container terminal operations, while in the context of bulk ports the problem of uncertainty has not been addressed at all. Also, few scholars have addressed the problem of real time recovery in berth allocation problem in port operations, which in practice is either based on local rescheduling techniques or simple rules of thumb. Our research problem is motivated by the real world issues and bottlenecks in operations at the SAQR port, RAK, UAE, where the planned operations are highly disrupted owing to a high degree of uncertainty in the vessel arrival and handling times.

3. Methodology

We develop a two stage model for the berth allocation problem to capture the uncertainty in the arrival information and the handling time information of the vessels. In this model, the first stage decisions are planned with a certain degree of anticipation of variability in the information using a robust optimization approach. The second stage planning is a dynamic recourse strategy to recover the schedule in the event of disruptions in real time as the actual information is revealed. The classical robust optimization approach has the main drawback that it is too conservative since the idea is to ensure that the solution is feasible for all potential realizations. The degree of conservatism is controlled by using uncertainty sets with budget parameters for constraints where only a certain number of coefficients can simultaneously take their worst-case value [1].

3.1. Modeling the uncertainty

At any given time instant in the planning horizon, certain information related to the actual arrival times and the actual handling times of the vessels is known, while the other part of the information remains to be revealed. Thus to plan for the remainder of the planning horizon, the unknown parameters are modeled by making certain assumptions about the probability distribution of the unrevealed part of the information. For example, let's assume that the arrival times of the vessels are symmetrically distributed in a time interval $[A_i - V, A_i + V]$ around a nominal expected value A_i. If the actual or expected arrival time of the vessel i is unknown at the time instant t, then the expectation of the arrival time of the vessel i at time instant t given by a_i^t lies in the interval $[t, A_i + V]$, and a_i^t is determined such that Prob ($a_i <= a_i^t$) $= \delta_a$, where δ_a is an input parameter such that $\delta_a \in [0,1]$. This implies that the actual arrival time of the vessel a_i can be later than the estimated arrival time value at time instant t given by a_i^t (thus possibly making the planned schedule infeasible, since the estimated berthing time of the vessel is greater than or equal to the arrival time) with a probability of $(1- \delta_a)$.

Similary based on the sample of the data obtained from the port, the uncertainty in the handling times of the vessels is modeled using a truncated exponential distribution. The expectation of the handling time of the vessel i at time instant t is given by

$$h_i^t(k) = -(1/\lambda)\ln(e^{-\lambda h_{iL}^t(k)} - \delta_h(e^{-\lambda h_{iL}^t(k)} - e^{-\lambda h_{iU}^t(k)}))$$

where $h_{iL}^t(k)$ and $h_{iU}^t(k)$ are the left and right extremes of the discrete truncated exponential distribution of the handling time of the vessel at time instant t, δ_h is an input parameter such that $\delta_h \in [0,1]$ and λ is the parameter of the distribution

3.2. Recovery Algorithm

The proposed methodology for schedule recovery in real time is based on the re-optimization of the unassigned vessels in the berthing schedule in the events of disruption using a set-partitioning method, and an alternative heuristic based smart greedy algorithm to assign each incoming vessel to quay location where the total realized cost of the schedule is minimized. At any given time instant, the uncertainty in the arrival times and the handling times of the vessels is modeled as discussed earlier.

To assess the added benefit of robust planning in the initial stage of the proposed two stage model, we also apply the recourse strategy on the deterministic variant of the first stage (initial planning stage) of the two stage model. The idea is to study the trade-off between the loss of revenue in the planning stage and cost savings in the recovery phase in the robust model depending on the extent of disruptions in real time. One would also expect feasible recovery actions to exist for a larger number of realizations in the robust model as compared to the deterministic solution.

4. Preliminary Results and Discussion

The proposed optimization based and smart greedy recovery algorithms have been tested and validated by numerical experiments based on real port data in which the baseline schedule is chosen as the solution of the deterministic version of the berth allocation problem. A simulation studies is carried out to assess the effectiveness of the proposed algorithms in which the disruption scenarios are applied to the baseline schedule and the total realized cost of the updated schedule is computed. A lower bound to the minimization problem is obtained by the aposteriori optimization method in which all the uncertain information is assumed to be available at the start of the planning horizon. The results indicate that the proposed algorithms can significantly reduce the total realized costs of the updated schedule, as compared to the traditional greedy method of reassigning vessels to the quay which closely represents the ongoing practice at the port. Moreover while the optimization based recovery algorithm is definitely superior to the smart greedy algorithm in terms of solution quality, it is computationally more expensive, and thus the heuristic is prefered for larger instances of the schedule recovery problem.

5. Conclusions and Future Work

In this work, we study pro-active and reactive methods to solve the berth allocation problem while addressing the problem of uncertainty in the arrival times and the handling times of the vessels. The underlying model is the dynamic, hybrid berth allocation model developed in context of bulk ports. To the best of our knowledge, few scholars have attempted to study the problem of robust and real-time algorithms in port operations. As part of the ongoing work, we are developing a robust formulation for the berth allocation problem with a certain degree of anticipation of delays and variability in information. In the future, we also plan to devise appropriate pricing strategies that can enable the port to partially recover the lost revenue from the late arriving vessels.

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Yard Storage Allocation with Multi-cluster Stacking for Export Containers

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1. Introduction

An important issue in container terminal management is how to stack containers in different locations throughout the stacking yard while minimizing the ship loading time. The challenge involved is to make the ship loading process more efficient, as containers to be loaded on the same ship are often grouped together, while the workloads should be distributed evenly across a container terminal. Hence, the terminal operator would prefer containers for a vessel to be stacked in several groups (or multiple clusters), such that these clusters can be distributed across the yard so as to utilize the yard storage space and to manage the yard workload more effectively. Thus, we are motivated to investigate the yard storage allocation problem in container terminals by introducing a multi-cluster stacking policy. We divide each yard block into sub-blocks as shown in Figure 1, where each sub-block is served by a yard crane. We propose a method of splitting a storage request into multiple clusters, such that individual clusters can be stored in different sub-blocks of yard blocks. As such, the fragmented storage space in the yard can be utilized more efficiently.

Previous works on yard storage planning mainly aimed to improve service and can be grouped according to different objectives: namely, to efficiently use the storage space [1]; to shorten containers transport distance between yard and quay [2]; to facilitate the operation of yard equipment [3]; and to manage workload in the yard [4]. A number of studies have considered the issue of how to group container locations into clusters, and some researchers have proposed a "single cluster stacking" policy that designates at most one cluster per block for a vessel service [5, 6]. Different from previous studies, we investigate the yard storage planning problem in which export containers are allocated in multiple clusters such that the peak workload for handling these containers is minimized.

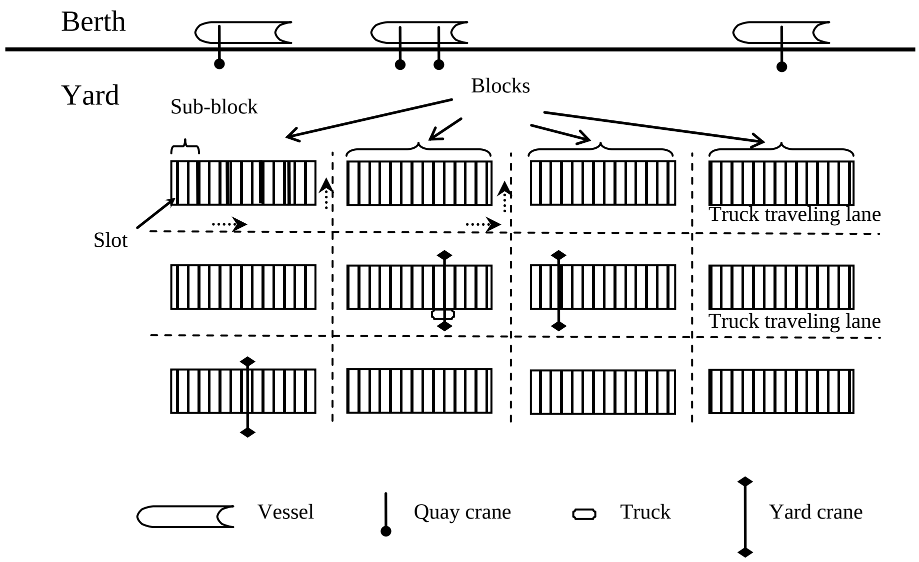

Figure 1. Layout of a container yard with classification of sub-blocks

2. Model Formulation

Let $\mathbf{I}$ be the set of blocks in the yard section, $\mathbf{J}$ be the set of vessel services, $\mathbf{S}$ be the set of sub-blocks in a yard block, and $\mathbf{T}$ be the set of time periods in the planning horizon. Let Ω_j be the time period in which vessel j arrives at the terminal for loading service, $R_{j,t}$ be the space requirement (in no. of slots) of vessel service j in period t, and C be the space capacity of each sub-block. Let $X^i_{j,s,t}$ be the number of slots in sub-block s of yard block i for stacking containers of vessel service j in period t. Let $W^i_{j,s,t}$ the highest slot position for stacking containers of vessel service j in sub-block s of yard block i in period t. Let $Y^i_{j,s,t}$ be 1 if slots of sub-block s in yard block i are made available to containers of vessel service j in period t (and 0 otherwise). Let $\sigma^i_{j,k,s}$ be 1 if slots for stacking containers of vessel service j is on the left side of those slots for stacking containers of vessel service k in sub-block s of yard block i (and 0 otherwise). Let Z be the peak workload (i.e., number of slots with loading jobs) among all yard blocks. We can formulate the problem as the following mixed integer linear program, denoted as problem P.

Minimize Z (1)

subject to

$$W^i_{j,s,t-1} \leq W^i_{j,s,t}, \qquad i \in \mathbf{I},\ s \in \mathbf{S},\ j \in \mathbf{J},\ t = 1,2,\ldots,\Omega_j \quad (2)$$

$$W^i_{j,s,t-1} - X^i_{j,s,t-1} + M(1 - Y^i_{j,s,t-1}) \geq W^i_{j,s,t} - X^i_{j,s,t}, \qquad i \in \mathbf{I},\ s \in \mathbf{S},\ j \in \mathbf{J},\ t = 1,2,\ldots,\Omega_j \quad (3)$$

$$W^i_{j,s,t} \geq X^i_{j,s,t}, \qquad i \in \mathbf{I},\ s \in \mathbf{S},\ j \in \mathbf{J},\ t \in \mathbf{T} \tag{4}$$

$$\sigma^i_{j,k,s} + \sigma^i_{k,j,s} \leq 1, \qquad i \in \mathbf{I},\ s \in \mathbf{S},\ j \neq k \in \mathbf{J} \tag{5}$$

$$\sigma^i_{j,k,s} + \sigma^i_{k,j,s} \geq Y^i_{j,s,t} + Y^i_{k,s,t} - 1, \qquad i \in \mathbf{I},\ s \in \mathbf{S},\ j \neq k \in \mathbf{J},\ t \in \mathbf{T} \tag{6}$$

$$W^i_{k,s,t} - W^i_{j,s,t} + M(1-\sigma^i_{j,k,s}) \geq X^i_{k,s,t}, \qquad i \in \mathbf{I},\ s \in \mathbf{S},\ j \neq k \in \mathbf{J},\ t \in \mathbf{T} \tag{7}$$

$$\sum_{i=1}^{I}\sum_{s=1}^{S} X^i_{j,s,t} = R_{j,t}, \qquad j \in \mathbf{J},\ t \in \mathbf{T} \tag{8}$$

$$X^i_{j,s,t} \leq MY^i_{j,s,t}, \qquad i \in \mathbf{I},\ s \in \mathbf{S},\ j \in \mathbf{J},\ t \in \mathbf{T} \tag{9}$$

$$Y^i_{j,s,t} + Y^i_{j,s+1,t} \leq 1, \qquad i \in \mathbf{I},\ s = 1,2,\ldots,S-1,\ j \in \mathbf{J},\ t \in \mathbf{T} \tag{10}$$

$$\sum_{j:\Omega_j = t}\sum_{s=1}^{S} X^i_{j,s,t} \leq Z, \qquad i \in \mathbf{I},\ t \in \mathbf{T} \tag{11}$$

$$W^i_{j,s,t} \in \{0,1,2,\ldots,C\},\ X^i_{j,s,t} \in \{0,1,2,\ldots\},\ Y^i_{j,s,t} \in \{0,1\}, \qquad i \in \mathbf{I},\ s \in \mathbf{S},\ j \in \mathbf{J},\ t \in \mathbf{T} \tag{12}$$

$$\sigma^i_{j,k,s} \in \{0,1\}, \qquad i \in \mathbf{I},\ s \in \mathbf{S},\ j \neq k \in \mathbf{J},\ t \in \mathbf{T} \tag{13}$$

Constraint (2) ensures that the highest slot position of a cluster is non-decreasing until period Ω_j, while constraint (3) ensures that the lowest slot position of the cluster is non-increasing until period Ω_j, where M is a large number. Constraint (4) specifies the relationship between variables $W^i_{j,s,t}$ and $X^i_{j,s,t}$. Constraints (5)–(7) ensure that the clusters for any two vessel services do not share the same slot in the same time period. Constraint (8) specifies that the total number of slots assigned to clusters in each time period must be equal to the vessel service's space requirement in that period. Constraint (9) specifies the relationship between variables $X^i_{j,s,t}$ and $Y^i_{j,s,t}$. Constraint (10) prohibits the assignment of the same vessel service to adjacent sub-blocks. Constraint (11) limits the workload in every block i and every period t to be no greater than Z. This constraint, together with objective function (1), enables us to minimize the maximum workload across different blocks and periods. Constraints (12) – (13) are non-negativity and integrality constraints of the decision variables. Constraint (12) also specifies an upper bound C for variable $W^i_{j,s,t}$.

3. Solution Method

Problem P can be shown to be NP-hard even when $|\mathbf{I}|=|\mathbf{T}|=1$. However, it possesses some special structure. Constraints (2)–(7) ensure that containers, which are grouped into various clusters, are properly arranged in each sub-block of the yard blocks. These constraints form a yard template configuration sub-problem which attempts to specify appropriate positions for the clusters in the sub-blocks. In addition, constraints (8)–(11) form a yard space allocation sub-problem, which assigns available storage slots to vessel services with certain restrictions. This special structure enables us to develop an effective heuristic by decomposing the problem into two sub-problems. Subproblem P1 decides the slot allocation in the yard, while subproblem P2 configures yard clusters in sub-blocks. We introduce a parameter $\gamma^i_{j,s,t}$ to control the upper bound values of decision variables in the first sub-problem in order to ensure the efficient convergence to a solution value. The initial values of $\gamma^i_{j,s,t}$ are determined by some heuristic rules. The overall decomposition heuristic is summarized below.

Heuristic H

Step 0: Set the initial values of $\gamma^i_{j,s,t}$.

Step 1: Solve problem P1. If P1 is infeasible, stop. Otherwise, let $(\overline{X},\overline{Y},\overline{Z})$ be the solution obtained; for each i, j, s, and t, set $\hat{Y}^i_{j,s,t}=1$ if $\overline{X}^i_{j,s,t}>0$, and set $\hat{Y}^i_{j,s,t}=0$ if $\overline{X}^i_{j,s,t}=0$.

Step 2: Solve problem P2. If $X^i_{j,s,t}=\overline{X}^i_{j,s,t}$ for all i, j, s, and t, stop. Otherwise, set $\gamma^i_{j,s,t}=X^i_{j,s,t}$ for each i, j, s, and t; go to Step 1.

To illustrate the effectiveness and efficiency of our proposed heuristic, we study different classes of problem instances, which consist of different problem sizes and initial yard conditions. We tested the performance of heuristic H using these test instances. We also attempted to solve these instances by applying CPLEX on the formulation of problem P directly. Experimental results indicate that even for large size instances under dense conditions, our solution procedure can obtain optimal solutions for most test instances. On the other hand, CPLEX failed to obtain feasible solutions for most test instances in this class.

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An adaptive large neighborhood search heuristic for ship routing and scheduling with fairly evenly spread requirements

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1 Introduction

Within maritime shipping efficient use of vessels is recognized as one of the most important factor for company profit. Operating a ship is costly and extra sailings with the sole purpose of repositioning the vessel should be kept to a minimum.

In this talk we present an adaptive large neighborhood search (ALNS) heuristic for the Ro-Ro ship routing and scheduling problem (RRSRSP). The RRSRSP is categorized under liner shipping, and meets different challenges than ship routing and scheduling problems within tramp and industrial shipping. Furthermore the deployment usually differ between roll-on roll-off liner shipping and container liner shipping. The problem we investigate originates from an international Ro-Ro company that serves several global trades. Operations are planned six month ahead, and include where and when to sail. This ship routing and scheduling problem is within the category of tactical decisions (Stopford, 2009). For container liner shipping Powell and Perkins (1997), Gelareh and Pisinger (2011), Blander Reinhardt and Pisinger (2012), Wang and Meng (2012a), Meng and Wang (2012) and Wang and Meng (2012b), among others, have studied the fleet deployment and scheduling problems.

One of the features of RRSRSP is that it include "fairly evenly spread" requirements.

This means that the sailings should be divided as good as possible on the entire planning horizon, which connects the schedules of the different vessels. Different ways of modeling this requirement gives different challenges in the ALNS heuristic. When evaluating a move for the routes in the heuristic a scheduling problem has to be solved to determine feasibility and attractiveness. In this talk we focus some on the modeling of this requirement and how this is solved in the heuristic.

The ALNS has been implemented for several vehicle routing problems (VRP) with great success. Ropke and Pisinger (2006) introduces the ALNS and implement it for the VRP with time-windows (VRPTW). The heuristic is tested for over 350 benchmark instances and the computational results show improved solutions on many of these. Pisinger and Ropke (2007) gives a general description of the framework, and a general ALNS framework for the vehicle routing problem is presented. They test the heuristic for five different versions of the vehicle routing problem and show good results. Laporte et al. (2010) and (Mattos Ribeiro and Laporte, 2012) also presents ALNS implementations for versions of the VRP.

The ALNS implementations for the VRPs are not directly transferable to the RRSRSP. In the RRSRSP there are multiple vessels of different types, there are no central depot and there are frequency and spread requirements on some of the arcs in the network. The demand in the RRSRSP is transported by multiple vessels and/or multiple trips by one vessel. A problem which is closer related to the RRSRSP than pure VRPs is ship routing and scheduling problem with split loads for tramp shipping. For this problem Korsvik et al. (2011) presents an ALNS heuristic. However, the problem does still not have the aforementioned characteristics of the RRSRSP. For the latest literature survey within ship routing and scheduling we refer to Christiansen et al. (2004).

2 Problem description

The Ro-Ro shipping company serves trades between regions around the world. A region is for example "North America East Cost", "Oceania" or "Europe". A trade is two regions with a transportation demand between them, for example "Europe - Oceania". There are demand for multiple products, in our case up to three different types of products. Figure 1 gives an example of such a network of regions. In the example there is three regions; "A", "B" and "C", and two trades; "A-B" and "C-A". In addition, between every node (a region) in the network there is a bi-directional arc (stippled) corresponding to the possibility of repositioning the vessel (ballast sailing).

To serve the trades the company operates a vessel fleet of heterogeneous vessels. The vessels differ in capacities, sailing speeds and cost structure. As this is a tactical planning problem the vessel fleet is assumed fixed. If the vessel fleet turns out too small the shipping

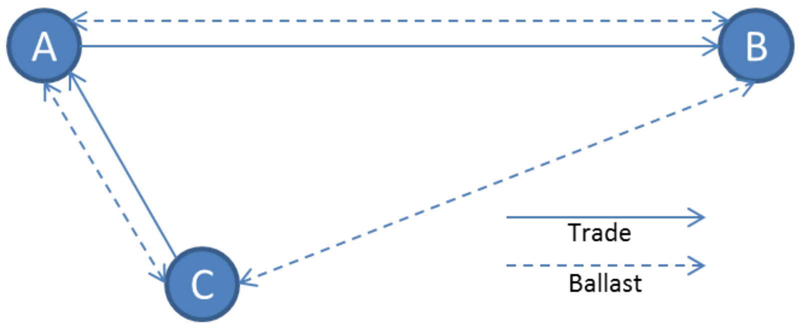

Figure 1: Example of a network

company can choose to either charter in entire voyages (they rent a vessel and perform a sailing on one trade) or to use space charter on other vessels. The different product types have both separate and interconnected capacities on the vessel and not every vessel have capacities for all products.

If there was demand for a product from "C" to "B" in Figure 1, it would be feasible to pick-up both product "C-B" and the product "C-A", and so sail to "A", unload the related product there and then sail to "B" to unload the last products. The company also have some special kind of products that are defined from one pick-up node to several delivery nodes. An example could be a product that has to be picked-up in "C" and could be delivered both in "A" or "B".

The shipping company plan their operations six month ahead. The plan include when and where the vessels should sail, and the sailing speed for each sailing. The vessels becomes available in a given region at a given point in the time horizon (where and when they finish their current sailings). The routing and scheduling solution, when voyage and space charter are includes, must be able to cover the demand of all products. The demand is given monthly and should be served within that month. The solution must also satisfy the frequency requirements, that is a minimum number of sailings that should be performed within a given time. In addition the sailings should be "fairly evenly spread".

3 Solution Method

The ALNS heuristic was introduced by Ropke and Pisinger (2006). It builds on the principle of large neighborhood search (LNS) (Shaw, 1997) where an initial solution is destroyed by some destroy operator and then repaired by a repair operator, while in the ALNS there are multiple destroy and repair operators. Which one to use in a given iteration is determined randomly based on the weight given to the operators according to their performance in earlier iterations. In our implementation of the ALNS we pair all destroy and repair operators that are feasible with each other, and then score the pair based on that pairs' performance. In each iteration we then pick a pair of operators to use. As there are differences in the time consumption of the operators we normalize the scores of the pairs to account for this. Instead of doing this based on the theoretical complexity as some have done, the time consumption is recorded during runtime and once every k'th iteration we adjust the scores. This not to favor very time consuming operators that give much better solution over operators that gives slightly better solution much faster.

We use the simulated annealing acceptance criterion when evaluating new solutions. If a new solution is better than the current solution, the new solution is accepted. But if the new solution is worse than the current solution the new solution is accepted with a probability p. p is larger with higher "temperature" T. We use a decreasing temperature T with the number of iterations, but with reheating at some points. This to control the diversification and intensification of the search.

The ALNS bases it search on an existing solution, so to make the first solution a construction heuristic is developed. The construction heuristic generate a feasible solution that not necessarily are any good.

4 Computational study and results

To evaluate the heuristic we solve the same test instances as Rakke and Desaulniers (2012) solve with an exact method. The instances are generated based on real data from a global Ro-Ro company, and range from small instances up to the real life problem size. Results will be presented and compared with the results of Rakke and Desaulniers (2012).

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Synergetic Service Network Design for Global Liner Shiping Carriers

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1 Introduction

In practice, liner shipping carriers must continuously reshape their global liner shipping networks to adjust to changing world trade patterns [3]. One of the characteristics that significantly differs the service network design problem for global liner shipping carriers from other service network design problems is that a liner container carrier through collaborating with other carriers to form alliances can provide a coordinated service network [2]. Such a coordinated network that is referred to as the *synergetic service network* can service a much wider and denser area than that of the carrier's individual network. Hence, this research addresses the synergetic service network design problem that not only contains the typical liner network-design tasks of route design and vessel deployment and scheduling, but also integrates the important issues of container transshipment, transshipment cost, carrier alliances, needed container estimation, empty container repositioning and laden container routing into the design problem. That is, this research deals with a comprehensive liner shipping service network design problem that is much more practical as well as complex than those in the literature (see, e.g., [4]).

To tackle such a complex synergetic service network design problem, we propose the following solution procedures. First, we construct a synergetic service network, a multi-layer time-space network that integrates the service networks of different carriers in one or more alliances. Then, we mathematically model the design problem by building on the constructed network. Finally, we develop a Benders decomposition-based approach for solving the mathematical program, i.e., the synergetic service network design problem.

2 Synergetic Service Network

The synergetic service network lies at the core of our proposed solution approach for tackling the synergetic service network design problem. We denote the network by $G(N, A)$ that is associated with node set N and arc set A. Network G is a directed multi-layer time-space network, in which one-day is used as the time unit because a transoceanic route generally does not visit more than one port in a given day [1]. Network G consists of three types of sub-networks: (1) a set of the carrier's candidate operating networks that are represented by

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$G_s(N_s, A_s), s \in S$, where S denotes the set of candidate operating networks; (2) a set of fixed strategic allies' operating networks that are represented as $G_q(N_q, A_q), q \in Q$, where Q denotes the set of strategic allies' operating networks; and (3) a dummy network represented by $G_e(N_e, A_e)$. Illustrative networks with respect to $G_s(N_s, A_s)$, $G_q(N_q, A_q)$ and $G_e(N_e, A_e)$ are shown in Figures 1(a), 1(b) and 1(c), respectively.

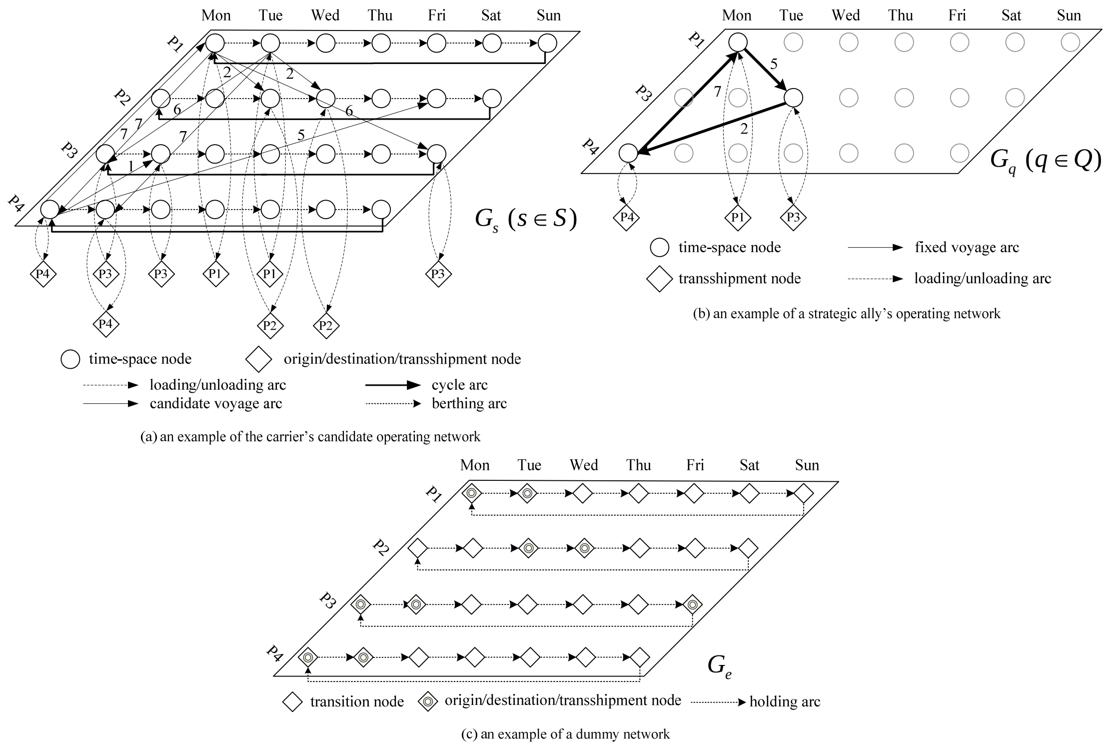

Figure 1. Components of the synergetic service network.

3 Mathematical Model

This section presents a mixed-integer programming formulation based on network G constructed above for the synergetic service network design problem for global liner shipping carriers. Three types of notations are used in the model. First, the notations concerning set are as follows: S denotes the set of candidate operating networks and Q denotes the set of strategic allies' operating networks; N_s, N_q and N_e denote the sets of nodes associated with networks G_s, G_q and G_e, respectively; A_s, A_q and A_e denote the sets of arcs associated with networks G_s, G_q and G_e, respectively; D^k denotes the set of potential destinations of commodity k in set N_e; $L \equiv \{1, 2, ..., T\}$ denotes the set of voyage sequence; K denotes the set of commodities. Next, the notations concerning parameter are as follows: h_{ijs} denotes the fixed operating cost on arc (i, j) and berthing cost at port i w.r.t. G_s; c_{ijn} denotes the unit laden container transportation, holding, loading, unloading, and slot rental/purchase/exchange cost on arc (i, j) in $G_n\left(n \in S \cup Q \cup \{e\}\right)$; b_{ijn} denotes the unit empty container transportation, holding, loading, unloading, and slot rental/purchase/exchange cost on arc (i, j) in $G_n\left(n \in S \cup Q \cup \{e\}\right)$; t_{ijs} denotes the travel time on arc (i, j) in $G_s(s \in S)$; o^k denotes the origin of commodity k in set

N_e; $d_{o^k}^{kl}$ denotes the demand of commodity k with origin o^k in the l^{th} voyage; u_s denotes the vessel capacity in G_s; r_{ijq}^l denotes the available capacity on arc (i,j) in G_q in the l^{th} voyage; w_s denotes the number of the same type of vessels w.r.t. G_s; p_i denotes the unit empty container purchase/rent cost at node $i\left(\in \bigcup_{k\in K}\{o^k\}\right)$. Then, the notations concerning variable are as follows: x_{ijn}^{kl} denotes the weekly volume of commodity k (TEUs/week) transported on arc (i,j) in $G_n(n\in S\cup Q\cup\{e\})$ in the l^{th} voyage; $y_{ijs}=1$ if arc (i,j) in G_s is a leg of liner voyage and is 0 otherwise; z_{ijn}^l denotes the weekly volume of empty containers (TEUs/week) transported on arc (i,j) in $G_n(n\in S\cup Q\cup\{e\})$ in the l^{th} voyage; v_i^l denotes the number of purchase/rent empty containers at node $i\left(\in \bigcup_{k\in K}\{o^k\}\right)$ in the l^{th} voyage; m_s denotes the needed vessels w.r.t. G_s.

