A Risk-Cost Approach to Routing & Scheduling Crude Oil Tankers

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Abstract

Maritime transportation, the primary mode for intercontinental movement of crude oil, accounts for 1.7 billion tons annually -bulk of which are carried by a fleet of large crude oil tankers. These tankers are very expensive to own and manage, and hence the relevant maritime literature has focused only on the cost-effective scheduling of these tankers. We argue that a cost-only approach may not be appropriate for a hazmat such as crude oil, since some of these shipments could lead to oil spills and occasional accidents resulting in significant environmental, social, and economic consequences. We propose a mixed-integer optimization program -with both the operating cost and transport risk objectives -for routing and scheduling a heterogeneous fleet of crude oil tankers. The optimization program was tested on realistic size problem instances to gain managerial insights.

Keywords
Marine Transportation, Crude Oil, Routing, Scheduling, Hazardous Materials

1. Introduction

Crude oil—one of the primary sources of energy, is procured from limited and dispersed sources around the world; this necessitates transportation over long distances. Bulk of this transportation is carried through maritime channels using very large and ultra large crude carriers (i.e., VLCC and ULCC). Volume of this maritime trade exceeds 1.7 billion tonnes annually (Rodrique et al., 2009). Maritime crude oil transportation has a long history of oil spills leading to significant environmental, social, and economic consequences. Two of the most prominent transportation-related oil-spill episodes are Exxon Valdez (United States) and Prestige (Spain), where the former necessitated a cleanup cost of over 2 billion dollars and the latter of around 100 million euros (ITOPF, 2009). Although disasters of such proportions are rare, smaller spills that still result in substantial cleanup costs are quite frequent (ITOPF, 2009). In this situation, a cost-only approach to transportation planning may not be appropriate, whereas the oil spills related risks deserves due attention (Siddiqui & Verma, 2013).

In response to these spills, various legislative measures have been put in place, such as MARPOL regulations covering pollution of the maritime environment from operational or accidental causes (IMO, 2011), the European Union the Erika legislative package for maritime safety (EU Legislations, 2011), and the United States the 1990 Oil Pollution Act (Douligeris et al., 1997). While these regulations have resulted in measures such as upgrading of fleet to the prescribed standards (e.g. single to double hulled tankers), interestingly, risk of oil-spill and its associated costs has not been explicitly incorporated in the intercontinental transportation planning. This is all the more important for international haulages, since 95% of the world’s ocean tonnage is insured through membership in one of the 17 not-for-profit prevention and indemnity (P&I) clubs. It is important to note a shipper’s insurance premium is established in accordance with the claims it is likely to bring to the club (Jin & Kite-Powell, 1999). Furthermore, these insurances provide only limited liability coverage (IMO, 2013), which means that rare catastrophic events that lead mostly to bankruptcies are not covered. It is thus imperative for an oil transporter to be cognizant of the potential oil spill risks resulting from routing and scheduling decisions. In this paper, we thus present a risk-cost based routing and scheduling framework for an oil supplier, who is serving multiple customers through alternative marine routes with varying risk-cost structures. An example of such a case is, a Middle Eastern crude oil supplier serving customers in North America and in Europe, using either the Suez Canal or going around the Cape of Good Hope. Here both routes differ significantly in distances (and thus cost) as well as in risk characteristics. It was observed that shorter (and less costly) routes may not necessarily be better from the perspective of risk, since the cost savings do not compensate for the increase in expected risk.
The rest of the paper is organized as follows. Section 2 provides a brief literature review, while problem definition is presented in section 3. The bi-objective risk-cost model, as well as the related parameter estimation is presented in section 4. Section 5 shows results from a numerical study performed over a realistic problem instance. Conclusions of the study are presented in Section 6.

2. Literature Review

In this section, we review the most relevant streams of research on: routing and scheduling of oil tankers; and, maritime transportation of hazardous materials (hazmat).

