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Joint service capacity planning and dynamic container routing in shipping network with uncertain demands

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ABSTRACT

Service capacity planning is a key tactic decision in container shipping, which has a significant impact on daily operations of shipping company. On the other hand, operational decisions such as demand fulfilment and shipment routing will impact on service capacity requirements and utilisation, particularly in the presence of demand uncertainty. This article proposes a two stage stochastic programming model with recourse to deal with the problem of joint service capacity planning and dynamic container routing in liner shipping. The first stage of the model concerns how to determine the optimal service capacity, and the second focuses on the optimal routing of shipments in stochastic and dynamic environments under a given service capacity plan. Initially, SAA (Sample Average Approximation) is employed to solve the model. Noting the computational complexity of the problem, Progressive Hedging Algorithm (PHA) is employed to decompose the SAA model into a number of scenario-based models so that reasonably large scale problems can be solved. To handle larger scale problems, we develop a new solution procedure termed as APHA (Adapted Progressive Hedging Algorithm) that further decomposes the scenario-based model into job (customer order) based models with measurable error bounds. Numerical experiments are conducted to illustrate the effectiveness of the proposed APHA in solving the problems under consideration.

1. Introduction

Container shipping industry plays a very important role in world economy. Each year container shipping industry transports two-thirds of the value of total global trade, which equals more than US$ 4 trillion. It also has direct gross output or GDP contribution – US$ 183.3 Billion per year (http://www.worldshipping.org/benefits-of-liner-shipping/global-economic-engine). Improving the efficiency of container transport system would benefit not only the shipping industry itself but also other broad industrial sectors and the general public.

One of the key decisions in container shipping is to determine the service capacity (i.e. supply) to meet fluctuating trade (i.e. demand). Basically, the issue concerns how to determine the capacity of each vessel deployed on the shipping service network, which includes the decisions on chartering in slot capacities from other companies' vessels (e.g. the slot exchange and purchase between members of a shipping alliance). The importance of the problem can be evidenced from several

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aspects. Firstly, the purchase of container vessel involves huge capital investment, e.g., in the current ship markets, one 4000-TEUs vessel costs \$60 million roughly, and a 12,000-TEUs vessel costs \$120 million. Secondly, it has a medium/long-term and significant impact on the operations of shipping companies, e.g., a container ship's life span can be as long as some 30 years. Thirdly, nowadays shipping alliance is becoming increasingly popular in shipping practice, which involves vessel sharing and slot chartering between different companies, e.g., CKYHE Alliance, G6 Alliance, and the recent proposals of 2M alliance (Maersk and MSC) and Ocean Three alliance (CMA CGM, UASC and CSCL). As the members of an alliance are independent from the financial and market perspective, it is vital for them to determine how much capacity of their own vessels should be kept and how much capacity of other members' vessels should be chartered in by considering their own market demands. Fourthly, a service capacity planning problem can also be regarded as a part of liner service network design problem, in which the shipping line needs to determine its service capacity (and vessel deployment) in the service network (that may consist of existing service routes and new candidate service routes). For example, Maersk uses the term 'network management' to describe the adjustment of their service routes and service capacity in response to the change of demand patterns and/or the deployment of new ships (e.g. the delivery of Triple-E vessels in 2013), and regards it as the heart of their business.

Determining service capacity is interwoven with the routing of container shipments on shipping network. The optimal service capacity can only be obtained when container flow is distributed in the best way. In shipping practice, container flows are driven by uncertain and dynamic customer demands. It is a challenging task to find the optimally distributed container flows and consequently the optimal service capacity in a stochastic and dynamic environment. In the paper, we will use a two-stage stochastic model with recourse to tackle the challenge. In shipping practice, container flows are driven by uncertain and dynamic customer demands. It should be pointed out that forecasting the market demand is difficult due to many external factors including the potential competitors and their behaviours. However, as most shipping lines have been running business for many years and their historical data could be used as reference data to fit into a probability distribution. In fact, probability distribution is a common approach to represent uncertain demands in the literature, e.g. (Christiansen et al., 2004; Meng et al., 2012). Furthermore, our model uses the average value of sample processes to approximate the expected value of the random variables, which essentially just takes historical demand information as input without the need to determine the distribution function of demand.

Many studies in relation to service capacity planning and container routing have been conducted. In previous studies, service capacity planning is partially dealt with under the name of Liner Ship Fleet Deployment (LSFD). LSFD aims to decide how many vessels for a specific type should be deployed to each service route on container shipping network. The solution to LSFD implies the capacities that a service route should have. Service capacity planning is significantly different from LSFD. LSFD normally selects vessels from a given set of vessel types and the vessels deployed on each service route are homogeneous, whereas service capacity planning in our context concerns more about the amount of TEU slots on each vessel rather than the vessel type, which implies that the available capacities could vary vessel by vessel even they belongs to the same service route. With regard to LSFD, the studies can be classified as deterministic models and stochastic models. The deterministic models have been proposed in Perakis and Jaramillo (1991), Jaramillo and Perakis (1991), Cho and Perakis (1996), Powell and Perakis (1997), Gelareh and Meng (2010), Wang et al. (2011), Meng and Wang (2011a,b), and Zacharioudakis et al. (2011). These models consider either direct shipping service or single service route, and therefore, transhipment issues are not concerned. Some other deterministic models have been designed for multiple service routes where transshipments have been considered, e.g., Mourão et al. (2002), Liu et al. (2011), Wang and Meng (2012a), Meng and Wang (2012), and Fagerholt et al. (2009). The research methods adopted in the deterministic models are mainly Linear Programming (LP), Integer Linear Programming (ILP) or Mixed Integer Linear Programming (MILP). The research community has also recognised the stochastic nature of the issue, and developed a number of stochastic models. Meng and Wang (2010) perhaps is the first study considering stochastic demands in containership fleet planning. The study focuses on the vessel deployment on a single service route with uncertain demands. A more complex model has been presented in Meng et al. (2012), which considers both transhipment and uncertain demands. Wang et al. (2012) have made some extension to the study by incorporating risk oriented costs into the objective function.

With regard to container routing problems in liner shipping, there was very little research before 2004 (Christiansen et al., 2004). In the last decade, it has attracted a lot of attention. The existing studies can be classified as link-based routing (Alvarez, 2009; Agarwal and Ergun, 2008; Bell et al., 2011, 2013; Meng and Wang, 2012; Yan et al., 2009) and path-based routing (Brouer et al., 2011; Song and Dong, 2012; Wang et al., 2013; Wang and Meng, 2012b). In general, the scale of link-based routing model is smaller than that of path-based routing model as path-based model is based on the enumeration of all possible paths or dynamical generation of the profitable paths (Wang, 2014). However, the majority of the existing studies tackle the container routing problems at the tactic level without considering the detailed operations, e.g. assuming that containers' travelling time on a path and waiting time at transhipment ports are fixed and known input data, and irrelevant to the container routing decisions; there are fixed weekly demands without uncertainties; there are no constraints on the delivery time.

In the study, we will consider service capacity planning and shipment routing with uncertain demands, container transhipment, and delivery time constraints. A two-stage stochastic model with recourse will be developed. The first stage centres on minimising the acquisition costs of service capacity, and the second stage is to seek the optimal dynamic routing plan of container flows with uncertainty. Our second stage model is a dynamic link-based container routing model in which