Based on the notations defined above, the synergetic service network design problem for global liner shipping carriers can be formulated as the following mixed-integer program:

$$\text{Min} \sum_{s\in S}\sum_{(i,j)\in A_s} h_{ijs}y_{ijs} + \sum_{l\in L}\sum_{k\in K}\sum_{n\in S\cup Q\cup\{e\}}\sum_{(i,j)\in A_n} c_{ijn}x_{ijn}^{kl} + \sum_{l\in L}\sum_{n\in S\cup Q\cup\{e\}}\sum_{(i,j)\in A_n} b_{ijn}z_{ijn}^{l} + \sum_{l\in L\setminus\{1\}}\sum_{i\in \bigcup_{k\in K}\{o^k\}} p_i v_i^l \tag{1}$$

s.t.

$$\sum_{j:(i,j)\in A_s} y_{ijs} - \sum_{j:(j,i)\in A_s} y_{jis} = 0 \quad \forall i\in N_s; s\in S \tag{2}$$

$$\sum_{(i,j)\in A_s} t_{ijs}y_{ijs} = 7m_s \quad \forall s\in S \tag{3}$$

$$\sum_{n\in S\cup Q\cup\{e\}}\sum_{j:(o^k,j)\in A_n} x_{o^k jn}^{kl} = d_{o^k}^{kl} \quad \forall k\in K; l\in L \tag{4}$$

$$\sum_{n\in S\cup Q}\sum_{i\in D^k}\sum_{i\in D^k}\sum_{j:(j,i)\in A_n} x_{jin}^{kl} = d_{o^k}^{kl} \quad \forall k\in K; l\in L \tag{5}$$

$$\sum_{j:(i,j)\in A_n} x_{ijn}^{kl} - \sum_{j:(j,i)\in A_n} x_{jin}^{kl} = 0 \quad \forall i\in N_n \setminus \bigcup_{k\in K}\left(\{o^k\}\cup D^k\right); n\in S\cup Q\cup\{e\}; k\in K; l\in L \tag{6}$$

$$\sum_{j:(i,j)\in A_n} z_{ijn}^{l} - \sum_{j:(j,i)\in A_n} z_{jin}^{l} = 0 \quad \forall i\in N_n \setminus \bigcup_{k\in K}\left(\{o^k\}\bigcup_{k\in K} D^k\right); n\in S\cup Q\cup\{e\}; l\in L \tag{7}$$

$$\begin{aligned} &\sum_{k\in k}\sum_{n\in S\cup Q}\sum_{j:(j,i)\in A_n \& i\in D^k} x_{jin}^{kl} + \sum_{n\in S\cup Q\cup\{e\}}\sum_{j:(j,i)\in A_n} z_{jin}^{l} = \sum_{k\in k}\sum_{n\in S\cup Q\cup\{e\}}\sum_{j:(j,i)\in A_n} x_{jin}^{k(l+1)} \\ &+ \sum_{n\in S\cup Q\cup\{e\}}\sum_{j:(j,i)\in A_n} z_{jin}^{(l+1)} - v_i^{(l+1)} \quad \forall i \bigcup_{k\in K}\{o^k\}; l\in L\setminus\{T\} \end{aligned} \tag{8}$$

$$\sum_{k\in K} x_{ijs}^{kl} + z_{ijs}^{l} \le u_s y_{ijs} \quad \forall (i,j)\in A_s\,(i,j\notin N_e); s\in S; l\in L \tag{9}$$

$$\sum_{k\in K} x_{ijq}^{kl} + z_{ijq}^{l} \le r_{ijq}^{l} \quad \forall (i,j)\in A_q\,(i,j\notin N_e); q\in Q; l\in L \tag{10}$$

$$x_{ijn}^{kl} \ge 0 \quad \forall (i,j)\in A_n; n\in S\cup Q\cup\{e\}; k\in K; l\in L \tag{11}$$

$$y_{ijs}\in\{0,1\} \quad \forall (i,j)\in A_s\,(i,j\notin N_e); s\in S \tag{12}$$

$$z_{ijn}^{l} \ge 0 \quad \forall (i,j)\in A_n; n\in S\cup Q\cup\{e\}; l\in L \tag{13}$$

$$v_i^l \ge 0 \quad \forall i\in \bigcup_{k\in K}\{o^k\}; l\in L \tag{14}$$

$$m_s\in\{0,1,\ldots,w_s\} \quad \forall s\in S \tag{15}$$

The objective function (1) minimizes the carrier's total operating costs. Constraints (2) ensure that every selected shipping line is cyclic. Constraints (3) ensure weekly service. Constraints (4)-(6) are the flow conservation constraints corresponding to laden containers. On the other hand, constraints (7) are the flow balance constraints with respect to empty containers. The main function of constraints (8) is to estimate the number of empty containers that the carrier should purchase and/or rent to meet the shortage of containers for loading the commodities. Constraints (9) ensure that both laden and empty containers can only be transported on selected voyage legs with imposed vessel capacities. By contrast, constraints (10) impose capacity restriction on the flow of both laden and empty containers on strategic allies' voyage legs. Constraints (11)-(15) restrict variable domains.

4 Solution Algorithm

This research proposes a Benders decomposition-based approach for solving problem (1)-(15). The approach is briefly described as follows:

Step 0. (*Initiation*) Set $Z_{ub} = +\infty$, $Z_{lb} = 0$, $P^t = \varnothing$, $R^t = \varnothing$ and $t = 1$.

Step 1. (*Phase-I*) Solve the following Benders Master Problem (BMP):

$$Z^{BMP(t)} = \sum_{s \in S} \sum_{(i,j) \in A_s} h_{ijs} y_{ijs} + \lambda$$

s.t. (2), (3), (12) and (15)

$$(\boldsymbol{\pi}_t^p)^T (\boldsymbol{d} + \boldsymbol{U}\boldsymbol{y}) \le \lambda \qquad \forall p \in P^t$$

$$(\boldsymbol{\pi}_t^r)^T (\boldsymbol{d} + \boldsymbol{U}\boldsymbol{y}) \le 0 \qquad \forall r \in R^t$$

λ unrestricted

Denote $\bar{\boldsymbol{y}}^t$ as the solution to the BMP, and let $Z_{lb} = Z^{BMP(t)}$.

Step 2. (*Phase-II*) Given $\bar{\boldsymbol{y}}^t$, solve the following Benders Sub-problem (BSP):

$$Z^{BSP(t)} = Min\left\{\theta(\bar{\boldsymbol{y}}^t) + \boldsymbol{c}^T \boldsymbol{x} + \boldsymbol{b}^T \boldsymbol{z} : \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{z} \le \boldsymbol{d} + \boldsymbol{U}\bar{\boldsymbol{y}}^t, \boldsymbol{x}, \boldsymbol{z} \ge \boldsymbol{0}\right\},$$

where $\theta(\bar{\boldsymbol{y}}^t) = \sum_{s \in S} \sum_{(i,j) \in A_s} h_{ijs} \bar{y}_{ijs}^t$. If the BSP is feasible, then generate the "optimality cut" $(\boldsymbol{\pi}_t^p)^T (\boldsymbol{d} + \boldsymbol{U}\boldsymbol{y}) \le \lambda$. In addition, let $P^{t+1} = \left\{P^t \cup p\right\}$ and $Z_{ub} = \min\left\{Z_{ub}, Z^{BSP(t)}\right\}$. Otherwise, generate the "feasiblity cut" $(\boldsymbol{\pi}_t^r)^T (\boldsymbol{d} + \boldsymbol{U}\boldsymbol{y}) \le 0$. Besides, let $R^{t+1} = \left\{R^t \cup r\right\}$.

Step 3. (*Optimality check*) If $Z_{lb}(1+\varepsilon) < Z_{ub}$, then set $t = t+1$ and go to Step 1. Otherwise, stop and output Z_{lb} and Z_{ub}.

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Fleet size and mix in liner shipping

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1 Introduction

What a fleet should be composed of in terms of size and mix is a core decision for all shipping companies. In any given market situation, the number of vessels and the variety of vessel types will determine the profit potential for the company. Operational optimization in terms of capacity utilization can only be done within the bounds imposed by the available fleet resources. History has shown that being positioned with the right fleet is even more important for profit than operational excellence, and that the most successful companies are those who are able to manage both. We refer to this as the fleet size and mix problem (FSMP).

The FSMP for road transport is well-known in the literature, with for example [1] and [2] that address the FSMP for a truck fleet. Also within air and rail transport there has been several studies of the FSMP, recent examples being [3] and [4] respectively. Within maritime transportation however, the literature is much more scarce. [5] and [6] are two of the few recent papers dealing with the maritime FSMP.

Our research has been performed in close collaboration with a major RoRo (Roll-on Roll-off) shipping company, which has provided us with real case data and tested our methods and tools. In the next section we will present the main charactiristics of the FSMP in a RoRo shipping company.

2 FSMP in a RoRo shipping company

2.1 The freight market

The cargoes in the RoRo shipping market can be divided into three main product segments:

1) Auto – small and medium sized cars
2) High and heavy (HH) – SUVs, trucks, tractors and other rolling machinery
3) Break bulk (BB) – yachts, trains and all other types of cargo that can be put on wheels and towed onboard

Product 1 and 2 make up most of the cargo volume and freight revenue, but the largest margins per volume are normally made on the BB cargoes.

The global transportation network is divided into approx. 20 trade lines, each defined with regions for origin and destination, distance and sea margins. Which ports that are called on a trade line varies from voyage to voyage and can changed close up to voyage start. Thus the port calls are only considered in the operational planning. The number of voyages performed on a trade line per year is determined either by a fixed frequency requirement set in the contracts with major customers or driven by a yearly demand volume to be lifted.

The normal contracts between the shipping company and the cargo owner only state the share of the yearly production to be transported with the liner, and hence the actual volume to be transported is uncertain. As a result of this, the RoRo companies need to monitor the car and vehicle market carefully in order to make qualified market volume estimations.

2.2 The fleet

A RoRo vessel can be characterized as a floating parking garage, with multiple decks and 1-2 roll-on roll-off ramps. The RoRo fleet, in general and in our case study, is highly diverged in terms size, age, loading capacity, speed and fuel consumption. However, some general classification is used to separate the specialized RoRo vessels from the less advanced Pure Car Truck Carrier (PCTC) and the simplest Pure Car Carrier (PCC).

The existing fleet in our case study contains about 50 vessels. 80% of these are PCTCs and 15% are specialized RoRo vessels. The remaining PCC vessels are being phased out this fleet based on a strategic decision to have a more advanced fleet, and these vessels are not considered for the future operation. Vessel capacities vary from 5000-8000 car equivalent units (CEU), giving a total fleet capacity of more than 300.000 CEU.

There is a limited market for short term chartering of RoRo vessels. Some standard tonnage (PCCs and PCTCs) should be available, but the more advanced vessels are rarely traded between the few major RoRo shipping players. Hence, the relationship to the shipbuilders that are able to build such vessels is important.

2.3 The planning process

The fleet size and mix planning process starts with a market outlook mapping. The normal planning horizon is 5 years, for which the volume be transported on each trade by the shipping company is estimated by a market intelligence group. Then, a fleet outlook is developed based on the maintenance calendar of the current fleet, and plans for delivery of new-buildings and scrapping of old vessels. The final important input for the FSMP analysis is the macro scenario where uncertain external factors are set. This could include changes in; bunker oil prices, environmental regulations, port and canal restrictions, etc.

The FSMP analysis is made by matching the number of sailing days available in the fleet with the number of sailing days required to transport the market volume. Different checks are made during the analysis to ensure; that enough transport capacity can be offered on each trade, that the product mix can be handled and that the flow in and out of regions is balanced. The output of the analysis is a fleet renewal plan, where the number of vessels to build or charter-in/out per year is determined.

Figure 1: Fleet size and mix planning process

3 Mathematical model

3.1 Model description

The *objective function* of the model is formulated as minimizing the total costs for the shipping company, being the sum of fuel expenses (heavy fuel oil + marine diesel oil), port and canal fees, and the charter cost of hiring the vessels (also the vessels owned by the shipping company's owners have an internal charter cost rate per day). Cost minimization is chosen based on the assumption that all the expected freight volume needs to be tranported at a given freight rate, and hence the total income is fixed.

The *decision variables* represents a suggested fleet with a given number of vessels within each vessel type that satisfy all constraints and represent the lowest objetive function. In order to find these values, variables for a deployment of the fleet are needed, determining how many trips will be made on each trade by a certain vessel type with a certain speed.

The main *constraints* of the model is listed below:

- Required frequency on trades
- Required volume transported of different products on trades
- Vessel capacities per product and in total volume
- Flow contraint balancing the number of voyages in and out of a region
- The sum of all voyage durations must not exceed the total sailing days available in the fleet
- Contraints regulating how many vessels of each type that can be chartered in and out

3.2 Model implementation

The model is implemented in Mosel and solved using Xpress-MP. The solver reads input data from Excel and writes output back to Excel.

4 Results and conclusions

4.1 Main results

The main results of our research are summarized in the following points:

- A mathemathical optimization model for the FSMP for RoRo shipping
- An implementation of the model into a decision support tool with suitable data and user interfaces
- Proven calculation effiency, solving instances with 60 vessels, 20 trades and 5 year planning horizon within 10 seconds
- Successful acceptance testing of the tool within a major RoRo shipping company

4.2 Concluding remarks

A fleet size and mix decision support tool has been developed based on the optimization model. The tool has been successfully tested by a major RoRo shipping company, and has proven to give valuable decision support for the fleet size and mix planning problem.

The effiency of the new tool allows the company to improve their strategic planning processes. The planners are able to spend more time on scenario building, what-if analysis and risk management instead of the time consuming manual calculations they previously did.

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Designing liner shipping networks

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1 Introduction

In the shipping market, three types of operations are distinguished: tramp shipping, industrial shipping and liner shipping ([**?**]). Tramp ships do not have a fixed schedule and are used for immediate deliveries where the most profitable freight is available. Therefore, the activities in tramp shipping are very irregular. In industrial shipping the cargo owner controls the ship and the objective becomes to minimize the cost of shipping. In liner shipping, ships follow a fixed route within a fixed time schedule; this is most common in the container trade.

The decision making in liner shipping can be distinguished on three different levels: the strategic, tactical and operational planning levels ([2]). In the strategic planning level the optimal fleet-design is determined. This means that both the optimal number of ships in a fleet and the optimal ship sizes are determined in this level. The ship-scheduling problem is solved in the tactical planning level. In this level, the service network is designed by creating ship routes and allocating the available ships to these routes. Finally, in the operational planning stage, it is determined which cargo is transported and which route(s) are used to ship the cargo. This problem is also referred to as the cargo-routing problem. The decisions made in a planning level influence the decision making in the other levels. Therefore, it could be profitable to solve the problems on the different levels simultaneously.

2 Problem definition

2.1 Fleet-design problem

In the fleet-design problem the composition of the fleet is optimized. For each ship size it has to be determined how many ships of that size should be included in the optimal fleet. Since fleet-related cost are very high, it is important for shipping companies to determine the optimal fleet design. Fleet-related costs can be distinguished in fixed costs capital and operating costs) and variable costs (fuel costs).

In order to determine the optimal fleet composition of liner shipping company, the underlying route network and demand have to be considered. The fleet design is usually determined for a period of 10-20 years, because replacing a ship is expensive. However, the demand structure can change in this time, so both present and future demand have to be considered when solving the fleet-design problem.

Another important factor in purchasing new ships is economies of scale. Large ships have higher fixed cost than smaller ships, but transportation cost per TEU are usually smaller for larger ships than for smaller ships. The size of the ship is also influenced by the demand on the route that the ship will serve.

2.2 Ship-scheduling problem

The liner shipping network is designed in the ship-scheduling problem. A liner shipping network consists of a set of routes. A route is a sequence of ports that are visited by a ship. Routes are cyclic, which means that they do not have a start and end port. Furthermore, ships has to be allocated to the routes and the sailing speed of each ship has to be determined.

Not all ports can handle every ship type and not all ship types can enter every port. Therefore, the allocation of ships to routes ca be restricted. However, once a ship is allocated to a certain route, it will serve this route during the whole planning horizon. It is most common that shipping companies operate schedules in which each routes is served weekly to maintain a customer base and to provide customers with a regular schedule ([2]). Therefore, the number of ships needed for a route is in general equal to the round tour time in weeks of the route (rounded up).

The demand between ports influences the design on the optimal ship routes. However, the shipping company can choose to reject part of the demand, if that will increase their profit. This is decided in the cargo-routing problem. Therefore, the ship-scheduling and cargo-routing problems are often solved at the same time.

2.3 Cargo-routing problem

In the cargo-routing problem it is decided which demands are accepted and which routes are used to transport this accepted cargo from the origin to the destination port. The goal of the cargo-routing problem is to maximize the profit. Revenues are obtained by transporting cargo between their origin and destination port. However, costs are also incurred by the transportation of the cargo. For some demand pairs the revenue that can be obtained will not exceed the cost incurred by transporting the cargo. This demand will then be rejected by the shipping company. Furthermore, it is possible that some profitable demands are rejected because other demands are more profitable.

When the demand of a demand pair is (partly) satisfied, the cargo will be picked up in the origin port and delivered at the destination port. When the origin and/or destination port is visited on several ship routes, it has to be determined to which route the cargo is allocated. Some origin and destination ports will be visited on the same ship route, while other demands have to be transhipped to other routes. All these decisions are made in the cargo-routing problem.

The cargo-routing problem can be formulated as a linear programming problem. This linear programming problem is referred to as the cargo allocation model.

2.4 Combined fleet-design, ship-scheduling and cargo-routing problem

The decisions made in the three individual problems affect the decision making in the other problems as well. For example, when the service network is determined in the ship-scheduling problem, the network structure and capacity limits for the cargo-routing problem are set. This implies that a bad choice of service network in the ship-scheduling phase can result into lower profits in the cargo-routing phase. Therefore, it may be profitable to consider the individual problems at the same time.

In the combined fleet-design, ship-scheduling and cargo-routing problem, all decisions explained above in the three individual problems have to be taken at the same time. The problem becomes to construct a service network and determine the routes used to transport cargo such that the profit is maximized given a certain demand matrix and cost/revenue data. The fleet design follows then directly from the allocation of ships to routes in the service network. The combined fleet-design, ship-scheduling and cargo-routing problem can be modeled as a mixed integer programming model.

3 Solution methods

The cargo allocation model can be used to find the optimal cargo allocation when the set of routes is given. However, when large instances of the cargo allocation model have to be solved repeatedly, the method becomes very time consuming. One way of reducing the computational time is to reduce the size of the problem. The problem size is reduced by aggregating ports into port clusters according to distance. In a model with aggregated ports, ships stop only once per cluster. For each port cluster, the stop should always be at the same place. It makes sense to stop only at the largest port in a cluster, since it can be expected that the largest amount of demand is directly available in that port. The demand to and from other ports of the cluster are transported to the largest port using a feeder service network.

The combined fleet-design, ship-scheduling and cargo-routing problem is solved by first aggregating the ports into clusters. Thereafter, a service network using only port clusters is generated, the sailing speed on each route in the network is optimized and the cargo allocation model is solved to optimality. Next, the feeder service network is designed and improved using heuristic methods. In this step, smaller ports can also be added to the main service network. Furthermore, a heuristic procedure is used to find good liner shipping networks.

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Coordination Mechanisms for Empty Container Repositioning

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1. Background

In global container liner networks, the costly operations of empty container repositioning are necessitated by imbalance of cargo flows. Empty repositioning costs are typically as high as 5-6% of shipping lines' revenues. Efforts to reduce repositioning costs are often complicated by the organizational structures of shipping lines. In particular, planning for shipping line operations is often done in a decentralized manner by individual trade lanes, which are in charge of businesses connecting different regions (e.g., Asia-North America, Asia-Europe, etc.). While these trade lanes are inherently interconnected in the global shipping network, they make revenue management (e.g., pricing and order admission) and vessel planning (e.g., capacity control) decisions independently of each other. As the interface among operations of trade lanes, empty container repositioning is typically managed by the headquarters that oversees global operations.

Following the typical accounting procedure adopted by shipping lines, trade lanes are accounted for the empty repositioning costs only via an aggregate measure instead of the actual cost. This cost measure is considered obscure and often neglected by trade lanes in their business planning, resulting in myopic decisions that largely disregard repositioning cost implications. Motivated by a new practice to be implemented by our industry partner, we study accounting mechanisms built on the framework of *internal pricing* (e.g., [1]) for trade lanes' usage of one another's containers. Furthermore, we study how the mechanisms should be adjusted to help overcome trade lanes' resistance against the new implementation due to possible reductions of their allocated divisional profits.

Our major contributions are two-fold. First, we show that an internal pricing scheme developed via Lagrangian duality achieves *efficiency* (i.e., inducing the system-optimal decisions) and exhibits desirable properties regarding trade lanes incentives to participate, using the notion of the core in cooperative game theory. Second, we further propose an optimization framework to determine redistribution of cost savings that balances *welfare* of trade lanes, i.e., the reception of the new mechanism compared with current practice, and *axiomatic fairness*. Our results shed lights on this trade-off in optimization, an aspect gaining recent interest in operations research (e.g., [2][3]), for a practical industry problem. This work complements the existing literature on empty container rebalancing (e.g., [4][5]),

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which mainly focuses on the operational details of managing rebalancing flows, by focusing on incentive issues arising from the prevalent organizational structure on a strategic level.

2. Internal Pricing and Efficiency

We consider a shipping network with a set of nodes N representing regions (e.g., Asia, Europe, etc.) and the set of directed edges E ($\subseteq N \times N$) representing shipping links. Each pair of shipping links connecting the same pair of regions (i.e., $(i,j) \in E$ and $(j,i) \in E$ for $i,j \in N$) are managed by a trade lane. The set of trade lanes is denoted by L. For each shipping link $(i,j) \in E$, there are two sources of shipping demand. First, a volume of d_{ij} TEUs has been contracted at unit price of q_{ij}. This portion of demand must be fulfilled. Second, depending on forecasted market price p_{ij}, the trade lane may accept s_{ij} TEUs of spot market demand, subject to the allocated vessel capacity K_{ij} for laden containers. We also assume that the reserved capacity allocated for empty containers is sufficient for rebalancing and denote the number of containers repositioned from i to j by r_{ij}, and the associated unit cost be c_{ij}.

To begin the discussion on internal pricing, we define the potential value of coordinating a subset of trade lanes, $S \subseteq L$, by considering its optimal profit under centralized control:

$$\nu(S) = \max \quad \sum_{(i,j)\in E^S} p_{ij}s_{ij} - c_{ij}r_{ij} \tag{1}$$

$$\text{subject to:} \quad s_{ij} + d_{ij} \le K_{ij} \text{ , for } (i,j) \in E^S$$

$$\sum_{j:(i,j)\in E^S} r_{ij} + s_{ij} + d_{ij} = \sum_{j:(j,i)\in E^S} r_{ji} + s_{ji} + d_{ji} \text{ , for } i \in V^S \tag{2}$$

$$s_{ij} \ge 0, r_{ij} \ge 0 \text{ , for } (i,j) \in E^S.$$

where (V^S, E^S) denotes the corresponding subgraph induced by S. It is clear that $\nu(L)$ gives the optimal centralized profit to the whole shipping network.

However, under current practice, trade lanes individually make decisions on the amount of spot market orders to accept, without accounting for empty container repositioning, which is managed by the headquarters in a centralized manner. Namely, trade lanes determines s_{ij} myopically, and the headquarters solves (1) with s_{ij} fixed accordingly. Then, empty repositioning costs are averaged upon trade volumes, namely $\frac{\sum_{(i,j)\in E} c_{ij}r_{ij}}{\sum_{(i,j)\in E} r_{ij}}(s_{kh} + d_{kh} + s_{hk} + d_{hk})$ for the trade lane serving k and h.

Our first result refers to ths construction of efficient internal prices. Let λ_i^S be the optimal Lagranguan multiplier corresponding to (2) for node i.

Proposition 1 *In a decentralized planning regime, an internal pricing scheme that charges (rewards) each trade lane λ_i^S for each empty and laden container shipped out of (into) node i for all $i \in V^S$ induces all individual trade lanes in S to choose the centrally optimal solution that solves* (1)*.*

3. Surplus Transfer, Welfare, and Fairness

Given that overall efficiency is induced by adopting internal pricing, we next propose an allocation of surpluses (cost savings) among trade lanes be conducted (on an accounting basis). On one hand, we hope such an allocation to provide trade lanes a reasonable level of incentive for reception of the new mechanism compared with current practice, while on the other hand, we delve into the fairness issue, and hope it would exhibit a reasonable level of *fairness*, i.e., reflect each trade lane's contribution to the whole network.

Incentives. We begin by defining a cooperative game (L, ν) with the characteristic function $\nu(S)$ for any coalition $S \subseteq L$ being the optimal objective value of (1).

Proposition 2 *The game (L, ν) is balanced. An imputation in the core can be obtained by constructing trade lane payoffs via the aforementioned internal pricing mechanism.*

Proposition 2 suggests that the internal pricing allocation provides some basic degree of incentives for participation. In particular, trade lanes are (weakly) better off joining the grand coalition than forming smaller coalitions. However, resistance will still likely be present, because some trade lanes may lose significantly *relative to current practice.* Therefore, in addition to internal pricing, we propose that transfers of divisional accounting profits between trade lanes be implemented to rebalance surpluses. Implementational details of such two-step mechanisms will be discussed in the paper.

We require that a desirable allocation must remain in the core of (L, ν). Moreover, we seek to ensure the allocation to provide a good *welfare* level. In welfare economics, utility functions for individuals and social welfare functions (SWF) are used to represent individual and overall happiness toward an allocation. The value of SWF towads a certain allocation will represent the overall reception of the new mechanism.

Fairness. Given an *axiomatic notion of fairness*, suppose we have a benchmark payoff allocation $\mathbf{f}$ considered to be fair. To measure the level of fairness of some allocation $\mathbf{x}$, we define the *fairness index* of $\mathbf{x}$ as $F(\mathbf{x}) = 1 - (\sum_i |x_i - f_i|)/(2\sum_i f_i)$, which can be interpreted as one minus the percentage absolute deviation from the fair allocation. A desirable allocation should have a reasonably high fairness index. One can infer that fairness to individual trade lanes and welfare can be in conflict. The problem of determining a desirable allocation, then, becomes a trade-off between welfare and fairness. Similar trade-offs has gained considerable interest in the operations research community recently (e.g., [2][3]). Although the trade-off is up to managerial decision making, one straightforward way is to maximize social welfare while ensuring the desired allocation to have a higher level of fairness than that under current practice, namely given an allocation $\mathbf{x}$:

$$\max \quad SWF(\mathbf{x}) \tag{3}$$

$$\text{subject to :} \quad \sum_{(i,j)\in S} x_{ij} \geq \nu(S) \text{ for each } S \subset L$$

$$F(\mathbf{x}) \geq F_{CP}. \tag{4}$$

where F_{CP} is the fairness index of current practice.

In the paper, we discuss various types of SWFs as well as different fairness benchmarks. In particular, it is known that the Nash solution of social welfare, which maximizes the product of individual utilities, being independent of utility origins and units, Paretian, symmetric, and independent of irrelevant alternatives [7], is axiomatically desirable. The Shapley value is a well-established measure to characterize each individual's contribution to a party's cooperative efforts [9] which satisfies a number of key axioms including efficiency, symmetry, additivity, dummy, marginality and consistency [6][8][10]. Hence, the allocation with Shapley value of (L, ν) for each trade lane could be employed as an axiomatic benchmark for its fair profit share under maximized efficiency. To obtain F_{CP}, we similarly define another cooperative game with s_{ij} in (1) fixed to the myopic values. The Shapley value can again be used as the benchmark for the fair share of each trade lane under current practice. We will examine the effects of using different SWFs and fairness benchmarks in the full paper, e.g., the resulting size of the feasible region of (3)-(4), i.e., the degree of flexbility for the company to allocate transfers. We shall also discuss guidelines and alternative options to define individual trade lanes' utility functions.

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Quickly Finding Good Solutions to Long-Horizon Maritime Inventory Routing Problems

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1 Introduction

We study a maritime inventory routing problem with a long planning horizon of up to 365 periods (days). Even when the planning horizon is limited to 90 or 120 periods, mixed-integer linear programming (MIP) solvers often require hours to produce good solutions for instances with many ports and many vessels. Building on the recent successes of approximate dynamic programming (ADP) for road-based applications within the transportation community, we develop an ADP procedure to quickly generate good solutions to these problems within minutes. Our algorithm operates by solving many small subproblems (one for each period) and, in so doing, collecting and learning information about how to produce better solutions. Our algorithm is one of the first of its kind for maritime transportation problems and represents a significant departure from the traditional methods used. In particular, whereas virtually all existing methods are "MIP-centric," i.e., they rely heavily on a solver to solve a nontrivial MIP in a couple of minutes to generate a good or improving solution, our framework puts the effort on finding suitable value function approximations and places much less responsibility on the solver.

The planning problem considered in this research is representative of one faced by a vertically integrated company managing a fleet of heterogeneous vessels to transport inventory from loading ports to discharging ports. A planner must decide how to route vessels over a given planning horizon while satisfying berth limits and pre-defined inventory bound constraints at ports. In the event that a vessel cannot delivery product in time, a spot market is assumed to be available where product can be purchased at a high price.

