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Flexible solutions to maritime inventory routing problems with delivery time windows

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ABSTRACT

This paper studies a Maritime Inventory Routing Problem with Time Windows (MIRPTW) for deliveries with uncertain disruptions. We consider disruptions that increase travel times between ports and ultimately affect the deliveries in one or more time windows. The objective is to find flexible solutions that can accommodate unplanned disruptions. We propose a Lagrangian heuristic algorithm for obtaining flexible solutions by introducing auxiliary soft constraints that are incorporated in the objective function with Lagrange multipliers. To evaluate the flexibility of solutions, we build a simulator that generates disruptions and recovery solutions. Computational results show that by incurring a small increase in initial cost (sometimes zero), our planning strategies generate solutions that are often significantly less vulnerable to potential disruptions. We also consider the effect of lead time in being able to respond to the disruptions.

1. Introduction

The classical Maritime Inventory Routing Problem with Time Windows (MIRPTW) is to find an optimal routing plan that minimizes the total cost of transportation, while satisfying inventory constraints and contractual delivery constraints. 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 affected by weather conditions. Focusing on this type of uncertainty, we consider MIRPTW with unpredictable disruptions.

The MIRPTW studied in this paper is motivated by the Annual Delivery Program (ADP) planning problem in the LNG industry. The overall ADP planning activity is to develop contractual agreements of delivery plans that specify delivery dates (or time windows) and the corresponding delivery quantities. Because customers receive product from numerous sources, they typically negotiate delivery amounts and delivery times with each of their vendors. Therefore, from the vantage point of a single vendor, final agreements are reached through many rounds of negotiations and discussions with multiple customers. At each iteration of the negotiations and after the final agreements are determined, the vendor must generate routing solutions according to the tentative (or final) agreements to check their feasibility, and examine the operational costs and their ability of accommodating unplanned random events. The scope of this paper is limited to developing an optimization framework that generates such routing solutions with given delivery time windows and quantities. Our goal is to demonstrate that the creation and solution of a model that contains the core difficulty of dealing with uncertainty can be achieved.

There is a subtle difference between *flexible* solutions and *robust* solutions in terms of dealing with uncertainty in optimization. In King and Wallace (2012, page 12), robust solutions are considered as those that help us withstand random events while flexible solutions are considered as those that help us accommodate those events. The former one is related to the question of whether a solution can be changed while the latter one is related to the cost of repairing an original solution in case of future random events. This distinction often depends upon whether recourse options are available after random events occur. In the ADP planning problem, the delivery dates (or time windows) and the total delivery quantities cannot be changed once final agreements are settled, but the corresponding routing solutions can be adjusted in a later stage in case of unplanned disruptions. In this paper, we develop an optimization framework that generates flexible routing solutions with given contractual agreements, and hence are interested in finding flexible solutions that can accommodate unplanned disruptions. To evaluate the flexibility of a planning solution, we built a simulation that generates random disruptions and re-optimizes the origi-

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nal plan in each case. The increase between the average simulated cost over all the simulated disruption scenarios under a planning solution and its original planning cost measures the flexibility of the planning solution. An optimal planning solution assuming no disruptions may yield a significant cost increase in case of random disruptions (low flexibility), while on the other hand, a planning solution with high flexibility can be much more expensive than an optimal plan assuming no disruptions. In this paper, we are concerned about finding solutions with high flexibility that have little or zero planning cost increase compared to an optimal one.