2.1. Routing and Scheduling

Earliest model that considers oil tanker scheduling is by Dantzig and Fulkerson (1954), who presented an integer programming model that minimized the total number of tankers under a fixed oil supply schedule. Their problem were extended by Briskin (1966) for the case of full shipload demand and a cluster of ports; and also by Bellmore (Bellmore, 1968) for the under capacity fleet situation. More recently, Brown et al. (1987) proposed an optimization model to solve a routing and scheduling problem, for a given set of cargo, faced by a supplier making crude oil shipments from the Middle East to Europe and to North America. Dealing with a very similar problem, Perakis and Bremer (1992) presented an integer programming formulation, whereas the algorithmic details and test results were presented in Bremer and Perakis (1992). Bausch et al., (1998) on the other hand developed a decision support system for the problem involving daily dispatch of liquid bulk products by ships and barges. Sherali et al., (1999) investigated the scheduling of a heterogeneous fleet of compartmentalized ships to transport a set of non-mixing cargo, and proposed a rolling horizon heuristic to solve the mixed-integer program. Finally, three works are reported that consider an alternative approach of arbitrary splitting of demand into multiple shipments. In this direction, McKay and Hartley (1974) proposed an integer programming formulation for oil tanker scheduling that permitted arbitrary splitting of ordered quantities. Similarly, Hennig et al. (2012) considered a case of multiple grades of crude oil, pickup and delivery time windows, and unpaired supply and demand quantities. Most recently, Siddiqui and Verma (2013) also proposed a mixed-integer program to solve the scheduling problem faced by an oil supplier, which is for a single grade of crude with global customers, and supply-quota and port-capacity constraints. All three allowed arbitrary splitting of bulk customer demand.

2.2. Hazmat Transportation

The literature considering hazmat transportation risk can be grouped under three threads: risk assessment; spill-cost estimation; and, risk-based routing. Under the first stream, one of the important pieces of work was the development and the use of U.S. Natural Resource Damage Assessment Model for Coastal and Marine Environment proposed in Grigalunas et al., (1988), which in turn spurred a number of relevant works focused mostly in the Gulf of Mexico (Li et al., 1996,Iakovou et al., 1999,Yudhbir & Iakovou, 2001). Most recently, Siddiqui and Verma (2013) have proposed an expected consequence approach for assessing oil-spill risk from intercontinental transportation of crude oil. The second stream – oil-spill cost estimation, received more attention, whereas notable works was reviewed in detail by Siddiqui and Verma (2013). Briefly, Etkin (1999) analyzed the oil-spill intelligence report international database to develop the basic estimates of area-wise cleanup cost, which were then revised to account for cleanup strategy, size of spill, oil type, and shoreline oiling (Etkin, 2000). Vanem et al., (2008) revised the numbers presented in Etkin (1999) and identified three main types of damage costs, i.e., cleanup, environmental, and socioeconomic. Later non-linear regression models of a similar form were proposed by Yamada (2009), Kontovas et al., (2010), Psarras et al., (2011) respectively, which were calibrated using different database including that of International Oil Pollution Compensation Funds (ITOPF) database. Finally, relevant to the third stream – risk-based routing, Li et al., (1996) developed a comprehensive model for the marine oil transportation in the Gulf of Mexico, which solves a case of oil flow distribution in a multicomodal and multipurpose network. In a subsequent work, the above idea was expanded to include multiple O-D hazmat routing planning for the Gulf of Mexico (Iakovou et al. 1999); in contrast, Iakovou (2001) presented a strategic interactive multi-objective network flow model that allowed for risk analysis and routing, which again was intentioned to help regulators assess risk and derive desirable routing schemes.
3. Problem Description

In this section, we briefly discuss the problem definition and the basic modeling assumptions. We consider the case of an oil supplier, who is preparing a routing and scheduling plan using an available fleet of large oil tankers. These tankers may access a customer location using multiple routes having different cost and risk structures. Note that we are assuming a single supply port situation only. However, the assumption may not be as restrictive given that most large suppliers either have a single supply port or a group of ports located in close vicinity (and thus assumed aggregated into a single port), while customers mostly at distant locations. Customer demand at any customer port (or group of ports) is defined periodically, which is characterized by quantity demanded in a demand period and a delivery time-window defining that period. Finally, a number of delivery periods constitute the planning horizon of interest, which would start with the receipt of orders and end when all demand time-windows are covered. It is also important to note that route choices between a pair of supply-demand ports pair is a function of the individual vessel. That is, the physical size and carrying load of a vessel may eliminate some available route choices due to the present geographical limitations (e.g. canal size restrictions).