It is important to address the question of why a solution for such a long planning horizon is even needed. The central reason is due to risk and lack of liquidity for certain commodities. Liquefied natural gas (LNG) is a case in point. Historically, LNG has been a highly illiquid commodity. As a consequence, LNG buyers have come to expect specific long-term plans, called "annual delivery plans," that specify exactly when they will be receiving cargoes so that they can plan for their operations based on a contractually bound delivery plan. In practice, delivery schedules are updated at regular intervals, e.g., monthly, based on how the schedules and market unfold. The buyer and seller typically work together to adjust their schedules based on how the uncertainty reveals itself. Even after negotiations occur, an updated annual delivery plan with the same granularity of detail must be generated.

2 Approximate Dynamic Programming

Over the past few decades, approximate dynamic programming has emerged as a powerful tool for certain classes of multistage stochastic dynamic problems. It was only in the last decade or so that ADP was successfully applied to truly large-scale applications arising in the transportation and logistics community. Our work builds on the ideas presented by Powell [3] and his associates in the context of stochastic dynamic resource allocation problems. Dynamic fleet management problems are a special case in this problem class. When modeled as MIPs, these problems take place on a time-expanded network involving location-time pairs. Service requests (demands for service) from location i to location j appear over time (randomly, in the stochastic setting) and profit is earned by assigning vehicles of different types to fulfill these service requests. Myopically choosing the vehicle type that maximizes the immediate profit is often not best over a longer horizon.

Our point of departure is the class of the dynamic fleet management problems studied in [1, 2, 6, 5]. In Godfrey and Powell [1], a stochastic dynamic fleet management problem is studied in which requests for vehicles to move items from one location to another occur randomly over time and expire after a certain number of periods. Once a vehicle arrives at its destination node (location-time pair), it is available for servicing another request or for traveling empty to a new location. A single vehicle type with single-period travel times is considered and an ADP algorithm in which a separable piecewise linear concave value function approximation is shown to yield strong performance. This work is extended in [2] to handle multi-period travel times between locations. Further extensions are made to allow for deterministic multi-period travel times with multiple vehicle types [6], random travel times with a single vehicle type [5], and random travel times with multiple types. In all of these studies, separable piecewise linear concave value function approximations are used and shown to work well.

Table 1: Additional time (sec) required by Gurobi 5.0 emphasizing feasibility to reach a solution of equal or better quality. The number of regions and vessels are shown next to each of the 10 instances. There is one port per region. '>36000' means that Gurobi could not find a better solution in a 10-hour time limit.

			120-Period Horizon		**180-Period Horizon**	
	Instance		**ADP**	**GRB**	**ADP**	**GRB**
#	**Regions**	**Vessels**	**Time to Best**	**Add. Time**	**Time to Best**	**Add. Time**
1	3	10	12	674	40	>36000
2	3	13	106	1753	139	2771
3	4	15	82	1110	145	5013
4	4	15	49	>36000	211	>36000
5	4	17	16	938	58	>36000
6	5	25	79	>36000	290	>36000
7	8	40	141	>36000	202	>36000
8	8	40	109	2198	346	30836
9	12	70	138	>36000	975	>36000
10	12	70	383	>36000	1112	>36000

There are two important observations to make regarding the above papers. First, they all treat dynamic fleet management problems, not inventory routing problems. That is, the movement of vehicles is critical, while the amount of a product on the vehicles or at each location is not an issue and, therefore, is not modeled. Second, they all use value function approximations that are only a function of the *vehicle state*, i.e., they value the number of each vehicle type that will be available at each location over future time periods.

In this work, we extend the ideas above by considering an inventory routing problem with multiple discharging regions and multi-period travel times. We first formulate the problem as a finite-horizon dynamic program. We then replace the true value function, which is a function of both the vessel positions and the inventory state, with a value function approximation that is only a function of the inventory state. A similar approach was taken in Toriello et al. [7], although several simplifying assumptions had to be made. Intuitively, the more inventory available at a port, the less valuable an additional unit of inventory becomes. Therefore, we also employ piecewise linear concave approximations. To update the approximations, we use information collected from the previous solves to give a more accurate value of inventory. In fact, when our primary interest is to obtain improving solutions, our main goal is to give a more accurately *relative* value of future inventory at one port versus another.

3 Computational Results

A subset of our computational results are shown in Table 1 and illustrate that our ADP approach is able to generate good solutions to instances with dozens of vessels and varying time horizons much faster than a commercial solver emphasizing feasibility. These experiments were meant to test our ADP method on instances with 120- and 180-period horizons in order to understand if it could be competitive with a rolling horizon framework. In a rolling horizon framework, a sequence of small MIPs with overlapping time intervals are solved to generate a solution over the entire planning horizon. For example, to generate solutions to planning problems with a 360-period horizon, Rakke et al. [4] solve subproblems involving 90 periods and piece together the solutions to these subproblems to create a solution for the full planning horizon. For several of our instances, one-way inter-regional travel times are over 30 periods in duration and we found that solving a reduced MIP with a 90-period time horizon could lead to solutions with odd end behavior. Extending these horizons over 120 periods seemed to yield more stable results. These results suggest that using our ADP approach within a rolling horizon framework could result in a substantial reduction in computing time.

In terms of impact to the transportation science and logistics community, perhaps the most significant contribution of this work is our success in extending existing ADP methods for "pure" routing problems to handle *inventory* routing problems. We accomplish this by employing value function approximations of current and future *inventories*, rather than vehicle positions. This extension is significant as complex supply chain problems that integrate routing and inventory management decisions become more prevalent.

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Joint Design and Pricing of Port-Hinterland Network Services

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1 Introduction

Container terminal operating companies around the globe have recently started to actively participate in land-side transport networks to enhance their connectivity to destinations inland while relieving some of the negative effects of freight transportation. In particular, they have developed so-called extended gates [1] in which sea port container terminals are connected to inland container terminals via frequent services of high capacity transport means such as river vessel and train. Customs clearance and other added value activities can be postponed to the inland terminals, which can be seen as "extended gates" of the sea port terminal. In doing so, the terminal operator extends its role of sea port node operator to the role of an multi-modal transport network operator or a so-called extended gate operator.

The design problem of a container transport network following the extended gate concept comes down to the following three decisions: (1) determine which inland terminals act as extended gates of the seaport terminal, (2) determine capacities of the network links , and (3) set the prices for the transport services on the network. The three decisions are interrelated. For example, the network operator could connect the seaport either to a limited number of inland terminals while using high frequent and high capacity transport services, or it could connect with more inland nodes using less frequent or lower capacity transport services.

Creating high frequent and high capacity transport services has a number of advantages. First of all, economies of scale can be achieved when large river vessels are utilized well. Moreover, higher frequency of transport services reduces the average throughput times of containers which enlarges the market potential for such services. Finally, [2] demonstrate that consolidation hubs help to hedge against demand uncertainty. In this paper, we propose a method to jointly design and price extended gate network services to reap possible benefits.

2 Modeling Approach

In our problem formulation, the extended gate operator acts as a Stackelberg leader by designing the capacities, frequencies, and prices of services on the transport network, anticipating the decisions of the customers that follow by choosing the minimum cost paths to their final destinations, possibly under time related service level constraints.

The mathematical model is a bi-level program where at the first level, the extended gate operator maximizes its profits which are given by the revenues of the extended gate services minus the fixed and variable costs of operating the extended gates. At the second level, the collective of customers minimizes the total system costs which consist of costs of transportation and handling at the container terminals. The total network consists of links and nodes controlled either by the extended gate operator or by the competition. In particular, each hinterland destination can also be served by a direct trucking option offered by the competition. Therefore, prices set by the extended gate operator are always constrained by a competitive price from above.

We consider the multi-commodity version of the problem in which each commodity represents a client that has demand for a specific OD pair and an upper bound for the total transport time. The total transport time includes the dwell time at the sea port terminal, which depends also on the frequency of service. The model formulation extends the one proposed by [3] by the consideration of high capacity modalities and by a set of total service time constraints. Our formulation resembles the usual Hub and Spoke (H&S) formulations with the addition of revenue management control through pricing; a fixed price applies for all flows transported through each extended gate. The relaxation of the above constraint yields the same network configuration as a H&S model.

We define the MIP equivalent formulation of the bi-level program and solve the problem with CPLEX. The computation times of our NP hard problem are considerably high even for medium size instances. We propose a heuristic that effectively solves the special formulation of our problem in substantially less time ($< 1\%$) and which achieves an average gap from optimality of less than 3%. The heuristic process consists of two parts; first, the MIP equivalent formulation is solved consecutively for all links controlled by E.G operator individually and second, the individual solutions are combined in a greedy fashion until a feasible and near optimal solution is achieved.

3 Results

In this section we assess the managerial relevance of our model and we summarize results from solving several instances with our model. A stylized example is developed and presented in Figure 1, that demonstrates the main differences between the solutions of H&S and JDP formulations. The network consists of 4 nodes, representing a seaport terminal and 3 inland terminals, and of 8 road and waterway links, where only the latter are controlled by E.G. operator. Road transport is offered by competitive trucking companies at fixed prices. We consider fixed costs of 20,000 for opening a hub (Extended Gate) and variable costs equal to 6,000, 5,000 and 5,000 per barge trip for three corridors respectively; the first terminal is considered to be further away than the rest. We consider the weekly expected demand for import containers between the seaport terminal and the inland terminal regions equal to 300, 300 and 100 containers respectively. To simplify exposition we do not consider terminals charges here, we aggregate clients in inland terminal regions, and we do not consider time constraints.

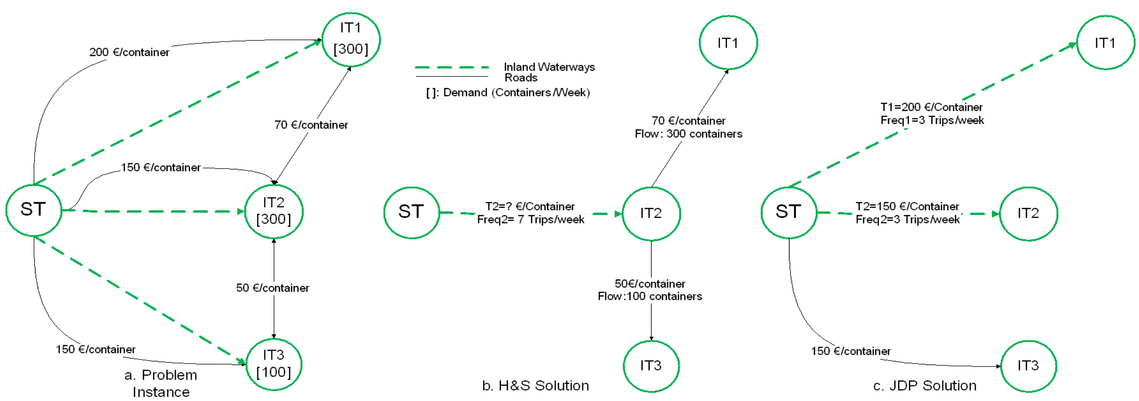

Figure 1: Stylized Example: H&S versus JDP solutions

The H&S model consolidates all flows in one corridor in order to take maximum advantage of economies of scale by incurring only one fixed cost for opening one hub, containers destined to the other terminals' regions are further transported via trucks. This solution minimizes the total costs of the system and would also maximize the profits of the E.G. operator if it were possible to set different prices to each client. This would be an option if the E.G. operator offered port-to-door transportation services or controlled all the links in the network. The prices charged for the barge service depend on the best alternative transport options and should be set such that routing through the corridors becomes the least cost path for the selected flows. In this case, if a fixed price applies it should be equal to 100 /container in order to make the ST-IT2-IT3 path cost neutral to the ST-IT3 alternative path and this would generate a profit equal to 15,000 (700x100 -7x5000-20,000). The JDP model on the other hand maximizes revenue and creates markets segments through pricing. In the optimal solution two hubs are opened each to serve its region while the IT3 demand will be left to competition because either the fixed costs incurred for opening the IT3 hub outweigh the generated revenues or routing through the existing hubs would force lower prices that would generate a revenue loss. The profits in this case would be equal to 32,000 (200x300 +150x300 - 3x6,000 - 3x5,000 -2x20,000).

Our results demonstrate that incorporating pricing in network design has substantial effects on the optimal network configuration. It follows that cost minimization is not equivalent to profit maximization in network design models. The H&S yields few corridors with high capacity taking maximum advantage of economies of scale. The JDP model yields more corridors with still high but lower capacity. Although revenue maximization would suggest more dedicated services, with higher prices, consolidation still takes place with our model but at a lower level. The trade-offs among revenue maximization, economies of scale and service levels are captured in our model. Both models, H&S and JDP, open a hub only when capacity and frequency of services can be set high enough, so that both economies of scale and low expected dwell times are achieved. It should be noted that the savings in costs and time from increasing the frequency or capacity is a positive but decreasing function. Thus, after a threshold on frequency or capacity, market segmentation has a higher effect on profit maximization than cost reduction.

4 Conclusions

A bi-level mathematical programing model to facilitate the main decisions of an extended gate operator was developed. The model incorporates and balances revenue management, economies of scale and time related service level constraints in network design. We take advantage of the special features of our problem and propose a heuristic that effectively solves our NP hard problem. Our results show that market segmentation can be in favor of maximizing profitability of extended gate operators.

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Flexible Solutions to Maritime Inventory Routing Problems with Delivery Time Windows

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1 Introduction

The classical Inventory Routing Problem with Time Windows (IRPTW) is to find routing plans that minimize the total cost of transportation and inventory, while satisfying the constraints that products are delivered within the stipulated time windows. However, in practice, unpredictable disruptions may affect the execution of an optimal deterministic plan. Among all the uncertain factors in maritime transportation, one of the most common ones is that travel times are easily affected by weather conditions. Focusing on this type of uncertainty, we consider IRPTW with travel disruptions.

Various definitions and approaches for schedule robustness have appeared in the literature. Robust optimization (Ben-Tal et al. [1]) is one modeling framework for dealing with uncertain data in optimization. However, the worst-case assumption of robust optimization can lead to solutions that are too conservative. On the other hand, because of the large number of uncertain scenarios that need to be taken into account, stochastic programming (Shapiro et al. [2]) has computational limitations for this class of problems. We propose a different approach for dealing with uncertainty which emphasizes adaptable or flexible solutions. To evaluate the flexibility of schedules, we build a simulator that generates disruptions and recovery solutions. By observing the performances in responding to the disruptions and identifying the most problematic time windows, we generate revised schedules that have more flexibility.

There are only a few studies that deal with robust planning in the shipping industry. Christiansen and Fagerholt [3] study a multi-ship pickup and delivery problem with soft time windows. The study designs robust schedules that are less likely to result in ships staying idle in ports during weekends by imposing penalty costs for arrivals at risky times. Agra et al. [4] investigates the vehicle routing problem with time windows where travel times are uncertain and belong to a predetermined polytope. A robust optimization framework is used to find routes that are feasible for all values of the travel times in the uncertainty polytope.

2 Simulator

It is difficult to evaluate how solutions respond to uncertain disruptions. Therefore, we built a simulator to study the process of recovery from disruptions in a planning solution. A disruption is defined at a discharge port by the triple (tw, d, l), which means that the travel times of all the ships that are going to serve time window tw are extended by d days when they are traveling to this discharge port, and this information is released l days (lead time) before the day that the time window tw begins. The simulator generates random disruptions of this type.

As soon as the disruption is known, the simulator generates a recovery solution. Three available recovery options are modeled in the simulator.

1. *Push-back.* If the slacks in the schedule or the time windows are sufficient to absorb the delays, we simply delay the affected routes and do not re-route any ships. Push-back does not increase cost.

2. *Ship re-routing.* If necessary, the simulator is able to re-route ships en route to ports that differ from their original destinations. This recovery option increases transportation costs.

3. *Spot market.* If it is impossible to meet all time window demands by only using the first two options, an expensive spot market acts as an additional supply source in the recovery model.

3 Robust planning strategies

Initially, we solve a deterministic planning model for IRPTW. From the simulation results, we observe that disruptions that require use of the expensive spot market are usually associated with a few time windows. To find a better planning solution, we penalize deliveries at the end of the problematic time windows that are identified by the recovery solutions, resolve the planning model and iterate this process until no improvement is made.

Song and Furman [5] introduce a practical modeling framework for Maritime Inventory Routing Problem (MIRP), and the model we use in this study shares many features with this proposed framework. The model is used to obtain an initial planning solution, a recovery solution and revised planning solutions after the problematic time windows are penalized.

Since a ship might have more time than needed to get from one port to another, there might be some slack in planning solutions. Therefore, as a post-processing procedure, we always re-allocate the slacks to force ships to depart as soon as possible. The procedure does not change the routing decisions.

4 An example

We show an example with one loading port, three discharging ports, four ships, sixty planning periods and twelve time windows in total to illustrate this process of improving the robustness of the schedules.

Mean: 17855
VAR: 43962511

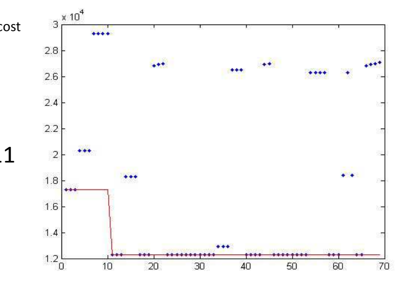

Fig. 1

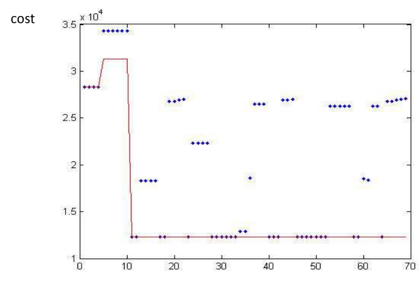

Fig. 2

Mean: 20933
VAR: 58574314

Mean: 14536
VAR: 25295874

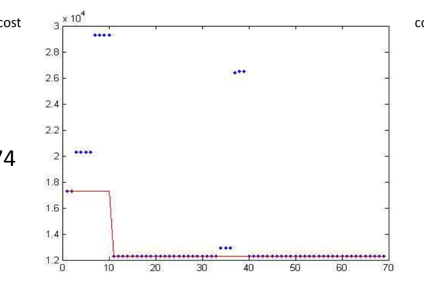

Fig. 3

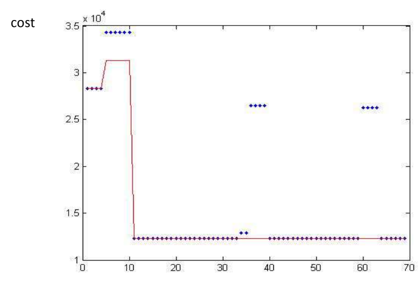

Fig. 4

Mean: 16793
VAR: 60684211

Mean: 13420
VAR: 7565465

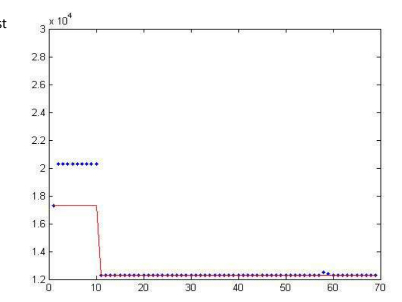

Fig. 5

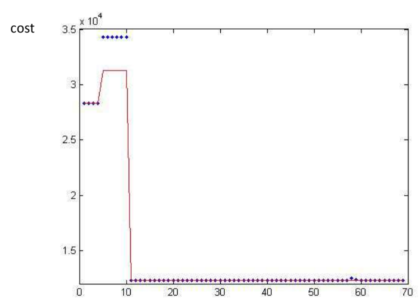

Fig. 6

Mean: 15145
VAR: 49552805

Each graph shows the simulation result of some particular planning schedule under various disruptions and different lead times. The mean and the variance of the actual cost over all the scenarios are given for each graph. The dots represent actual costs, and the lines correspond to lower bounds on total cost calculated by solving the planning model with the disruption already known. All the scenarios are one-day disruptions in figure $1, 3, 5$; and two-day disruptions in figure $2, 4, 6$. Figure 1 and 2 show the performance of the basic solution. Figure 3 and 4 show the performance of the solution to which the slack-reallocation is applied. After applying the penalty approach upon the problematic time windows that are identified in figure 3 and 4, and re-allocating the slacks in the schedule, we get a solution with limited vulnerability to the disruptions, whose performance is shown in figure 5 and 6.

We are now in the process of automating the iterative process of choosing the time windows to penalize and deciding the values of the penalties.

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The Impact of Bimodal and Lognormal Distributions in Ocean Transportation Lead Time on Logistics Costs: An Empirical & Theoretical Analysis

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1. Introduction

Maritime transportation traffic has seen tremendous growth in recent years due to the surge in globalization and international trade. Container shipments between North America, Asia, and Europe have more than tripled in the last 15 years, rising from just over 15 million twenty foot equivalent units (TEU) in 1995 to 48 million in 2010[1].

The higher trade volumes coupled with the increase in the number of different shipping locations used by firms have made the conducting and coordinating of shipping operations a very complex task. The total end-to-end transportation of a shipment from the point of origin (typically the manufacturer) to the final destination (usually a distribution center) is made up of a series of individual and often independently managed activities. The transportation lead-time is simply the cumulative effect of all of these individual movements. Companies shipping goods across the globe are concerned with the average lead-time as well as the unreliability in the shipments, variability, and shape of the distribution itself.

In recent years, a number of issues have impacted global ocean lead times; port congestion, bad weather, slow steaming, and sailing longer distances to avoid pirating to name a few. Uncertain schedule reliability was identified as a major problem for manufacturers in separate surveys carried out in 2011 by the US Federal Maritime Commission and logistics firm BDP International. As discussed in a recent news article [2], only 63.7% of containers were on time in the first 20 weeks of 2012 versus 65.9 % a year earlier, according to INTTRA, a US e-commerce platform that handles 525,000 shipments a week. Higher fuel costs, increased competition and lower revenues are affecting the service quality of container shipping companies and leading some to even shed service on certain trade lanes.

Variability and unreliability in ocean transport ultimately affect the shippers' operational performance. In theory, the uncertainty in lead-time can be modeled as a probability distribution and considered explicitly in the calculation of an optimal inventory policy for a shipper. However, our review of common practices in industry and conversations with companies and academic experts suggest that the companies do not necessarily consider transport time variability or unreliability in their inventory planning. In fact, most planning systems such as SAP and Oracle are configured to only consider deterministic lead times. Other systems, such as SAP APO, use a simplified approach to address variability: standard deviation of the lead-time is calculated and used in the classical Hadley-Whitin formula [3]. However, calculations done using this formula usually assume that the lead times are normally distributed. Eppen and Martin [4] discuss the fallacy of incorrectly assuming normality in the distribution of lead time when applying this formula.

Our analysis of over 250,000 container movements from 4 major US shippers that occurred in 2011 and 2012 has shown that ocean transport times are rarely normal and are often either lognormal or bimodal. Neither of these lead-time distributions has been well examined. Lognormal distributions occur due to having very few and very long delayed shipments, while bimodal lead times can occur for several different reasons. For example, because ocean carriers tend to follow weekly strings, where shipments from a particular origin are picked only once a week, if a container arrives late or are bumped the container will have to wait a week for the next vessel. A bimodal distribution will also arise when a shipper has multiple carriers, each with a different lead-time, serving the same trade lane.

Following the observation that lead time distribution are often either lognormal or bimodal, our aim is to characterize the impact of the variability due to such distributions on shippers under (1) common inventory planning practices and (2) ocean transportation lead time distributions observed in practice. Using transactional data from several shippers (importers and exporters) on their ocean shipments, we analyzed and characterized the lead-time distributions. Unlike data available in well-recognized sources such as Drewry Shipping Consultants Ltd and Lloyds Maritime Intelligence, which only focus on the port-to-port component of a global shipment, we analyzed the end-to-end transit times of ocean transportation in global supply chains as observed by the shippers. We then examine the performance of common inventory practices to account for variability under the two dominant lead-time distributions observed in our data. We provide insights on the conditions (in terms of the characteristics of the lane and service level) for when shippers should (and should not) consider transit time variability in setting their inventory levels. Finally, we aim to recommend an effective policy for shippers who observe bimodally/lognormally distributed transit times and a specific service level.

2. Methodology

Each container shipment in our dataset has timestamps associated with major milestones during its travel, origin/destination information, and the ocean carrier responsible for the transportation. This information is used to characterize the lead-time distribution for an origin-destination pair.

Interestingly, for a significant portion of the shipments, the null hypothesis that the lead times are unimodally distributed is rejected using Hartigan's Dip test of unimodality (Hartigan and Hartigan[5]). This test calculates a dip statistic, which is defined as the maximum difference between the empirical distribution and the unimodal distribution that minimizes the maximum difference. Non-unimodality is also consistent across shippers, although at different levels: for the retailer, non-unimodal distributions occurred in only 2-4% of origin-destination lanes but account for 12% of shipment volume. On the other hand, for the manufacturer, the corresponding number averaged for 24% of lanes accounting for 60-85% of shipment volume. In many trade lanes, we also observe that the lead times are heavy right-tailed.

We examine the impact of unreliability of lead times in the case of three different policies. *Policy I* corresponds to the case of completely ignoring variability and only using the average lead time when setting inventory levels. This is the most common policy used in practice. *Policy II* corresponds to the case where the inventory policy is calculated using the Hadley-Whitin formula (with the inherent assumption that lead times are normally distributed). Finally, *Policy III* denotes optimizing inventory decisions using the actual lead-time distribution. Inventory calculations involve simulating the demand over lead time that is observed in reality and then comparing the inventory levels calculated separately for each of the policies to obtain the costs that the firm incurs in case of stocking excess or not enough of the product. The analysis of inventory cost is based on a given critical ratio (that is the ratio of underage to overage cost). We assume a holding cost, a penalty cost for stock outs and an ordering cost or the value of the item. We consider a stationary infinite horizon inventory model, in which the optimal base stock is calculated from the critical ratio. The critical ratio discussed is considered to be equivalent to service level targeted by the firm.

We evaluate the impact of variability of lead-time on logistics cost. The analysis for calculation of safety stock and order-up-to levels is performed with a simulation model. It is assumed that lead-time and demand are independent of each other. For the purposes of the simulation, it is assumed that we observe a normally distributed demand. The resulting value of safety stock is the average of 10000 runs of Monte Carlo simulation. We analyze the performance of different policies by varying (1) critical ratio (CR) and (2) level of bimodality for bimodal lead-time distribution (captured as the difference between the two modes of lead-time distribution under a fixed mixture rate and standard deviation) which could also translate to coefficient of variation (CV) of the distribution. Similarly, CV is varied for the case of lognormal distribution.

A stochastic inventory model and simulations for the calculation of the cost and safety stock level capture the impact of variability in lead times. For non-unimodal lanes, we model the lead-time as a bimodal distribution for tractability and for consistency with our data (as most of the lanes that were not unimodal tended to have bimodal lead times). We create the bimodal lead-time distribution by mixing two normal distributions (an example for such a mixture distribution is provided in Figure 1). We represent the lanes with right tails using lognormal distribution.

3. Results

3.1 Effect on Logistics Cost under Bimodal Distribution

3.1.1 Comparing Policy II & Policy III

We observe two main regions based on the critical ratio and the level of bimodality for the comparison of Policy II and III. In the first region, the two policies are not very different for small critical ratios for values equal to or lower than 0.55 for any level of bimodality. In the second region we observe a non-trivial relationship: a significant difference between the costs of Policies II & III where Policy II is worse or more expensive. This region occurs in intermediate (between 0.60 and 0.75) and very high values of

CR (greater than 0.95) and high levels of bimodality. Maximum difference in costs between the two policies is observed to be 30%.

3.1.2 Comparing Policy I & Policy III

Broadly, we observe that ignoring variability in lead-time could have grave impacts on the inventory cost. Policy I always performs worse than Policy III. For a given level of bimodality, the cost for Policy I become significantly worse (more expensive) than Policy III with increasing critical ratio (reaching as high as 553%). This said, for lower critical ratios (i.e., less than 0.55), Policy I is *not significantly different* from the Policy III with increasing levels of bimodality. The maximum difference reaches to only about 7%. But with higher critical ratios, the difference *increases significantly* for increasing levels of bimodality. Results show that the difference in costs for a critical ratio of 0.5 ranges from 1%-4% whereas for a critical ratio of 0.95 the difference ranges from 51%-553%.

3.2 Effect on Logistics Cost under Lognormal Distribution

As the critical ratio increases, Policy I becomes significantly worse than the optimal policy. The critical ratio and the coefficient of variation of lead-time affect the performance of the policies. If the critical ratio is below 0.7, the shipper is better off ignoring lead-time variability, regardless of how much variability there is. Above that sharp threshold in critical ratio, companies facing some variability should use Policy II. The amount of variability needed to trigger using Policy II asymptotically declines from a coefficient of variation of 0.2 at a critical ratio of 0.7 to a coefficient of variation of 0.05 as critical ratio approaches 1.

4. Conclusion

In this paper we investigated the effect of completely ignoring the variability or incorrectly assuming the distribution of lead-time to be normal when in reality it is more often either a lognormal or a bimodal distribution (Policy I, II&III). We demonstrated that the different policies considered result in different safety stock levels and logistics cost. We simulated a number of instances of bimodality and lognormality to quantify these differences using Monte Carlo sampling. Additionally, in order to examine the effect on logistics cost we varied the service level targets (CR's).

