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A decision support system for vessel speed decision in maritime logistics using weather archive big data

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ABSTRACT

Speed optimization of liner vessels has significant economic and environmental impact for reducing fuel cost and Green House Gas (GHG) emission as the shipping over maritime logistics takes more than 70% of world transportation. While slow steaming is widely used as best practices for liner shipping companies, they are also under the pressure to maintain service level agreement (SLA) with their cargo clients. Thus, deciding optimal speed that minimizes fuel consumption while maintaining SLA is managerial decision problem. Studies in the literature use theoretical fuel consumption functions in their speed optimization models but these functions have limitations due to weather conditions in voyages. This paper uses weather archive data to estimate the real fuel consumption function for speed optimization problems. In particular, Copernicus data set is used as the source of big data and data mining technique is applied to identify the impact of weather conditions based on a given voyage route. Particle swarm optimization, a metaheuristic optimization method, is applied to find Pareto optimal solutions that minimize fuel consumption and maximize SLA. The usefulness of the proposed approach is verified through the real data obtained from a liner company and real world implications are discussed.

1. Introduction

Speed optimization in liner shipping has significant economic and environmental impact for reducing fuel cost and Green House Gas (GHG) emission as the shipping over maritime logistics takes more than 70% of world transportation (UNCTAD, 2010; Psaraftis and Kontovas, 2013). While slow steaming is widely used as best practices for liner shipping companies, they are also under the pressure to maintain service level agreement (SLA) with their cargo clients (Lee et al., 2015; Parthibaraj et al., 2016). Thus, deciding optimal sailing speed which minimizes fuel consumption while maintaining SLA is an important managerial decision problem for liner companies.

Sailing speed decision mainly depends on the vessel schedule and it is a challenging problem due to the uncertainties imposed in maritime logistics such as stochastic port times and weather conditions. Port time uncertainty significantly affects the time that vessels spend at ports in anchorage, berthing, unberthing or drifting status. Increased port congestion and delays can negatively affect service level of shipping lines to their customers and put pressure on schedule reliability and might incur logistics costs to the customer (Notteboom, 2006). On the other hand, weather conditions including current and wind affect journey times and the routing decisions (Kontovas, 2014).

The majority the literature work on the speed optimization problem based on a theoretical fuel consumption function. For example, Fagerholt et al., (2010) and Yao et al., (2012) propose a fuel consumption function which is based on the empirical data from a shipping company. However, these functions do not reflect the actual fuel consumption of vessels that are affected by weather conditions. In reality, certain routes may encounter harsher weather conditions than others and speed optimization needs to consider such different voyage environments.

In Fig. 1, we compare the theoretical fuel consumption based on the empirical model proposed by Yao et al., (2012) with the historical fuel consumption data obtained from a liner shipping company. The data belongs to a Turkish liner service with 10 ports-of-call operated in the Mediterranean region. 15 voyages performed by the same vessel of this service in 2013 are analyzed. Fig. 1 illustrates the change in total fuel consumption with respect to time in sea in terms of day. Although fuel consumption mainly depends

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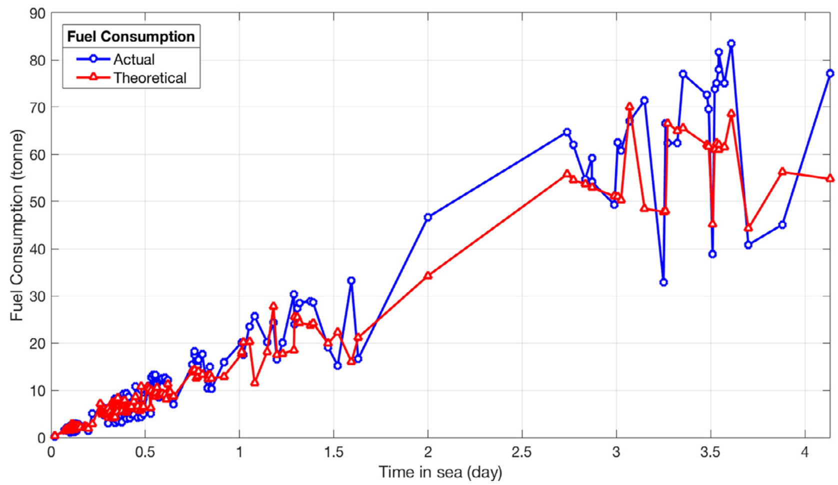

Fig. 1. The actual and theoretical fuel consumption levels with respect to time in sea.

on the vessel sailing speed, there are other affecting factors such as the weather conditions (winds, currents, etc.). The differences between the estimated consumption and the actual one illustrate the effect of these factors. In particular, fuel consumption difference becomes larger when the time in sea is longer. In this study, we focus on the speed optimization problem by considering the effect of weather conditions on fuel consumption.

