European Journal of Operational Research 238 (2014) 858-862

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Innovative Applications of O.R.

Distribution-free vessel deployment for liner shipping

ManWo Ng*

Department of Modeling, Simulation and Visualization Engineering, Old Dominion University, 1318 Engineering and Computational Sciences Building, Norfolk, VA 23529, USA Department of Information Technology and Decision Sciences, Old Dominion University, Norfolk, VA 23529, USA

A R T I C L E I N F O

Article history: Received 23 January 2014 Accepted 13 April 2014 Available online 24 April 2014

Keywords: Transportation Liner fleet deployment Liner shipping Container shipping Maritime transportation

ABSTRACT

One important problem faced by the liner shipping industry is the fleet deployment problem. In this problem, the number and type of vessels to be assigned to the various shipping routes need to be determined, in such a way that profit is maximized, while at the same time ensuring that (most of the time) sufficient vessel capacity exists to meet shipping demand. Thus far, the standard assumption has been that complete probability distributions can be readily specified to model the uncertainty in shipping demand. In this paper, it is argued that such distributions are hard, if not impossible, to obtain in practice. To relax this oftentimes restrictive assumption, a new distribution-free optimization model is proposed that only requires the specification of the mean, standard deviation and an upper bound on the shipping demand. The proposed model possesses a number of attractive properties: (1) It can be seen as a generalization of an existing variation of the liner fleet deployment model. (2) It remains a mixed integer linear program and (3) The model has a very intuitive interpretation. A numerical case study is provided to illustrate the model.

© 2014 Elsevier B.V. All rights reserved.

1. Introduction

The massive scale of global freight movement observed today would not have been possible without maritime transportation (Talley, 2009). Indeed, estimates of the tonnage transported in world trade by sea are as high as 90% (Rodrigue, Comtois, & Slack, 2009). One important sector within the shipping industry is liner shipping. A liner shipping company transports cargo, following a published sailing schedule on the routes it serves (Bell, Liu, Rioult, & Angeloudis, 2013; Plum, Pisinger, Salazar-González, & Sigurd, 2014). Competition among ocean carriers is known to be especially fierce in liner shipping (Talley, 2012).

Liner companies face various routing and scheduling problems at the strategic, tactical, and operational planning levels (e.g. see Christiansen, Fagerholt, Nygreen, & Ronen, 2013; Kosmas & Vlachos, 2012; Meng, Wang, Andersson, & Thun, 2014; scheduling in liner shipping: overview, 2014; Mulder & Dekker, 2014; Pantuso, Fagerholt, & Hvattum, 2014; and the references therein). One critical decision at the tactical planning level is the fleet deployment problem in which the number and type of ships to be assigned to the various shipping routes need to be determined in order to maximize their profits, while at the same time ensuring that (most of the time) sufficient vessel capacity exists to meet shipping demand. This fleet deployment problem has been first addressed in the literature by Perakis and Jaramillo (1991) and Jaramillo and Perakis (1991) who formulated (integer) linear programming models to solve this planning problem. In these early and subsequent studies (such as Gelareh & Meng, 2010; Liu, Ye, & Yuan, 2011), shipping demand has been assumed to be known with complete certainty. Only until recently has this assumption been relaxed, and has shipping demand been more realistically modeled as random variables (e.g. see Meng & Wang, 2010; Meng, Wang, & Wang, 2012; Wang, Meng, Wang, & Tan, 2013). It is interesting to note that other researchers, assuming deterministic demand, have embedded the fleet deployment problem within the liner shipping network design problem (e.g. see Brouer, Alvarez, Plum, Pisinger, & Sigurd, 2014 and Plum, Pisinger, & Sigurd, 2013).

In this paper, we further advance the stochastic modeling of the liner ship fleet deployment problem introduced by Meng and co-workers by relaxing the currently standard assumption that probability distributions are readily available to characterize uncertain shipping demand (cf. Ben-Tal & Nemirovski, 2002). Indeed, there might be a lack of historical data to estimate these distributions with confidence (especially when there is a new shipping route), or historical data might simply not be representative due to a changing economic outlook. In the proposed modeling approach, instead of having to specify complete probability distributions, a distribution-free approach is adopted in which the modeler only needs to specify the mean, standard deviation and an upper bound on the shipping demand. Clearly, these quantities





CrossMark

form a strict subset (i.e. they are easier to specify) of what is needed in order to specify a complete probability distribution (cf. Meng & Wang, 2010; Meng et al., 2012; Wang et al., 2013). Another attractive feature of our approach is that the computational requirements remain unchanged compared to current state-of-the-art fleet deployment models that account for demand uncertainty through complete probability distributions. More specifically, as in currently available models, the proposed model is of the mixed integer linear programming class. Lastly, the proposed modeling approach has a very intuitive interpretation.

The remainder of this paper is organized as follows. In Section 2, a brief review of a variation of a currently available stochastic demand fleet deployment model is presented, followed by the proposed distribution-free model. Fundamental properties of the model are analyzed and discussed. Section 3 provides a case study to illustrate the model. Finally, Section 4 summarizes and concludes the paper.

2. Model formulation and properties

Before we introduce the proposed distribution-free model, let us first briefly review a recent variation of the liner fleet deployment problem that accounts for stochastic shipping demand, e.g. see Meng and Wang (2010) and Wang et al. (2013). To this end, let us first define some notation.