Before outlining the mathematical program in section 4, we list key model assumptions: 1) demand (known) is defined periodically, 2) single pick-up and single full-delivery at customer locations, 3) no return cargoes, 4) a heterogeneous fleet of owned tankers 5) tankers not necessarily return to the supply point within the planning horizon, and that they become available for service at different times due to prior commitments, and 6) only one supply source is available.

4. Bi-Objective Risk-Cost Model

In this section, we present the basic notations as well as the bi-objective risk-cost optimization model. However, we first outline three key definitions. Route: A complete path followed by a tanker, which starts from the supply point, passes through a delivery point \( d \) and returns back to the supply point. Voyage: Comprises of all elements of an oil tanker journey on a route i.e. waiting for loading at the supply point, the loading of crude oil, traveling to a demand point, unloading and then returning to the supply point. Loaded Leg: Partial voyage of a tanker till it finishes unloading at a demand point. Return Leg (Ballast): Partial voyage starting from the return of a tanker from a demand point to its supply point.

Sets and Indices
\( D \): Set of demand points, indexed by \( d \)
\( V_d \): Set of vessels, indexed by \( v \), compatible/allowed to service at demand point \( d \)
\( \Gamma_v \): Set of all routes available for vessel \( v \in V_d \), to deliver crude oil to demand point \( d \)
\( I \): Number of requirement periods at a customer location, indexed by \( i \)
\( j \): Trip number index

Variables:
\[
X_{vrji} = \begin{cases} 
1 & \text{if vessel } v \text{ using route } r_i \text{ during trip } j \text{ delivers oil to demand point } d \text{ in period } i \\
0 & \text{otherwise}
\end{cases}
\]
\( B_v^j \): Waiting/idling time of vessel \( v \) (at the supply point) before starting trip \( j \)
\( L_v^j \): Time until vessel \( v \) finishes loaded-leg on trip \( j \)
\( E_v^j \): Time until vessel \( v \) finishes (or ends) its voyage on trip \( j \)

Parameters:
\( Q_i^d \): Quantity of crude oil demanded at a customer location \( d \) during requirement period \( i \)
\( K_v^d \): Available cargo carrying capacity of vessel \( v \), to a demand point \( d \), when taking route \( r \)
\( A_v^d \): Percentage allowance on periodic requirements at \( d \) (due to contractual flexibility on customer demand (Sherali et al., 1999))
**Cost:**

\[ C_{vr}^d \] : Total trip cost to deliver crude oil by vessel \( v \), to a demand point \( d \), when using route \( r \)

\[ IC_v \] : Idling cost per unit time of vessel \( v \)

**Risk:** (in equivalent dollar amount)

\[ G_{vr}^d \] : Risk associated with a crude oil delivery by vessel \( v \), to a demand point \( d \), when using route \( r \)

**Time:**

\[ T(L)_r^d \] : Time needed by vessel \( v \), for the loaded leg, to demand point \( d \) using route \( r \)

\[ T(E)_r^d \] : Time needed by vessel \( v \), for the return (or empty) leg, from demand point \( d \) using route \( r \)

\[ T_s \] : Time until vessel \( v \) is available for service at the supply point (starting service time)

\[ TL_v \] : Time needed to load vessel \( v \)

\[ TU_v^d \] : Time needed to unload vessel \( v \), at demand point \( d \)

\[ ET_v^d \] : Earliest delivery time at \( d \) for period \( i \)

\[ LT_v^d \] : Latest delivery time at \( d \) for period \( i \)