Different vessel routes have different weather conditions hence, it is difficult to have unified weather adjustment functions to correct the differences between actual and theoretical fuel consumption. The impact of current and winds on fuel consumption varies depending on the routes due to the geographical characteristics. Thus, it is more realistic to identify different impacts of weather conditions in different routes based on historical voyage data and weather data. The analysis of weather archive big data which is publicly available on the Internet in comparison with actual fuel consumption data from liner companies provides an opportunity to measure different impacts of weather conditions on fuel consumption of vessels.

Despite the opportunity, using weather archive big data in vessel speed optimization requires overcoming following challenges. Firstly, weather archive data provides an opportunity to apply big data analytics to estimate the degree of the impacts of weather conditions on fuel consumption of vessels in different routes based on its huge volume of historical data. However, most of such archive data is not easy to use due to the format, volume, and velocity of data. Secondly, the relationship between weather conditions and fuel consumption is different for different routes and difficult to model as a single mathematical formula. In this study, we apply a data mining technique to explore such non-linear relationships based on historical weather and voyage big-data from a liner company.

This paper proposes a decision support system (DSS) that uses weather archive big data in vessel speed optimization overcoming above challenges. To the best of our knowledge, the impact of weather conditions on fuel consumption in liner shipping has not been explicitly considered in the literature. This paper aims to fill this research gap. In particular, we focus on speed optimization problem in liner shipping by considering the weather impact. The speed decision affects the transit time between ports, and in turn, affects the service level. Hence, we also study the trade-off between minimizing fuel cost and maximizing service level. A particle swarm optimization (PSO) technique based solver is proposed to solve this multi-objective problem. Based on a real shipping data, we analyze the impact of weather conditions on the fuel consumption.

The remainder of the paper is organized as follows. Section 2 reviews related studies with regard to speed optimization in maritime logistics. Section 3 then formulates the target problem as a multi-objective optimization problem. The details of the decision support system are given in Section 4. In Section 5, experiment results based on data obtained from a real liner shipping company are provided to verify the usefulness of the proposed decision support system. Finally, Section 6 concludes the paper.

2. Literature review

Optimization techniques have been widely applied to maritime operations including ship routing and scheduling, fleet management, disruption handling, and bunkering. Christiansen et al., (2013) provide a survey of studies on ship routing and scheduling. The literature on bunker optimization methods in maritime shipping has been summarized by Wang et al., (2013). Tran and Haasis (2015) review the literature on container liner shipping with respect to container routing, fleet management and network design. Recently, Mansouri et al., (2015) have reviewed existing studies in maritime operations from sustainability and decision support perspective.

Speed optimization is one of the important problems for sustainable maritime operations as the CO_2 emission is directly affected by the fuel consumption which is determined by vessel speeds. Early studies on the speed optimization problem assume deterministic port times and strict time windows (Fagerholt et al., 2010; Hvattum et al., 2013; Norstad et al., 2011; Andersson et al., 2015). The proposed models restrict vessels to arrive at the contracted time windows to meet 100% service level agreement. However, in reality such assumption is too strong and it is reported that only 55% to 89% vessels arrive on time at ports (Drewry, 2016). Port and travel times can be highly variable due to congestion, handling and weather conditions (Notteboom, 2006). Thus, recent studies in this field extend the speed optimization problem by considering uncertainties at ports and voyage routes (Qi and Song, 2012; Aydin et al., 2017). Qi and Song (2012) propose a vessel scheduling model to minimize the total fuel cost by considering uncertain port times and frequency requirements. In their formulation, they relax the port time window constraint and allow vessels to arrive at any time. On the other hand, Aydin et al., (2017) extend the problem by considering the time windows and bunkering decisions.

The speed optimization models generally assume that fuel consumption solely depends on the vessel speed (Psaraftis and Kontovas, 2013). Yao et al., (2012) propose optimal bunker manage-