There are three major takeaways from this analysis. First, logistics cost is a function of the distribution of lead-time and the service level targeted. Secondly, the firms that observe lower variability in lead-time and low coefficient of variation (CV) should opt for Policy I as compared to II. However, Policy II should be used for high variability and high CR over Policy I. Thirdly, Policy II & III differ significantly for high CV's (or levels of bimodality) and intermediate and high CR's. We are currently working on designing recommendation of a specific policy to a firm given their target service levels and the lead-time distribution observed. We also want to calculate the bounds of the theoretical model to compare the three policies. Finally, we intend to develop a method for incorporating the effect of variability in lead-time into traditional ERP systems.

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List of figures

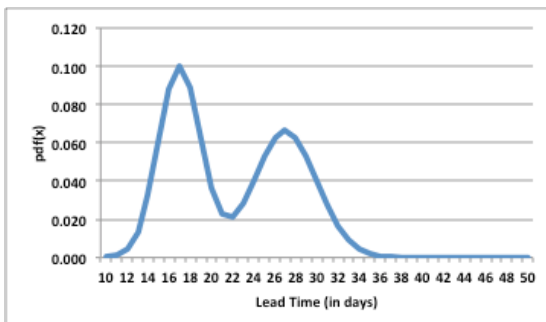

Fig .1 Example of a bimodal distribution created from a mixture of two normal distributions

Inventory Management in Global Supply Chains Using Simulation and Transaction Data

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1 Introduction

Inventory Theoretic models are pervasive in supply chain management, but they often provide results significantly different from reality. Examples include situations subject to non-normal distributions [1], order crossing [2], and counterintuitive associations between cycle service levels and fill rates [3]. Simulation provides a convenient way to explore these problems both because it requires fewer assumptions and because it is capable of modeling virtually any distribution seen in practice [4]. The availability of transaction level data for many segments of the door-to-door transportation move has made simulation of global supply chains more feasible [5]. Further simulation can be used to examine how interruptions affect supply chains in ways that deterministic models cannot duplicate. We use simulation based on transaction level data from two independent sources to evaluate the relative importance of various drivers of port delays, including origin, carrier, port terminal availability, and inland transportation mode. This exercise allows us to rank order and characterize sources of uncertainty in global supply chains and the associated inventories to offset these operational realities. Then we estimate cost differentials for scenarios involving the major sources of port delay and typical global supply chain conditions.

To fully explore these and other questions we model a complex global supply chain extending from Asia to U.S. destinations. To better reflect what many companies are facing, the model has the capability of covering both transload shipments and direct shipments, single weekly shipments or multiple weekly shipments moving through a multi-stage supply chain utilizing postponment strategies to reduce local DC stocks by pooling orders nationally across all DCs and allocating local shipments after imports clear the import port of entry.

2 Literature Review

2.1 Inventory Theoretic and Multi-Stage/Multi-Echelon Supply Chains

Previous efforts to examine important questions about inventory theoretic models are covered here. The topics include, but are not limited to: order splitting, order crossing, and various distributional assumptions of lead-time demand such as gamma, normal and bi-modal, and modeling risk pooling strategies. How these and other issues affect multi-stage and multi-echelon supply chains is also reviewed to see what assumptions are made and how those assumptions limit our understanding of these complex systems.

2.2 Supply Chain Risk and Resilience

Supply chain risk has become an increasingly important area for research as numerous incidents e.g. Thailand floods, Japanese tsunami, have made it clear that global chains inevitably are associated with increased chance of disruption. Although we make no claim to being able to accommodate rare events ("Black Swans"), we propose using simulation to augment our understanding of the limits of optimization approaches and therefore the reasonable assumptions that can be made using optimization when modeling global supply chains.

3 Hypotheses

Distributional and other assumptions made to simplify mathematical modeling approaches for modeling global supply chains can mis-specify the cost of holding system wide inventory and the impact of customer service. Some examples of the difficulties associated with the typical normality assumption can be found in Chopra et al. [3] and Eppen and Martin [65. Furthermore, work by Saldanha et al. [5] and Caplice and Kalkanci [4] confirms that normality is not a tenable assumption for many segments of global supply chains. Thus it becomes important to investigate what are the appropriate distributions for link times and nodal delays in global supply chains.

Hypothesis 1 Delays in major ports and on major global lanes are not normally distributed.

Hypothesis 2 The effects of empirically derived delay distributions will have a material influence on overall performance as shown in the simulation models.

Hypothesis 3 Empirically derived distributions will substantially change the "savings calculus" and projected costs vs. the results from normal distributions.

Hypothesis 4 Empirically derived distributions will substantially affect the costs and benefits that can be attributed to such programs as postponement and risk pooling.

4 Experimental Design

We create a simulation model using a base level inventory system to make weekly replenishment orders from Asian firms. Data and the network are modeled after Jula and Leachman [7], including the potential for transloading. Two weeks before the orders leave Asia, they are allocated to move either to a transload port or to a distribution center (DC). The allocation is made using the equal fractile method that maximizes the minimum safety stock (measured as the ratio of actual to desired safety stock in the supply chain) for each receiving port (or DC with direct movements) and assumes that no inventory can be transferred between ports or DCs. When shipments arrive at a port of entry, they are either distributed among DCs (using equal fractiles in the transload case) or sent directly on to the DC (direct case). The simulation keeps track of DC inventory, DC safety stock, pipleline stock, and back orders. From these numbers and transportation costs, total cost for each DC and for the system are calculated, including widely accepted procedures such as transloading and postponement.

Random samplings from relevant distributions are done using @Risk working with MS Excel and MS Access. Distributions can be modeled as normal, gamma, truncated normal, or truncated gamma. The many options provide for a rich exploration of how supply chains respond when distributional and other modeling assumptions are relaxed to match many "real-world" conditions.

5 Results

Although the simulated safety stock closely matches that predicted by an inventory theoretic model, the performance of the inventory theoretic model overestimates the amount of safety stock needed to attain a set service level as assumptions are relaxed to better match actual conditions. These conditions include using gamma distributions instead of a normal distribution to more closely approximate real conditions, removing the ability to split orders, and truncating distributions to reflect minimum actual transit time.

6 Conclusions and Discussion

When feasible, the ability to split orders where significant variance in lead-time exists can yield dramatic reductions in safety stock. While multiple containers from one origin to one destination are frequently assigned to different ships, it is not clear that variations in lead-time for containers traveling in esentially the same period would be independently distributed becasue conditions affecting one ship might affect all ships. This is an area where more research is needed.

Because the actual shape of distributions is critical to determining how much safety stock is neede to acheive a set fill rate, it is important that non-standard distributions can be accurately modelled. While gamma provide better accuracy than normal with right skewed distributions,simulated, tailored distributions may be necessary for estimating safety stock for many realistic and even bimodal distributions of transit times and overall order cycle times.

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Collaborative Logistics in Shipping

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1 Introduction

Denmark is the 7th largest shipping nation in the world. Danish owners and operators transport approximately 10% of the world's seaborne trade. In 2008 Danish shipping's foreign currency earnings was 25 billion EUR. Thus, shipping maintains its position as the single most important contributor to the Danish balance of payments. Developing effective methods for the planning of intermodal transportation and tools to facilitate carrier collaboration will lead to a more sustainable transportation sector, save energy, reduce cost, improve service levels and enhance capacities but optimizing intermodal transportation is difficult due to the complex interplay of the different modes.

Logistics and transportation are activities that provide many opportunities for collaboration between companies and such collaboration have been practiced to some extent in air transport (code sharing), sea transport (pool collaborations) and public transport (ticket sharing). Collaboration logistics has however only been superficially researched in the complex setting of intermodal transportation and based on optimization methods.

The present paper will deal with optimization of Collaborative Logistics (CL) on the sea side of a supply chain.

A code sharing agreement (also called an alliance) makes it possible for each participating company to sell capacity on routes operated by another carrier under its own name and code. We can classify code sharing agreements into two types. The first is parallel operation in which two carriers competing on the same route sign a code sharing agreement thereby increasing the frequency as viewed by the customers. The second type, complementary operation, involves facilitating interconnections, that is, eg. a trucking company feeds goods to a freight rail company. [2] uses simulation to conclude that code sharing agreements increase welfare.

Although code sharing is well-studied for airline companies (see eg. [9, 7]), the nature of liner shipping is significantly different. In liner shipping vessels are making round trips, while airline companies mainly fly in a star structure from the hubs. In addition, for freight the exact routing of the delivery from source to destination is in general not important as long as certain deadlines are met, whereas passengers indeed care about the route that gets them from source to destination. The same arguments are valid concerning tankers.

An initial problem is to define what services such a collaborative service network establishes. This essentially means establishing from where to where and with what frequency the alliance can service customers.

Seen from an optimization point-of-view the area of cost allocation and profit sharing is highly interesting and can bring substantial benefits wrt. decision support. The literature is relatively theoretical. Most approaches are based on game theory (see eg. [8, 4]) and combinatorial optimization games (see e.g. [3]). One of the few more general perspectives is presented in [5]. The only slightly general setup of CL to our knowledge is given in [6]. An empirical study is presented in [1]. Although the foundation will be extensions of existing routing problems especially the cost allocation and profit sharing is creating new challenges. The model and the proposed exact approach should be flexible enough to work with all reasonable cost and profit allocation schemes as objective functions.

2 The solution approach

The model is composed by the following five modules:

a. A simulator
b. An order generator
c. A tanker (or ship) planner
d. A profit sharing module
e. A visualization module

Based on data from a shipping company operating a large fleet of product tankers the **order generator** generates new orders – one at a time – and creates a dynamic environment.

The simulator receives the order and sends the order to the tanker planner who determines if the order fits into the previous plans and determines if the order should be accepted. A "sea network database" is connected to the simulator making it possible to create a matrix with distances between all harbors in the model. Special passages such as passing the Panama Canal or The North East Passage are taking into account.

In **the tanker planner** module a pick-up and delivery problem with additional constraints is solved. The model and its implementation are partly based on a column generation approach in line with the current state-of-the-art for routing problems and partly based on metaheuristics. The result – accept or do not accept and which vessel should transport the order – is sent to the simulator.

After a certain time period – say e.g. six months – the simulator has collected performance information from the different vessels in use. This information is sent to the profit sharing module.

In **the profit sharing** module it is determined how to do the cost allocation and profit sharing. We are using game theory to design fair models for the compensation fee paid to each operator. Even without changing the network structure or code-sharing, there may be significant benefits by collaboration. Our approach continues along the more pragmatic proposals of [5]. The result is sent to the simulator.

Finally the whole decision process is visualized in **the visualization module** where the results are shown.

3 Computational results

Instances from two different product tanker operators will be presented.

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Modeling and Solving Inter-Terminal Transportation

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1 Extended Abstract

Around the world, ever larger ports are constructed to keep up with the growth of containerized shipping. Ports routinely contain multiple terminals serving container ships, railways, barges and other forms of hinterland transportation. Containers are often transferred between terminals when they are transshipped between different modes of transportation. The movement of containers between terminals, which is called *inter-terminal transportation* (ITT), represents not only an operational problem for port authorities and terminal operators to deal with, but also a strategic one to be considered during the planning of new terminals and container ports. That is, ITT refers to the movement of containers between terminals (sea, rail or otherwise) within a port. It may represent a significant source of delay for containers being transshipped with considerable economic impact as well as an influence on a ports reputation.

The correct choice of the layout of terminals and the transportation connections between them, as well as vehicle type and the number of vehicles, represent expensive and critical decisions that ports must make. The goal of an efficient ITT system is to minimize the delay of containers moving between terminals, so as to reduce and, ideally, eliminate the delayed departure of containers. We use an abstract view of ITT operations using a time-space graph with congestion (with fan arcs similar to the general graph approach

in [3]) to model vehicles as flows through the network with cargo demands given as a multi-commodity flow. We focus on minimizing the overall delay experienced by cargo, an important consideration for port planners, as the costs of delaying outgoing shipments are very high.

Previous work in the area of strategic analysis of ITT primarily deals with simulating inter-terminal operations at the Maasvlakte area of the port of Rotterdam and analyzing the resulting delay of the pickup and delivery of containers ([5, 2, 4]). In contrast to this work, we optimize the flows of cargo through the network in order to provide port planners with a better estimation of the cost of using particular vehicles, roadway designs, new infrastructure or traffic planning.

At first glance, ITT might seem avoidable, either through scheduling container vessels that will transship cargo to arrive at the same terminal, or by placing key logistics components of a port all in the same location. However, in nearly every mid to large sized port some amount of ITT is required, simply due to the fact that avoiding ITT would involve building rail, barge, and container ship connections all in one place, and there simply is not enough space.

There are therefore two important problems within the topic of ITT. The first is the purely operational problem of dispatching and routing vehicles to move containers between terminals on a day to day basis in an already constructed port. The second problem is a strategic planning problem for new ports and the expansion of existing ports, which involves several key questions:

- Is the planned infrastructure sufficient to handle ITT forecasts?
- How many vehicles and what types of vehicles are necessary to handle ITT cargo?
- What kind of delays will be experienced on average given a particular infrastructure and vehicle configuration?

An important endeavor in this respect is to build an optimization model that can assist in answering these questions, as well as assist port and terminal authorities in examining the impact of new infrastructure, such as tunnels or bridges, on the overall delay experienced by ITT cargo. Thus, while we primarily address the strategic planning issues, our model is also capable of dispatching and routing vehicles in the operational problem at a high level.

One may consider a range of types of vehicles for ITT that each comes with pros and cons that must be evaluated by decision makers.

- Automated Guided Vehicles (AGV)

  AGVs are driverless vehicles that can carry up to one forty-foot container or two twenty-foot containers, and have no lifting capabilities of their own. This means that

AGVs require cranes for (un)loading operations. In general, AGVs are only allowed in areas where there are no humans to prevent accidents.

- Automated Lift Vehicles (ALV)

  ALVs, like AGVs, are also driverless vehicles that can carry two twenty-foot containers or one forty-foot container. As their name implies, ALVs have lifting capabilities and do not require external assistance to transport containers. This makes ALVs significantly more versatile than AGVs. However, they generally travel slower.

- Multi-Trailer System (MTS)

  MTSs consist of several container carrying trailers, that can generally transport up to five 40-foot containers. MTSs require cranes to load them as in the case of AGVs. MTSs are not automated and require a human to drive a tractor unit that pulls the trailer. While this allows more flexibility in the places an MTS can travel, the coupling time of the tractor unit to the trailer can result in a slower turn-around time for the vehicles than AGVs or ALVs. This process is described in detail in [2].

- Barges

  Barges can be used to transport large quantities of containers between terminals all at once and are driven by humans. Barges are loaded slowly and travel slowly, but have an advantage over road vehicles in that waterways tend to offer shorter connecting distances between terminals than roads, as well as being less congested.

In order to solve the steep logistical challenges of ITT as container volumes around the world substantially increase, new infrastructure ideas must also be considered. The construction of ropeways, monorails, dedicated lanes, tunnels and bridges to connect ports to shunting yards/hinterland logistics centers or to avoid bottlenecks could provide answers for effective ITT. For example, the cost of tunnels and ropeways were considered for connecting the port of Hamburg to hinterland transportation depots in [1].

To this end, we introduce an optimization model based on a time-space graph to determine optimal flows of vehicles and cargo in ITT scenarios in order to assist port authorities in their decision making process. We present a novel integer programming model for analyzing ITT in which we solve a vehicle flow combined with a multi-commodity container flow problem on a carefully constructed time-space graph to optimality [6]. Our model incorporates a number of important real-world aspects of ITT, such as vehicle congestion, penalized late container delivery, and multiple ITT transportation modes. We show that our model can scale to real-world sizes and provide ports with important information for their long term decision making. Moreover, we provide ideas on incorporating issues of greenhouse gas emissions into the model. Analysis is performed regarding the port of Hamburg, Germany, and the port of Rotterdam, The Netherlands. Computational results show that our model not only provides useful information about ITT, but also that it can be computed by CPLEX in a reasonable amount of time [6].

That is, our model scales to the sizes of real world ports, time periods, and container throughput, as shown using examples from the Maasvlakte area of the port of Rotterdam and the port of Hamburg, and provides important analysis on not only the feasibility, but also the delay of containers reaching their destinations. Our model of ITT is the first to incorporate optimization of vehicle routes and cargo flows in order to provide ports and terminals with the best performance a particular configuration of vehicles and infrastructure is capable of delivering.

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Real-Time Container Storage Location Assignment at a Seaport Container Transshipment Terminal: Dispersion Levels and Math Programming Strategies

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1 Introduction

We consider the problem of assigning storage locations to containers that arrive at a seaport container transshipment terminal. While many articles in the literature consider this problem, this investigation is unique in that it shows how various systems for *real-time* container storage location assignment affect the *overall* performance (e.g. average vessel turnaround time, average quay crane work rate) of a container terminal. This research expands upon the work that was presented at Odysseus 2009 and Odysseus 2012. In 2009, we defined the problem and presented the results of an initial experiment that illustrated the main trade-offs involved in container storage decisions and validated our main methodological approach:

discrete event simulation. In 2012, we presented preliminary results from three additional experiments. In this research, we present the final results from four experiments.

2 Problem Description

We investigate how various real-time container storage location assignment algorithms affect the long-run *GCR* (gross crane rate, quay crane rate) of a multiple-berth container terminal where all cargo is transshipped from vessel to vessel. GCR is defined as the average number of lifts achieved at a terminal per quay crane (QC) working hour and is probably the most important measure of operational performance at a container terminal. *QCs* are the machines that load and unload vessels. They transfer cargo between vessels and *YTs* (yard trucks). YTs transport cargo between the shore and a *storage yard* (yard). *YCs* (yard cranes) transfer containers between YTs and stacks in the yard. Every container that passes through a vessel-to-vessel transshipment terminal is attached to one piece of equipment and/or location at all times according to the following sequence: vessel-QC-YT-YC-yard-YC-YT-QC-vessel. The container is *unloaded* and *stored* in the first half of the sequence. A container typically spends 0-7 days in the yard in the middle of this sequence. It is then *retrieved* and *loaded*. At Odysseus 2009 and 2012, we presented four ways for the storage system to maximize GCR:

A) minimize container travel distance from quay to yard during unloading/storage
B) minimize container travel distance from yard to quay during retrieval/loading
C) minimize storage yard congestion near cargo storage locations during unloading/storage
D) minimize storage yard congestion near cargo storage locations during retrieval/loading.

The current study has two immediate goals: (1) to evaluate the relative importance of the four *objectives* above in various terminal environments and (2) to identify specific real-time container storage assignment systems that maximize GCR at one or more terminals.

3 Literature Review

Our literature review includes all papers on container terminals that discuss container storage location assignment, simulation modeling, or the literature. More than 70 such papers were found by the author. Excellent surveys of recent research on container terminal operations include [1], [2], and [3]. A good description of container terminal operations is given in [4]. A concise summary of the operational decisions made in container terminals is given in [5].

Fewer than 30 articles address the problem of export container storage location assignment. Among these, only [6], [7], and [8] present models in which the arrival, stay, and departure of each container are explicitly modeled, and only [6], [7], and [8] present models that obtain numerical results on *real-time* container storage location assignment. Moreover, no article presents a model that shows how alternate real-time container storage location assignment systems affect the *overall* performance (e.g. GCR) of a container terminal. This research, however, has produced such a model—a discrete event simulation model that has been used to study several container terminal problems ([9], [10], and [11]).

4 Container Storage Location Assignment System

The real-time container storage location assignment system developed in this research is the result of several ideas that have evolved over many years. The core of this system is a seven-step algorithm that includes rule-based and math programming features to decide the storage location for each container. This system is embedded within a simulation model.

5 Experiment One: Dispersion Levels

In the first experiment, we show how the level of dispersion of the containers loaded onto a particular vessel (i.e. liner service) affects the overall productivity of a container terminal. As its name suggests, the *dispersion level* specifies the level of dispersion in the yard for containers that are loaded onto the same vessel. A low (high) dispersion level means that containers loaded onto the same vessel are stored in concentrated (dispersed) fashion near to that vessel's home berth (throughout the yard). Results show that GCR is usually a concave function of the dispersion level. In most cases, GCR is maximized by an intermediate dispersion level in which containers are stored somewhat close to, but not necessarily very close to, the home berth of the vessel onto which they will be loaded. This indicates there is a trade-off between objectives B and D. In many cases, the results show that containers should be dispersed up to 2 km away from the vessels they are loaded onto, but no further.

6 Experiment Two: Math Programming Approach

In the second experiment, we consider if a math programming approach can improve the performance of an otherwise rule-based container storage system. The results show that math programming-based (priority-based) storage systems, which assign to each vessel certain high-priority storage areas where cargo loaded onto the vessel is to be stored, perform no better than simple, rule-based systems when both systems are embedded within a fully integrated simulation model and tested under a simulated operating environment. Another result from Experiments 1-2 is that container storage objectives A-D can be ranked C, D, A, B from most to least important for most of the terminals we consider. Thus, minimizing congestion is usually more important than minimizing container travel distance.

7 Experiment Three: Impact of Vessel Berthing Policy

In this experiment, we examine how the storage systems considered in Experiments 1-2 perform under two different vessel berthing policies—HomeBerth and FCFS. Experiments 1-2 are conducted assuming a HomeBerth berthing policy. In the (HomeBerth/FCFS) policy, vessels (always/do not always) dock at their home berths but they (do not always/always) dock in order of their arrival. Results from this experiment indicate that the vessel berthing policy only impacts the performance of container storage systems that to some degree pursue objective B. For such storage systems, the HomeBerth berthing policy always achieves a higher GCR than the FCFS policy. For all other container storage systems, the HomeBerth and FCFS policies achieve roughly the same GCR.

8 Experiment Four: Impact of Yard Truck Traveling Speed

In this experiment, we investigate the impact of YT traveling speed on the performance of the container storage systems considered in Experiments 1-2. In Experiments 1-2, all YTs travel 40 (25) km/hr on average when empty (laden) and spend an average of 10 sec making a turn. In this section, we reduce the YT speed by 50% so that YTs travel 20 (12.5) km/hr on average when empty (laden) and spend an average of 20 sec making a turn. Regarding Experiment 1, our results show that the optimal dispersion level is much lower with YTs traveling at half speed than with YTs traveling at full speed. Results also show that a slower YT traveling speed tends to even out the performance of different storage systems, making the storage system itself less important.

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New Lower Bound and Exact Method for the Continuous Berth Allocation Problem*

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1 Introduction

The *berth allocation problem (BAP)* is to optimize the berthing locations and timings of vessels to be handled at a terminal. All vessels need to be berthed within the boundaries of the quay without occupying the same space at any one time. The quay can have different layouts. In a discrete layout, it is partitioned into a number of sections, and only one vessel can be berthed in each section at any one time. In a continuous layout, there is no partitioning of the quay, and vessels can be berthed at arbitrary locations.

In this paper, we develop a new exact method for the BAP with a continuous layout (or known as the CBAP in short), which aims to minimize the total weighted port stay time of vessels whose lengths, arrival times, and handling times are given. It is equivalent to the problem studied by Guan and Cheung [2] and Lee et al. [4], although other variants of the problem have also been studied in the literature [3, 5, 6]. A recent survey on the CBAP can be seen here [1]. Many heuristics and meta-heuristics have been presented in the literature for the CBAP and its range of variants [2, 4, 6]. However, studies on exact methods are scarce, and in the main they have used commercial solvers directly [2, 4].

The main contributions of this paper can be summarized as follows: (1) We present a new lower bound for the CBAP. It is based on a new relaxation of the CBAP by constraint aggregations; (2) We present a new branch-and-bound algorithm for the CBAP. It is based on the new lower bound, together with a new heuristic algorithm for a fast upper bound computation, and several new pruning rules for the search space reduction; (3) Computational results on a large number of test instance sets are presented. In significantly less running time, our new method can solve to optimality more instances than existing exact methods in significantly less running time. It is also able to generate better feasible solutions to large sized instances than existing heuristic and meta-heuristic methods; (4) Our new method can be extended for the development of exact algorithms for other variants of the CBAP, providing a foundation for further enhancement.

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2 Formulation, Lower Bound and Exact Method

Consider a set of n vessels, denoted by $V = \{1, 2, ..., n\}$, and a quay of length L. For each vessel $v \in V$, it has a length l_v, arrival time a_v, handling time t_v, and weight w_v. Without loss of generality, vessels' lengths and handling times are assumed to be integers. We use a rectangle with width l_v and height t_v to represent each vessel $v \in V$. The position of the rectangle, indicated by (x_v, y_v), needs to be determined, where x_v denotes the starting (or left-hand) berthing location of vessel v with $0 \leq x_v \leq L - l_v$, and y_v denotes the starting (or bottom-end) berthing time y_v of vessel v with $y_v \geq a_v$. Thus, the cost associated with the position (x_v, y_v) equals the weighted port stay time $w_v(y_v + t_v - a_v)$ of vessel v. Let $T_{\max} := \max\{a_v : v \in V\} + \sum_{v \in V} t_v$. Thus, the CBAP is equivalent to minimizing the total cost of packing the n rectangles into a time-space diagram of width L and height $T_{\max}$ without overlaps.

Two integer programming (IP) models are known for the CBAP [2]. One, denoted by $\mathbf{IP}_1$, is based on the relative positions of vessel rectangles in the time-space diagram, and its linear programming relaxation is known to be weak. The other, denoted by $\mathbf{IP}_2$, is based on the absolute positions of vessel rectangles. It uses a binary variable g_{vxy} to indicate whether or not the left-bottom corner of rectangle v is located at (x, y), for each $v \in V$, $0 \leq x \leq L - l_v$ and $a_v \leq y \leq T - t_v$. Let A be the set of left-bottom corners of the $L \times T_{\max}$ unit-sized squares of the time-space diagram defined by vertical lines $x = 0$, $x = 1$, ..., $x = L$, and horizontal lines $y = 0$, $y = 1$, ..., $y = T_{\max}$. Let $A_{vxy} \subseteq A$ be the subset of bottom-left corners of those unit-sized squares covered by vessel rectangle v when the rectangle is located at (x, y). Let $c_{vxy} := w_v(y + t_v - a_v)$. Thus, $\mathbf{IP}_2$ is to minimize $\sum_{\forall v,x,y} g_{vxy} c_{vxy}$ by assigning 1 to exactly one g_{vxy} for each $v \in V$, restricted to non-overlapping constraints, i.e., each unit-sized square in A can be covered by at most one vessel rectangle with $g_{vxy} = 1$. Although the linear programming relaxation of $\mathbf{IP}_2$ is tighter, its computational complexity is much higher, since it contains a large number of variables and constraints, which can grow exponentially with respect to the instance size.

We propose a new relaxation of the CBAP as follows, by aggregating the non-overlapping constraints in $\mathbf{IP}_2$ and reducing the number of variables, so that both the size and tightness of the relaxation can be controlled by parameters. Consider any subset $\hat{X} = \{\hat{x}_1, \hat{x}_2, ..., \hat{x}_{|\hat{X}|}\}$ of $\{0, 1, 2, ..., L\}$ and subset $\hat{Y} = \{\hat{y}_1, \hat{y}_2, ..., \hat{y}_{|\hat{Y}|}\}$ of $\{0, 1, 2, ..., T_{\max}\}$, which are the given parameters with $\hat{x}_1 = 0 < \hat{x}_2 < ... < \hat{x}_{|\hat{X}|} = L$, and $\hat{y}_1 = 0 < \hat{y}_2 < ... < \hat{y}_{|\hat{Y}|} = T_{\max}$. Split the time-space diagram into $(|\hat{X}|-1)(|\hat{Y}|-1)$ blocks by lines $x = \hat{x}_i$ for $1 \leq i \leq |\hat{X}|$ and $y = \hat{y}_j$ for $1 \leq j \leq |\hat{Y}|$. Let (i, j) indicate the index of the block with its left-bottom corner at $(\hat{x}_i, \hat{y}_j)$ and its right-up corner at $(\hat{x}_{i+1}, \hat{y}_{j+1})$ for $1 \leq i \leq |\hat{X}|-1$ and $1 \leq j \leq |\hat{Y}|-1$. Let $B(i, j) = \{(x, y) | \hat{x}_i \leq x \leq \hat{x}_{i+1} - 1, \hat{y}_j \leq y \leq \hat{y}_{j+1} - 1\}$ indicate the left-bottom corners of those unit-sized squares covered by block (i, j). Let $\hat{X}_v = \{x : 0 \leq x \leq L - l_v\} \cap (\bigcup_{i=1}^{|\hat{X}|} \{\hat{x}_i, \hat{x}_i - l_v\})$ and $\hat{Y}_v = \{y : a_v \leq y \leq T_{\max} - t_v\} \cap [\{a_v\} \cup (\bigcup_{j=1}^{|\hat{Y}|} \{\hat{y}_j, \hat{y}_j - t_v\})]$. Consider an integer programming model, denoted by $\mathbf{IP}_2(\hat{X}, \hat{Y})$, that aims to minimize

$\sum_{v \in V} \sum_{x \in \hat{X}_v} \sum_{y \in \hat{Y}_v} c_{vxy} g_{vxy}$ subject to the following constraints:

$$\sum_{x \in \hat{X}_v} \sum_{y \in \hat{Y}_v} g_{vxy} = 1, \ \forall v$$

$$\sum_{v \in V} \sum_{x \in \hat{X}_v} \sum_{y \in \hat{Y}_v} |B(i,j) \cap A_{vxy}| g_{vxy} \leq |B(i,j)|, \ \forall 1 \leq i \leq |\hat{X}| - 1, 1 \leq j \leq |\hat{Y}| - 1$$

$$g_{vxy} \in \{0,1\}, \ \forall v \in V, x \in \hat{X}_v, y \in \hat{Y}_v$$

Let $\mathbf{LP}_2(\hat{X}, \hat{Y})$ indicate its linear programming relaxation, which contains only $O(|\hat{X}||\hat{Y}| + |V|)$ constraints and $O(|V||\hat{X}|(|\hat{Y}| + |V|))$ variables. We can prove that $\mathbf{LP}_2(\hat{X}, \hat{Y}) = \mathbf{LP}_2$ when $\hat{X} = \{0, 1, .., L\}$ and $\hat{Y} = \{0, 1, ..., T_{\max}\}$, and that $\mathbf{LP}_2(\hat{X}, \hat{Y}) \leq \mathbf{IP}_2(\hat{X}, \hat{Y}) \leq \mathbf{IP}_2$, which implies that $\mathbf{LP}_2(\hat{X}, \hat{Y})$ is a valid lower bound for the CBAP. This lower bound can be further extended for other variants of the CBAP, including those studied by Park and Kim [5] and Wang and Lim [6].