\( \tau \) : Maximum number of allowable trips in a planning horizon

**Periodic Requirements based Routing and Scheduling Model – With Risk:**

(PRRS-WR)

**Minimize**

\[
\text{Cost: } \sum_{v \in V, i \in I, r \in R} \sum_{r \in R} \sum_{d \in D} C_{vr}^d X_{vr}^d + \sum_{r \in R} IC_v \left( \sum_{j \in J} B_v^j \right)
\]  

(1)

**Risk:**

\[
\text{Risk: } \sum_{v \in V, i \in I, r \in R} \sum_{r \in R} \sum_{d \in D} G_{vr}^d X_{vr}^d
\]

Subject to:

**Demand Fulfillment:**

\[
\sum_{v \in V, r \in R} \sum_{d \in D} K_{dr}^v X_{vr}^d \geq Q^i \left( 1 - A_i^d \right) \quad \forall d \in D, i \in I
\]  

(2)

**Delivery Window:**

\[
\sum_{r \in R} ET_v^d X_{vr}^d - P \left( 1 - \sum_{r \in R} X_{vr}^d \right) \leq L_v^d \leq \sum_{r \in R} LT_v^d X_{vr}^d + P \left( 1 - \sum_{r \in R} X_{vr}^d \right)
\]  

\[
\forall v \in V_d, 1 \leq j \leq \tau, d \in D, i \in I
\]  

(3)

\[
L_v^d = T_s + B_v^d + \sum_{d \in D, r \in R} \sum_{r \in R} (TL_v^d + T(L)_r^d + TU_v^d) X_{vr}^d \quad \forall v \in V_d
\]  

(4)

\[
L_v^d = E_v^{i-1} + B_v^d + \sum_{d \in D, r \in R} \sum_{r \in R} (TL_v^d + T(L)_r^d + TU_v^d) X_{vr}^d \quad \forall v \in V_d, 2 \leq j \leq \tau
\]  

(5)

\[
E_v^d = L_v^d + \sum_{d \in D, r \in R} \sum_{r \in R} T(E)_r^d X_{vr}^d \quad \forall v \in V_d
\]  

(6)

\[
E_v^d = L_v^d + \sum_{d \in D, r \in R} \sum_{r \in R} T(E)_r^d X_{vr}^d \quad \forall v \in V_d, 2 \leq j \leq \tau
\]  

(7)

**Structural:**

\[
\sum_{d \in D, r \in R} \sum_{r \in R} X_{vr}^d \leq 1 \quad \forall v \in V_d, 1 \leq j \leq \tau
\]  

(8)

\[
\sum_{d \in D, r \in R} \sum_{r \in R} X_{vr}^d \leq \sum_{d \in D, r \in R} \sum_{r \in R} X_{vr}^{(j-1)d}
\]  

\[
\forall v \in V_d, 2 \leq j \leq \tau
\]  

(9)
(PRRS-WR) is a bi-objective mixed-integer programming formulation. Here, the cost objective in (1) represents the total cost of operations resulting from all the voyages made by vessels and the idling/waiting cost of vessels at its supply point. The risk objective in (1) represents the total risk resulting from the same vessel voyages (as in the cost objective). Constraints to the problem i.e. constraints (2) – (10), for expositional reasons, are divided into three categories: demand fulfillment, delivery window, and structural, which are presented as follows:

Constraints (2) ensure that the total committed delivery capacity to location \( d \) in period \( i \) equals or exceeds the requirement. Note that here that the capacities of tankers are a function of demand point being served and the route being used. Furthermore, the route choices to \( d \) are dependent upon individual vessels together with the route characteristics. It is important to note that the proposed model will only assign a set of vessels with sufficient total capacities, which the transport manager would use to meet demand for a requirements period by distributing the ordered quantity amongst the recommended vessels.