Sets	
R	set of routes
Κ	set of ship types
Para	neters
C_{kr}^{v}	the operating cost of a voyage for a ship of type
	$k \in K$ on route $r \in R$
C_k^i	the cost of chartering in a ship of type $k \in K$
C_k^0	the revenue of chartering out a ship of type $k \in K$
l_k	the number of ships of type $k \in K$ available in the
	liner company's own fleet
m_k	the maximum number of ships of type $k \in K$ that
	can be chartered from other ship owners
n _r	the number of voyages required on route $r \in R$ to
	maintain the liner's desired minimum sailing
	frequency
р	the planning horizon under consideration (in
	days)
t _{kr}	the transit time of a ship of type $k \in K$ to traverse
	router $\in R$ (in days)
q_k	the capacity of a ship of type $k \in K$ (in TEU)
α_r	the maximum probability the liner company fails
	to meet shipping demand on route $r \in R$
D_r	the maximum (random) shipping demand
	among all legs of the voyage on route $r \in R$
Decis	sion variables
u_{kr}	the total number of ships of type $k \in K$ to be
	deployed on route $r \in R$
v_k	the number of ships to be chartered from other
	ship owners
w_k	the number of ships to be chartered out
x_{kr}	the number of voyages ships of type $k \in K$
	completes on route $r \in R$

One variation of the liner fleet deployment problem with uncertain shipping demand can now be stated as Model (P1):

Model (P1)

$$\min \quad \sum_{k} \sum_{r} c_{kr}^{\nu} x_{kr} + \sum_{k} c_{k}^{i} v_{k} - \sum_{k} c_{k}^{o} w_{k} \tag{1}$$

subject to:

$$\sum_{r} u_{kr} \leqslant l_k + v_k, \quad \forall k \in K$$
(2)

$$v_k \leqslant m_k, \quad \forall k \in K$$
 (3)

$$w_k = l_k + v_k - \sum_r u_{kr}, \quad \forall k \in K$$
(4)

$$x_{kr} \leq u_{kr} \lfloor p/t_{kr} \rfloor, \quad \forall k \in K, \quad \forall r \in R$$
 (5)

$$\sum_{k} x_{kr} \ge n_r, \quad \forall r \in R \tag{6}$$

$$\Pr\left(\sum_{k} x_{kr} q_{k} \ge D_{r}\right) \ge 1 - \alpha_{r}, \quad \forall r \in R$$
(7)

 $u_{kr}, v_k, w_k, x_{kr} \ge 0$ and integer, $\forall k \in K, \forall r \in R$ (8)

The objective function (1) denotes the goal to minimize the total cost (the sum of the operating cost and the cost of chartering ships, minus the revenue obtained by chartering ships out). Constraint (2) ensures that the total number of ships (of type k) deployed does not exceed what is available to the liner company, i.e. the sum of ships (of type *k*) it owns plus the number of ships (of type *k*) chartered from other ship owners. In constraint (3), a maximum is imposed on the number of ships that can be chartered from others, whereas constraint (4) is a conservation constraint that ensures that all ships that are not deployed are chartered out to maximize profit (cf. Meng et al., 2012). The maximum number of voyages (on route r) ships of type *k* can complete within the planning horizon of *p* days is given by the product of u_{kr} (the number of ships of type k assigned to route r) and $|p/t_{kr}|$, where |a| denotes the largest integer smaller or equal to *a*. This is captured in constraint (5). Constraint (6) states that the number of voyages to be completed on route r should at least correspond to the liner's desired minimum sailing frequency on route r. If shipping demand is random, when a ship on route r rotates among the *N* ports $j_1, j_2, j_3, \dots, j_N$, then the shipping demand $D_r^{(j_i, j_{i+1})}$ on each leg (j_i, j_{i+1}) of the voyage (with $j_{N+1} \equiv j_1$) will be a random variable as well since it is the sum of the (stochastic) shipping demand over all port pairs that utilizes leg (j_i, j_{i+1}) in transporting cargo to their final destinations (e.g. see Wang et al., 2013). Following previous models, the planning philosophy to design for the highest shipping volume among all legs, i.e. $D_r = \max_{(j_i, j_{i+1})} \{D_r^{(j_i, j_{i+1})}\}$, is adopted. Specifically, constraint (7) guarantees that, with a probability of at least $1 - \alpha_r$, the deployed vessel capacity is sufficient to transport the uncertain shipping demand on all legs of route r. Finally, constraint (8) enforces non-negativity and integrality of the decision variables in the model. In fact, although Model (P1) differs from the two-stage stochastic programming model in Meng et al. (2012), using the same proof as in the aforementioned paper, it is easy to show that the integrality constraints on v_k and w_k can be relaxed.

Lemma 1. The integrality constraints on v_k and w_k in Model (P1) can be relaxed without changing the optimal solution.

As stated, until now, the liner fleet deployment problem has been solved with the assumption that probability distributions characterizing shipping demand are completely known (cf. constraint (7)). More specifically, prior studies typically define distributions for the shipping demand between origin–destination port pairs that, in turn, determine the distributions of $D_r^{(i,i_{i+1})}$ and D_r . For example, Meng and Wang (2010) employ the normal distribution, whereas Wang et al. (2013) use the lognormal distribution. To support these assumptions, the authors argue that (log)normal distributions are typically used in inventory management. The Download English Version:

https://daneshyari.com/en/article/479670

Download Persian Version:

https://daneshyari.com/article/479670

Daneshyari.com