Based on the new lower bounds from $\mathbf{LP}_2(\hat{X}, \hat{Y})$, we have developed a new branch-and-bound algorithm for the CBAP, which performs branching operations by assigning absolute positions to vessel rectangles one by one as it goes down the search tree. Consider a decision node of depth d, which represents a partial solution that has assigned absolute positions to a certain subset $V' \subseteq V$ of d vessel rectangles. It is explored to generate new nodes by selecting each vessel rectangle $v \in V \setminus V'$ and assigning v into all the admissible positions. Admissible positions may be pruned through rules based on properties that break symmetry and imply non-optimality. Moreover, to find good feasible solutions from partial solutions, we have developed a new heuristic that has a fast running speed and guarantees a local optimality so that its solution cannot be improved by simply changing the position of one vessel rectangle. At each decision node, a lower bound on the minimum packing cost is computed based on $\mathbf{LP}_2(\hat{X}, \hat{Y})$, using the fixed positions for the vessel rectangles that were assigned in the partial solution. For each iteration of the branch-and-bound algorithm, we adopt a best-first search strategy that always selects the node having the smallest value of the lower bound, from which to generate new nodes.

3 Experimental Results

Our new method has been coded in C++, compiled by g++ 4.6.1, and run on a desktop PC equipped with an Intel Core 2 Duo CPU 2.33GHz. ILOG CPLEX 12.2 was used as the linear programming solver for computing the new lower bound described in Section 2.

To evaluate the performance of our method compared with existing exact methods, we used four instance sets, with each having 30 instances and with at most 15 vessels. Among these four sets, two, *ra05* and *ra10*, were from Lee et al. [4], and the other two, *ra12* and *rna15*, were newly generated by following the approaches of Lee et al. [4] and Guan and Cheung [2]. The overall results are shown in Table 1, where T, G, $G_{\max}$, S indicate the running time, the average gap (from the best lower bound), the maximum gap, and the

Table 1: Comparison between the new method (BB) and other existing exact methods

		New BB		CPLEX on $\mathbf{IP_1}$				CPLEX on $\mathbf{IP_2}$			
Set	n	T	S	T	G	$G_{\max}$	S	T	G	$G_{\max}$	S
ra05	5	0.00	30	0.00	0.00	0.00	30	–	–	–	0
ra10	10	65.50	30	459.93	0.00	0.00	30	–	–	–	0
ra12	12	1581.00	30	3653.38	3.93	25.93	24	–	–	–	0
rna15	15	2907.00	30	3908.00	20.57	37.74	6	4249.00	0.00	0.00	30

number of instances solved to optimality, and '–' indicates that there is no feasible solution returned. According to the results, our new method can solve all instances to optimality, which is much more than existing methods can do, and it can do so in significantly less time and using considerable less memory.

To evaluate the performance of our method compared with existing heuristic and meta-heuristic methods, we used another five instance sets from Lee et al. [4] with vessel numbers in the range $[40, 200]$. According to the results, our new method can produce solutions of significantly higher quality than existing methods. Solutions produced by the new method guarantee an average gap of 14.6% from the best lower bound, whereas solutions produced by existing methods have an average gap of 43.9% or more.

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Ad-hoc port assignment due to a port outage

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1 Introduction

Natural disasters are a pervasive threat to the health and reliability of networks. This is particularly true at seaports, which are vulnerable to weather events and acts of terror. If an outage occurs at a seaport, goods transferring between water and ground transport at the seaport will be impeded unnecessarily. Such an outage highlights the vulnerability of the transportation network [1], [2]. In this research we propose a methodology to utilize alternative ports in an *ad-hoc* manner to reduce network vulnerabilities. In doing so, we address the following question: If irregular operations force the closure of a port, how should the freight distribution network be altered to meet the objective of minimizing transportation and related costs while protecting freight movement and deliveries to unaffected areas? In addressing this question, we propose a mathematical model, termed the *Ad-hoc Hub Location Problem with Single Assignment* (hereafter AHLP-SA). The main idea of AHLP-SA is to re-organize the spatial structure of disrupted hub networks with unaffected seaport hubs serving as *ad-hoc* replacement ports and the establishment of alternative routes connecting supply and demand nodes with the ad-hoc ports. The definition of Single Assignment (SA) restricts the number of alternative routes between a node and the ad-hoc port to one.

2 Background

As gateways connecting Foreign Trade Areas (hereafter FTAs) and inland demand/supply nodes, seaport hubs are recognized as critical facilities in transportation systems. The entire logistics system from FTAs to land-based surface transport systems can be vulnerable to any seaport hub malfunction that may result from human errors (i.e. fire), natural disasters (i.e. hurricanes), or intended threats (i.e. terrorist attacks). As extensively discussed by [3], a network design to improve resilience of networks and protect critical network components such as hubs, terminals, and seaports is an important goal in transportation security because of its consequence in economies and human activities. Models employed in network design focus on mitigating the negative effects of hub disruption with alternative plans [4]. Hub-and-spoke network design has evolved in various forms since its introduction by [5]; however, it is very recent that the protection of hubs has been incorporated into hub-and-spoke network design models. Recent examples span networked systems. For example, Kim and O'Kelly [4] propose a reliable hub network design for telecommunications network design with the constraints of mandatory dispersion of hubs [4]. Nair et al. [6] measure resilience of a system of seaports using simulation methodologies and a case study of Poland, concluding that directing resources to undamaged portions of the network is critical to maintain its system functionality at a desired level. More recently, [7] develop a survivable hub network design, in which a hub network is organized to enhance resilience to all possible hub disruption scenarios. The models pinpoint the location of *p*-regular and *q*-back up hubs and the necessary back-up routes to replace the disrupted hubs. However, it should be noted that the models take a *preventive* rather than post-disaster *recovery* approach, which deals with the ways to minimize the impact after disruptions.

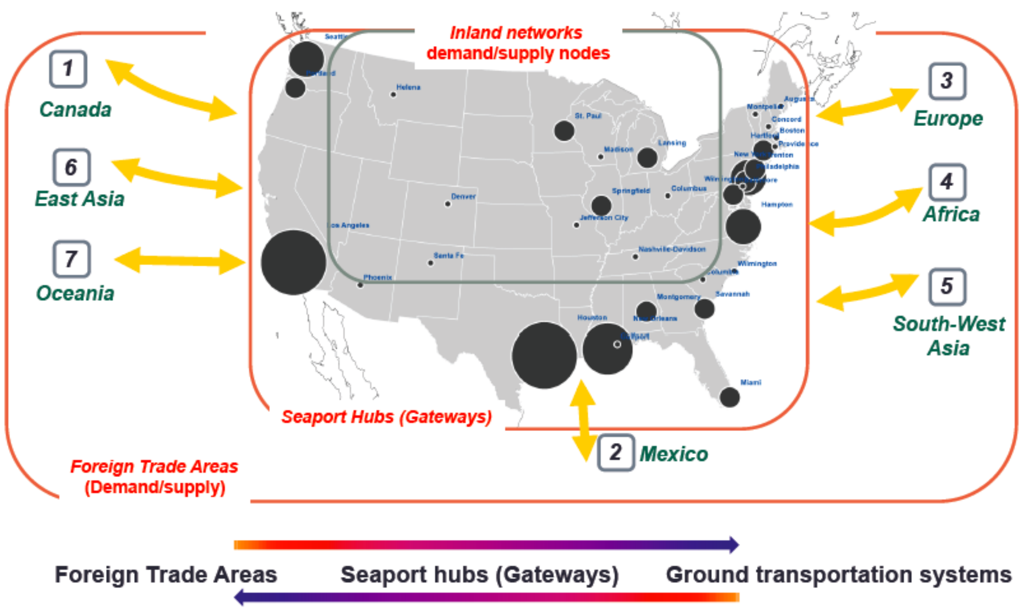

Figure 1. 3 transport levels: FTAs, Seaport hubs, and Inland demand/supply nodes

In a departure from the literature, we formulate the AHLP-SA as a recovery model to focus on resilience to a specific hub disruption event. As illustrated in Fig 1, the model is applied to logistics systems involving seaports and landside connections such that three different transport levels (FTAs, Seaport hubs, and Inland demand nodes) are involved. We establish a baseline status quo logistics system (routes and flows) given the assumption that goal of the logistics systems is to minimize total transport costs. We then introduce the disaster scenario of a seaport hub outage. The routes associated with the disrupted hubs are no longer effective but freight can be transported via ad-hoc hubs. Optimal ad-hoc hubs are identified from a set of candidate seaports, the level of their usage is established, and backup routes between the nodes and the ad-hoc hubs are identified.

We begin with a baseline system from which we model recovery with ad-hoc hubs. This baseline system is illustrated in Fig. 2-a, which shows the configuration of routes and the location of seaport hubs in the *status quo* using a classical hub network design with single assignment scheme. For a system with p=5 hubs, we have four seaport hubs (H_1, H_2, H_4, and H_5) and one inland hub (H_3). The purpose of the inland hub is to aggregate freight bound for nodes not in proximity of the hubs. However, if hubs H_1 and H_5 experience an outage (Fig. 2-b), flow from the FTAs are rerouted to other unaffected hubs. The AHLP-SA determines both the *location* of ad-hoc hubs and their corresponding *allocations* to supply and demand nodes according to the single assignment scheme, simultaneously. The new allocations can be considered to either other unaffected *existing* hubs or a *set* of candidate nodes (for example, all unaffected gateway nodes). Here, we name the selected q number of unaffected hubs as ad-hoc hubs.

Fig. 2-b. shows the AHLP-SA result of a p=5 hub network for r disrupted hubs (here, r=2) resulting in q=2 ad-hoc hubs. The selection of ad-hoc hubs is considered from a set of candidate gateways nodes. The disruption of H_1 and H_5 results in ad-hoc hubs of existing hub H_2 and new gateway node H_6, respectively. Notice that backup routes have been established to connect the nodes previously connected to H_1 and H_5 to H_2 and H_6.

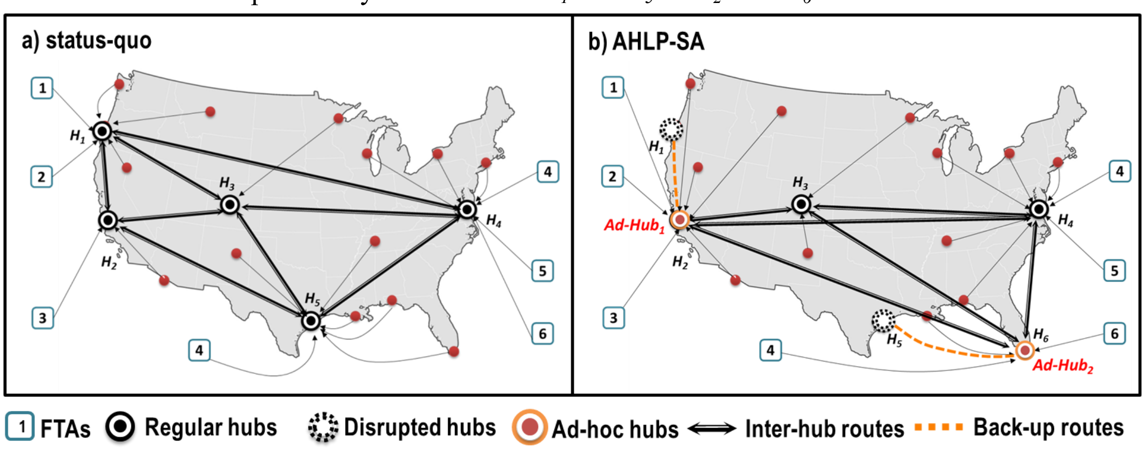

Figure 2. Concepts of AHLP-SA model (for th two hubs disruption and ad-hoc hubs q=2).

3 AHLP-SA Models

The AHLP-SA follows the structure of a classical hub location problem. The objective of the AHLP-SA is to minimize the total transport cost with a set of constraints regarding flows. The AHLP-SA solution will be necessarily greater than the *status quo* because the AHLP-SA is the solution to a constrained version of the *status quo*. The seaport hubs at *status quo* can be obtained using the AHLP model by removing the constraints (3), (8), (12) and replace q in the constraint (2) with p-regular hubs. Given a set of seaport hubs, the AHLP-SA examines the responses to various levels of r and q. In this abstract, we only provide the model formulation to the single assignment (SA) scheme and the behavior for the selected setting of *r* and *q*. However, the model can be extended to a multiple assignment scheme (MA) to achieve the AHLP-MA, which will be explored in the full manuscript. The formulation of the AHLP-SA is detailed below.

3.1 AHLP-SA (Ad-hoc Hub Location Problem with Single Allocation)

Minimize $$\Omega = \sum_i \sum_k \sum_m W_{ij} \left(\sum_{j(j \notin R)} (C_{ik} + \alpha C_{km} + C_{mj}) X_{ijkm} + \sum_{j(j \in R)} \sum_n (C_{ik} + \alpha C_{km} + C_{mn}) X^B_{ijkmn} \right) - \Omega^s \quad (1)$$

Subject to

$$\sum_{k \notin R} Z_k = q \qquad (r \le q) \qquad (2)$$

$$\sum_{k \in R} Z_k = 0 \qquad (3)$$

$$\sum_k Z_{ik} = 1 \qquad \forall\, i \qquad (4)$$

$$Z_{ik} - Z_k \le 0 \qquad \forall\, i, k\ (k \notin R) \qquad (5)$$

$$\sum_m X_{ijkm} - Z_{ik} = 0 \qquad \forall\ j > i;\ k\ (k, m \notin R) \qquad (6)$$

$$\sum_k X_{ijkm} - Z_{jm} = 0 \qquad \forall\ j > i;\ m\ (k, m \notin R) \qquad (7)$$

$$\sum_n X^B_{ijkmn} - X_{ijkm} = 0 \qquad \forall\ j\ (j \in R) > i;\ X_{ijkmn} \in Q \qquad (8)$$

$$Z_k \in \{0,\ 1\} \qquad \forall\, k \qquad (9)$$

$$Z_{ik} \in \{0,\ 1\} \qquad \forall\, i, k \qquad (10)$$

$$0 \le X_{ijkm} \le 1 \qquad (11)$$

$$0 \le X^B_{ijkmn} \le 1 \qquad (12)$$

where

Ω^s = objective function at *status quo*

p = number of regular hubs

q = number of ad-hoc hubs ($1 \le q$)

r = number of disrupted hubs ($1 \le r \le p$)

R_d = a set of disrupted hubs d

W_{ij} = flow from node i (FTAs) to node j (inland demand nodes)

C_{ij} = cost of flow interaction from node i to node j

α_{km} = discount factor for inter-hub flows between hubs k and m

X_{ijkm} = fraction of flow of the regular route traveling via hubs k and m ($i \to k \to m \to j$)

X^B_{ijkmn} = fraction of flow of the back-up route to the route X_{ijkm} ($j \in R$). The back-up route transports the flows to the back-up node n but not j

Q = a set of back-up routes X^B_{ijkmn} ($i \to k \to m \to n$)

Z_k = 1: if node k is selected as ad-hoc hub, 0: Otherwise

Z_{ik} = 1: if node *i* is allocated to hub *k*, 0: Otherwise

The AHLP-SA optimizes flows from FTAs (*i*) to the demand nodes (*j*) via *q* ad-hoc hubs to the *r* disrupted hubs with either re-allocated or back-up routes. The objective function (1) minimizes the loss of total transport costs with ad-hoc hubs and alternative routes to the set of disrupted hubs *k* ($k \in R$) against the *status quo* (Ω^s). The first terms and the second terms with parenthesis calculate the transport costs of unaffected routes (X_{ijkm}) and the back-up routes (X^B_{ijkmn}) via ad-hoc hubs. Notice that Ω^s represents the objective function value at *status quo*; which can be obtained *a priori* by omitting constraints (3), (8) and (12). Constraint (2) requires a set of *q* ad-hoc hubs (i.e. seaports) to be open. Constraint (3) prevents the flow from *i* to *j* being routed through disrupted hubs. Constraint (4) forces each node to be assigned to only one hub *k* (consistent with single assignment). Constraint (5) ensures that a hub should be open before a node is allocated to hub *k* ($k \notin R$). Constraints (6) and (7) together ensure X_{ijkm} should be routed through hubs *k* and *m* ($k \notin R$ and $m \notin R$). Constraint (8) determines the best alternative route to the disrupted route of X_{ijkm} due to $j \in R$. For example, this special case includes X_{ijjj} ($i \rightarrow j$, $j \in R$) or X_{ijkk} ($i \rightarrow k \rightarrow j$, $j \in R$). The variable X^B_{ijkmn} forces the flow should be routed to the back-up node *n* ($n \notin R$) Constraints (9) to (12) impose the property of binary variable to prevent partial facility location.

4 Data and Numerical Results

4.1 Data and Model Experiment

In applying the model developed in section 3 to a case study scenario, we develop a dataset utilizing data from the Freight Analysis Framework (FAF) [8] and trade data from RITA [9]. The data includes 2015 estimated freight flows from the seven Foreign Trade Areas (Canada, Mexico, Europe, Africa, Central Asia, East Asia, and Oceania) to the 17 U.S. major seaports nodes and 20 inland destinations. The flow and distance matrices are used as proxy of transport cost for travel between nodes and FTAs are prepared using ArcGIS 10. For illustrative purposes, we restrict the results presented herein to those with a fixed discount factor of α=0.90 and examine the model behavior for the range a range of *q* from $q=r$ and $q=r+1$ where *r* (r=1–4). The *status quo* result for a possible eight hub model (p=8) is obtained *a priori* and four hubs result as the optimal number of seaports. All instances are solved to optimality using CPLEX 12.1 on a Quad Core 3.4 GHz with 3.2 GB of RAM over the course of several seconds.

4.2 Selected Results

Fig. 3 presents the AHLP-SA results for the set range of disrupted hubs (*r*). The number of ad-hoc hubs (*q*) is considered for two levels, $q=r$ (red lines) and $q=r+1$ (blue lines). Notice that the worst or least-worst cases of the impact of disruptions are ientified at each *r* and form an *envelope* with increase of *r*. For example, there are 4 possible cases of disruption at r=1 ($={}_4C_1$), 6 cases at r=2 ($={}_4C_2$), and so on. Not surprisingly, the objective function value increases with r. Notice that better defense scenarios are made if q is increased. For example, in Fig. 3, all else equal, the model with ad-hoc hubs $q=r+1$ consistently outperforms the the model with $q=r$. Such results are consistent across α, ranges of r, and q in our tests. The model is looking to spread freight flows across many ad-hoc hubs rather than be restricted to few options.

The model informs the location of ad-hoc hubs and re-assignment of routes from a geographical perspective. Fig. 4 demonstrates the optimal location of ad-hoc hubs and back-up routes in a case study example. For example, with the case of p=8 possible hubs in the *status quo*, four is the resulting optimal number and their locations are Anchorage, Seattle, Boston, and Houston (Fig. 4-a). Suppose of the two hubs, Anchorage and Boston experience an outage, and freight will be redistributed from the seven FTAs via two ad-hoc hubs (r=2 and q=2). Fig. 4-b shows the best defense scenario. Hawaii and New York are selected as the ad-hoc hubs in place of Ancorage and Boston, respectively. The model also indicates that the network requires one-inland hub to be open at Arizona (Fig. 4-b) because the role of the seaport New York is shifted from the regular hub to the ad-hoc hub in the disruption of Boston so that the network needs another inland hub to serve the changed spatial configuration. In Fig. 4-b, the selected hub at Arizona plays as inland hub to handle the unaffected flows as well as the flow by the back-up route (X^B_{ijkmn}) which is transported to the destination n in the case of $j \in R$.

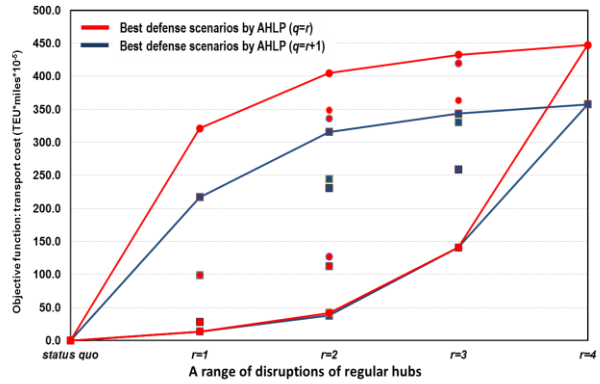

Figure 3. Model response: defense scenario envelopes for $a=r$ and $a=r+1$ at α=0.90.

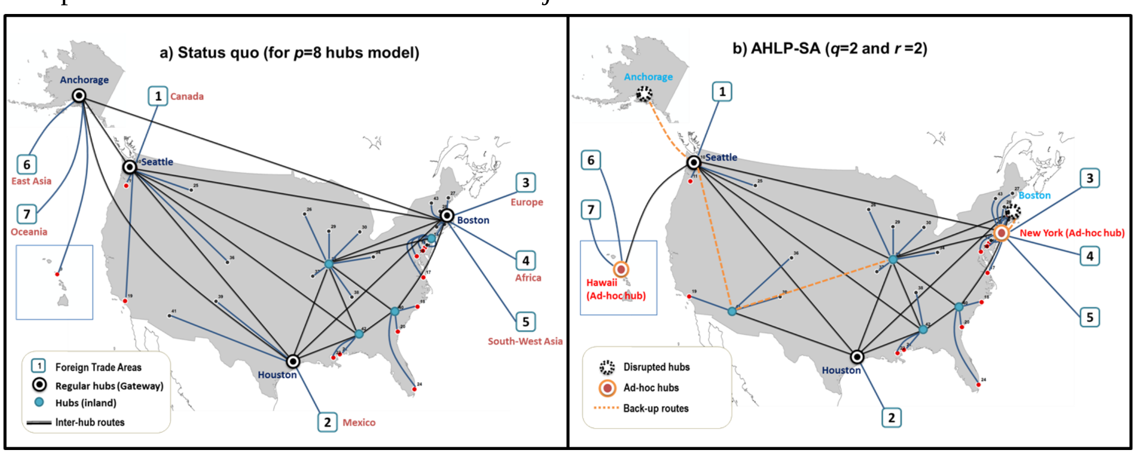

Figure 4. Ad-hoc hubs and the changed spatial configuration for two disrupted hubs.

5 Concluding Remarks

This research presents a novel spatial optimization model to address how a combined transportation system including foreign trade areas, seaports, and surface networks can respond effectively to the potential disruptions of seaport hubs. The AHLP-SA employs hub network design and prescribes ad-hoc hubs to improve network resilience and network performance. The model also explores the strategic locations of ad-hoc hubs to replace regular hubs. As a future research, with development of efficient algorithm, the model can be blended with large logistics models such that the models can yield analytic insights as well as provide numerical results. Further, different allocation schemes (i.e. multiple assignments) and constraints (i.e. capacity of hubs and threshold of inter-hub flows) are considered as a way of model expansion to make models more practical and realistic. The algorithms can greatly enhance our ability to understand and facilitate coordination of disaster response. Such results can benefit regional studies and policy (for example, the Boston region could be encouraged to coordinate a disruption plan with the New York region given the result in Fig. 4). Results can also benefit national policy; combined with probablistic functions for disaster scenarios, we can prioritize investments in ports which are most likely to serve as ad-hoc hubs.

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Scheduling double girder bridge crane with double cycling in rail based transfer automated container terminals

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1 Introduction

In automated container terminals, rail based horizontal transfer systems are newly proposed and regarded to be more suitable to intermodal transportation [1]. However, improvements are required in operations scheduling in rail based transfer automated container terminals (RBT-ACT) to take advantage of the infrastructure improvement [2].

In this paper a double girder bridge crane (DGBC) is introduced, whose benefits can be obtained with modest investments, such as combining the existing twin 40-ft double trolley container cranes with a double girder [3]. Each girder has one independent spreader, and the two spreaders work on containers in adjacent bays simultaneously with no change to the safety distance constraints. As a result, operating costs are reduced, protential collision of QCs can be avoided and the vessel service time is reduced.

Most research in this area aims to minimizing crane cycles, not processing times [4], however is it processing time that is of ultimate interest [5]. Our objective is to minimize total processing time, and the sequence dependent setup time is considered [6]. It is well established that double cycling can greatly improve quay crane productivity [7], and we consider its performance in the scheduling strategy for DGBC.

2 Problem description

2.1 Problem setting

Ordinarily, one unloading/loading operation is divided into two parts: one is moving and the other is lifting. The former can be executed automatically by the spreader. However, the latter requires the driver manually control the spreader. Thus, spreaders of DGBC work similar to ordinary quay cranes.

In order to raise or lower a container, the spreader first moves to the assigned location. The full movement YV denotes that the spreader carrying the container moves from the shore (Y) to the vessel (V) while VY denotes the reverse. Then the empty movements $\overline{YV}$ and $\overline{VY}$ imply that only the spreader itself moves between the yard and vessel. In addition, the empty movement VV represents within the vessel in the double cycling strategy.

2.2 Notation

B	: container bay, $B=1,2$	s_i	: the start time of the node i
n_B	: number of nodes in the bay B	o_{ij}	: the setup time between the activity i and j
n	: number of total nodes $n=n_1+n_2$	V	: set of nodes, $\|V\|=n$
Ψ	: set of movements, $\Psi=\{YV, VY, VV, \overline{VY}, \overline{YV}\}$	O	: set of setup activities
Φ	: set of lifting activities, $\Phi=\{U, L\}$	E	: set of edges of the network
p_l	: moving time of type $l\in\Psi$	b_i	: blocking of i between moving and lifting
H	: the unary resource driver for the lifting	$C_{\max}^B$	: makespan of the bay B
p_i	: processing time of lifting operation for activity i	r_{ik}	: requirement for resource $k\in R$ by activity / setup i
π	: the permutation of the whole nodes	R	: set of all resources $R=\{Q_1, Q_2, H\}$
π^B	: the permutation of the nodes in bay B	σ	: Large number

Decision variables:

$$X_{ij}^l=\begin{cases}1 & \text{, if setup between activity } i \text{ and } j \text{ is of the movement type } l\in\Psi \\ 0 & \text{, otherwise}\end{cases}$$

$$Y_i^c=\begin{cases}1 & \text{, if the activity } i \text{ is of the lifting type } c\in\Phi \\ 0 & \text{, otherwise}\end{cases}$$

$$Z_{ij}=\begin{cases}1 & \text{, if the activity } i \text{ precedes the activity j} \\ 0 & \text{, otherwise}\end{cases}$$

$$\pi=\begin{cases}(\pi_{[1]}^1, \pi_{[1]}^2, \pi_{[2]}^1, \pi_{[2]}^2, \ldots, \pi_{[n_1]}^1, \pi_{[n_1]}^2, \pi_{[n_1+1]}^2, \ldots, \pi_{[n_2]}^2) & , \; n_1\le n_2 \\ (\pi_{[1]}^1, \pi_{[1]}^2, \pi_{[2]}^1, \pi_{[2]}^2, \ldots, \pi_{[n_2]}^1, \pi_{[n_2]}^2, \pi_{[n_2+1]}^1, \ldots, \pi_{[n_1]}^1) & , \; n_1> n_2\end{cases}$$

2.3 Graph definition

The project can be described by an activity-on-node graph G (V, E). The set of nodes $|V|=n$ corresponds to the n activities. The nodes can be further divided into two subsets $|V_B|=n_B$, $B=1,2$, in which V_B is the nodes set in each bay B, and $V_1\cup V_2=V\wedge V_1\cap V_2=\Phi$. One unloading/loading activity needs exactly one lifting operation. Arc set $E=\{(i,j): i,j\in V; i\rightarrow j\}$ represents the temporal precedence constraints between two activities, i.e. $i\rightarrow j$ if activity i must finish before activity j can start. Adjacent lifting operations are separated by a series of movements. Spreader movements before/after each lifting operation are defined as the sequence dependent setup o_{ij}, which must be required by the consequently scheduled activities in the same bay. In addition, dummy activities *0* and *n+1* with zero duration are added to make sure only one starting and one finishing node in G. Each node is characterized by its processing time, resource requests (Q_1, Q_2, H) and precedence relations with other activities.

There are three resources: one driver H and two spreaders Q_1 & Q_2. Driver is the dedicated resource [8] only required for lifting operation, while spreaders are the allocable resource [9] used in lifting and movement. All the three are unary resource [10,11] with the available amount 1. In detail, Q_1/Q_2 serves bay 1/2, and the capacity of each is 1.

2.4 Setup modes

A series of movements may be executed between the adjacent lifting activities. Unloading (U)/ loading (L) in the single or double cycling strategy usually require their own combination of movements. Therefore, the setup has four movement modes (o^1~o^4) according to the sequence of the lifting operations [12], as listed in Table 1.