Constraints (3) – (7) concern delivery time windows and the associated variables. Constraints (3) ensure that vessel \( v \) on trip \( j \) makes a delivery at demand location \( d \) in period \( i \) feasibly, i.e. \( X_{v}^{ij} = 1 \) when \( L_{v} \) (the time until vessel \( v \), during trip \( j \), finishes its loaded leg) falls within the relevant time window. The relationship between \( X_{v}^{ij} = 1 \) and the corresponding \( L_{v} \) is established through constraints (4) – (7). Where constraints (4) estimate the time until vessel \( v \) finishes its first loaded leg, constraints (5) indicate vessel availability for all other used trips, and constraints (6) and (7) estimate \( E_{v}^{i} \) and \( E_{v}^{j} \) (time until a voyage ends for vessel \( v \), during trip \( j \)), which is required in constraints (5).

Please note that travel times are a function of route a tanker takes. Also note that we have defined \( r \) as the maximum allowable trips during a planning horizon, which bounds the actual number of used trips. Assuming \( j \) to be the last used trip by vessel \( v \), then for the remaining unused trips, (5) yield \( L_{v}^{in} = L_{v} \ \forall \ 1 \leq o \leq (r - j) \).

Constraints (8) – (9) ensure the structural integrity of the problem. Constraints (8) ensure that vessel \( v \) on trip \( j \) makes a single delivery of the entire cargo, while (9) ensures that trip \( j \) for a vessel is utilized if and only if \( j - 1 \) has already been utilized i.e. enforcing trip sequencing. Finally, constraints (10) ensure the integer and sign restrictions of the variables used.

### 4.1. Parameters Estimation

For each vessel, four sets of parameters have to be estimated, and they are: capacity; operating cost; travel time; and, risk for each route.

#### 4.1.1. Capacity

As discussed in the problem description (section 3), the capacity of a tanker varies with its destination (due to demand point restrictions) as well as the route it takes to that destination. If \( H_{r} \) represents ports handling capacity in terms of maximum weight a vessel can carry, and \( \bar{K}_{r}^{v} \) represents the maximum carrying capacity of a vessel on route \( r \), then \( K_{r}^{v} \) can simply be estimated as: \( K_{r}^{v} = \min(H_{r}, \bar{K}_{r}^{v}) \).

#### 4.1.2. Risk

To estimate risk parameters \( G_{r}^{d} \) we resorted to the approach of (undesirable) expected consequence proposed in Siddiqui and Verma (2013), which defines risk as the probability of accident times the resulting consequence – the traditional risk. We thus consider a route-link \( l \) of known length, for a vessel \( v \) traveling on a route \( r \) to a demand point \( d \). This link is assumed to have homogeneous characteristics relevant to the risk being estimated i.e. the probabilities of accident and the associated per unit cost structure do not change within the link. If for this link \( l \), \( p_{l}^{M} \) and \( p_{l}^{m} \) are the probabilities of a tanker meeting with an accident resulting in major (\( S_{l}^{M} \)) or minor spills (\( S_{l}^{m} \)) respectively, then the risk of an accident leading to oil spill by a vessel \( v \) i.e. \( g_{v}^{d} \) can be represented as:

\[
g_{v}^{d} = p_{l}^{M} S_{l}^{M} AC_{l}^{M} + p_{l}^{m} S_{l}^{m} AC_{l}^{m}
\]

Here \( AC_{l}^{r} \) is the per unit oil-spill cost on link \( l \). It should be clear that the risk for a whole route, e.g. the one composed of two links \( l \) and \( l+1 \), is a probabilistic experiment since the expected consequence for link \( l+1 \) depends on whether the tanker meets with a major accident on the first link \( l \) or not. Hence, the expected consequence for link \( l+1 \) is: \((1 - p_{l+1}^{M})(p_{l+1}^{M} S_{l+1}^{M} AC_{l+1}^{M} + p_{l+1}^{m} S_{l+1}^{m} AC_{l+1}^{m}) \). Thus to generalize for the whole route \( r \) having \( s \) links, we evaluate the