1.1. Relevant studies

Various definitions and approaches for dealing with uncertainty in optimization have appeared in the literature. Robust optimization (Ben-Tal et al., 2009) is one modeling framework for dealing with uncertain data in optimization. However, as stated in the above paragraph, in this study we are interested in flexible solutions that can accommodate random events with low-cost recourse options rather than robust solutions that are sometimes too conservative under the worst-case assumption of robust optimization. On the other hand, the two-stage Stochastic Programming (SP) approach provides a framework for dealing with uncertainty in optimization where the first-stage (second-stage) variables are determined before (after) the actual realization of uncertain parameters. To deal with a large number of uncertain scenarios that need to be considered in the SP framework, the Sample Average Approximation (SAA) method was introduced. Convergence results and efficient algorithms are very well studied when integrality conditions are not required in the two-stage SP (We refer to Shapiro et al., 2009 for a survey of SP and SAA). Kleywegt et al. (2002) and Verweij et al. (2003) extend the results of the SAA approach when first-stage variables are discrete and finite. However, much less is known when second-stage decisions contain integer variables as the associated objective function is generally nonconvex and discontinuous. Schultz (1996) and Ahmed et al. (2002) study the SAA method for SP when second-stage variables are purely integer. In addition to the most common approaches mentioned above, Fischetti and Monaci (2009) propose a general heuristic scheme for robustness called Light Robustness where a set of slack variables is used to measure an estimate of the solution robustness and their sum is minimized in the objective function. In this study, we focus on generating flexible solutions with limited vulnerability to unpredictable disruptions, and use a different approach for dealing with the uncertainty. After analyzing problem characteristics that may provide solutions with flexibility, we quantify them as soft constraints that are incorporated in the objective function with Lagrange multipliers. We use a subgradient algorithm to find candidate solutions to evaluate. Furthermore, to evaluate the flexibility of schedules, we build a simulator that generates disruptions and recovery solutions. By simulating various disruption events, we show that the actual operational costs in case of disruptions can be significantly reduced when flexible plans are implemented. To the best of our knowledge, only Cacchiani et al. (2012) discuss this kind of approach for dealing with robustness in the literature. They propose a Lagrangian heuristic for solving a robust train timetabling problem. The process collects a set of “Pareto optimal” heuristic solutions, and the robustness of a solution is evaluated by calculating a predefined measure.

Christiansen et al. (2007, 2004) and Papageorgiou et al. (2012) give comprehensive reviews of maritime inventory routing problems. However, there are only a few studies that deal with planning under uncertainty in the shipping industry. Christiansen and Fagerholt (2002) study a multi-ship pickup and delivery problem with soft time windows. They design robust schedules that are less likely to result in ships staying idle at ports during weekends by imposing penalty costs for arrivals at risky times. Also motivated by uncertainties in maritime transportation, Agra et al. (2012); 2013c) investigate a vehicle routing problem with time windows (VRPTW) 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. To solve large instances of the robust VRPTW with budgeted uncertainty, Braaten et al. (2017) proposes a heuristic based on adaptive large neighborhood search. Similarly, the robust optimization framework is applied in Alvarez et al. (2011) to solve a multi-period fleet sizing and deployment problem with uncertainty in price and demand. A simulation study for a liquefied natural gas (LNG) ship routing problem with uncertainty in sailing time and production rate is presented in Halvorsen-Weare et al. (2013), and several robustness strategies are discussed in the paper. Tirado et al. (2013) applies three heuristics to a dynamic and stochastic maritime routing problem, and demonstrate that average cost savings of 2.5% can be achieved by including stochastic information in the model. Agra et al. (2015) considers a stochastic short sea shipping problem with uncertainty in weather conditions and unpredictable waiting times in ports. A two-stage stochastic programming model is presented where the first-stage decisions consist of routes, loading and discharging quantities while the schedule of loading and discharging operations can be adjusted in the second stage.

More work has been done on stochastic airline scheduling problems. Various studies of scheduling under uncertainty in the airline industry can be found in Ageeva (2000), Rosenberger et al. (2003), Rosenberger et al. (2004), Schaefer et al. (2005), Lan et al. (2006), Shebalov and Klabjan (2006), Smith and Johnson (2006), Yen and Birge (2006) and Chiraphadhanakul (2010). Vehicle routing problems with stochastic travel times is an extensively studied topic in the literature. One of its most important variants accounts for customer time windows or service deadlines. We refer to Gendreau et al. (2016) for a comprehensive review on stochastic vehicle routing problems.

1.2. Uncertainty in maritime transportation

Christiansen et al. (2007) discuss some problems from the shipping industry where robustness plays an important role and categorize them into strategic, tactical and operational planning problems. At the strategic level, the uncertainties can affect the quality of decisions regarding fleet sizing and composition. At the tactical level, they state that “several unpredictable factors influence the fulfillment of plans and should be considered in the planning process. The two most important are probably: (1) weather conditions that can strongly influence the sailing time, and (2) port conditions such as strikes and mechanical problems that can affect the time in port”. At the operational level, we may consider delays due to tides and restricted opening hours at ports. This paper is concerned with the disruptions at the tactical level. To mitigate the effects of such disruptions, at the planning stage, we can strategically develop routes possessing characteristics that allow for flexible re-routing when a disruption occurs. At the operational level, there are some other recovery options such as adjusting ship speed in the presence of disruptions. Ronen (1982) considers the effect of oil price on the optimal speed of ships. A cubic function is used to approximate the relationship between sailing speed and fuel consumption in his models. Decisions at the planning and operational levels usually require separate models and including operational decisions into a planning model over a long time horizon can significantly increase the computational effort. Therefore, the uncertainties at the operational level such as travel times and service times (time to load/discharge) are considered when we generate