Table 1 Four movement modes

Strategy	lifting	movements	lifting
Single cycling	U	$o^1 = VY + \overline{YV}$	U
	L	$o^2 = \overline{VY} + YV$	L
Double cycling	U	$o^3 = VY + YV$	L
	L	$o^4 = VV$	U

Setups may overlap with different required resources at the same time (Q_1 and Q_2 can be in parallel). For description convenience, setups are treated as the additional activities denoted as O. Each setup can be depicted as a virtual node o_{ij} inserted between the original defined activity i and j in G. As a result, setup activity has the duration of setup time o_{ij} and the demand of the allocatable resources (spreaders corresponding to the bay).

2.5 Mathematical model

The problem is defined as resource-constrained project scheduling problem with sequence dependent setup [13], characterized by directed acyclic graph, and formulated into an integer programming model. The formulation is excluded here for brevity.

3 Methodology

In order to minimize the completion time of two bays, a two step heuristic is proposed. Firstly, double cycling is used for each bay since it achieves better crane processing efficiency than single cycling. However, because there is only one driver in charge of all the lifting operations on both two spreaders with DGBC. Two spreaders cannot be treated as two independent cranes. As a result, there exist resource conflicts between two double cycling schedules, in which one spreader cannot perform lifting directly after moving, and has to wait for the driver released from the previous lifting with the other spreader. Therefore, a timetabling heuristic is presented after the double cycling procedure to settle the conflicts. The double cycling procedure can be transferred from the traditional method in [7], then the emphasis will be focused on the timetabling step. Two step heuristic is described as below:

1. Scheduling B_1 and B_2 in double cycling. Obtain π^1 and π^2.
2. Compute the double cycles D and C in π^1 and π^2.
3. Mix π^1 and π^2 basing on FirstComeFirstServe to form the initial timetable π_0.
4. Fix one schedule of the bay B with $D_B \geq D_{B'}$ and $C_B \geq C_{B'}$.
5. While ($D_{B'} \geq 0 \vee C_B \geq C_{B'}$) $\quad // B' \neq B$
   - 5.1 iteratively local search
     - 5.1.1 right shift activities to remove conflicts
     - 5.1.2 make the schedule π_1 more tighter, and update $C_{B'}$.
     - 5.1.3 If better than π_0, then replace.
   - 5.2 change π_1 by $D_{B'} - 1$.
6. Alter the permutation and timetable by FirstComeFirstServe to solve the rest conflicts.

4 Results and Discussion

We assume two typical quay crane respectively serve the two bays in single cycling. Then the maximum completion time of this traditional transportation is $180(n_1+n_2)$. By contrast, single cycling is uesd in both spreaders of DGBC, and the driver is scheduled for two bays assuming that the spreader that first arrives at the lifting position will be first served. Therefore, the maximum completion time is $\max\{n_1,n_2\}180+60$. Furthermore, we consider a specific case that is DGBC cooperates one spreater (B_1) in single cycling with another (B_2) in double cycling. There are 7 different resource conflicts (one driver) between two bay schedules. Through the experiments, we find that all conflicts in one case will coexist periodically in three styles as (1, 4, 7), (2, 5, 8) or (3, 6, 9). Moreover, the latter two styles can be transformed into (1, 4, 7). Therefore, the maximum completion time of this specific case can be reduced as $\max\{C_{B2}+50*NumberOfConflicts, C_{B1}+60*NomberOfConflicts\}$.

Because double cycling greatly facilitates one bay operation, DGBC with both two spreaders in double cycling is considered. According to the presented method, the crane utilization rate is 69% higher than typical cranes. Various scenarios with different degrees of double cycling are investigated to explore its impact on crane processing efficiency. The results demonstrate that crane efficiency can be improved up to 32%. However, the best DGBC productivity does not require the highest degree of double cycling in both bays. The most important point is the cooperation between two bays schedules which results in less blocking. As the result, DGBC can significantly improve terminal productivity, and using double cycling can further enhance processing efficiency.

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Fleet deployment with speed optimization and demand considerations

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1 Introduction

We consider a fleet deployment problem for Wallenius Wilhelmsen Logistics, a large shipping operator in the roll on-roll off segment of liner shipping. Liner shipping is one of the three modes of transportation and can be compared to a bus line with the ships following a published itinerary and schedule [4]. The roll on-roll off segment of liner shipping mainly deals with the transportation of cars, trucks and other types of vehicles that can be loaded onto and unloaded from a ship without the help of external machinery like cranes.

The planning of a liner service is complex and include strategic, tactical and operational decisions [7]. Fleet deployment is a tactical decision with a planning horizon of typically a few months up to a year. Given a fleet of ships and a number of itineraries that the company must service, the problem is to assign a ship to each itinerary to minimize the cost. It has received some attention in the research literature, see for example [1], [2], [3], [5], [6], [8]. [3], [6] and later [8] formulate a mathematical programming model incorporating among other things ship capacity constraints and chartering issues. They all assume that the number of containers between a pair of ports on each itinerary is a priori known. To relax this assumption, [1] develop a mixed-integer linear programming model for the problem, in which the container shipment demand between two specific ports can be served by any itinerary passing through both ports. [2] introduce sailing speed as a decision in the fleet deployment problem, while [5] incorporate uncertain demands through chance constraints.

The purpose of this work is to formulate and solve the fleet deployment problem of Wallenius Wilhelmsen Logistics. Unlike many of the previous studies, both frequency requirements for the itineraries and demand between different geographical areas are considered. This means that the routing and scheduling of individual ships are important. The sailing speed is also a decision in the model and creates the possibilities to utilize each ship better. A third aspect not often discussed in the literature is the chartering option.

Wallenius Wilhelmsen Logistics can both charter ships to serve an itinerary that cannot be served by the own fleet and charter space in other ships to handle peaks in demand.

2 Problem description

The fleet deployment problem is the problem of allocating ships from a fleet to voyages on predefined trade routes to serve a given demand for transportation. A typical shipping company has a fleet of ships accessible for planning. In many cases, the fleet is heterogeneous with ships having different capacities and cargo type capabilities. Speed properties and bunker consumption also vary from ship to ship. The ships have the possibility to vary sailing speed within a given interval. At the beginning of the planning horizon each ship is at an initial position, either in a port or somewhere at sea. The ships can be available at the start of the planning horizon or they may be available at a later time because of other obligations such as finishing commenced voyages or docking.

A trade is defined as a transportation arrangement from one geographical region to another. Within a trade, there are several trade routes. An example is the trade Europe - North America where there is a trade route from Europe to the east coast of North America and another to the west coast. A trade route consists of a number of loading ports in one region and a number of discharging ports in the other. Depending on demand, a number of voyages have to be carried out on each trade route within a specific planning period. After a ship has sailed a voyage on one trade route it often needs to reposition to be ready for the next. Differences in contractual requirements and the types of cargo transported on the various trade routes may restrict what ships that can be assigned to a particular trade route, regarding both capacity and vessel type. Figure [1] illustrate two trade routes and the needed repositioning of the ship.

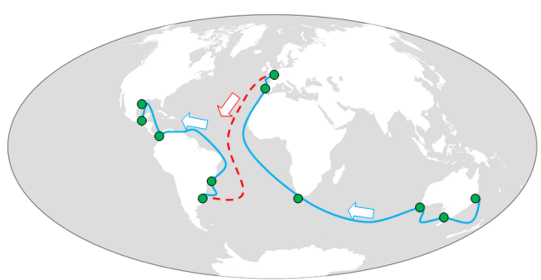

Figure 1: Illustration of two trade routes, Oceania to Europe via South Africa, and South America to North America, with a repositioning from Europe to South America.

It is also possible to charter additional spot ships in the market to serve a voyage. Spot ships are available to serve any voyage during the planning horizon and there is no repositioning associated with chartering a spot ship. There is a certain number of mandatory voyages scheduled on each trade route within the planning horizon. There is a monthly demand for transportation for each trade that must be met by the trade routes serving the trade. To fulfill these cargo obligations on the various trades, there may sometimes be a need for additional voyages. These are however optional since excess cargo could also be space chartered from other companies.

Each voyage has an estimated duration depending on which speed is chosen. This duration includes the sailing time between all ports along the route and the time spent in the ports. There are time windows associated with the voyages which determine at what time the voyages must start. A time window is defined with an earliest start time and a latest start time. For each voyage there is a penalty associated with a delayed start of voyages. This cost may vary between the trade routes and voyages depending on how strict the time windows are. The earliest start time is set as the day when the voyage is scheduled to start, and the latest start time determine an upper limit for delay. The longer the delay, the higher the total penalty cost.

There are costs associated with sailing a voyage. These costs include port and canal costs and fuel costs. All costs vary with ship and the fuel cost also vary with the speed chosen. The cost of chartering a spot ship is equal for all voyages on the same trade route, but considerably higher than having a ship from the own fleet sailing the voyage. The cost of space charter is paid per unit and is also higher than the per unit cost of a fully loaded ship from the own fleet.

The objective of the fleet deployment problem is to assign ships to the voyages throughout the planning horizon to minimize total cost and at the same time make sure that all planned voyages are sailed within the required time window and that the transportation demand is met. Spot ships can be chartered to ensure that voyages are served. The reasons for this may either be to exploit the market by saving costs or because of insufficient fleet capacity. Additional voyages and space chartering is available to make sure that transportation requirements are met.

3 Solution method

The problem is formulated as a mixed-integer linear program where the non-linear relation between speed and fuel consumption is approximated with a piecewise linear function. To solve problems of real size, a rolling horizon heuristic is developed. The principle of the rolling horizon heuristic is to solve the problem iteratively through the planning horizon. The planning horizon is partitioned into time periods; each consisting of two sections. The first section is the central section and the second is the forecasting section. During a given iteration, the planning problem for that time period is solved. Parts of the solution in the central section is then frozen and a new planning problem for the following time period is defined. In the new problem, the forecasting section of the previous iteration becomes the new central section. The algorithm continues until the solution for the whole planning horizon is frozen.

4 Computational results

The method has been tested on real data provided by Wallenius Wilhelmsen Logistics. The largest instances have more than 50 ships and 300 voyages, covering a nine month planning horizon. The tests show that the proposed method performs well and produces good solutions.

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Joint Planning of Fleet Deployment, Speed Optimization and Cargo Allocation for Liner Shipping

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1 Introduction

Since the global financial crisis in 2008, demand for container shipping services has shrunk significantly, while the service network has kept expanding. Consequently, carriers have come to face tremendous surplus of tonnage. The overcapacity in the shipping industry is probably here to stay for some time because the upcoming capacity in the pipeline cannot be fully absorbed by restoration of the growth in demand within a short period. In addition to capacity surplus, profit margins of carriers have come under pressure because of increase in fuel price and emission taxes also. In order to save fuel costs and to absorb excess capacity, as of January 2011, over 90 percent of the Far East-North Europe loops and over 70 percent of Far East-US East Coast loops have adopted *extra slow steaming* strategy in their daily operations [8]. However, speed reduction for cost saving is not sustainable. This is because when ships are operated at low speed, costs saved from deploying additional ships can hardly offset the increased operating costs whereas the correlation between fuel costs and ship speed is a convex curve. Besides adopting slow steaming, carriers are also systematically coordinating their service networks in order to make their fleets not only cost efficient but also market oriented. This has motivated our work to address an aggregate planning model for carriers to operate their fleets.

Liner shipping fleet deployment has been widely studied in extant literature. Two early studies [5, 7] provided comprehensive investigations into relevant objectives, considerations, and models for fleet deployment in liner shipping. In [1, 4], the authors considered routes for both ships and cargos while deploying ships on cycles with weekly frequency and combined decision making for hub location, port connection, and cargo allocation. Other studies [6, 9] have considered managing nonempty and empty container flows and focused on container transshipment operations. Issues related to speed optimization were also studied. For example, a non-linear mixed integer programming model was developed in [3] to decide optimal transit time for each link. In [2], the authors defined a run in terms of ship type, service route and specific speed, and formulated the problem as a mixed integer programming model, but one of the deficiencies in both models is that speeds on different legs within the route are assumed equal.

The contribution of this work is twofold - to introduce a comprehensive model that jointly copes with fleet deployment, speed optimization and cargo allocation, so as to maximize total profits at the strategic level, and to simultaneously optimize ship speeds and cargo allocation on every single link for routine operations faced by decision-makers.

2 Problem Statement

As we consider fleet deployment together with ship speed and cargo, containerships of different types are first assigned to a candidate set of services rotated around different regions in the world. We then optimize ship speeds on each by reformulating fuel consumption rate of a ship in terms of both speed and load. As a non-linear term, the reformulated fuel cost makes the problem more difficult to solve.

We first apply aggregation when representing the carrier's service network. The aggregation scope is adjustable for different planning levels. Within the aggregated service network, we further enumerate the candidate route set and define a weekly service by a combination of ship type, operated route and the number of ships assigned on that route. Our planning model determines the operated services ($y \in \mathbb{B}$), the quantity of cargos allocated ($x \in \mathbb{R}$), and ship speeds on each link of the operated services ($v \in \mathbb{R}$). Decision vector $\mathbf{x}$ is limited by minimal and maximal demand on each link between a demand pair. Decision vectors $\mathbf{x}$ and $\mathbf{y}$ follow the fact that distributed cargo flows on each link do not exceed the assigned capacity. Decision vector $\mathbf{y}$ satisfies that the number of deployed ships does not exceed the available fleet size. Decision vector $\mathbf{v}$ specifies a weekly frequency for services in operation. Let Ω_1, Ω_2, Ω_3 and Ω_4 denote the demand, capacity, fleet and frequency constraints, respectively. Given the revenue vector $\mathbf{p}$ and service cost function vector $\mathbf{c}$, we formulate a conceptual model Π as follows.

$$\begin{aligned} \text{Maximize} \quad & \mathbf{px} - \mathbf{c}(\mathbf{v}, \mathbf{x})\mathbf{y} \\ s.t. \quad & \mathbf{x} \in \Omega_1 \quad \mathbf{x}, \mathbf{y} \in \Omega_2 \quad \mathbf{y} \in \Omega_3 \quad \mathbf{v} \in \Omega_4 \end{aligned}$$

3 Methodology

Constraints Ω_1, Ω_2 and Ω_3 consist of a linear space for $\mathbf{x}$ and $\mathbf{y}$, while $\mathbf{c}(\mathbf{v}, \mathbf{x})$ is a non-linear term in the objective. Applying approximation, we separate the non-linear $\mathbf{c}(\mathbf{v}, \mathbf{x})$ into two terms $\mathbf{c}'(\mathbf{v})$ and $\mathbf{c}''(\mathbf{x})$, respectively, associated with a possibly non-linear ship speed and a linear ship load. In model Π_{LA}, $\mathbf{v}$ can be optimized individually for each service by solving shortest path problems in a time-space network, where $\mathbf{c}'(\mathbf{v})$ can be minimized under Ω_4. By generating all candidate services with optimal speeds, Π_{LA} is reduced to a Mixed-IP. Given $\mathbf{x}$, we re-optimize $\mathbf{v}$ by minimizing $\mathbf{c}(\mathbf{v}, \mathbf{x})$ under Ω_4. The obtained solution is then regarded as an approximated optimal decision for Π.

It is worth noting that the approximation from Π to Π_{LA} produces errors. Therefore, we develop an iterative algorithm, dynamically transforming Π into Π_{LA} by tangent approximation. We first initialize $\mathbf{x}$ and $\mathbf{v}$ by dummy values, and then apply tangent approximation to transform Π to Π_{LA}. We solve Π_{LA}, re-optimize $\mathbf{v}$ and update $\mathbf{x}$ and $\mathbf{v}$ before tangent approximation in the next iteration. The algorithm is terminated when a convergence is reached. Best solutions among all iterations are recorded and selected.

4 Computational Results

Computational results based on a five-region service network are presented in Table 1. Eight instances with random demand based on information from the shipping industry are generated. The Mixed-IP model Π_{LA} for determining $\mathbf{x}$ and $\mathbf{y}$ is solved by both a commercial solver CPLEX 12 and a classical column generation algorithm. In Table 1, objective values (OBJ) and ($\overline{\text{OBJ}}$), number of iterations (ITER) and ($\overline{\text{ITER}}$), computation time (TIME) and ($\overline{\text{TIME}}$) are associated with experimental results from CPLEX 12 and the column generation algorithm respectively. We further indicate the gaps (GAP) between (OBJ) and ($\overline{\text{OBJ}}$), fleet utilizations (FU) and the idle capacity ratios (ICR).

Results from Table 1 show that our model can optimize a practical service network with five regions with successful convergence for all instances. The column generation algorithm generates slightly worse objective values with significantly shorter computation times, which indicates potential for application of the model to larger cases. Finally, the approach is very adaptable for evaluation of fleet performance by decision-makers under different scenarios by considering trade-offs between fleet scale, market demand and freight tariffs, etc.

Table 1: Computational Results

INST	OBJ	ITER	TIME (s)	$\overline{\text{OBJ}}$	$\overline{\text{ITER}}$	$\overline{\text{TIME}}$ (s)	GAP (%)	FU	ICR
INST1	58205.4	22	2230.88	58039.2	6	8.84	0.29	0.91	0.08
INST2	62676.7	29	3988.61	62466.7	10	23.69	0.34	0.99	0.01
INST3	66466.8	44	51729.11	65997.6	17	79.90	0.71	1.00	0.00
INST4	54908.1	17	3201.28	54609.8	39	82.74	0.54	0.99	0.02
INST5	61536.1	14	1137.66	60884.5	9	23.58	1.06	0.95	0.02
INST6	61779.9	29	11154.81	61541.2	9	22.66	0.39	0.99	0.01
INST7	58548.1	40	14909.37	57855.5	17	51.90	1.18	0.99	0.01
INST8	57691.1	32	5572.48	57364.9	12	21.60	0.57	0.94	0.03

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Designing robust liner shipping schedules: Optimizing recovery actions and buffer times

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1 Introduction

Liner shipping networks consist of fixed routes and time schedules that are published on forehand. However, ships can encounter delays both when they are sailing between ports and when they are berthing in a port. When ships arrive delayed, additional costs are incurred depending on the amount of delay. These costs can be categorized in three different groups. First, the terminal can encounter extra costs, for example because the berth schedule has to be adapted. The containers that have to be loaded on the ship, are placed near the scheduled berth. If the ship is delayed and has to arrive at another berth, the costs of transporting the container to the ship are higher than planned. The terminal can charge the shipping company for these extra costs. Next, the containers that are unloaded in the port have to be transported to their destination. When a ship is delayed, the containers can be unloaded too late, so that they miss their connection. Finally, ships can encounter demurrage costs. Demurrage is an additional cost that represents liquidated damages for delays. Demurrage occurs when the ship is prevented from (un)loading the containers within the scheduled time.Delay can be caused by several reasons, including terminal operations delay, port access delay, maritime passage delay and chance [1]. Furthermore, a delayed ship will have a higher probability of arriving delayed in the next ports to visit. The incurred delay can increase during a round tour, because new delays are encountered or because delayed ships have to wait until the berths are free before they can enter the port. Therefore, it is important for liner shipping companies to develop robust shipping routes.

When ships are delayed, they can reduce their delay by taking recovery actions against certain costs. Examples of recovery actions are: increasing the sailing speed or port handling capacity. Furthermore, buffer time can be incorporated in the route to capture (a part of) the delay. The total buffer time of a route depends on the time needed to perform one round tour of the route. Since liner shipping routes are usually serviced once a week, the round tour time is rounded to an integer number of weeks. The total buffer time is chosen in such a way that the time of a single round tour including buffer times equals an integer number of weeks. The goal of the ship delay recovery problem is to determine a recovery policy and buffer time allocation that minimizes the costs associated with delays and recovery actions for a given liner shipping route.

A problem in railway networks that is related to this shipping problem is discussed in [2]. The authors propose a stochastic optimization model that can be used to allocate time supplements, which have the same function as buffer times in liner shipping, in a given timetable in such a way that the expected average delay of the timetable is minimized.

2 Markov Decision Process

When the buffer time distribution is fixed, the ship delay recovery problem can be formulated as a Markov decision process. The states of the Markov process denote the position of the ship together with the amount of delay encountered by the ship with respect to the original schedule. The position of the ship contains both the port that the ship is visiting and whether it is arriving or leaving the port. Since a finite number of states are needed, delay is discretized and a maximum amount of delay that can be encountered is introduced. The recovery policy is then defined as a policy that describes for every state of the Markov chain which action has to be performed given that the process is in that specific state.

Next, we need to determine the probability of a transition from one state to another for all possible combinations of states. We defined the states in such a way that the Markov property holds. Thus, the transition probability of going from one state to another is independent on the past states of the process. In each state of the Markov process a decision is made on which recovery action to take in that state. Thus, the transition probabilities depend on the current delay and on the decision made at the end of the state. Now, introduce the following sets:

- $\mathcal{P}$: set of possible positions of a ship (port name and arriving/leaving).
- $\mathcal{D}$: set of possible hours of delay.
- $\mathcal{I}$: set of possible states of the Markov process, $\mathcal{I} = \mathcal{P} \times \mathcal{D}$.
- $\mathcal{K}$: set of possible actions, which can be performed when in a specific state.

A Markov decision process can be defined as a discrete time Markov chain in which after each transition an action $k \in \mathcal{K}$ has to be chosen from a set of available actions ([3]). A cost C_{ik} is associated to performing recovery action $k \in \mathcal{K}$ in state $i \in \mathcal{I}$. As already mentioned, the probability of a transition from state $i \in \mathcal{I}$ to state $j \in \mathcal{I}$ only depend on the current state i and the recovery action $k \in \mathcal{K}$ chosen in state i. These transition probabilities are denoted by p_{ijk}.

In Markov chains, transitions usually take place after a fixed time interval. Then, the (long-run) expected average cost per time unit is used as performance measure of the Markov decision process. However, in our model the liner shipping route is fixed, which means that the order in which ports are visited is fixed, but the time needed in a state will depend on the ship position. Therefore, we will use the (long-run) expected average cost per ship position defined as

$$\mathbb{E}[C] = \sum_{i \in \mathcal{I}, k \in \mathcal{K}} \pi_i C_{ik} D_{ik}$$

as performance measure, where D_{ik} denotes the current policy, $D_{ik} = 1$ if action k is chosen in state k and 0 otherwise, and π_i represents the steady-state probability of being in state i under the evaluated policy. Furthermore, the values of D_{ik} are relaxed such that they can obtain all values between 0 and 1 in order to obtain a linear programming model. However, the optimal solution to the linear programming model has the property that all values of D_{ik} are either 0 or 1 ([3]).

Next, we want to include the buffer times as action in the Markov decision process. However, in stead of choosing one buffer time for each state, we want to choose only one buffer time for each ship position (which corresponds to a set of states). We can adjust the linear programming formulation in such a way that it models this new problem. However, the linear programming model will convert to an integer model after adding the additional constraints.

3 Mixed Integer Programming Formulation

We start with the LP formulation of a Markov decision process as given in [3] and show how it can be extended to obtain a formulation for the new problem. First, introduce the following sets needed to formulate the new model:

- $\mathcal{B}$: set of possible values of buffer time per ship position.
- $\mathcal{A}$: set of possible actions in the new Markov decision problem, $\mathcal{A} = \mathcal{K} \times \mathcal{B}$.

The decision variables now become y_{ia} in stead of y_{ik}. A same adjustment has to be made to the constraints of the linear programming model. The probability of a transition from state $i \in \mathcal{I}$ to state $j \in \mathcal{I}$ still only depends on the current state and actions, so the Markov property still holds and the constraints are still valid.

However, using only the modified constraints will result in multiple buffer times for a ship position, since for each possible value of delay another buffer time can be chosen. Therefore, additional constraints have to be added that ensure that the same buffer time is chosen for all different values of delay for each ship position. Thereto, the binary decision variables ξ_{pb} are introduced, which take the value 1 if buffer time $b \in \mathcal{B}$ is allocated to ship position $p \in \mathcal{P}$ and 0 otherwise. Exactly one possible buffer time has to be allocated to each ship position, so the first constraints needed are

$$\sum_{b \in \mathcal{B}} \xi_{pb} = 1 \quad \forall p \in \mathcal{P}.$$

Furthermore, the total allocated buffer time may not exceed the maximum amount of buffer time available (M), so it has to hold that

$$\sum_{p \in \mathcal{P}, b \in \mathcal{B}} b\xi_{pb} \leq M.$$

Finally, the steady-state probabilities y_{ia} can only be positive for combinations of ship position and buffer times for which $\xi_{pb} = 1$. This results in the constraints

$$\sum_{d \in \mathcal{D}, k \in \mathcal{K}} y_{(pd),(kb)} \leq \xi_{pb} \quad \forall p \in \mathcal{P}, b \in \mathcal{B}.$$

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Improved Large Neighborhood Search for LNG Inventory Routing

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1 Introduction

Liquefied Natural Gas (LNG) is steadily becoming a common mode for commercializing natural gas. Due to the capital intensive nature of LNG projects, the optimal design of LNG supply chains is extremely important from a profitability perspective. We address an LNG inventory routing problem where optimized ship schedules have to be developed for an LNG project. In this paper, we present an arc-flow formulation based on the MIP model of Song and Furman [5]. We also present a set of construction and improvement heuristics to solve this model efficiently. The heuristics are evaluated based on a set of realistic test instances that are very large relative to the problem instances seen in recent literature. Extensive computational results indicate that the proposed methods find optimal or near optimal solutions and are substantially faster than commercial optimization software.

LNG inventory routing can be considered as a special case of maritime inventory routing problems (MIRP). MIRP combines inventory management and ship routing, which are typically treated separately in industrial practice. A basic maritime inventory routing problem [2] involves the transportation of a single product from loading ports to unloading ports, with each port having a given inventory storage capacity and a production or consumption rate, and with the number of visits to a port and the quantity of product to be loaded or unloaded are not predetermined. Rakke *et al.* [4] seems to be the first MIRP to address problems of developing ADPs for large LNG projects. Andersson *et al.* [1]

provide an excellent overview of the business cases and common characteristics for LNG inventory routing.

The LNG inventory routing problem (LNG IRP) shares the fundamental properties of a single product MIRP with special features such as variable production and consumption rates, LNG specific contractual obligations, and berth constraints. The LNG IRP seeks to generate schedules where each ship may make several voyages over a much longer than typical time horizon. In this work we develop improved solution methods for the LNG IRP model presented by Goel *et al.* [3].

2 Formulation

The mathematical model proposed by Goel *et al.* [3] is a mixed integer programming (MIP) problem formulated on a time-space network. The network includes two types of nodes: dummy source (SRC) and sink (SNK) representing initial and final locations for the ships and regular nodes (i,t) and (j,t) representing each terminal at a given time period. For each ship v, there are five types of arcs: (1) dummy arc from SRC to SNK representing that the ship is not utilized; (2) entering arc from SRC to a regular node representing the arrival of the ship to its initial destination; (3) exiting arc from a regular node to SNK representing the final departure of the ship; (4) waiting arcs allowing the ship to wait at a terminal without occupying a berth; and (5) travel arcs between regular nodes with different terminals representing the loading (or unloading) and travel activities. A typical network is shown below in Figure 1.

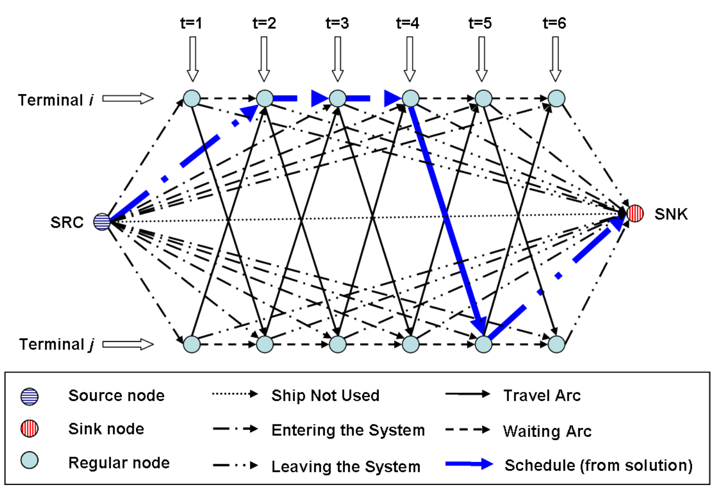

Figure 1: Example of Time-Space Network Structure

In the MIP formulation based on this network, the objective is to minimize the sum of weighted lost production, stockout, and unmet demands. The primary decision variables are the binary variables on the arcs and regas rates at each regas terminal during each time period. The model has four major types of constraints: flow conservation constraints, inventory management constraints, berth management constraints, and contractual requirement constraints(See Goel *et al.* [3] for details).

3 Solution Methods

Our solution method includes two phases: Phase I constructs good feasible solutions; Phase II improves the solution by applying a suite of neighborhood search operators.

3.1 Construction Heuristics

Round-Trip Rolling Time Algorithm In this algorithm, a feasible solution is constructed by solving a sequence of optimization subproblems, each of which corresponds to one day. The subproblem attempts to schedule a round-trip for each ship in the considered periods. Depending on the length of the considered periods, two variations of this algorithm are posed: (1) a “one day” variant in which we only consider the ships that are available at the current day and (2) a “multi-day” variant in which we consider ships that will be available over multiple days.

Greedy Randomized Adaptive Search Procedure (GRASP) In this algorithm, the initial feasible solution is also constructed day by day. On each day, we make a sequence of decisions, each of which corresponds to a selection of a new voyage that starts from this day. To select a voyage, we need to create the candidate list first, then calculate a benefit value for each candidate, and finally select one at random based on a probability distribution which is associated to the benefit values. Depending on the steps that we create the candidates, this algorithm has two variants: (1) a “one step” variant in which a voyaged is decided by selecting ship and destination simultaneously and (2) a “two-step” variant in which a voyage is decided by selecting a ship first and then its destination.