Variable Types:

\[
X_{w}^{ik} \in \{0,1\}, B_{v}^{i} \geq 0, L_{v}^{i} \geq 0, E_{v}^{i} \geq 0
\]
total route risk \( G_{sr}^d \) in a similar manner i.e. using an event tree built-up along the links of a route. Thus we assume that the loaded leg segment, carrying crude oil and bunker fuel supplies, is divided into \( s \) segments (i.e. indexed 1,2,...,s) while for the return leg, carrying bunker fuel supplies only, the links are indexed from \( s+1 \) to \( s \). Thus the expected consequence over the whole route \( r \) i.e. \( G_{sr}^d \) can be expressed as:

\[
G_{sr}^d = g_{vr}^d + \sum_{k=1}^{s} \left( g_{vr}^{dk} \prod_{j=2}^{k} (1 - p_{j-1}^d) \right) + \sum_{k=s+1}^{s'} \left( g_{vr}^{dk} \prod_{j=2}^{k} (1 - p_{j-1}^d) \right)
\]

Here the first term represents the risk of spillage in the first link; the second term represents the risk of spillage on the remaining links of the loaded leg; while the third term represents the corresponding risk on the return leg segment of the journey. Expression in equation (12) requires three more parameters i.e. the probabilities of accidents, the spill sizes and adjusted cost per tonne of spillage which are calculated as follows:

**Probability of accident:** Oil-spill statistics from 1974 to 2010 was parsed, and the around 1200 relevant data points representing major spill were spliced in a maritime map comprised of Marsden squares, which are physical spaces defined by 10 degrees each of longitude and latitude. The number of accidents resulting in major spills was divided by the total number of tanker voyages through a given square to yield the respective probability. Probability of minor spill on the other hand was calculated by determining the probability of a major spill for a square (or a link) with identical flow density; and then prorating the average probability using the historical split of 0.81 and 0.19 for minor and major spills, respectively.

**Size of oil-spill:** For \( S_l^d \) i.e. large spill size, we assume the full cargo loss scenario, thus \( S_l^d \) will be estimated as \( S_l^d = K_s^d \) for the loaded leg, while for the return leg we will use the bunker fuel amount loaded for the return route segment. It is important to note that the full spill scenario entails the most conservative approach for a decision maker and alternative approach, e.g. average spill size can be used (Siddiqui & Verma, 2013). However, we argue for its justification given 1) rare extreme events are not covered by the insurance, and 2) from the overall socio-economic, political and environmental stand points, averting such catastrophic spills are essential. For minor spills, we assume the threshold value of 7 tonnes which is the largest value defined for minor spills.

**Cost of oil-spill:** Although Siddiqui and Verma (2013) have presented results using four of the most popular spill-cost estimation models available in maritime literature, it was demonstrated that using the only linear model by Etkin (1999) together with the nonlinear model of Psarros et al. (2011) may be enough to get meaningful results. Thus the two models were used to estimate per-unit cost of oil spill using the following two equations.

\[
g_{vr}^d = p_{vr}^d (S_l^d AC_l^d) + p_{vr}^m (S_l^m AC_l^m)
\]

where:

\[
AC_l^d = 2.5C_i^d \times (SLO \times OT \times CLS \times SS)
\]

\[
g_{vr}^d = \{p_{vr}^d (S_l^d)^{0.6472} + p_{vr}^m (S_l^m)^{0.6472}\} \times 61150
\]

5. **Problem Setting**

We focus on the tanker fleet operation of Vela International Marine Limited (www.vela.ae), the wholly owned subsidiary of Saudi Aramco – the largest producer and exporter of crude oil. Vela is primarily responsible for deliveries to North America and Europe, which is handled from its Persian Gulf ports (Figure 1). The distance from its supply point to the U.S. Gulf of Mexico demand point when the south route (around Africa) is used is 12084 nautical miles, while it is 6792 nautical miles when the north route (passing through the Suez Canal) is used. Similarly for Europe, the lengths of the south and the north routes are 6393 and 3803 nautical miles respectively. Vela assumingly use a heterogeneous fleet of tankers that includes 10 VLCC class tankers (>200,000 DWT), besides tankers of other classes including 10 Suezmax (120,000–199,999 DWT) and 10 Aframax (80,000–119,999 DWT) tankers.
The periodic crude oil requirements for the U.S. (through the Gulf of Mexico region) is based on the June, 2011 oil import data from Saudi Arabia (www.eia.gov), while the European numbers are approximated to be 25% of the U.S. oil demand (Table 1).