3.2 Advanced Neighborhood Searches

Singleton Search We present four neighborhood structures that each vary one aspect of the problem at a time: (1) One-ship neighborhood search: optimizes schedule for one ship at a time; (2) One-terminal search: optimizes schedule for one terminal at a time; (3) One-direction search: optimizes inbound (or outbound) voyages to production terminals while fixing reverse voyages; and (4) One-day-flexibility search: finds better solutions by allowing a voyage to be advanced or delayed by one day or multiple days. When these singletons are applied sequentially, we define it as “sequential singleton search”.

Two-Ship Neighborhood Search This neighborhood structure was originally proposed by Song and Furman [5] and was extensively studied by Goel *et al.* [3]. In this search, schedules for two ships are optimized at a time. Motivated by our intuition that this search might be sped up if the ships are sorted in an optimal order, we present four different sorting rules.

Rolling Time Windows Search This neighborhood search involves the use of time windows in a rolling fashion. Within each time window, all arcs are freed up; outside the time windows, many or all arcs are fixed. Two approaches are considered for fixing the arcs outside the time windows: (1) all arcs simultaneously or (2) arcs in one direction (inbound to production terminals) and then the other (outbound from production terminals).

4 Results

Computational results show that, the newly proposed construction heuristics yield strictly better initial solutions than the benchmark construction heuristic Goel *et al.* [3] and the sequential Singletons is the most efficient solution-improvement scheme among all advanced neighborhood schemes developed here. Combined with any of the construction heuristics and the sequential Singletons, our method can yield significantly better solutions than the benchmark set of heuristics Goel *et al.* [3] with significantly less CPU time. The results indicate that the combination of multiple inexpensive heuristics is a good strategy to solve large scale problems.

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A Cargo Prioritization Model for Inland Waterway Disruptions

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1 Introduction

The commercially important U.S. inland waterway system is an open system comprised of 12,000 miles of navigable waterways managed by the U.S. Army Corps of Engineers [1]. Inland and intracoastal waterways serve thirty-eight States with nearly 200 commercially active lock sites [2]. The Nation's "marine highways" are an important component of the nation's transportation system and considered as a critical transportation mode for certain commodities and geographical regions. Disruptions on the inland waterway system can have widespread economic and societal impacts. In order to mitigate these impacts, key stakeholders including the U.S. Coast Guard and U.S. Army Corps of Engineers need pre- and post-disruption response plans to provide decision support regarding how to respond to disruptive events along the inland waterways. The value of the cargo transported by disrupted barges decreases in terms of economic value, societal benefit, and customer expectation as time elapses. Intelligently prioritizing these cargoes for offloading can minimize the total value loss of the cargoes, subsequently mitigating the negative impacts of the waterway disruption.

The objective of this work funded by the U.S. Department of Homeland Security is to formulate and solve a cargo prioritization and terminal allocation problem (CPTAP) that minimizes the total value loss of the barge cargoes due to disruption on the inland waterway transportation system. The problem is graphically shown in Figure 1. As an example, one of the lock and dam (L/D) systems located along the river section is disrupted and no longer functioning, which causes the inland waterway to close thus halting traffic traveling up and down the river at the point of disruption. The barge tows (typically consisting of five to twelve barges) that are traveling in the direction away from the disruption are unaffected and able to continue transport to their destination. Barge tows (depicted in bold) that are traveling towards and beyond the disrupted L/D are affected and no longer able to travel to their destination via the disrupted waterway. The cargo on the disrupted barges is the focus of our CPTAP model. We need to determine (1) an accessible alternative terminal for each disrupted barge that will allow its cargo to be offloaded to another mode of transportation and continue transport to its final destination and (2) the prioritized turn each barge takes at its assigned terminal.

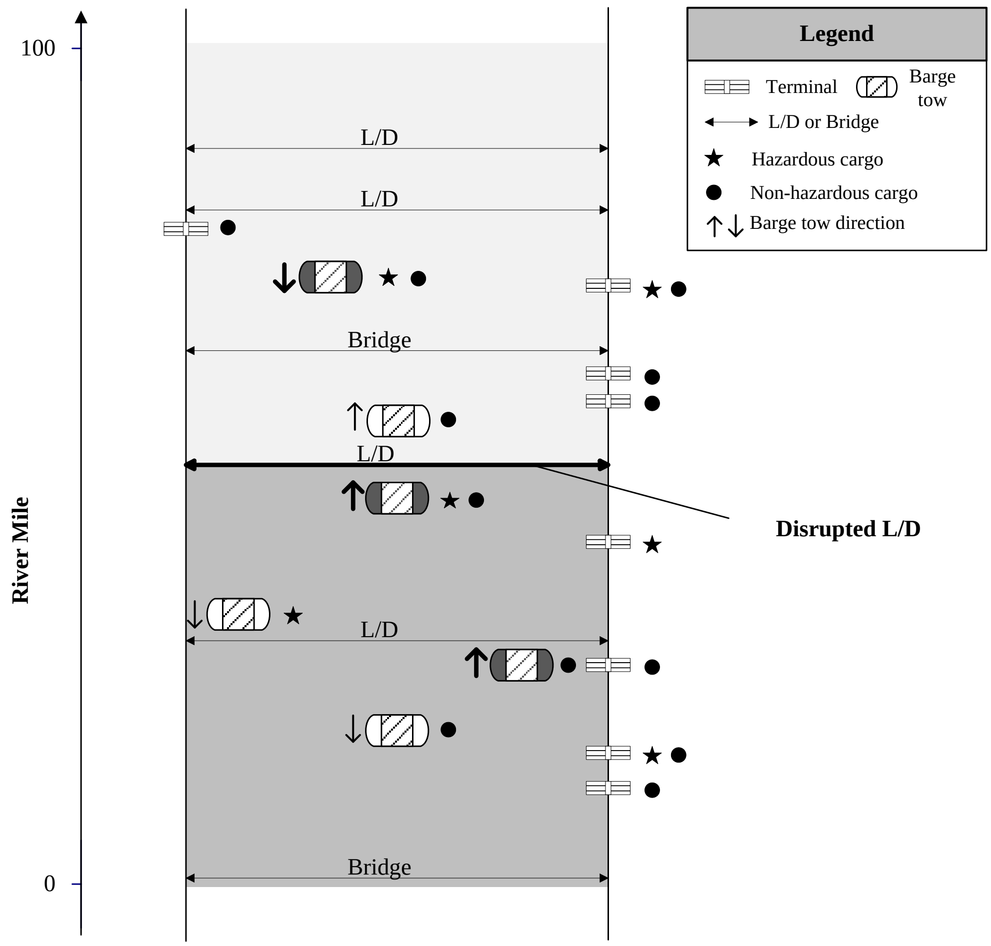

Figure 1: Graphical Representation of CPTAP

2 Model Formulation

Our representation of the CPTAP has similar features to the general framework of the berth allocation problem (BAP) [3-5]. Based on the literature review of the extensive BAP papers, we formulate CPTAP model as a nonlinear binary integer programming model.

The two-piece objective function minimizes the total value loss of the barge cargoes due to disruption on the inland waterway transportation system. The first piece refers to the cargoes that are offloaded at the terminals and transported to the final destination through alternative land-based transportation modes. The second piece considers the non-hazardous cargoes that remain on the inland waterway and are assumed to lose all value.

The constraints are categorized into eight constraint sets: Constraint set (1) ensures that each barge with non-hazardous cargo either transports for offloading at an alternative terminal in some priority order or remains on the inland waterway. Constraint set (2) guarantees that each barge with hazardous cargo must be serviced at an alternative terminal in some priority order. Constraint set (3) assures that each terminal services no more than one barge at each priority order ((1) – (3) are adapted from [3-5]). Constraint set (4) aesthetically ensures that the priority order at each terminal starts from the first priority turn. Constraint set (5) indicates that the overall terminal capacity for a particular cargo commodity type is not exceeded. Constraint set (6) ensures that the barge draft plus a safety level cannot exceed the water depth at the terminal (adapted from [6]). Constraint set (7) assures that the total value loss of the barge cargo that is transported for offloading to an alternative transportation mode is less than or equal to the product of the sinking threshold and the total cargo value. Constraint set (8) defines the decision variables as binary variables.

3 Solution Approach

The Genetic Algorithm (GA)-based heuristic is employed to solve realistically sized instances of the CPTAP. A numerical string is used to represent terminals and barges as the chromosome representation of the prioritization solution. Steps of crossover, mutation, repair and population update are included in the GA-based heuristic.

4 Experiments

Our model and solution approach are tested on twenty-seven small-sized experimental instances by comparing the GA-based heuristic to the corresponding optimal solutions obtained through total enumeration. Problems of size (# of terminals + # of barges +1) 12, 13, and 14 are considered. Three combinations of terminal and barge counts for each problem size are created with three instances for each combination that vary in offload time and land transport time. All experimental instances are randomly but systematically generated on the basis of data collected from the Upper Mississippi River.

5 Results and Discussion

We derive the experiments' objective function values and the CPU solution times from both the GA-based heuristic and total enumeration for all twenty-seven instances:

- GA-based heuristic is capable of solving all instances, and total enumeration can provide optimal solutions for problems of size less than fourteen.
- GA-based heuristic obtains the optimal solution for each problem instance of sizes twelve and thirteen and outperforms the total enumeration CPU time tremendously.
- Focusing on the GA-based heuristic results, we observe that the more barges that require offloading and the fewer terminals to accept them, the greater the total value loss and the higher the CPU time.
- We observe that CPU time increases moderately as the problem size increases for the GA-based heuristic approach; while a large increase in CPU time is observed in the total enumeration method as the problem size increases.

- We further examine validity of our results by examining a particular problem instance of size twelve with five terminals and six barges. Hazardous cargoes are all assigned to the real terminals on the river section and offloaded as the model requires.
- Sensitive analysis indicates that decreasing the sinking threshold leads to an increase in both the total value loss and the number of barges that remain on the inland waterway.

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Container Vessel Stowage Planning with Ballast Tanks

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1 Introduction

Over the past two decades, the demand for cost efficient containerized transportation has seen a continuous increase. In order to answer to this demand, shipping companies have deployed bigger container vessels, that nowadays can transport over 15,000 containers and are wider than the extended Panama Canal. Like busses, container vessels sail from port to port through a fixed route loading and discharging thousands of containers. Before the vessel arrives at a port, it is the job of a stowage coordinator to devise a stowage plan. A stowage plan is a document describing where each container should be loaded in the vessel once terminal operations start. In general a stowage plan must ensure that the loaded container ship is seaworthy. The vessel must have sufficient *transversal stability* when sailing, the its *draft* (immersion depth) and *trim* (longitudinal inclination) must be within limits, and the weight distribution must satisfy the stress limits of the structure (*shear forces* and *bending moment*). The stowage of containers must respect stacking contraints, such as allocating refrigerated containers (*reefers*) near power plugs, disallowing 40' long containers to be on top of 20' long containers, and obeying weight and capacity limits. The main objective of stowage planning is to minimize time at port by reducing the number of moves through overstowage minimization (avoid containers from blocking each other) and maximizing the utilization of the assigned cranes.

Stowage plans are hard to produce in practice. First, they are made under time pressure by human stowage coordinators just hours before the vessel calls the port. Second, deep-sea vessels are large and often require thousands of container moves in a port.

Third, complex interactions between low-level stacking rules and high-level stress limits and stability requirements make it difficult to minimize the makespan of cranes and, at the same time, overstowage. Fourth, containers to be loaded a later ports must be taken into consideration to minimize potential negative impacts of the current stowage plan.

The interaction between the stability of the vessel and the objectives of stowage planning can be very complex. To counter this complexity, stowage coordinators use *ballast water*, which can be pumped in and out of the *ballast tanks* distributed along the vessel. These tanks can be used to adjust the weight distribution of the vessel. This can be seen as a small relaxation of the stability constraints which gives more solution flexibility.

Container stowage planning has received increasing attention from the academic community in the past few years. Most of the published works (e.g. [4],[1],[3],[2]), however, are difficult for the industry to evaluate due to their level of abstraction and the assumptions made. Our work attempts at reducing this gap by showing how the container stowage planning problem can be efficiently solved even when several industrial requirements are taken into account. In order for the generated stowage plans to be accepted by the industry, it is necessary to rise the level of precision concerning the seaworthiness of the vessel. In [6] we presented a number of linear approximations for the non-linearities that rise when dealing with the actual calculations of vessel stability and the use of ballast water.

The work presented in this abstract is a combination of the approximations introduced in [6] and the overstowage modeling developed in [5]. To the best of the authors knowledge, this is the first mathematical optimization model that includes ballast water. Moreover, this optimization model is able to efficiently find solutions to the stowage planning problem with a level of accuracy that is considered satisfactory by the industry. The paper following this abstract will present and extended experimental evaluation on a set of 130 industrial instances, which is the largest industrial benchmark used until now.

2 Model Approach and Results

In [5], we have developed a stowage planning optimization approach that, similar to the most successful current approaches (e.g, [7, 3, 1]), decomposes the problem hierarchically as depicted in Figure 1. First the *multi-port master planning* phase decides how many containers of each class to stow in a set of storage areas in the vessel. Containers are divided into weight classes of standard 20' and 40' containers, and reefer containers. We model the

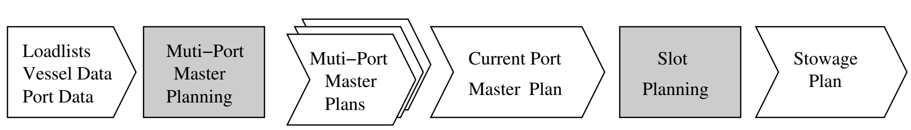

Figure 1: Hierarchical decomposition of stowage planning into master and slot planning.

	MP	MPWB	MP-H	MPWB-H	MP'	MPWB'	MP-H'	MPWB-H'
SMALL (45)								
Avg. CPU	1045,6	346,7	625,3	100,2	1089,8	553,7	185,8	193,1
Best CPU	86,3	10,8	0,2	0,18	2,3	2,4	0,1	0,1
Solved (%)	6,7	24,4	31,1	35,6	28,9	51,1	53,3	95,6
In 10 min.(%)	2,2	20,0	20,0	35,6	15,6	40,0	51,1	88,9
MEDIUM (34)								
Avg. CPU	8,4	1621,2	369,9	408,5	1118,9	1465,8	239,4	519,2
Best CPU	8,4	1,5	0,6	0,1	4,0	0,7	0,3	0,2
Solved (%)	2,9	8,8	32,4	44,1	26,5	38,2	61,8	97,1
In 10 min.(%)	2,9	2,9	23,5	35,3	14,7	17,6	58,8	79,4
LARGE (51)								
Avg. CPU	951,9	833,9	607,7	269,1	1226,8	1792,3	547,7	186,0
Best CPU	2,5	0,3	1,5	2,3	2,5	0,1	0,5	0,1
Solved (%)	5,9	11,8	23,5	45,1	23,5	52,9	37,3	80,4
In 10 min.(%)	2,0	5,9	15,7	39,2	11,8	19,6	29,4	70,6

Table 1: Master planning preliminary results using CPLEX 12.5

vertical, longitudinal and transversal stability of the vessel, trim and draft limits, weight distribution and stress forces, and optimize hatch-overstowage and crane makespan. The model takes ballast tanks into account in order to achieve move flexibility in the solution process. The master plan for the first port (the one we are making the stowage plan for) is used as input for the second phase, *slot planning*, to assign the containers of the classes defined in the master plan to concrete slots. In slot planning, all major stacking rules apply: containers must form stacks, 20' containers cannot be stowed on top of 40' containers, reefer containers can only be stowed in reefer slots, stack maximum height and weight limits must be fulfilled and cell capacity must be observed. Containers are assigned with the aim of minimizing overstowage, clustering containers with the same discharge port and freeing stack and reefer slots for robustness.

Following are the preliminary results of the master planning phase. Master planning is solved using a mixed-integer programming model where each decision variable, x_{tl}^{tau}, defines the amount of containers of a specific type τ to be stowed into storage area l, during transport t (an origin, destination pair). The model includes boolean indicator variables for the hatch-overstowage calculation, and continuous variables, u_{bp}, for the ballast water to be loaded in tank b at port p. The full model will be presented in the paper following this abstract.

We evaluated the model on an industrial benchmark of 130 instances. The benchmark includes a wide range of vessels with capacities ranging from 2.500 to over 15.000 Twenty-Equivalent Units (TEUs), and routes between 3 and 17 ports. The instances include vessel utilization in the range of 29% and 93%, and include both 20', 40' reefer and *release* containers (those last are the containers already onboard the vessel). Table 1 presents an aggregated overview of the preliminary results. It groups the instances based on the size of the vessel: Small (2500-4999 TEU, 45 instances), Medium (5000-8999 TEUs, 34 instances), Large (9000-15000 TEUs, 54 instances). The table presents results from 4 versions of the model: master planning with (*MPWB*) ballast water and without (*MP*), and their corresponding relaxations (*MP-H* and *MPWB-H*). In the relaxed model only the overstowage indicator variables are kept integer. The last 4 columns of Table 1 present the results of the same 4 model variations where the optimization was stopped at a 5% integrality gap. For each result we present the average and best CPU time (seconds), the number of solved instances (with 1 hour time limit) and the number of solved instances within 10 minutes (which is a requirement from the industry). The table clearly shows promising results, which we believe confirms the fact that mathematical models can be used by the industry for efficient stowage planning. The paper following this abstract will have a more in-depth analysis of the results and comparison with earlier work.

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Adapting a fleet of ships to uncertain market development

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1 Introduction

The maritime business faces uncertainty at all levels of planning. While operating planners are mainly challenged by uncertain weather conditions, strategic plans have to deal with particularly volatile market conditions. Shipping markets can in fact be described as capital intensive, cyclic, volatile, seasonal and exposed to the international business environment [1]. Also, [2, p. 325] points out that while shipping companies can save a few hundred thousand dollars a year by careful ship management, the value of a single ship can change by that amount in a few days.

Ships represent the core asset in the maritime industry. Renewing a fleet of ships to adapt to market changes is a crucial task as it affects future competitiveness and returns. It consists of deciding how many and which types of ships to include in or exclude from the fleet, when and how to do so in order to meet the (uncertain) service demand. We refer to this as the *maritime fleet renewal problem* (MFRP).

Despite the evidence, uncertainty has not yet found attention in operations research applications to fleet renewal problems. While the research literature presents methods to support an initial, ”static”, composition of the fleet (see e.g. [3] and[4]), the adaption of the fleet to changes in market conditions has not received much attention. Yet, almost all the available applications describe deterministic problems.

This paper, based on the case of Wallenius Wilhelmsen Logistics (WWL), a major liner shipping company, investigates whether taking uncertainty into account can improve decision making. By using stochastic programming we examine in which circumstances including a proper model of uncertainty is crucial and in which deterministic programming works equally good, and explore the reasons of this. The important elements of the problem (i.e. those emphasizing the role of uncertainty) are also investigated and pointed out.

In Section 2 we describe the problem while in Section 3 we present results to the tests we performed. Conclusions are drawn in Section 4.

2 Problem description and modeling approach

WWL is a liner shipping company transporting rolling vehicles between all continents. They move basically three types of products: cars, high & heavy vehicles (HH) (e.g. agriculture and construction vehicles) and static cargo (BB) (e.g. train coaches, boats, big turbines). WWL currently operates ships of three main types: *pure car carrier* (PCC), *pure car-truck carrier* (PCTC) and *roll-on roll-off* (RORO). PCCs are mainly fitted for cars and can also accommodate some taller vehicles. PCTCs can accommodate more HH vehicles than PCCs and, finally, ROROs are mainly designed for HH and BB vehicles with cars as complementary cargo.

WWL is currently engaged in 18 trades all over the world. Each trade consists of moving cargo between specific geographic regions (e.g. Europe-North America, Asia-Europe and Asia-Oceania). When a ship is assigned to a given trade it visits the corresponding ports, loading and unloading cargoes, according to a pre-published itinerary. After servicing one trade a ship starts on another (or the same) trade, possibly with a ballast sailing in between, and begins a new service.

WWL is engaged in long-term contracts committing the company to move a given percentage of the customers' production. The future demand is therefore uncertain since the production is not specified in advance, and so are most other problems parameters, such as ship costs and charter rates.

The problem consists of deciding how to modify the fleet given the uncertain future market situation. This includes which ships to build, to buy in the second-hand market, to sell, to scrap, or to charter in and out. Fleet renewal decision cannot be made without also considering the fleet deployment. The aim is therefore to minimize the total expected cost of providing and operating ships over the planning horizon, while servicing the (uncertain) demand.

We have developed a mathematical model for the MFRP that consists of minimizing the total expected cost of providing and deploying ships over the planning horizon, such that:

- The balance between ships leaving and joining the fleet in two following periods is respected
- Ships sold, demolished or chartered out are actually available

- The number and capacity of ships assigned to each trade is suffcient to cover the demand of each type of product

3 Tests and Results

The main scope of the tests is that of evaluating whether and in which cases stochastic programming can provide better decision support than deterministic programs built over average data. For each instance built from the WWL case, we measure the Value of the Stochastic Solution (VSS). The higher is the VSS the more decision makers can benefit from using stochastic programing. Moreover, we evaluate how the VSS depends on specific problem features such as the availability of charters, the frequency required on the trades and the correlations between the random elements of the problem.

Results show that, in the case of WWL, the solutions provided by the stochastic program can significantly improve decisions by leading to a noticeable potential decrease of the total expected cost. The fleet size and mix proposed by the stochastic program ensures higher flexibility in sight of uncertain market scenarios.

The availability of time charters resulted is one of the most crucial elements in the problem. Scarcity of charters (as in the WWL case) leads to stategic plans more exposed to failure. In such case stochastic programming represents a precious tool for decision support. On the other hand, imposed frequency on some of the operated trades can partially cut off uncertainties. Finally, tests on the correlation between the random elements of the problem show that including uncertainty in the model is more important than having accurate descriptions of the random phenomena, yet the value of the stochastic solution is almost not influenced by changes in the correlations.

Finally, running deterministic model over average data, often provided a fair composition of the fleet (fleet mix), but equally often a bad fleet size.

4 Conclusions

Fleet renewal plans in maritime transportation can benefit from using stochastic programming to support decisions. This is especially true in specialized markets (e.g. RORO shipping) where chartering ships in or out, to recover from poor renewal plans, may result particularly difficoult.

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An Integrated Framework for Risk Assessment in Maritime Transportation

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1 Introduction

Maritime transportation systems represent a core building block of global supply chains and display an inordinately large number of risk dimensions that must be managed effectively: cargo security, volatility in transport costs, liability for loss or delays (e.g. due to maritime piracy), and fines for non-compliance (sometimes running into millions of dollars) represent just a few complicating features of these logistical systems. For instance, at the beginning of 2007, fuel cost less than $300 a ton, but by mid-summer of 2008, prices had risen to $750 a ton (Harrington [1]). Maritime risk can also originate from carriers filing for bankruptcy, or due to mergers and acquisitions. The goal of this paper is to provide a comprehensive review of risk issues in maritime transportation and to develop an integrated framework for risk assessment, taking the perspective of a *maritime carrier*. The paper also makes some specific proposals for managing risk in the areas of capacity management, commodity risk and maritime piracy. An alternate and more generic risk management framework for global supply chains is provided in Van Mieghem [2]. The current work is specifically applicable to marine logistical systems.

2 The Integrated Risk Management Framework

The proposed framework addresses risks in five areas: i) shipper capacity risk ii) commodity price risks, e.g. due to volatile fuel prices iii) market risk due to factors such as short/long-term contracts at locked-in prices (for long-term) and spot prices (for short term) iv) operational risks due to weather induced accidents, oil spills or traffic-induced collisions and v) miscellaneous factors such as maritime piracy and cargo security risks.

2.1 Capacity Risk Management

Harrington [1] indicates that it may be on occasion cheaper for a carrier to add ships rather than operate ships at a higher speed in order to increase capacity reserves. In marine logistics, carriers must maintain adequate capacity to provide appropriate levels of service to their shippers – in managing capacity risk, there must be a coherent plan that simultaneously balances three factors a) ships being de-commissioned b) new ships being commissioned (with often a long lead time for delivery) and c) changing demand landscapes and service requirements imposed by shippers. In the taxonomy of Van Mieghem [3], ship capacity is subject to lead times, physical deterioration and discrete capacity sizes. Rajagopalan [4] also proposes a model that unifies capacity acquisition with equipment replacement.

2.2 Commodity Risk

The management of fuel prices is closely related to an operational problem, viz., optimizing vessel speeds to conserve fuel. Lu and Neftci [5] provide a contemporary overview of financial derivatives that are used to manage commodity risk, including fuel price movements. Derivative strategies include:

a) *Plain Vanilla options*: A *Call option* can protect fuel buyers against unusually large hikes in fuel prices. In a Call option, the buyer gains the right to purchase fuel at a strike price K (determined when the option is written) and the option is exercised when the market price is higher than K. However, risk management with plain vanilla options are expensive. Lu and Neftci [5] therefore propose two additional derivative mechanisms to lower the cost of managing risk.

b) *Risk Reversals*: This strategy lowers the cost of plain vanilla options by writing other options. In this structure, the earnings accrued from a short position offset the insurance cost of a long option position.

c) *Barrier options* are a third strategy proposed by Lu and Neftci [5] to overcome any residual shortcomings with the risk reversal approach.

Finally, Singh [6] also provides a case study of a company (Anheuser-Busch) that executes options to hedge commodity prices.

2.3 Market Risk

Shippers may prefer to strike up long-term contracts with carriers, obviating the need for frequent contract re-negotiation. Moreover, long-term contracts may afford shippers preferential treatment when capacity is tight. However, carriers are in the practice of applying various surcharges to account for contingencies. While shippers may prefer long-term contracts with fixed surcharges, with a long-term contract, shippers feel shortchanged if the (spot) market rate is lower than the long-term contract rate and carriers are likewise sub-optimal in performance if the spot rate is higher than the long-term contract rate. *Index-linked contracts* offer a compromise that enable both shippers and carriers to manage market risk originating from volatile spot freight rates (Brown [7], Drewry Supply Chain Advisors [8]).

2.4 Operational Risk

Operational risks in maritime transportation could stem from safety related concerns, e.g., the grounding of the Exxon Valdez caused public and government concern about the safety of oil transportation in the Prince William Sound, Alaska. Merrick et al. [9, 10] propose a systems engineering approach to manage risk in oil transportation and examine policies for averting other operational disasters similar to Exxon Valdez. Merrick and Van Dorp [11] also provide an enhanced methodology that combines Bayesian simulation and Bayesian multi-variate regression analysis to perform a full-scale risk assessment for two recent case studies. Kleindorfer and Kunreuther [12] compare the efficacy of managing risk by either adopting *risk mitigating precautions* or via the purchase of *risk insurance*. Operational accidents could also originate due to collisions and accidents caused by poor weather or increased traffic intensity ([13]).

2.5 Miscellaneous Risks

Under this header, we can classify maritime piracy risk as well as cargo security risks arising either from terrorism or pilferage. Graf [14] provides a comprehensive overview of issues related to maritime piracy. Several risk mitigation strategies are proposed in this article to minimize the impact of maritime piracy: i) vessel re-routing via safer paths ii) purchasing insurance a priori to safeguard against the loss of goods iii) lobbying governments to provide safe-passage corridors iv) adopting on-board security measures and v) developing a formal syndication procedure with other shippers to reduce risk management costs.

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An exact method for routing and scheduling of vessels for one of the world's leading RoRo carriers

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1 Introduction

Transportation of cars by sea is mainly performed by specialized vessels. These vessels are purpose built for transporting cars and trucks, but some also transport other rolling equipment like high and heavy (trucks etc.) and break bulk. In this paper we introduce an exact method for routing and scheduling a fleet of roll-on roll-off (RoRo) vessels. The problem discussed is based on a real-world problem faced by Wallenius Wilhelmsen Logistics (WWL), one of the world's leading RoRo carriers. WWL operates more than 60 RoRo vessels, and transports more than 2.3 million vehicles, rolling equipment, and static cargo each year to destinations around the world.

Maritime planning problems are often divided by mode of operation, and based on the length of the planning horizon. In literature one often refers to three modes of operation : liner, tramp, and industrial shipping as proposed by Lawrence (1972). In liner shipping the ships operate according to a published itinerary, in tramp shipping the ships follow the available cargoes and in industrial shipping operators usually own and control both the cargoes and the ships. Traditionally, planning is also divided into three classes based on the length of the planning horizon: strategic, tactical, and operational. Strategic problems are long term planning problems, which in shipping usually means 5 to 20 years. *Fleet size and mix*, *network design*, and *contract evaluation* are all typical strategic planning problems. Problems with a planning horizon length of a few weeks up to 18 months are usually referred to as tactical planning problems and include problems such as *ship routing and scheduling* and *inventory ship routing* in addition to *fleet deployment* studied in this paper. Short-term, or operational, planning is usually applied when the decisions only have a short-term impact (sometimes as short as only one sailing leg) or the operational environment is highly uncertain. Decisions such as *ship loading* and *speed optimization* are examples of important operational planning problems. For a summary of the major articles within maritime planning see Christiansen et al. (2007).

Container and RoRo vessels usually operate within the category of liner shipping, and operate according to given trade routes or trades. These trades specify two or more regions that goods are moved between. An illustration of trade is given in Figure 1. When creating a fleet deployment plan, the fleet is assumed given from the strategic fleet size and mix, or strategic fleet renewal problem.

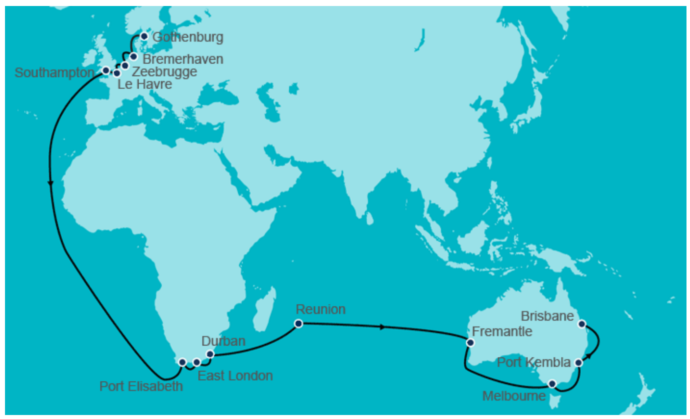

Figure 1: A trade from Europe to Oceania.
source: `http://www.2wglobal.com/www/Images/productsServices/routeMaps/eu_oc2.gif`

The literature on maritime routing and scheduling is quite scarce compared to literature on land based problems, and the number of papers discussing deployment in liner shipping is quite small. Recently, Wang and Meng have published several papers on liner shipping of containers, and some of these discuss deployment of the fleet (see Wang and Meng, 2012a,b). Another recent paper discussing deployment of RoRo vessels is by Fagerholt et al. (2009). Here the authors present a new formulation for fleet deployment in liner shipping, where they consider deploying vessels on trades, not closed loops which is more common in literature. They argue that the simplification of the problem using closed loops imposes an unnecessary restriction from which the solution suffers. We follow the modeling choices made by Fagerholt et al. (2009), but also include some new aspects and introduce additional details to the problem. E.g. we do not have a fixed number of voyages that has to be sailed and time windows for these. Instead we propose a more detailed stowage planning and let the expected demand drive the number of voyages on each trade. We also remove time windows and impose spread, minimum frequency, and week day requirements where this is needed.

We present two models for this problem where the number of sailings on each trade is decided based on the transportation demand, minimum frequency, and vessels used, and use these to solve a set of instances generated from real problem data.

2 Problem description

A RoRo carrier operates a set of trades for customers around the world and is responsible for transporting three main cargo classes, namely cars, high and heavy (HH), and break bulk (BB). There are two main types of trades in addition to ballast legs: charter out and operational trades. A charter out trade is a contract of usage of a vessel with given specifications (e.g. minimum ship capacity) for a number of sailings between two regions during the planning horizon. When chartering out vessels the contract specifies a number of sailings, together with a fixed time for each charter.

On operational trades customers have monthly quantities of different cargo classes that are to be transported during a planning horizon. This is specified in number of units for cars, and in m^3 for HH and BB. Customers may also have a frequency requirement, stating the number of visits in the planning horizon or a time period. There may also be a minimum capacity requirement for one or several cargo classes on the vessels serving the ports or regions. In addition to the frequency requirements there may be requirements regarding the spread of the sailings on a trade.

To operate these trades a large heterogeneous fleet of vessels is used, consisting of a mix of large car carriers and RoRo vessels. Capacities of these vessels are given in RT43, an old measurement for the size of a car based on a 1966 Toyota Corona. Since RT43 is an old measurement the number of cars to be transported is adjusted using a conversion factor to align with the capacity of the vessels. This conversion factor describes the average ratio between the new cars from a given port or region and RT43. Demands for HH and BB are usually given in m^3, but converted to RT43 using the dimensions of RT43 and an adjustment for average space lost due to HH and BB being less uniform than cars.

The capacities of the vessels is given in the following way: there is a capacity for each of the cargo classes, and a total capacity for the vessel. There is also a maximum total capacity for subsets of the product classes, meaning that a vessel with a total capacity of 5000 RT43 may have a HH capacity of 3000, a BB capacity of 1500, and a total capacity of 3000 RT43 equivalents of HH and BB, i.e. there is only a certain fraction of the total capacity of the vessel that may be used for HH and BB. The reason for this is that HH and BB have stronger requirements with regards to deck strength. In addition, some decks are not properly fitted to store cars in an efficient way, so the total capacity in RT43 for cars may be less than the capacity for HH or BB.

There exist region - vessel compatibility restrictions defining which vessel types that can operate trades to a given region. These restrictions are based on physical constraints and experience. The physical constraints are usually connected to the vessels length, width, or maximal draft. Experience based constraints are connected to the historical performance of a vessel in a given region with regards to loading time, capacity utilization and so on. It may also be based on customer preferences.

If there is insufficient capacity in the operators fleet to handle the demands it is possible to transport cargo using one of two options: 1) Voyage charter or 2) space charter. When using voyage charter, the operator charters in a vessel for one voyage on a specific trade and has to schedule this vessel, while if using space charter the cargo is loaded on a vessel scheduled by another operator.

3 Model and solution method

In the paper we present two formulations for the problem, one arc flow and one path flow model. The objective is to fulfill the operator's responsibilities to the customers at minimum cost. Several valid inequalities are proposed to strengthen the formulations. The path flow formulation is based upon paths for each vessel, and solved using a branch-price-and-cut algorithm. Both formulations are implemented using C++ and solved using a commercial solver. Computational results obtained on a proposed set of benchmark instances will be presented for both formulations.

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Decision support for flexible liner shipping

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1 Introduction

Decision makers in liner shipping are often facing problems like fluctuating demand creating capacity problems and delays due to congested ports, strikes, inclement weather etc. For industrial customers, such disturbances may have severe consequences because goods in transit are increasingly used as pipeline inventory in global supply chains where buffers are kept at a minimum to reduce costs. Currently, a common solution to the problem is introducing slack in the sailing schedule, resulting in a longer pipeline for the customers, and demanding more vessels for the same capacity [1]. An alternative might be *flexible liner shipping*, using a tighter schedule, but having flexibility in terms of the opportunity to skip some port calls and leave some cargo behind. Some of the ports skipped might still be served via a visited port using various modes of pre or post transportation (i.e., feeder service by barge, truck, etc.), given that vessel capacity allows for it. This is different from how a shipping line is normally operated, where vessels follow a published schedule, which lists both the ports to be visited and the corresponding arrival/departure times.

In Section 2 we describe an operational decision problem in flexible liner shipping, this is followed by computational experiments in Section 3 and results in Section 4.

2 An operational decision problem in flexible liner shipping

Decision problems in liner shipping typically deal with strategic or tactical issues; which ports to visit and in which order, the number and type/size of vessels to use, the frequency of service etc. For an overview of ship routing problems in general, see, e.g, [2], a description of routing and scheduling problems in liner shipping can be found in [3]. The flexible liner shipping problem described here differs from other decision problems found in liner shipping in that it is operational and appears in a situation where time and capacity constraints may limit the number of port calls and the total amount of cargo transported on a given tour. However, deciding which ports and cargo to skip, and how to serve the accepted demand, is a complex planning problem. The motivation for investigating this type of problem arose from a research project on goods tracking [4], where a shipping operator is facing this kind of decision problem on a daily basis.

The application presented here is transportation of seafood from Russia and Norway to ports in Norway and continental Europe. Every week, a 2500 dwt reefer vessel leaves Murmansk in northwestern Russia, visits several ports along the Norwegian coast to collect and deliver pallets of frozen fish, and visits Velsen in the Netherlands and Grimsby in Great Britain as the two last stops. The vessel will be back in Murmansk, ready to start the next trip, three weeks later. This means the shipping company uses three identical reefer vessel to operate the line. More than 50 ports in Norway are typically visited during a year, but normally not more than 20 on a single trip. In the low season, when the demand for transportation is low, the vessel can visit all ports that have demand without facing time or capacity problems. This is different in the high season, when the demand often exceeds the vessel capacity, and in addition the time schedule does not allow the vessel to visit all ports. The shipping company deals with this problem by either leaving load behind or by using land transportation (reefer trucks) as pre or post transportation.

If load is left behind, it means that a port is not visited, and the demand has to be picked up by a different vessel on the next trip one week later. The demand should then have higher priority to ensure that it is not left behind again. Some customers (ports) might be considered more important than others, demand from these ports may always get high priority.

If pre or post transportation is used, one or more ports are not visited by the liner vessel. The demand is still served, the goods are transported by reefer truck to or from a port which is visited by the vessel, in this way the reefer vessel saves time by skipping one or more port calls. This policy can also be used to overcome capacity problems, as goods may be transported by truck to a terminal where goods are unloaded and thus some capacity is released. In the application described here, the customer pays a fixed price for the transportation, the shipping company pays for any land transportation used.

2.1 Model description

We formulate the planning problem associated with each tour as a Mixed Integer Problem. In the following, we give a brief description of the model. The mathematical formulation is omitted because of space restrictions.

The objective is to maximize profit for the shipping company. The profit is computed as the price paid by customers for the goods transported minus costs for sea and land transportation. We assume that it is always beneficial to serve as much of the demand as possible, cargo is thus left behind only if capacity restrictions makes it necessary.

The constraints can be summarized as follows: All high priority demand and some or all optional demand should be serviced. Correct flows in the network are ensured, in terms of vessel and reefer truck movements as well as goods moved. This means, e.g, that if a certain demand is met, the corresponding quantity has to leave the origin/source node and arrive at the destination/sink node. Flow conservation is ensured at all intermediate nodes. If goods leave from a node or arrive at a node, the node has to be visited either by the reefer vessel or by a truck. The load when the vessel leaves a node must not exceed the vessel capacity, and time windows for arrivals and departures must be satisfied.

3 Computational experiments

We have generated 13 problem instances based on information about ports/terminals along the route (including time windows and estimates of port efficiency), road and sea distances, cost parameters, vessel speed and demand patterns. The instances contain from ten to 25 terminals, the instances with 20 terminals correspond to real-world problem instances during the high season. The problem instances are listed, together with computational results, in Table 1. The number in each instance name refers to the number of terminals, for each of the three instance sizes (10, 16 and 20) there are four instances with different characteristics. In instances named “Basic” there is enough of both time and capacity to serve all demand. The instances named “Cap” lead to capacity problems, in “Time” instances the schedule does not allow all terminals to be visited, and in “CapTime” instances both types of restrictions occur. The MIP model described in Subsection 2.1 has been coded in Pyomo and solved with Gurobi 5.0.

4 Results

The computational results are listed in Table 1. Our focus is on the solution times, as our first goal is to find out if the solver can handle these instances. We see that problem instances with up to about 20 ports can be solved to optimality in less than 20 minutes. The 25 terminal instance is included to show that if the number of terminals increases beyond 20, the solution time increases significantly. This means that, for a different application with a higher number of nodes to be visited, an alternative solution method might be needed.

For the problem described in this paper, 20 ports represents a realistic problem size, and a solution time of 20 minutes should be acceptable. This means there is a potential for savings, both in terms of solution time and in terms of solution quality. Currently,

Table 1: Computational results

Name	**Terminals**	**Objective**	**Solution time**
n10Basic	10	5 342 519	0.05 sec
n10Cap	10	5 812 519	0.06 sec
n10Time	10	4 868 305	0.06 sec
n10Captime	10	5 163 046	0.08 sec
n16Basic	16	5 281 221	34 sec
n16Cap	16	5 629 170	2 min 13 sec
n16Time	16	5 172 354	1 min 23 sec
n16Captime	16	5 294 624	2 min 20 sec
n20Basic	20	5 503 990	30 sec
n20Cap	20	6 038 877	12 min 17 sec
n20Time	20	4 958 486	17 min 55 sec
n20Captime	20	6 005 406	17 min 56 sec
n25Basic	25	5 786 227	15 hours 45 min

decisions about which ports to visit and which ports to skip are made in an ad hoc manner, and a significant amount of time is spent on manual planning. In addition, it is not given that an optimal solution is easily found without the help of an optimization based decision support system. Being able to tackle this type of decision problem also represents a means of improving the efficiency of intermodal transportation chains.

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Assessment of profit, cost and emissions by varying power as a function of sea conditions, freight market and vessel designs

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1 Introduction

Traditionally seagoing vessels has been designed and optimized to operate at maximum economic speeds based on hydrodynamic considerations. These design speeds have been quite standardized for vessels of similar type and size. More recently, high prices of fuel and increased environmental concerns have challenged this practice. For this reason, there has emerged a growing interest in the relationship between speed and emission reductions. The core insight is straightforward: the power output required for propulsion is a function of the speed to the power of three this simply implies that when a ship reduces its speed, the fuel consumption per freight work, i.e. ton nautical, mile is reduced.

Traditionally, fuel and emission calculations in these studies have been based on still water conditions or an average sea state, despite that a calm sea is quite the exception in shipping [1]. Lloyd [2] has studied how additional wind and wave resistance increases the power needed compared to what is required for calm water conditions. The results show that the resistance increases rapidly with increasing wave height and that the peak resistance occurs in head waves when the average length of the waves is close to the length of the vessel. Another observation is that bulk and tank vessels, which traditionally have been designed with focus on maximizing the cargo-carrying capability at the lowest possible building cost, is more impacted by rough sea than more slender vessels built for higher speeds such as RoRo and Container. Even at calm sea bulk and tank vessels with their shoebox-shape with short bow and aft ship sections have higher resistance compared to more slender designs with the same cargo carrying capacity. If we assume that a typical bulk or tank vessel is operated 25 years before it is scrapped, the difference in cost and energy consumption adds up to significant amounts for each vessel. In total bulkers and takers accounted for more than 70 % of the worlds total sea freight work of 41 000 billion ton nm in 2007 [3].

2 Problem description

The aim of the analysis has been to identify cost, emissions and profit as a function of vessel design and hull slenderness, sea condition and cargo load for vessels speeds ranging from zero up to the design speed. Second, to combine them to evaluate cost, emission and profit by varying speed as a function of sea condition, fuel cost and freight market. And third, to apply the model in combination with weather data to investigate potential cost and emission reductions which can be achieved with weather routing [4].

3. Model and solution method

The developed model is based on combining the models and results from three previous studies [5], [6], and [7]. The first two of these studies, focused on vessel operation and the third, focused on vessel design and hull slenderness. The developed model consists of five main equations, of which the power model is the most important. The power model takes into account propeller efficiency K, the power needed for still water conditions P_s, the additional power required for waves P_w, the power needed for wind P_a, and the necessary auxiliary power $P_{aux.}$ The propeller K (propulsion) efficiency is a function of the vessel speed, sea state and power output in percentage of total maximum available power.

$$P = K \cdot (P_s + P_w + P_a) + P_{aux}\ ,\ K = \eta(v,\ H_{1/3}) = max\left(\frac{1}{\eta\left(j+k\cdot\sqrt{\frac{v}{V_d}}\right)}, \frac{1}{\eta(1-r\cdot H_{1/3})}\right)$$

$$P_s = \frac{\rho\cdot C_{ts}\cdot S\cdot v^3}{2}\cdot\left(\frac{M\cdot m}{DWT} + (1-m)\right),\ P_w = \frac{C_w\cdot\rho\cdot g\cdot\left(\frac{H_{1/3}}{2}\right)^2\cdot B^2}{L}\cdot(v+u),\ P_a = \frac{C_a\cdot\rho_a\cdot A\cdot(v+u_a)^3}{2}$$

In the study the developed model is applied to compare Standard Panamax vessel with alternative designs which all can pass through the Panama Canal when the expanded canal locks opens in 2014. Apart from the maximum beam given by the locks, there is no unique definition of a Standard Panamax dry bulker, however the reference vessel used in this study has a length (loa) of 225 meter, a maximum draft of 14.5 meter, a block coefficient of 0.87 and a dead weight of 80 000 ton. The dead weight is the measure in ton for how much weight a ship can carry at most. The fuel price used for comparison is 600 USD per ton of fuel, all tons and measurements are metric. Four vessels are compared. The first is a Standard Panamax built to maximize cargo carrying capacity through the Panama Canal, before the lock extension in 2014. The second vessel is a slender bulk vessel, compared to a standard Panamax the width has been increased by 30 %, the length and the draft is unchanged and in combination this enables a reduction of block coefficients from 0.87 to 0.68 while the maximum cargo capacity is kept equal to the Standard Panamax, at 80 000 ton. The third vessel, the Handy Cape is 30 % wider and 8 % longer than the Standard Panamax, built to maximize the cargo carrying capacity at the lowest building cost. This gives a maximum cargo carrying capacity of 120 000 tons. The fourth vessel is a Capesize of the Dunkerque class which can pass through the new locks when it is short loaded reducing the maximum cargo carrying capacity from 175 000 tons to 150.000 tons. Figure 1 shows cost and emissions for each of these vessels with calm water conditions. In figure 2 real sea conditions has been included and the focus is on the vessels with a cargo carrying capacity up to 120 000 tons. For this comparison 4 meter head waves is used as a proxy for real sea conditions based on typical sea condition in the North Atlantic [8]. These waves will come from different directions, which gives different power impact, however if an assessment shall be made based on two sea conditions only, 4 meter head waves in addition to calm water conditions gives a good benchmark for comparison.

The figures contain two separate parts for each of the vessels with a common vertical axis. The vertical axis represents the cost per ton nm as a function of vessel speed on the right hand side of the figure, and the same cost as a function of emissions on the left hand side. By plotting the results this way, it is possible to obtain the emission reduction as a function of speed reduction.

The graphs to the right demonstrate a minimum cost for a speed lower than the design speed for all the investigated vessels. And the graphs on the left hand side demonstrate a minimum emission for a speed lower than the design speed. This means that reducing speed from the design speed of 14 – 15 knots down to the cost minimum speed of 8 – 10 knots gives cost reduction in the size of 15 – 30 % per ton nm and emission reductions of 30 – 60 %.

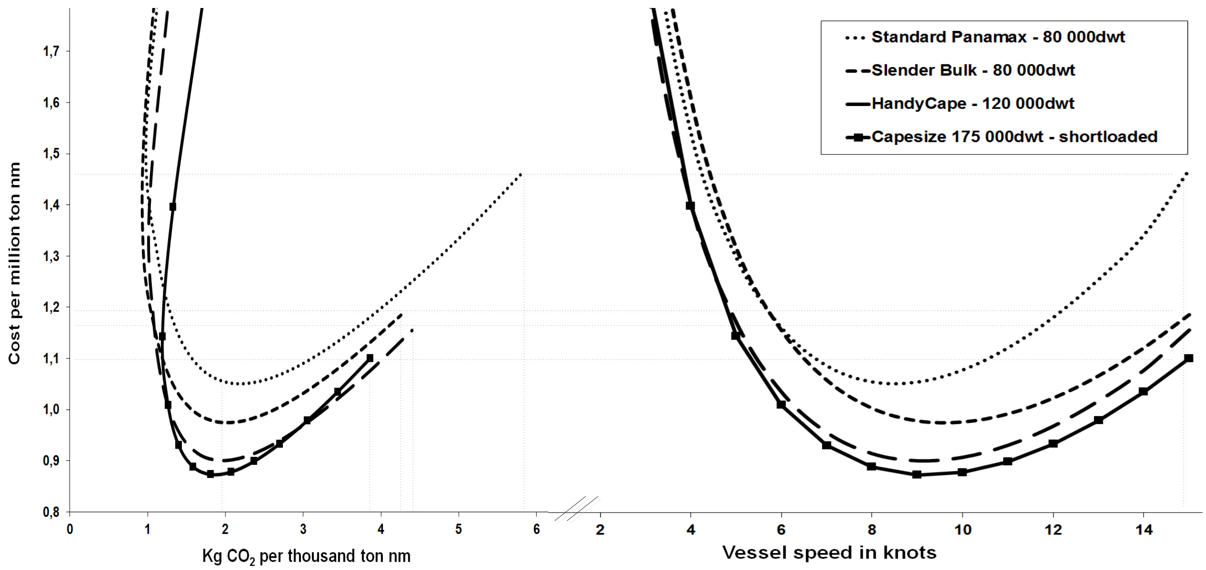

Figure: 1 Emission and cost as a function of vessel – speed, - design and - size

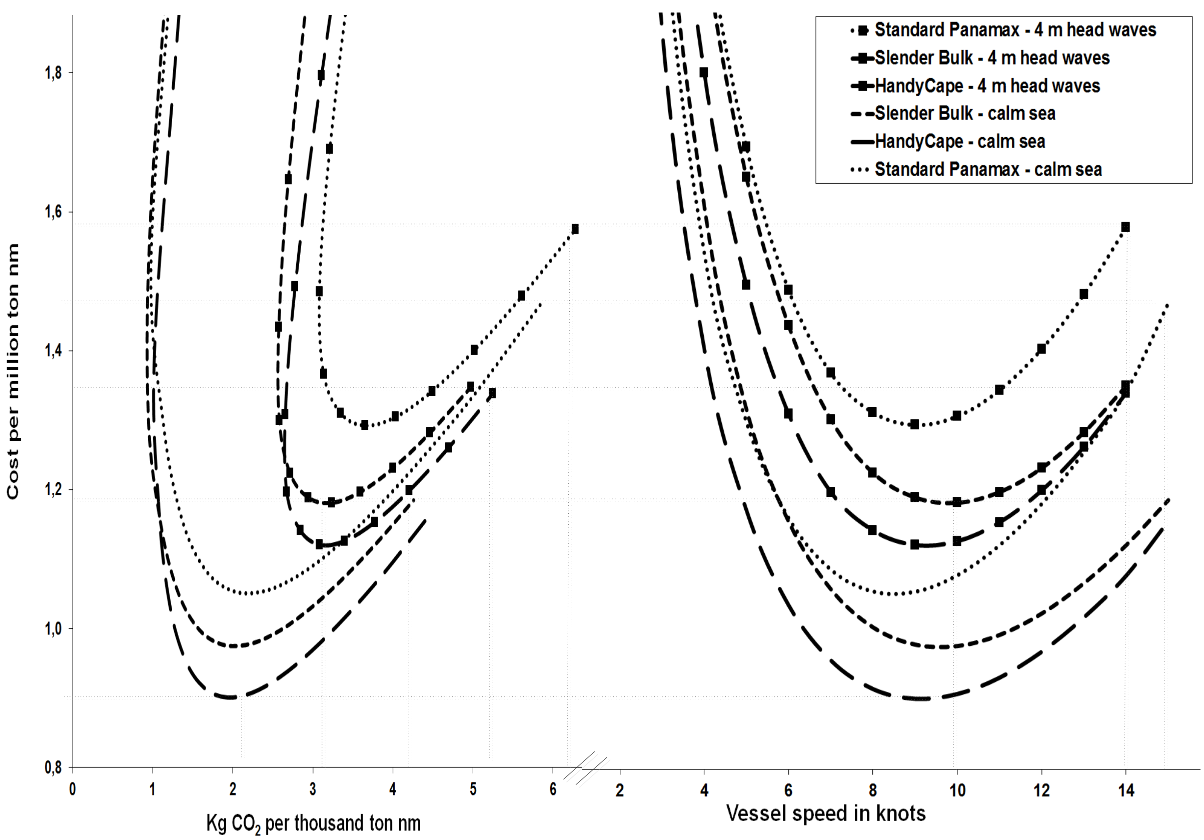

Figure: 2 Emission and cost as a function of vessel - speed, - design, - size and sea state

The graphs to the right demonstrate a minimum cost for a speed lower than the design speed for all the investigated vessels. And the graphs on the left hand side demonstrate a minimum emission for a speed lower than the design speed. This means that reducing speed from the design speed of 14 – 15 knots down to the cost minimum speed of 8 – 10 knots gives cost reduction in the size of 15 – 30 % per ton nm and emission reductions of 30 – 60 %.

Another observation is that the slender bulk vessel performs much better than the standard Panamax vessel. And when comparing between the slender bulk vessel and the Handy-cape, the Handy-cape is slightly better, but the difference is much smaller than what could be expected based on economies of scale effects [9]. This applies both with calm sea conditions and when we compare based on 4 meter head waves. These results implicates that more focus should be put on investigating the benefits of slender designs and that shipowners should consider to build slender bulk vessels to become more competitive. These slender bulk vessels will be even more competitive versus the Handy-Cape vessel in a future scenario where the expansion of the Panama Canal only marginally increases the standard bulk shipment sizes through the canal compared with the existing shipment sizes. A main argument for such a scenario is that there are size restrictions in the ports and fairways these vessels will be serving anyhow, in addition to limitations in the supply chains. Examples of supply chain restrictions are physical constraints such as storage capacities and increased financial cost for carrying large stocks in average.

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The Greening of the Maritime Supply Chain: in Search of Win-Win Solutions

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1 Introduction

Typical problems in maritime logistics include, among others, optimal ship speed, ship routing and scheduling, fleet deployment, fleet size and mix, weather routing, intermodal network design, modal split, transshipment, queuing at ports, terminal management, berth allocation, and total supply chain management. The traditional analysis of these problems has been in terms of cost- benefit and other optimization criteria from the point of view of the logistics provider, carrier, shipper, or other end-user. Such traditional analysis by and large either ignores environmental issues, or considers them of secondary importance. Green maritime logistics tries to bring the environmental dimension into the problem, and specifically the dimension of emissions reduction, by analyzing various trade-offs and exploring ‘win-win’ solutions. This paper takes a look at the trade-offs that are at stake in the goal of greening the maritime supply chain and takes stock at models that can be used to evaluate these trade-offs.

2 Trade-offs and win-win scenarios

Balancing the economic and environmental performance of the maritime supply chain may involve several trade-offs. A typical example can be seen by considering the impact of ship speed. Given that emissions grow as a non-linear function of ship speed, if ship speed were to be reduced, perhaps uniformly across the board, or even selectively for some categories of vessels (containerships being the most serious candidate), emissions would be reduced too, perhaps drastically. Reducing speed could also have important side benefits: cost reduction is one, and helping a depressed market in which shipping overcapacity is the norm these days is another. In that sense, reducing ship speed may conceivably be a ‘win-win’ proposition.

At the same time, reducing speed may have other ramifications which may not be beneficial. For instance, in the long run more ships will be needed to produce the same transport throughput, and this will entail some costs, some of them financial and some environmental (emissions due to shipbuilding, recycling, etc). Also, cargo in-transit inventory costs will generally increase, due to the increased transit time of the cargo. These inventory costs are proportional to the value of the cargo, so if a ship hauls high-value goods, sailing at a lower speed may entail significant costs to the shipper. Another side effect of speed reduction is that in the short run, freight rates will go up once the overall transport supply shrinks because of slower speeds. Reducing speed may help a depressed market, but it is the shippers who will suffer and in fact they will do so in two ways: they will pay more, and receive their cargo later. Yet another possible side effect concerns effects that speed reduction may have on other modes of transport, to the extent these are alternatives to sea transport. This is the situation as regards many short sea trades, in Europe but also in North America. If ships are made to go slower, shippers may be induced to prefer land-based transport alternatives, mostly road, and that may increase overall emissions, as road is certainly worse than maritime in terms of GHG emissions per tonne-km.

Issues such as the above, which have become more important in recent years, necessitate taking stock at models, studies or other research in which both the economic and environmental dimensions of the maritime supply chain are taken on board. However, even though the literature on the broad area of ship emissions is immense, it is mostly centered on aspects such as ship design, technology, propulsion, fuels, combustion, and impact of emissions on weather and climate. The literature on the interface between maritime logistics and environmental aspects is relatively scant. Still, there is some work that can be considered as relevant.

3 Problems and models

Among related references, Psaraftis and Kontovas [1] survey over 40 papers in which ship speed is a decision variable. Some of these papers deal with environmental aspects. For instance, Eefsen and Cerup-Simonsen [2] examine the tradeoffs between lower fuel costs and higher inventory costs associated with speed reduction, as well as their impact on emissions. Faber et al. [3] estimate that emissions of bulkers, tankers and container vessels can be reduced maximally by about 30% in the coming years by using the current oversupply to reduce speed, relative to the situation in 2007. Fagerholt et al. [4] consider a single route speed optimization problem with time windows and proposed a solution methodology in which the arrival times are discretized and the solution is based on the shortest path of the directed acyclic graph that is formed. Reduction in ship emissions are also computed. Qi and Song [5] investigate the problem of designing an optimal vessel schedule in the liner shipping route to minimize the total expected fuel consumption (hence also emissions) considering uncertain port times and frequency requirements on the liner schedule. Cariou [6] investigates slow steaming strategies especially in container shipping and measures the reduction of CO_2 achieved in various container trades. Lindstad et al. [7] present an analysis at the strategic level. They explore pareto-optimal policies and recommend speed limits as a possible way to achieve emissions reduction. An opposing view is presented by Cariou and Cheaitou [8], who investigate policy options contemplated by the European Commission and compare speed limits versus a bunker levy as two measures to abate GHGs. Gkonis and Psaraftis [9] have developed a series of models that optimize speed in both the laden and ballast legs for several tanker categories and for a variety of scenarios, and compute emissions reductions for these scenarios. In Psaraftis and Kontovas [10], the impact of speed reduction on modal split is investigated, in the sense that marine cargoes that go slower may choose land-based modes of transport, and increase overall emissions.

Port and terminal operations are another key component of the overall supply chain and the most feasible way to reduce time in port (with positive impact on emissions) is through operational decisions regarding quayside and yard operations, such as berth allocation, quay crane scheduling, vessel stowage and yard management (see Stahlblock and Voss [11] for a comprehensive survey). However, literature that combines logistical and environmental considerations, and especially within the terminals themselves, is quite scant. We discuss related trade-offs and the concept of 'virtual arrival'.

Last but not least, we review the results of EU project SuperGreen, especially as they relate to Key Performance Indicators (KPIs) for green transport corridors and the relationship between green corridors and the Trans-European Transport (TEN-T) core network [12]. Green corridors are defined as corridors that exhibit a set of desirable environmental and logistical attributes, and the TEN-T core network is a major pillar of the EU transport policy.

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Index of Authors