<table>
<thead>
<tr>
<th></th>
<th>US</th>
<th>Europe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week1</td>
<td>1174.6</td>
<td>293.7</td>
</tr>
<tr>
<td>Week2</td>
<td>466</td>
<td>100.8</td>
</tr>
<tr>
<td>Week3</td>
<td>1000.8</td>
<td>216.4</td>
</tr>
<tr>
<td>Week4</td>
<td>1140.2</td>
<td>246.6</td>
</tr>
</tbody>
</table>

Table 1: Weekly Crude Oil Imports in K. Tonnes (Source: www.eia.gov)

5.1. Problem Solution

To solve PRRS-WR, we employ a weighted sums approach to solve the problem. Thus the objective function (1) is re-written as:

$$\text{Min } \alpha \left( \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{l} \sum_{d=1}^{D} C_{w,d}^{i} X_{w,d}^{i,j} + \sum_{j=1}^{m} J C_{v} \left( \sum_{r=1}^{R} B_{r} \right) \right) + (1-\alpha) \left( \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{l} \sum_{d=1}^{D} G_{w,d}^{i} X_{w,d}^{i,j} \right)$$

(15)

Where $\alpha$ is the weight associated with the operational cost function and $(1-\alpha)$ the weight associated with the risk function. For the base-case analysis we set $\alpha=0.5$ and $(1-\alpha)=0.5$ i.e. equal weight for both the cost and the risk objectives. The other parameters are estimated using the method described in section 4.1 for the Vela case. The problem instances were solved using CPLEX 12.1 (IBM, 2010), with the input files generated using MATLAB (Mathworks, 2004). The base-case of (PRRS-WR) contained 1782 variables, including 1600 binary variables, and 1180 constraints. The solution to both the problems i.e. where risk parameters are generated by Etkin’s (2000) and the Psarros et al. (2011) models are presented in Table 2. Problem with Etkin’s (2000) is solved within 1% gap to optimality when the solution is terminated at 1000 seconds, while with Psarros et al. (2011) the problem was fully solved within 24.32 seconds. The total optimal risk when risk parameters are based on Etkin’s (2000) model is around $693 million, while it is around $119 million when the Psarros et al. (2011) model is used. The large discrepancy in the two total-risk values is expected as Etkin’s (2000), due to its linear form, estimate values that are far inflated as compared to the Psarros et al. (2011) model when spill sizes are large i.e. roughly over the average major spill size of 3181 tonnes. The total operational costs with the two models are shown to be around $9.4 million and $9.6 million respectively. Note that the total risk values appear much larger than the total operational cost values; this is because the risk estimates are based on full loss scenarios resulting in highly conservative (large) values for the risk parameters.

<table>
<thead>
<tr>
<th></th>
<th>Total Cost (million)</th>
<th>Total Risk (million)</th>
<th>VLCC Trips</th>
<th>Suezmax + Aframax Trips</th>
<th>Total Trips</th>
<th>Through Longer Routes</th>
<th>S. Time (Secs.)</th>
<th>Gap (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Etkin’s</td>
<td>9.38</td>
<td>692.95</td>
<td>7</td>
<td>17</td>
<td>24</td>
<td>24</td>
<td>1000</td>
<td>0.28</td>
</tr>
<tr>
<td>Psarros</td>
<td>9.60</td>
<td>119.34</td>
<td>10</td>
<td>11</td>
<td>21</td>
<td>21</td>
<td>24.32</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table 2: Solution of the Base-Case
In terms of vessel preference, the solution with Etkin’s (2000) model clearly shows a higher preference for smaller ships i.e. it relies on only seven VLCC class vessels which is ten when the Psarros et al. (2011) model is used. The total number of vessel trips in the first case is 24 while it is 21 (due to heavier reliance on larger ships) in the second case. It is also notable that all the trips are scheduled through longer routes to both the U.S. and the European destinations i.e. using the south route passing around the Cape of Good Hope (South Africa). This is reasonable as given the larger values of the risk estimates \(G^d_v\), compared to the corresponding cost values \(C^d_v\); the vessels avoided the riskier although cheaper routes i.e. the riskier north routes passing through the Suez Canal.

5.2. Risk-Cost Tradeoff Analysis

The base-case presented in section 5.1, assumes equal weights to both the risk and cost functions. We also performed an analysis where the weight \(\alpha\) is varied from 1-0 i.e. covering the full range of risk-cost preferences between the two extreme cases of pure cost minimization (\(\alpha=1\)) and pure risk minimization (\(\alpha=0\)) problems. The results are shown in Figure 2 (showing plots of Pareto frontier of non-dominated solutions) for the two cost-of-spill models used.

![Figure 2: Risk-Cost Curve (Left: Etkin's, Right Psarros et al.)](image)

In these problems, especially where Etkin’s (2000) model is used, the results (similar to the ones presented in Table 2) show a much greater dominance of risk minimization as compared to cost except for \(\alpha\) values very close to 1. Note that, any adjustment in risk/cost can be achieved through adjusting the two factors i.e. the number (or the size - resulting in proportional sizes of spill scenarios) of the vessels utilized and the longer and safer vs. shorter and riskier routes used. The employment of these factors in the solutions with the Psarros et al. (2011) estimates is relatively straightforward, i.e. as the weight on the risk function increases, the trend is to firstly to use fewer (& consequently bigger) vessels, then to increasingly schedule these vessels over lengthier but safer routes. For example, with \(\alpha = 1\) total number of tankers in Psarros et al. (2011) are 21 (10 VLCCs) will all tankers taking the African route. The first approach i.e. fewer vessels reduces the risk by reducing the number of trips while the second approach reduces risk by routing vessels through the safer but more expensive routes. In the cases where Etkin’s (2000) estimates are used, risk reduction is primarily achieved through using the lengthier routes. The results also showed a tendency towards using smaller sized vessels. This is explainable, as with the Etkin’s (2000) model, larger vessels results in very high-risk estimates. In this case, with \(\alpha = 1\) total number of tankers 25 (6 VLCCs) with all tankers tanking African Route. All the problems are either solved to optimality or are seen to be well within 1% gap to optimality whereas the termination is set to 1000 seconds.

6. Conclusions

In this paper, we presented an integrated approach towards the risk-cost based routing and scheduling of crude oil deliveries. The results show that risk is a major factor, which if ignored in the delivery scheduling planning, may bear significant risk-related cost consequences. In fact, the risk factor appears to dominate the operational cost factor due to large risk estimates for individual tanker voyages. This is even more prominent when these risk estimates are based on the linear Etkin’s (2000) model. An important point here is that we have varied the weight \(\alpha\) values (between 0-1) to capture the full range of preferences of a decision maker i.e. between cost and risk. However,
determination of its suitable value, in a real world situation, is an important question that needs to be addressed and is not analyzed in our work.

In terms of solution, the model seems to balance the total risk and total cost values by either controlling the type (or size) of vessels or through exploiting the routing options. Use of these two options is more prominent when the risk estimates are based on the Psarros et al. (2011) model. In contrast, with the Etkin’s (2000) model resulting in highly inflated risk estimates, the model seems to rely more on the smaller vessels with the routing options balancing the risk and cost factors.

This work can be extended in many different ways. For example, we assumed crude oil to be delivered only, which is moved from its supply to demand points i.e. the cargo moving in one direction only. With smaller class vessels i.e. Suezmax and Aframax capable of carrying petroleum products, the problem can be extended for the case of multi-product deliveries, which can assume ports acting as both supply points and demand points and the products being transported in both directions.

References

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